UCLA
UCLA Previously Published Works

Title

Party On: The Labor Market Returns to Social Networks in Adolescence

Permalink

https://escholarship.org/uc/item/8754375x

Journal

Journal of Labor Economics, 44(1)

ISSN

0734-306X

Authors

Lleras-Muney, Adriana
Miller, Matthew
Sheng, Shuyang
et al.

Publication Date

2026

DOI

10.1086/731308

Peer reviewed

eScholarship.org Powered by the California Digital Library
University of California

Party On: The Labor Market Returns to Social Networks in Adolescence*

Adriana Lleras-Muney, Matthew Miller, Shuyang Sheng, and Veronica Sovero†

March 25, 2024

Abstract

We investigate the returns to adolescent friendships on earnings in adulthood using data from the National Longitudinal Study of Adolescent to Adult Health. Because both education and friendships are jointly determined in adolescence, OLS estimates of their returns are likely biased. We implement a novel procedure to obtain bounds on the causal returns to friendships: we assume that the returns to schooling range from 5 to 15% (based on prior literature), and instrument for friendships using similarity in age among peers. Having one more friend in adolescence increases earnings between 7 and 14%, substantially more than OLS estimates would suggest.

1 Introduction

An individual's social capital (the number and quality of their connections) impacts many economic outcomes. Individuals' classroom and school peers impact their education (Sacerdote, 2001; Carrell, Fullerton, and West, 2009), earnings (Carrell, Hoekstra, and Kuka, 2018; Michelman, Price, and Zimmerman, 2021) and health (Carrell, Hoekstra, and West, 2011).

*We are grateful to seminar and conference participants at Northwestern University, Santa Barbara University, USC, Peking University, SOCCAM, the All-California Labor Economics conference, the North American Winter Meeting of the Econometric Society, the Asian Meeting of the Econometric Society in China, and the China Labor Economist Conference. We are particularly grateful to Larry Katz for his very insightful suggestions. This project was supported by the California Center for Population Research at UCLA (CCPR), which receives core support (P2C- HD041022) from the Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD). Research done prior to joining Audible. Audible is a subsidiary of Amazon. All views contained in this research are the author's own and do not represent the views of Amazon or its affiliates. All errors are our own.

†Adriana Lleras-Muney, Department of Economics, UCLA, email: alleras@econ.ucla.edu; Matthew Miller, Audible Inc, email: mattmm@audible.com; Shuyang Sheng, Department of Economics, UCLA, email: ssheng@econ.ucla.edu; Veronica Sovero, Department of Economics, UC Riverside, email: vsovero@ucr.edu.

Whom one befriends from among these peers also influences important lifetime outcomes: Chetty et al. (2022) show that the number of high SES friendships and economic mobility in a neighborhood are positively associated. However, there is little evidence on whether the number of one's friends (not just the types they are exposed to) causally affect labor market outcomes.

Using data from the National Longitudinal Study of Adolescent to Adult Health (hereafter Add Health), which follows individuals from adolescence into adulthood, we study the labor market returns to adolescent friendships. During adolescence, individuals develop important cognitive and social skills, have key educational outcomes determined and form friendships (Heckman and Mosso, 2014). Friendships are associated with better larbor market outcomes: Figure 1 plots log annual earnings at ages 24–34 against the number of friends at ages 12–20, separately for males and females. The non-parametric lines show a striking positive association between adolescent friendships and young adult earnings for both sexes.[1] OLS estimates of this association may be biased downward however: individuals with social skills may engage in activities excluded from regressions, like drinking and partying, that help them make friends but reduce their education and earnings. This "taste for partying" is unobserved and omitted from earnings regressions, and can cause the return to friendships to be downward biased. Conversely, social individuals may prefer productive social activities (working together), which improve their networks and yield higher earnings, biasing the return to friendships upward.[2]

To estimate the causal returns to friendships, we construct an instrument for the number of friends that exploits the fact that homophily (similarity in traits) predicts friendship formation (Boucher, 2015; Jackson, 2014). Our instrument is the average absolute difference in age between a student and the peers in her school and grade, which we refer to as age distance. Because our baseline regression controls for own age and the average age of individuals in the school-grade, as well as grade and school fixed effects, age distance will vary across individuals because the distribution of ages varies across schools and grades. For example, a 13.5 year old with two peers aged 12.5 and 14.5 has an age distance of 1 while mean age is 13.5. If the same 13.5 year old were instead in a group with a 13 year old and a 14 year old, mean age would be the same, but age distance would be smaller (0.5), resulting in more friends. This variation is similar to what is used in Bifulco, Fletcher, and Ross (2011) and Carrell, Hoekstra, and Kuka (2018), who leverage variation across cohorts within schools to estimate the effects of peer characteristics on outcomes.[3] In our setting, there is

[1] We detail later in the paper how we measure the number of friends.

[2] Social skills are associated with large and growing returns in the labor market (Weidmann and Deming, 2021; Deming, 2017).

[3] These papers typically investigate the direct (reduced form) relationship between peer traits and out-

also variation in the instrument *within* school-grade because age distance depends both on the mean age in their group and the student's own age. Our identification strategy is most similar to Fletcher, Ross, and Zhang (2020) who investigate the effect of friendships on education outcomes using similarity in race/ethnicity and socioeconomic status as instruments for friendships. We investigate the effect of friendships on earnings instead.

Education is also endogenous in these regressions because educational and social investments are determined jointly in adolescence. Studies with well-identified causal returns to education make use of large data sets and typically exploit state-level variation in compulsory schooling or the cost of schooling, such as distance to school (Mountjoy, 2022) or school openings (see Card (2001) for a review and Gunderson and Oreopolous (2020) and Psacharopoulos and Patrinos (2018) for more recent examples). In our data, these instruments are weak predictors of education.

We propose a novel approach to estimating the returns to friendships that does not require instruments for education. We rely on the findings from the previous literature and assume that the causal returns to a year of schooling range from 5 to 15% (Gunderson and Oreopolous, 2020; Psacharopoulos and Patrinos, 2018). Under this assumption, and making use of the homophily-based instrument for friendships, we derive bounds for the returns to friendships.[4]

We find that the returns to having one more friend during adolescence range between 7 and 14%, similar to the returns to one more year of schooling. Our identifying assumption is that age distance determines earnings only through its effects on education and friendships, conditional on own characteristics, mean peer characteristics, and grade and school fixed effects. The results are robust to a number of checks, including addressing the potential concern that parents sort into schools or grades based on relative age. These instrumented returns to friendships are larger than OLS estimates. Computations suggest that measurement error can explain the discrepancy, consistent with Griffith (2021). The result is also consistent with downward omitted variable bias: the data show that preferences for activities like drinking are associated with more friendships but lower GPA and earnings.

We contribute to the well-established literature examining peer effects among adolescents and young adults (see the review by Jeon and Goodson, 2015).[5] For example, having peers

comes. Although we leverage similar (though not identical) variation, we use this variation in peer characteristics as an instrument for friendships – we do not study the direct effect of peer similarity on outcomes.

[4]We are grateful to Larry Katz for suggesting this approach.

[5]Identifying how the behaviors and characteristics of peers affect individuals was first discussed by Manski (1993). A few early papers (Bramoullé, Djebbari, and Fortin, 2009) attempted to use friendship networks to instrument for peer outcomes and overcome the joint determination of outcomes (the reflection problem). These papers assume that a friendship network is exogenous or endogenous through unobserved group heterogeneity.

with good academic outcomes improves one's academic outcomes (Carrell, Malmstrom, and West, 2008; Carrell, Fullerton, and West, 2009; Sacerdote, 2011; Bifulco, Fletcher, and Ross, 2011; Denning, Murphy, and Weinhardt, 2023). Peer effects in adolescence can also carry into adulthood. Carrell, Hoekstra, and Kuka (2018) find that having disruptive peers in the classroom during adolescence has deleterious effects on individuals' labor market outcomes as adults, partly because disruptive peers lower test scores.

Our paper suggests a new mechanism by which peer characteristics might operate: friendship formation. A few papers investigate the effects of friendship networks on educational outcomes using data on friendship nominations (Babcock, 2008; Lavy and Sand, 2018; Fletcher, Ross, and Zhang, 2020). However, friendships may also matter for labor market outcomes, separately from their effects on education attainment. Previous work documents that the size and connectedness of an individual's social network in adulthood can improve wages and job match quality (Granovetter, 1973; Montgomery, 1991; Calvo-Armengol and Jackson, 2004; Cappellari and Tatsiramos, 2015; Dustmann et al., 2015). In addition to the number of friends, the types of friends one is associated with may also impact labor market outcomes (Chetty et al., 2022). Although our results on this are only suggestive (we do not have powerful instruments for different types of friendships), we find that almost all types of friendships have returns in the labor market, including friends from low SES backgrounds and with weak connections. This suggests that the overall number of friendships – not just their type – is a relevant factor in determining earnings.

There are no papers we are aware of that estimate the *causal* returns to the number of friendships on labor market outcomes – this is the main contribution of this paper. The closest paper to ours is by Conti et al. (2013), who estimate returns to high school friendships on wages using data from the Wisconsin Longitudinal Survey. Their estimation strategy corrects for non-classical measurement error in the number of friendships due to under-sampling, but they do not account for endogeneity in both education and friendships which this paper addresses.

Our second contribution is methodological. A strand of econometric literature considers models with *endogenous* networks (Goldsmith-Pinkham and Imbens, 2013; Hsieh and Lee, 2016; Badev, 2021; Johnsson and Moon, 2021; Auerbach, 2022; Griffith, 2022; Sheng and Sun, 2023). But these papers do not consider the joint determination of education and friendships. As a result, they do not address how the endogeneity in education complicates the identification of causal labor market returns to friendships.

Our identification approach is motivated by the econometric literature on partial identification, which is widely used as a remedy for identification failure in various applications such as interval data (Manski and Tamer, 2002), missing data (Manski, 2003), auctions (Haile

and Tamer, 2003), and games with multiple equilibria (Tamer, 2003). We exploit the idea of partial identification to resolve a new challenge where we lack a good instrument for one of the endogenous regressors, but the coefficient of that regressor is not of primary interest and can be bounded. To our knowledge, this is the first paper that proposes a partial identification approach to avoiding instrumenting for a secondary endogenous regressor.

2 Conceptual Framework: How are Friendships Formed in Adolescence?

We start by summarizing a basic model of education and friendship formation (Appendix B) and describe its implications for the empirical analysis.[6]

During adolescence, individuals decide how to allocate their time between studying, socializing, and leisure. Studying increases educational attainment, and socializing increases one's number of friends, both of which have positive returns in the labor market. In deciding how to allocate their time, individuals consider the returns to each activity, which depend on their innate intelligence and social skills (Proposition B.4).

Because time spent investing in education and friends is determined at the same time, both education and friendships are potentially endogenous in a Mincer earnings equation and thus OLS estimates of their returns may be biased. However, the sign of the bias in friendship returns is not clear ex-ante (Proposition B.2). On the one hand, social skills may determine the number of friendships and have an independent effect on earnings, causing an upwards bias in the returns to friendships. On the other hand, partying and drinking may increase friendships but negatively affect skill accumulation and labor market outcomes, causing a downward bias in the returns to friendships.

To account for the endogeneity of friendships, we will exploit the fact that an individual's accumulated social capital also depends on the traits and decisions of their school-grade peers because the production of friendships requires coordination with others – you cannot "party alone". Conditional on time spent socializing, individuals that are more similar to each other are more likely to become friends.[7]

3 Data

We use the restricted-use National Longitudinal Study of Adolescent to Adult Health (Add Health). The in-school sample is a complete census of all students enrolled in a given school

[6] All figures and tables designated with a letter (e.g., "A", "B") are shown in the Online Appendix.
[7] In equilibrium this may not hold (see Proposition B.3).

during the 1994–95 school year. The in-school sample data include basic demographics as well as friendship nominations. A random sample of the students interviewed in school was selected for in-home interviews in Wave 1 during the 1994–95 school year (ages 12–20 years) and tracked over in subsequent survey waves. In Wave 4 (which was conducted in 2008–09), respondents were age 24 to 34, on average 29 years old. For this in-home sample, we observe measures of endowments, investments, and cognitive and social outcomes.

Our estimation sample is constructed from the in-home sample, but we use information from the in-school sample to construct friendship and homophily measures. We include 10,605 individuals with complete data for gender, age, and race. Summary statistics for the estimation sample are presented in Table 1.

Outcomes. The main outcome of interest is total earnings from wages or salary in the last year. If a respondent replied "do not know" to the earnings question, they were prompted with twelve categories of earnings. We use the midpoint of the selected range for these respondents (approximately 2% of the sample). We drop individuals who reported zero earnings (~6%), which means they were unemployed the entire year. Individuals in our sample made roughly $38,000 in the previous year.

Intermediate outcomes: friendships and education. Our primary measure of the number of friendships is a person's *grade in-degree*. For a given student, grade in-degree is the number of people *within the same school and grade* who nominate them as one of their friends in Wave 1.[8] In-degree has been widely used in the social network literature as an objective measure of an individual's number of friendships because it does not rely on self-reporting (Conti et al., 2013). Importantly, we observe all nominations sent to students in the in-home sample because the network data is derived from the in-school sample. Unlike Add Health's measure of in-degree, we exclude nominations from students in different grades: the majority of nominations (77%) occur within the same grade (on average, school in-degree is 4.4, whereas grade in-degree is only 3.4 (Table 1)).

Education is measured by years of schooling. On average, individuals in our data obtain almost 15 years of schooling. We also observe GPA, a measure of how much students learned in school.

Endowments. We use self-reported extroversion, collected in Wave 2, as the main measure of the social endowment of individuals. Extroversion is one of the "Big Five" psychological traits. About 65% of individuals report being extroverted.[9] Consistent with existing

[8]Individuals could list up to five nominations of each gender.

[9]The survey question is "You are shy?", and the the choices are "strongly agree / agree / neither agree nor disagree / disagree / strongly disagree". Individuals choosing last three categories are defined as extrovert. Due to the survey design this measure is missing for 26% of individuals in the data. To maximize sample size, we impute this measure and include a dummy for whether it is missing.

evidence (Lenton, 2014), extroverts have larger earnings, and perhaps not surprisingly, more friends (Columns 2 and 3 of Table 1). Most interestingly, they also have more years of schooling.

The Add Health Picture Vocabulary Test (AHPVT) score is our main measure for cognitive endowments. This test, administered in Wave 1, is an abbreviated version of the widely used Peabody Picture Vocabulary test and measures verbal ability. While it is not an overall measure of intellectual ability, it has a high correlation with other intelligence tests (Hodapp and Gerken, 1999; Dunn and M.Dunn, 2007). For simplicity, we refer to it as IQ. As expected, individuals with above median IQs have greater earnings and education (more years of education and higher GPA). Perhaps surprisingly, they also have more friends (Columns 4 and 5 of Table 1).

4 Empirical Strategy

We now turn our attention to estimating the labor market returns to friendships. We follow the previous literature and estimate the following earnings equation (conditional on employment):

$$Y_i = r_e E_i + r_f F_i + \beta' X_i + \gamma' \bar{X}_{gs} + \alpha_g + \lambda_s + \epsilon_i,$$

where the outcome of interest is the log annual earnings Y_i in Wave 4 for a given individual i (observed in grade g and school s during Wave 1), E_i stands for years of schooling, and F_i is a measure of i's number of friends (such as in-degree). We control for $i's$ characteristics X_i (age in Wave 1, sex, race, IQ, and extroversion) and mean characteristics in $i's$ school-grade $\bar{X}_{gs}$ (mean age, fraction female, fraction white, mean IQ and fraction extrovert). We control for grade fixed effects (α_g) to account for differences across grades within a school. We include school fixed effects (λ_s) to control for unobserved school-level characteristics that could be correlated with labor market outcomes and potentially sort individuals into schools. Standard errors are clustered at the school level.

The object of interest is the coefficient r_f, measuring the returns to having one more friend. Proposition B.2 shows that OLS estimates of r_f are biased because education and friendships are jointly determined. We take an instrumental variable approach to overcome the endogeneity issue, which will also address classical measurement error in number of friends.

We use homophily measures as instruments for friendships, following the evidence that individuals that resemble each other are more likely to become friends (Jackson, 2008). Unfortunately, the instruments for education used in the literature (quarter of birth, distance

to school) are weak in our data. Instead, we propose a novel approach to estimating the returns to friendships that does not require an instrument for education.[10]

4.1 Bounding the returns to friendships

There is a substantial literature estimating the (causal) returns to schooling in the United States using various approaches. While estimates differ across studies and populations, causal estimates of r_e typically lie between 5 and 15% (Card, 2001; Psacharopoulos and Patrinos, 2018; Gunderson and Oreopolous, 2020). Instead of estimating r_e, we assume that r_e, while unknown, lies in this range. Then by instrumenting for friendships only, we derive upper and lower bounds for the (causal) returns to friendships.

Let $\theta = (r_f, \beta', \gamma', \alpha', \lambda')'$ denote the vector of parameters, where $\alpha = (\alpha_g, \forall g)'$ is the vector of grade fixed effects, and $\lambda = (\lambda_s, \forall s)'$ is the vector of school fixed effects. Let $\tilde{X}_i$ denote the vector of friendships F_i and other covariates (individual characteristics X_i, school-grade mean characteristics $\bar{X}_{gs}$, and grade and school dummies), and Z_i the vector that consists of the instruments for F_i (homophily measures) and the covariates. Ideal instruments for friendships satisfy two conditions: (i) they predict friendships F_i ($\mathbb{E}[Z_i\tilde{X}_i']$ has full column rank); and (ii) they are excluded from the earnings equation ($\mathbb{E}[Z_i\epsilon_i] = 0$). Instruments for friendships can also predict education. The exclusion restriction is satisfied if the instruments do not affect earnings except through friendships and education. This exclusion restriction implies the moment condition

$$\mathbb{E}[Z_i(Y_i - r_eE_i - \theta'\tilde{X}_i)] = 0. \tag{1}$$

Suppose that W is a positive definite weighting matrix. If the education return r_e were known, the parameter θ would satisfy $\theta = \mathbb{E}[Q_i(Y_i - r_eE_i)]$, where Q_i denotes the vector $(\mathbb{E}[\tilde{X}_iZ_i']W\mathbb{E}[Z_i\tilde{X}_i'])^{-1}\mathbb{E}[\tilde{X}_iZ_i']WZ_i$. Because the true value of r_e lies between $r_e^l = 0.05$ and $r_e^u = 0.15$, the parameter θ is bounded between $\mathbb{E}[Q_i(Y_i - r_e^lE_i)]$ and $\mathbb{E}[Q_i(Y_i - r_e^uE_i)]$.

In practice, we can estimate the bounds by setting r_e at r_e^l and r_e^u and estimating a GMM regression of $Y_i - r_eE_i$ on friendships F_i and other covariates, using Z_i as the instrument. For example, if we set $r_e = r_e^l$ and regard $Y_i - r_e^lE_i$ as the dependent variable, then the GMM estimator yields an estimator for the bound $\mathbb{E}[Q_i(Y_i - r_e^lE_i)]$. The bound $\mathbb{E}[Q_i(Y_i - r_e^uE_i)]$ can be estimated similarly.[11] For each component of θ, we then obtain a consistent estimator

[10] The education literature shows that relative age within a classroom also affects educational attainment (e.g., Black, Devereux, and Salvanes, 2011). However, we experimented using homophily measures for education as well as for in-degree and found that homophily instruments fail the weak IV tests if we use them to predict both education and friendships.

[11] To ensure that the upper and lower bounds are estimated using the same weighting matrix, we use

for the upper (lower) bound by taking the maximum (minimum) of the two estimates of the component.[12]

Inference. We follow Imbens and Manski (2004) to construct a confidence interval for any true value of θ that lies between the bounds. These confidence intervals are asymptotically valid regardless of whether θ is point identified or partially identified. If a component of $\mathbb{E}[Q_i E_i]$ is 0, the upper and lower bounds for the corresponding component of θ coincide, and this component of θ is point identified. In general, the components of $\mathbb{E}[Q_i E_i]$ are not equal to 0, the bounds do not coincide, and θ is only partially identified.

We can assess whether r_f is point identified or not by regressing education E_i on friendships F_i and other covariates, using Z_i as the instrument, as noted in footnote 12. If the coefficient of friendships is not significantly different from zero, then we cannot reject the null that r_f is point identified – the exact returns to education are not important because F_i and E_i are not correlated. In this case, we would not need to instrument for education in order to obtain an unbiased estimate of r_f. In our data, the coefficient on friendships is significant from zero – we can reject the null that r_f is point identified.[13]

To be specific about the confidence intervals, denote the upper and lower bounds of θ by θ_u and θ_l. Let $\hat{\theta}_u$ and $\hat{\theta}_l$ be the estimators for θ_u and θ_l and $se(\hat{\theta}_u)$ and $se(\hat{\theta}_l)$ the standard errors of the estimators.[14] Imbens and Manski (2004, Lemma 4) proposed a $(1-\alpha)$ confidence interval for the true value of θ that takes the form of $[\hat{\theta}_l - c \cdot se(\hat{\theta}_l), \hat{\theta}_u + c \cdot se(\hat{\theta}_u)]$, where the critical value c satisfies $\Phi(c + \frac{\hat{\theta}_u - \hat{\theta}_l}{\max\{se(\hat{\theta}_u), se(\hat{\theta}_l)\}}) - \Phi(-c) = 1 - \alpha$, with $\Phi(\cdot)$ being the cdf of the standard normal distribution.[15] In practice, each component of θ has a critical value

the GMM estimator that assumes homogeneous errors, that is, we set $W = \mathbb{E}[Z_i Z_i']^{-1}$. This estimator is equivalent to 2SLS.

[12]Whether the upper or lower bound of a component of θ is achieved at r_e^l or r_e^u depends on the sign of the corresponding component of $\mathbb{E}[Q_i E_i]$. For example, let $Q_{i,1}$ denote the first component of Q_i. Then r_f has the upper bound $\mathbb{E}[Q_{i,1}(Y_i - r_e^l E_i)]$ if $\mathbb{E}[Q_{i,1} E_i] \geq 0$ and $\mathbb{E}[Q_{i,1}(Y_i - r_e^u E_i)]$ if $\mathbb{E}[Q_{i,1} E_i] < 0$. The lower bound of r_f can be derived by swapping r_e^l and r_e^u. In practice, the components of $\mathbb{E}[Q_i E_i]$ can be recovered by regressing education E_i on friendships F_i and other covariates, using Z_i as the instrument. The sign of the coefficient on friendships determines whether the upper bound of r_f is achieved when r_e is high or low. A positive friendship coefficient implies that the upper (lower) bound of r_f is achieved at low (high) r_e.

[13]This also ensures that the estimated upper and lower bounds are jointly asymptotically normal, as required by Imbens and Manski (2004, Assumption 1(i)).

[14]In Section 4.2 we also consider an instrument constructed using estimates from a pairwise regression. In general, standard errors in two-step estimators should account for the presence of first-step estimators. However, we are in a special case where the moment condition in equation (1) has a zero derivative with respect to the first-step parameters (coefficients in the pairwise regression). Therefore, the first-step estimation has no impact on the standard errors in the second step and standard calculation of standard errors is valid (Newey and McFadden, 1994, p.2179).

[15]The confidence intervals proposed by Imbens and Manski (2004) require a superefficient estimator of the length of an identified set (Assumption 1(iii) in their paper). Nevertheless, Stoye (2009, Lemma 3) provides a simple sufficient condition for the superefficiency to hold: the estimated upper and lower bounds are almost surely ordered. Our estimated bounds are ordered because we take the maximum/minimum of the two estimates. Therefore, by Stoye (2009, Proposition 1) the confidence intervals in Imbens and Manski

c, and we need to solve for it numerically. Using the critical values for each component of θ, we can construct confidence intervals for each component of θ.[16]

Advantage of bounding. Provided that the true return to education is between 5 and 15%, our approach provides consistent bound estimates and valid confidence intervals for the returns to friendships. This approach is preferable to a simple calibration that assumes the return to education is known and equal to a particular value (e.g., $r_e = 10\%$), which yields a biased estimator if the true return to education is different from the presumed value and provides no confidence intervals.

4.2 Using age distance as an instrument

McPherson, Smith-Lovin, and Cook (2001) report the results of various studies documenting that in many settings (including schools) individuals of the same age are much more likely to be friends. Based on this evidence, we compute age distance for each pair of individuals as the absolute difference between their ages to use as an instrument.

The distance between individuals i and j is defined at the pair level – that is, between two students of the same school and grade. To construct an instrumental variable for in-degree at the individual level, we average the pairwise distances over all j that are in i's school-grade. We call this measure "age distance". In Appendix C we consider another aggregating approach. We run a Probit regression of friendships among pairs of students on the pairwise age distance and basic controls. We then use the predicted in-degree, calculated by the sum of the predicted friendships, as an instrument for in-degree.

To be valid our instrument must operate only through friendships and education (the two endogenous variables). Although age distance also potentially affects educational attainment (Black, Devereux, and Salvanes, 2011), the returns to friendships are still (partially) identified because we estimate the returns to friendships after subtracting off the impact of education from log earnings. The instrument satisfies the exclusion restriction so long as it is uncorrelated with the remaining unobservables.

4.3 Identifying variation and identifying assumptions

We use a similar set of controls and identifying variation as Murphy and Weinhardt (2020) who study the effects of academic rank on academic outcomes, and Cicala, Fryer, and Spenkuch (2017) who show that where an individual ranks within a given social distribution determines their choice of friends, behaviors, and outcomes. Given that we control

(2004) are appropriate.

[16]The STATA code for the bound estimates and confidence intervals can be found in Appendix E.

for cohort-mean age and own age, this leaves variation in age distance among students with the same age and cohort-mean age for identification.

Table A.1 illustrates this variation for a simple example. In the first cohort, students are aged 13, 13.5, and 14 (mean age 13.5). The second cohort has three students aged 13.2, 13.5, and 13.8 (same mean age of 13.5). In both cohorts, there is a student aged 13.5. However, the age distance for this student is smaller in cohort 2 (0.3 years) compared to cohort 1 (0.5 years). In the absence of coordination effects, our model predicts that the student in cohort 2 will have more friends than the student in cohort 1 because they are closer in age to their peers. The greater variance in the distribution of ages in cohort 1 compared to cohort 2 results in a greater age distance in cohort 1 (0.67) than cohort 2 (0.4).

Following Bifulco, Fletcher, and Ross (2011), we document in Table A.2 that there is sufficient variation of this kind in our data after accounting for the basic set of controls. The variation in age distance, measured by the standard deviation (s.d. 0.435), is about halved by the inclusion of individual age (s.d. 0.2). But 45% of the original variation (s.d. 0.2) remains after including the full set of controls, regardless of whether we control for grade FE or mean age in the cohort. This residual variation in age distance is significant, and larger than the residual variation in Bifulco, Fletcher, and Ross (2011).

A key identifying assumption is that conditional on our basic controls, age distance does not predict earnings except through its effects on education and friendships (exclusion restriction). Because the identifying variation in age distance is generated from differences in the age distribution across cohorts, we must assume that individuals do not sort into schools and grades based on the variance in age – that is, parents do not care or know about age distance and do not sort using this criterion.

Our identification assumption is not violated if parents want to place their child in a cohort where the child is older relative to their classmates (the practice sometimes referred to as red-shirting). In our previous example, both cohorts have the same mean age, which means that parents would be indifferent between the two cohorts because the child's age relative to the cohort mean will be identical in both cohorts. However, age distance will be on average smaller in cohort 2. Alternatively, parents may care about their child's *age rank* within a cohort. In our example, a 13.7 year old child would still be indifferent between the two cohorts, because they would be the second oldest in both cohorts. But this student would be closer in age to their peers in cohort 2, and we expect they would have more friends.

4.3.1 Empirical Support for the Exclusion Restriction

While we cannot test the exclusion restriction directly, we conduct a series of placebo tests using observable pre-determined characteristics (parental education, parental and own na-

tivity, religion, birthweight and breastfeeding, height, disabilities, etc.): age distance should not predict these variables conditional on our basic controls. We select the variables using two criteria. First, they are mostly determined early in life, before adolescent friendships are formed. Second, the prior literature and our data suggest they determine earnings.[17] Table A.3 shows that age distance does not predict any of the 14 variables we consider, conditional on basic controls: the coefficients on age distance are statistically insignificant in all regressions. Moreover, if we regress age distance on all of these variables (Column 3 of Table A.4), we cannot reject the null that they do not predict age distance, conditional on the basic controls (the p-value of the joint F-test is 0.56).

These placebo tests show that many important pre-determined characteristics that predict earnings are not statistically associated with age distance, providing support for the exclusion restriction.

4.4 First stage results: the effect of age distance on friendships

Table 2 documents that age distance has a negative and statistically significant effect on in-degree. If the average age distance between a student and the students in their school-grade increases by one year, the student has one less friend (Column 1). Increasing the age distance by one standard deviation (0.44) lowers the number of friends by about 0.44 friends, a 13% decline relative to the mean (3.4). The F-statistic is about 94, well above the standard thresholds required to rule out weak instruments and large enough for standard t-statistics in the second stage to be valid (Lee et al., 2022). These results are similar if we estimate the first stage using the pairwise data where an observation is a potential link between two students in the same school-grade (22 million potential links). Using a Probit probability model, we show that pairwise age distance is a strong predictor of friendships between two individuals, even after controlling for the age of the nominated individual in the pair and the mean age in the cohort (Column 1 of Table A.5).[18]

4.5 Monotonicity

In settings with heterogeneous treatment effects, IV estimates are interpretable only under monotonicity: the endogenous variable (number of friends) must be weakly monotonic in

[17] We check that these variables predict earnings by regressing log earnings with and without the predetermined variables, conditional on the basic covariates (Columns 1 and 2 of Table A.4). We reject the null that these variables do not jointly predict earnings (p-value < 0.001). The R^2 increases from 0.059 to 0.066 (a 12% increase) with the addition of these variables, confirming that they predict earnings.

[18] We do not control for the age of the individual who nominates the friendship because otherwise there is no variation in the pairwise distance.

the instrument (age distance) for all individuals. From a theoretical standpoint, increasing an individual's homophily level has ambiguous predictions on socializing and the number of friends because of coordination effects (Proposition B.3). For example, suppose that an adolescent is placed in a cohort with adolescents that are older instead of being of the same age. If older individuals socialize more than younger individuals, then the adolescent may socialize more and accumulate more friends in the older cohort because it is more productive to socialize in this group, despite the larger age difference.

Although monotonicity remains an untestable assumption, we empirically investigate whether it appears to be violated. Figure 2a shows a bin-scatter plot of friendships and age distance, in the raw data (left plot) and with basic controls (right plot). The slope is negative. A non-parametric plot (Figure A.1) further confirms that the relationship is weakly decreasing: age distance does not increase the number of friendships.[19] Column 2 of Table 2 shows that age distance squared has a negative but insignificant effect on friendships. In the pairwise first stage, age distance squared is significant, so the relationship is not exactly linear (Column 2 of Table A.5). However, the coefficients still imply a monotonic relationship: these negative coefficients imply that the curve is strictly decreasing and concave.

We also investigate whether the effect of age distance is symmetric. Column 3 of Table 2 shows that it is not: it is more detrimental — from the point of view of making friends — to be young among older peers than it is to be older among young ones (this is also true in the pairwise estimation, see Column 3 of Table A.5). However, age distance is still negatively correlated to friendships regardless of whether peers are older or younger.

Angrist and Imbens (1995) discuss what is needed for the monotonicity assumption to be met in the case of a continuous treatment. A testable implication of monotonicity is that the CDFs of the treatment (in-degree) at different levels of the instrument (age distance) should not cross. A visual representation of this test is given in Figure A.2. We plot the difference in the CDF of in-degree as age distance increases by one unit.[20] The CDF differences are non-negative throughout the support, whether we control for the basic covariates or not. A formal test of this no-crossing condition is provided by Barrett and Donald (2003). We split the data evenly into high and low values of age distance. The null hypothesis is that the distribution of in-degree with high age distance is first-order stochastically dominated by the distribution of in-degree with low age distance.[21] The p-values for the raw and residual

[19] There is a small portion where this is not true but this occurs for very high values of age distance that are uncommon.

[20] Let X denote in-degree and Z age distance. We estimate the CDF difference $\mathbb{E}[1\{X \leq x\}|Z = z'] - \mathbb{E}[1\{X \leq x\}|Z = z]$ for all x and $z' \geq z$ by regressing the indicator variable $1\{X \leq x\}$ on Z. The coefficient of Z provides an estimate of the CDF difference by one unit increase in Z (Rose and Shem-Tov, 2021).

[21] Let N_H and N_L denote the number of individuals with age distance higher and lower than the median in the sample. Let $F_H(x)$ and $F_L(x)$ denote the CDFs of in-degree for the subgroups with high and low age

distributions are 0.927 and 0.993 respectively, suggesting that we cannot reject the null, further supporting the monotonicity assumption.

5 IV Results: The Causal Returns to Friendships

We now turn our attention to estimating the causal returns to friendships.

5.1 Reduced form results: homophily and earnings in adulthood

Figure 2b shows the correlation between log earnings and age distance in a bin-scatter plot. Greater age distance is associated with lower earnings in the raw data (left plot), and with basic controls (right plot). Conditional on basic controls, individuals in cohorts with more dissimilar peers in terms of age have lower earnings as adults: increasing age distance by one standard deviation (0.44) lowers earnings by 7.5% (Column 1 of Table A.6). This relationship is statistically significant.

5.2 The causal returns to friendships: IV results

Table 3 reports the estimated bounds on the returns to adolescent friendships. The OLS estimates for in-degree are reported in Column 1 for reference, where the return to one more friend is 0.025. If in-degree is treated as endogenous but education is not, the estimate for in-degree increases to 0.12 (Column 2). If we take a calibration approach, where we assume the return to education is 10%, the returns to in-degree remain at 0.11 (Column 3).[22]

Our main specification, which allows for the returns to education to vary anywhere from 5 to 15%, bounds the returns to friendships from 0.093 to 0.137 (Column 4). The confidence interval (CI) for the returns does not include zero – these estimates are also statistically significant. The upper bound corresponds to the lower return to schooling, and vice versa. This is because the correlation between in-degree and schooling is positive (Figure A.3 and Table A.7): if we regress education on in-degree, controlling for covariates and instrumenting for in-degree, the coefficient on in-degree is 0.44 and statistically significant. The significant coefficient also implies that the returns to friendships are not point identified.

distance. The null and alternative hypotheses are $H_0 : F_H(x) \geq F_L(x)$ for all x and $H_1 : F_H(x) < F_L(x)$ for some x. Barrett and Donald (2003) propose the test statistic $\hat{S} = \left(\frac{N_H N_L}{N_H + N_L}\right)^{1/2} \sup_x(\hat{F}_L(x) - \hat{F}_H(x))$, where $\hat{F}_H(\cdot)$ and $\hat{F}_L(\cdot)$ are estimators of $F_H(\cdot)$ and $F_L(\cdot)$. They suggest that the p-value can be computed by $\exp(-2(\hat{S})^2)$.

[22] This estimate is obtained by running a regression on in-degree, controlling for covariates and instrumenting for in-degree, where the dependent variable is given by log earnings minus 10% times years of schooling.

Robustness. If we use a Probit probability model to predict links using the pairwise data and then use the predicted in-degree as an instrument, the bounds are similar and range from 0.065 to 0.096 (Column 5), although the estimates are not significant.

The results are robust to using alternative measures of friendships (Table A.8), including reciprocated friendships, which suggests that we are not simply capturing the returns to popularity.

We also check if the results are robust to the inclusion of additional controls (Table 4). Column 1 reproduces our preferred specification for reference and shows bounds of 0.093–0.137. Our estimates are similar (and the CI does not include 0) if we control for age rank (Column 2), predetermined individual-level controls (the ones we used for the placebo tests in Section 4.3.1, Column 3), variables capturing current SES including parental income and living with parents (Column 4), or their respective cohort-level means (Column 5). The last two regressions are potentially problematic because income (or living with parents) is endogenous (it is not truly predetermined) but it is nevertheless reassuring that the results are similar.

Table A.9 investigates another potential violation of the exclusion restriction. Perhaps in settings where age distance is larger, there is greater bullying. Because bullying can affect mental health (Arseneault, Bowes, and Shakoor, 2010) which in turn affects earnings, our instrument could affect earnings through this additional channel. We test this by controlling for measures of social cohesion in adolescence. These controls do not individually or jointly affect the estimated bounds.

Magnitudes. The magnitude of the returns to friendships ranges from 0.07 to 0.14 across specifications. Since recent estimates of the returns to schooling are on the larger side (more than 10%), the more likely bound for the returns to friendships is the lower bound, which hovers around 0.07–0.09. Thus an increase of one standard deviation in the number of friends (3.2) increases earnings by 22% – a large and economically significant return. By comparison, a one standard deviation increase in years of schooling (2.1) would increase earnings by 21% so the effect size is similar.[23] While the return to in-degree seems large, it represents the returns to having a friend during adolescence – we are not measuring the returns to one year of friendship but the returns to having a friend. These friendships likely last many years, potentially into adulthood (Section 6).

Our bounds are larger than the point estimates in Conti et al. (2013) of around 2%. In addition to methodological differences (they do not account for the endogeneity of education and friendships), they study men who were seniors in high school in Wisconsin in 1957,

[23]The implied elasticity of earnings with respect to friendships is 0.24, whereas the elasticity of earnings with respect to education is 1.5, assuming the return to education is 10%.

whereas the Add Health data is nationally representative and surveys students in middle or high school in 1994–95, at a time when the returns to education and other individual traits in the labor market are much larger. They measure labor market outcomes 35 years later whereas we observe them 15 years later. The returns to friendships in adolescence may attenuate over time, yielding larger returns when respondents are surveyed earlier in their careers.

5.3 Why are OLS estimates downward biased?

Our preferred bounds do not include the OLS estimate of 0.025.[24] We explore two reasons why the estimated bounds are larger than the OLS estimate: omitted variable bias and measurement error.[25]

Omitted variable bias. Omitted variable biases in our model are in general ambiguous (Proposition B.2). The sign of the OLS bias is determined by the correlation between in-degree and the error term ϵ_i.[26] A downward (upward) bias arises if in-degree is positively correlated with an unobserved factor that negatively (positively) affects earnings.

The data suggest possible omitted factors that could explain our findings: partying and drinking. Alcohol consumption among adolescents is largely motivated by its capacity to facilitate social interactions (Feldman et al., 1999; Kuntsche et al., 2005), but it may have detrimental impacts on other outcomes. We find that drinking alcohol increases friendships but lowers GPA and the odds of working in cognitively demanding jobs (Table A.11).[27] Drinking also increases depression and lowers self-reported health in adulthood. However, time spent with friends is associated with more friends and better health, lowers the odds of working in jobs with high cognitive demands, but it does not lower GPA. Thus *certain* social behaviors, like drinking, increase friendships but lower cognitive productivity and lower health, both of which likely affect wages.

Additional results suggest that OLS is downward biased. Table A.12 shows that the addition of covariates in OLS regressions of earnings on grade in-degree increases the estimated

[24] However, the confidence interval for the returns to friendships [0.008, 0.224] includes the confidence interval for the OLS estimator [0.018, 0.031], so we cannot reject the null that the IV and OLS estimates are the same.

[25] IV estimates might also exceed OLS estimates if treatment effects are heterogeneous. OLS estimates in Table A.10 suggest that while there is some heterogeneity in the returns to friendships across subpopulations, it is too small to explain the discrepancy between OLS and IV estimates.

[26] Strictly speaking, the bias is given by the covariance between in-degree and ϵ_i, multiplied by the inverse of a matrix $X'X$, where X consists of residualized education and in-degree. In our sample this inverse matrix has positive diagonal elements and relatively small off-diagonal elements (Table A.7). Therefore, the sign of the bias is mostly determined by the correlation between in-degree and ϵ_i.

[27] We use data from the O*NET to construct indices of the extent to which occupations require social or cognitive skills and match these scores to a person's occupation. See Appendix D for details.

returns to friendships. We control for education only (Column 1), and then we progressively control endowments (IQ and extroversion - Column 2), personal demographics (age, gender, race - Column 3), mean characteristics of one's peers (Column 4), grade fixed effects (Column 5) and school fixed effects (Column 6). The model with all the controls yields the largest coefficient. This evidence suggests that individual characteristics and school fixed effects capture preferences and environments that cause OLS to be downward biased.

Measurement error. Classical measurement error in friendships would attenuate the OLS coefficient. The direction and magnitude of the OLS bias depend on the ratio of the covariance between in-degree and the true measure, divided by the variance of in-degree: if the ratio is smaller than one then OLS is attenuated (Bound, Brown, and Mathiowetz, 2001). Suppose that high-engagement friendships are the "true" number of friends and grade in-degree is a poor proxy. What would the OLS bias be in this case? In our sample, the covariance between (residualized) grade in-degree and (residualized) high-engagement degree is 2.28. The (residualized) variance of grade in-degree is 8.67 (Table A.13). Their ratio is about 0.26, which suggests that a consistent estimate could be 4 times larger than OLS, roughly 0.09, similar to our IV estimates.

Limitations. Measurement error may also come from the fact that individuals in the survey are only allowed to list up to five friends of each gender, generating censoring – a non-classical form of measurement error. In this case our IV might be inconsistent – an IV estimate is consistent only if the instrument is uncorrelated with measurement error (Bound, Brown, and Mathiowetz, 2001).

6 Discussion: Which Friends Matter and How do Friendships Affect Earnings?

We end with an informal discussion of two important issues. First, do all friendships yield positive returns in the labor market? Second, what are the mechanisms by which adolescent friendships increase earnings? While we cannot fully answer these questions in a causal manner, we discuss some suggestive evidence.

Figure A.4 plots the non-parametric relationship between in-degree and earnings, for different measures of in-degree suggested by prior studies: same vs. opposite gender (McDougall and Hymel, 2007; Hall, 2011), high vs. low engagement (Gee, Jones, and Burke, 2017), high vs. low SES (Lavy and Sand, 2018; Fletcher, Ross, and Zhang, 2020; Chetty et al., 2022), and disruptive vs. non-disruptive peers (Carrell, Hoekstra, and Kuka, 2018). The friendships that are expected to have higher returns indeed appear to have higher returns: it pays off

more to be friends with people of the same gender, to have more close friends, to have more friends who are not disruptive or come from higher SES families. However, all friendships (except for disruptive ones) appear to have positive returns, albeit smaller ones. Table A.14 confirms these descriptive patterns using OLS. Unfortunately, our instruments are not powerful enough to produce precise estimates of different types of friendships so further work is needed in this area.[28]

Why do friendships in adolescence matter for adult earnings? We do not have estimates of the causal effect of education on potential mediators, so we cannot estimate the ideal IV bounds. Instead, we summarize the suggestive evidence from OLS regressions. Friendships formed in adolescence are associated with higher likelihood of working (Column 1 of Table A.16), consistent with the previous literature that friends help workers find jobs (Dustmann et al., 2015). Adolescent friendships are associated with a lower likelihood of working in repetitive occupations (Column 2) and a greater likelihood of working in supervisory roles (though this relationship is not statistically significant, Columns 3). Individuals with more friends are more likely to be employed in occupations that require greater social skills, which on average pay larger wages (Column 4). Individuals with more friends appear to have greater social and management skills and broader networks as adults. They have more friends in adulthood (Column 5) and are more likely to be married (Column 6). Controlling for extroversion in adolescence, those with more adolescent friends are more likely to be extroverted in adulthood (Column 7). Individuals with more friends also have greater GPAs (Columns 1 of Table A.17), are less likely to get in trouble while they are in school (Columns 2 and 3), and ultimately are more likely to work in jobs that require higher cognitive skills (Column 4). They are also less depressed and healthier (Columns 5 and 6). Thus the returns to friendships in the labor force do not operate uniquely through social skills and networks – friendships also help in the formation of other cognitive and non-cognitive skills that are rewarded in the labor market.

7 Conclusion

We show that individuals that have more friends in adolescence have higher earnings in adulthood, partly because they are employed in higher paying occupations that require higher social and cognitive skills, and partly because they turn into more socially connected adults that are also more extroverted.

Our results confirm recent findings emphasizing the importance of adolescence as a for-

[28] Although all the first stages are strong (Table A.15), we do not have sufficient variation to *separately* identify the effects of, e.g., male and female friendships.

mative period for socio-emotional outcomes (Jackson et al., 2020) and particularly for friendships (Denworth, 2020). Our findings also suggest that when students are more similar to each other they are more likely to form friendships. Therefore, how students are allocated in groups in schools has important long-term consequences. Re-structuring classrooms to be more homogeneous in age would appear to benefit all students involved, from the point of view of friendships and adult earnings. An important direction for future research is to investigate which other contexts and student compositions are most conducive to the creation of friendships.

The importance of socialization during schooling years has further implications for higher education policy. Many colleges and universities face criticism for investing in infrastructure for non-academic, recreational facilities that are believed to contribute to increasing tuition (Jacob, McCall, and Stange, 2018). These investments are more reasonable in the presence of high returns to socialization. Our results help rationalize why, for instance, Greek fraternities and sororities persist, despite the fact that they can detract from strictly academic endeavors. While partying may decrease education, particularly if it is associated with drinking, it does not necessarily decrease earnings. Overall if schools can promote productive social activities (like working together), it might be possible to improve both students' social connections and their educational attainment.

Like recent work (Xiang and Yeaple, 2018; Heckman and Kautz, 2012), our findings suggest that paying excessive attention to traditional education measures like test scores might lower the long-term outcomes and well-being of individuals because they reduce investments in other important forms of human capital. They also suggest that educational interventions that are becoming common, such as remote learning, might deter from social capital formation and result in lost lifetime earnings. In contrast, interventions that target soft skills might have large returns, partly through their effects on network formation. Indeed an emerging literature shows that interventions targeting non-cognitive skills among young adults can have large returns (Katz et al., 2022, Heller et al., 2017). Our paper complements this research by documenting the importance of having friends, separately from social skills.

There are many unanswered questions that remain. For example, we don't know much about which environments best foster friendships while maintaining academic performance. We provide some evidence that not all friendships matter equally in the labor market but our evidence is only suggestive. Finally, we only track the impact of adolescent friendships – not whether earlier friendships matter, how social networks evolve from adolescence onward and how adult networks affect labor markets. These important questions are left to future research.

References

Angrist, Joshua and Jörn-Steffen Pischke. 2009. *Mostly harmless econometrics: An empiricist's companion*. Princeton, NJ: Princeton University Press.

Angrist, Joshua D. and Guido W. Imbens. 1995. Two-stage least squares estimation of average causal effects in models with variable treatment intensity. *Journal of the American Statistical Association* 90 (430):431–442.

Arseneault, L., L. Bowes, and S. Shakoor. 2010. Bullying victimization in youths and mental health problems: 'Much ado about nothing'? *Psychological Medicine* 40 (5):717–729.

Auerbach, Eric. 2022. Identification and estimation of a partially linear regression model using network data. *Econometrica* 90 (1):347–365.

Babcock, Philip. 2008. From ties to gains? Evidence on connectedness and human capital acquisition. *Journal of Human Capital* 2 (4):379–409.

Badev, Anton. 2021. Nash equilibria on (un)stable networks. *Econometrica* 89 (3):1179–1206.

Barrett, Garry F. and Stephen G. Donald. 2003. Consistent tests for stochastic dominance. *Econometrica* 71 (1):71–104.

Bifulco, Robert, Jason M. Fletcher, and Stephen L. Ross. 2011. The effect of classmate characteristics on post-secondary outcomes: Evidence from the Add Health. *American Economic Journal: Economic Policy* 3 (1):25–53.

Black, Sandra E, Paul J Devereux, and Kjell G Salvanes. 2011. Too young to leave the nest? The effects of school starting age. *Review of Economics and Statistics* 93 (2):455–467.

Boucher, Vincent. 2015. Structural homophily. *International Economic Review* 56 (1):235–264.

Bound, John, Charles Brown, and Nancy Mathiowetz. 2001. Measurement error in survey data. In *Handbook of econometrics*, vol. 5, edited by James J. Heckman and Edward Leamer, chap. 59. Elsevier, 3705–3843.

Bramoullé, Yann, Habiba Djebbari, and Bernard Fortin. 2009. Identification of peer effects through social networks. *Journal of Econometrics* 150 (1):41–55.

Calvo-Armengol, Antoni and Matthew O Jackson. 2004. The effects of social networks on employment and inequality. *American Economic Review* 94 (3):426–454.

Cappellari, Lorenzo and Konstantinos Tatsiramos. 2015. With a little help from my friends? Quality of social networks, job finding and job match quality. *European Economic Review* 78:55–75.

Card, David. 1999. The causal effect of education on earnings. In *Handbook of labor economics*, vol. 3A, edited by Orley C. Ashenfelter and David Card. Elsevier, 1801–1863.

———. 2001. Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica* 69 (5):1127–1160.

Carrell, Scott E., Richard L. Fullerton, and James E. West. 2009. Does your cohort matter? Measuring peer effects in college achievement. *Journal of Labor Economics* 27 (3):439–464.

Carrell, Scott E., Mark Hoekstra, and Elira Kuka. 2018. The long-run effects of disruptive peers. *American Economic Review* 108 (11):3377–3415.

Carrell, Scott E., Mark Hoekstra, and James E. West. 2011. Is poor fitness contagious? *Journal of Public Economics* 95 (7-8):657–663.

Carrell, Scott E., Frederick V. Malmstrom, and James E. West. 2008. Peer effects in academic cheating. *Journal of Human Resources* 43 (1):173–207.

Chetty, Raj, Matthew O. Jackson, Theresa Kuchler, Johannes Stroebel, Nathaniel Hendren, Robert B. Fluegge, Sara Gong, Federico Gonzalez, Armelle Grondin, Matthew Jacob, Drew Johnston, Martin Koenen, Eduardo Laguna-Muggenburg, Florian Mudekereza, Tom Rutter, Nicolaj Thor, Wilbur Townsend, Ruby Zhang, Mike Bailey, Pablo Barberá, Monica Bhole, and Nils Wernerfelt. 2022. Social capital i: Measurement and associations with economic mobility. *Nature* 608:108–121.

Cicala, Steve, Roland G. Fryer, and Jörg L. Spenkuch. 2017. Self-selection and comparative advantage in social interactions. *Journal of the European Economic Association* 16 (4):983–1020.

Conti, Gabriella, Andrea Galeotti, Gerrit Mueller, and Stephen Pudney. 2013. Popularity. *Journal of Human Resources* 48 (4):1072–1094.

Deming, David J. 2017. The growing importance of social skills in the labor market. *Quarterly Journal of Economics* 132 (4):1593–1640.

Denning, Jeffrey T., Richard Murphy, and Felix Weinhardt. 2023. Class rank and long-run outcomes. *Review of Economics and Statistics* 105 (6):1–16.

Denworth, Lydia. 2020. *Friendship: The evolution, biology, and extraordinary power of life's fundamental bond*. New York, NY: W. W. Norton & Company.

Dunn, Lloyd and Douglas M. M.Dunn. 2007. *Peabody Picture Vocabulary Test–Fourth Edition*. Minneapolis, MN: Pearson Assessments.

Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker. 2015. Referral-based job search networks. *Review of Economic Studies* 83 (2):514–546.

Feldman, Linda, Bart Harvey, Philippa Holowaty, and Linda Shortt. 1999. Alcohol use beliefs and behaviors among high school students. *Journal of Adolescent Health* 24 (1):48–58.

Fletcher, Jason M., Stephen L. Ross, and Yuxiu Zhang. 2020. The consequences of friendships: Evidence on the effect of social relationships in school on academic achievement. *Journal of Urban Economics* 116:103241.

Gee, Laura K., Jason Jones, and Moira Burke. 2017. Social networks and labor markets: How strong ties relate to job finding on Facebook's social network. *Journal of Labor Economics* 35 (2):485–518.

Goldsmith-Pinkham, Paul and Guido W. Imbens. 2013. Social networks and the identification of peer effects. *Journal of Business & Economic Statistics* 31 (3):253–264.

Graham, Bryan S. 2017. An econometric model of network formation with degree heterogeneity. *Econometrica* 85 (4):1033–1063.

Granovetter, Mark S. 1973. The strength of weak ties. *American Journal of Sociology* 78 (6):1360–1380.

Griffith, Alan. 2021. Name your friends, but only five? The importance of censoring in peer effects estimates using social network data. *Journal of Labor Economics* 40 (4):779–805.

———. 2022. Random assignment with non-random peers: A structural approach to counterfactual treatment assessment. *Review of Economics and Statistics* :1–40.

Gunderson, Morley and Philip Oreopolous. 2020. Returns to education in developed countries. In *The economics of education*, edited by Steve Bradley and Colin Green. Cambridge, MA: Academic Press, second ed., 39–51.

Haile, Philip A. and Elie Tamer. 2003. Inference with an incomplete model of English auctions. *Journal of Political Economy* 111 (1):1–51.

Hall, Jeffrey A. 2011. Sex differences in friendship expectations: A meta-analysis. *Journal of Social and Personal Relationships* 28 (6):723–747.

Heckman, James J. and Tim Kautz. 2012. Hard evidence on soft skills. *Labour Economics* 19 (4):451–464.

Heckman, James J. and Stefano Mosso. 2014. The economics of human development and social mobility. *Annual Review of Economics* 6 (1):689–733.

Heller, Sara B., Anuj K. Shah, Jonathan Guryan, Jens Ludwig, Sendhil Mullainathan, and Harold A. Pollack. 2017. Thinking, fast and slow? Some field experiments to reduce crime and dropout in Chicago. *Quarterly Journal of Economics* 132 (1):1–54.

Hodapp, Albert F. and Kathryn C. Gerken. 1999. Correlations between scores for Peabody Picture Vocabulary Test III and the Wechsler Intelligence Scale for Children III. *Psychological Reports* 84 (3_suppl):1139–1142.

Hsieh, Chih-Sheng and Lung Fei Lee. 2016. A social interactions model with endogenous friendship formation and selectivity. *Journal of Applied Econometrics* 31 (2):301–319.

Imbens, Guido W. and Charles F. Manski. 2004. Confidence intervals for partially identified parameters. *Econometrica* 72 (6):1845–1857.

Jackson, C. Kirabo, Shanette C. Porter, John Q. Easton, Alyssa Blanchard, and Sebastián Kiguel. 2020. School effects on socioemotional development, school-based arrests, and educational attainment. *American Economic Review: Insights* 2 (4):491–508.

Jackson, Matthew O. 2008. *Social and economic networks*. Princeton, NJ: Princeton University Press.

———. 2014. Networks in the understanding of economic behaviors. *Journal of Economic Perspectives* 28 (4):3–22.

Jacob, Brian, Brian McCall, and Kevin Stange. 2018. College as country club: Do colleges cater to students' preferences for consumption? *Journal of Labor Economics* 36 (2):309–348.

Jeon, Kwon Chan and Patricia Goodson. 2015. US adolescents' friendship networks and health risk behaviors: A systematic review of studies using social network analysis and Add Health data. *PeerJ* 3:e1052.

Johnsson, Ida and Hyungsik Roger Moon. 2021. Estimation of peer effects in endogenous social networks: Control function approach. *Review of Economics and Statistics* 103 (2):328–345.

Katz, Lawrence F., Jonathan Roth, Richard Hendra, and Kelsey Schaberg. 2022. Why do sectoral employment programs work? Lessons from WorkAdvance. *Journal of Labor Economics* 40 (S1):S249–S291.

Kuntsche, Emmanuel, Ronald Knibbe, Gerhard Gmel, and Rutger Engels. 2005. Why do young people drink? A review of drinking motives. *Clinical Psychology Review* 25 (7):841–861.

Lavy, Victor and Edith Sand. 2018. The effect of social networks on students' academic and non-cognitive behavioural outcomes: Evidence from conditional random assignment of friends in school. *Economic Journal* 129 (617):439–480.

Lee, David S., Justin McCrary, Marcelo J. Moreira, and Jack Porter. 2022. Valid t-ratio inference for IV. *American Economic Review* 112 (10):3260–3290.

Lenton, Pamela. 2014. Personality characteristics, educational attainment and wages: An economic analysis using the British Cohort Study. Sheffield Economic Research Paper Series 2014011, Department of Economics, University of Sheffield.

Manski, Charles F. 1993. Identification of endogenous social effects: The reflection problem. *Review of Economic Studies* 60 (3):531.

———. 2003. *Partial identification of probability distributions*. New York, NY: Springer-Verlag.

Manski, Charles F. and Elie Tamer. 2002. Inference on regressions with interval data on a regressor or outcome. *Econometrica* 70 (2):519–546.

McDougall, Patricia. and Shelley. Hymel. 2007. Same-gender versus cross-gender friendship conceptions: Similar or different? *Merrill-Palmer Quarterly* 53 (3):347–380.

McPherson, Miller, Lynn Smith-Lovin, and James M Cook. 2001. Birds of a feather: Homophily in social networks. *Annual Review of Sociology* 27 (1):415–444.

Michelman, Valerie, Joseph Price, and Seth D Zimmerman. 2021. Old boys' clubs and upward mobility among the educational elite. *Quarterly Journal of Economics* 137 (2):845–909.

Montgomery, James D. 1991. Social networks and labor-market outcomes: Toward an economic analysis. *American Economic Review* 81 (5):1408–1418.

Mountjoy, Jack. 2022. Community colleges and upward mobility. *American Economic Review* 112 (8):2580–2630.

Murphy, Richard and Felix Weinhardt. 2020. Top of the class: The importance of ordinal rank. *Review of Economic Studies* 87 (6):2777–2826.

Newey, Whitney K. and Daniel McFadden. 1994. Large sample estimation and hypothesis testing. In *Handbook of econometrics*, vol. 4, edited by Robert F. Engle and Daniel L. McFadden. Elsevier, 2111–2245.

Psacharopoulos, George and Harry Anthony Patrinos. 2018. Returns to investment in education: A decennial review of the global literature. *Education Economics* 26 (5):445–458.

Rose, Evan K. and Yotam Shem-Tov. 2021. How does incarceration affect reoffending? Estimating the dose-response function. *Journal of Political Economy* 129 (12):3302–3356.

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

Sacerdote, Bruce. 2011. Peer effects in education: How might they work, how big are they and how much do we know thus far? In *Handbook of the economics of education*, vol. 3, edited by Eric A. Hanushek, Stephen Machin, and Ludger Woessmann. Elsevier, 249–277.

Sheng, Shuyang and Xiaoting Sun. 2023. Social interactions with endogenous group formation. *arXiv: 2306.01544* .

Stoye, Jörg. 2009. More on confidence intervals for partially identified parameters. *Econometrica* 77 (4):1299–1315.

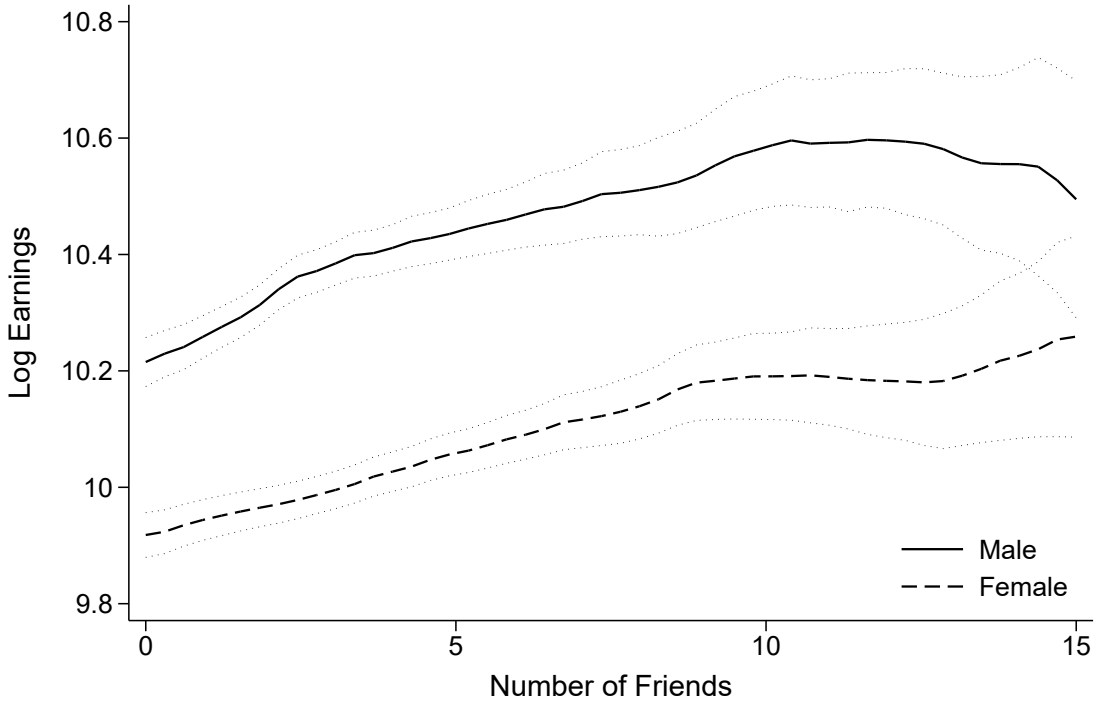
Tamer, Elie. 2003. Incomplete simultaneous discrete response model with multiple equilibria. *Review of Economic Studies* 70 (1):147–165.

Weidmann, Ben and David J. Deming. 2021. Team players: How social skills improve team performance. *Econometrica* 89 (6):2637–2657.

Wooldridge, Jeffrey M. 2010. *Econometric analysis of cross section and panel data*. Boston, MA: MIT Press.

Xiang, Chong and Stephen Yeaple. 2018. The Production of Cognitive and Non-cognitive Human Capital in the Global Economy. NBER Working Paper 24524, National Bureau of Economic Research, Cambridge, MA.

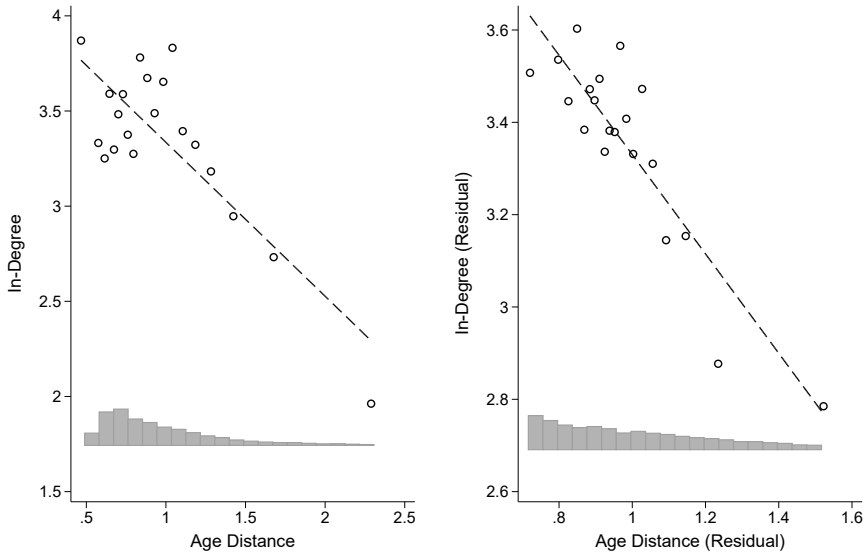
Figure 1: Log Earnings in Adulthood and Friendships in Adolescence



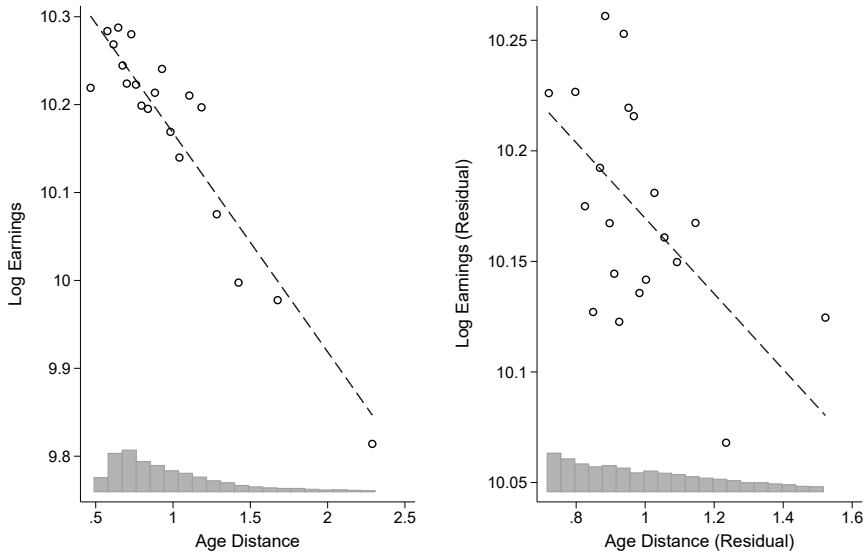
Note: Add Health restricted-use data. Local polynomial nonparametric plots and 95% confidence intervals of log earnings on number of friendships in adolescence measured by grade in-degree (see data section for explanations on how grade in-degree is defined). The series separate males and females with non-zero earnings.

Figure 2: Homophily, Friendships, and Earnings: First Stage and Reduced Form

(a) Friendships and Homophily in Age



(b) Log Earnings and Homophily in Age



Note: Add Health restricted-use data. Bin-scatter plots of grade in-degree (panel a) and log earnings (panel b) on age distance with the histogram of age distance (gray bars). In both panels, the left plot uses the original variables, and the right plot uses their residuals after removing individual characteristics (age, IQ, and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects.

Table 1: Summary Statistics

	(1) All Students	(2) Extrovert	(3) Shy	(4) Hi IQ	(5) Low IQ
Annual Earnings (W4)	38073.2	37753.8	35312.9	41988.6	33578.1
	(46674.4)	(43283.4)	(38818.7)	(45419.6)	(45555.9)
School In-Degree (W1)	4.359	4.733	3.928	4.682	3.998
	(3.729)	(3.891)	(3.386)	(3.896)	(3.507)
Grade In-Degree (W1)	3.352	3.688	3.069	3.645	3.024
	(3.153)	(3.347)	(2.847)	(3.271)	(2.975)
Grade Out-Degree (W1)	3.285	3.484	3.250	3.638	2.883
	(2.688)	(2.747)	(2.620)	(2.694)	(2.618)
Grade Reciprocated Degree (W1)	1.388	1.491	1.311	1.597	1.147
	(1.564)	(1.616)	(1.469)	(1.640)	(1.429)
Grade Network Size (W1)	5.248	5.681	5.009	5.686	4.760
	(3.843)	(4.025)	(3.555)	(3.887)	(3.722)
Years of Schooling (W4)	14.76	14.82	14.73	15.37	14.08
	(2.125)	(2.122)	(2.110)	(1.930)	(2.126)
GPA (W2)	2.839	2.850	2.818	2.997	2.649
	(0.746)	(0.739)	(0.758)	(0.735)	(0.714)
IQ (W1)	101.5	102.1	100.6	112.4	89.30
	(13.95)	(13.50)	(14.59)	(7.447)	(9.408)
Extrovert (W2)	0.650	1	0	0.663	0.632
	(0.412)	(0)	(0)	(0.407)	(0.418)
Very Hard Study Effort (W1)	0.381	0.383	0.419	0.346	0.419
	(0.486)	(0.486)	(0.494)	(0.476)	(0.494)
Some Study Effort (W1)	0.511	0.515	0.483	0.536	0.484
	(0.500)	(0.500)	(0.500)	(0.499)	(0.500)
Frequently Hang with Friends (W1)	0.387	0.401	0.344	0.376	0.399
	(0.487)	(0.490)	(0.475)	(0.485)	(0.490)
Sometimes Hang with Friends (W1)	0.523	0.514	0.553	0.541	0.505
	(0.499)	(0.500)	(0.497)	(0.498)	(0.500)
Frequently Drink (W1)	0.163	0.158	0.121	0.174	0.152
	(0.369)	(0.365)	(0.326)	(0.379)	(0.359)
Sometimes Drink (W1)	0.299	0.306	0.265	0.316	0.283
	(0.458)	(0.461)	(0.441)	(0.465)	(0.450)
Age (W1)	16.06	15.70	15.83	16.04	16.05
	(1.670)	(1.534)	(1.546)	(1.619)	(1.716)
Age Distance (W1)	0.980	0.964	0.984	0.903	1.061
	(0.435)	(0.421)	(0.438)	(0.341)	(0.497)
Observations	10,605	5,124	2,765	5,384	4,741

Note: Add Health restricted-use data. Standard deviations in parentheses. W1 stands for Wave I, etc. Due to missing values in IQ and Extrovert, the numbers of observations in Columns 2 and 3 do not sum up to that in Column 1, and the same for Columns 4 and 5.

Table 2: What Predicts Friendships in Adolescence? First-Stage Results

	(1) In-Degree	(2) In-Degree	(3) In-Degree
Age Distance	-1.0760***	-0.7023**	
	(0.1111)	(0.2767)	
Age Distance Squared		-0.1120	
		(0.0721)	
Age Distance to Older Peers			-2.0300***
			(0.2822)
Age Distance to Young Peers			-0.2571
			(0.3130)
Age	0.2895***	0.2534***	-0.5636*
	(0.0841)	(0.0813)	(0.3046)
Mean Age	-0.3538*	-0.3669*	0.0784
	(0.1982)	(0.2010)	(0.2314)
F-stat of Homophily Measures	93.846	49.464	72.139
P-value	0.000	0.000	0.000
R^2	0.038	0.038	0.039
Observations	10,605	10,605	10,605

Note: Add Health restricted-use data. In-degree refers to the number of friendships nominated by other students in the same school-grade. Age distance refers to the average age distance to other students in the same school-grade. Age distance to older (younger) peers refers to the average age distance to other students in the same school-grade who are older (younger) than the respondent. Additional covariates include individual characteristics (IQ and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Standard errors in parentheses are clustered at the school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Labor Market Returns to Friendships: Main Results

	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV
In-Degree	0.0245	0.1242	0.1146	[0.0926, 0.1367]	[0.0650, 0.0956]
95% CI	[0.0177, 0.0312]	[0.0130, 0.2354]	[0.0155, 0.2138]	[0.0075, 0.2242]	[-0.0308, 0.1936]
First Stage for In-Degree		Aggregate	Aggregate	Aggregate	Pairwise Probit
Education Endogenous	N	N	Y	Y	Y
Education Returns	10.30%	7.83%	10%	5-15%	5-15%
Observations	10,605	10,605	10,605	10,605	10,605

Note: Add Health restricted-use data. The dependent variable is the log annual earnings. In-degree refers to the number of friendships nominated by other students in the same school-grade. Column 1 presents OLS estimates for the returns to in-degree. Column 2 presents estimates where in-degree is endogenous, but education is not (estimated returns to education are reported in the second to last row). Column 3 presents estimates where in-degree is endogenous and the returns to education is assumed to be 10%. Columns 4-5 present estimates where in-degree is endogenous and the returns to education are bounded between 5 and 15%. All specifications include individual characteristics (age, IQ, and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. The confidence intervals are constructed based on standard errors clustered at the school level.

Table 4: Labor Market Returns to Friendships: Robustness Checks

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV
In-Degree	[0.0926, 0.1367]	[0.0908, 0.1347]	[0.0952, 0.1356]	[0.0951, 0.1355]	[0.0694, 0.1157]
95% CI	[0.0075, 0.2242]	[0.0068, 0.2212]	[0.0002, 0.2333]	[0.0030, 0.2303]	[0.0033, 0.1841]
Additional Individual Controls	N	Age Rank	Pre Controls	SES Controls	N
Additional Cohort Mean Controls	N	N	N	N	SES Controls
Observations	10,605	10,605	10,605	10,605	10,605

Note: Add Health restricted-use data. The dependent variable is the log annual earnings. In-degree refers to the number of friendships nominated by other students in the same school-grade. All specifications include individual characteristics (age, IQ, and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Column 2 controls for age rank, which refers to the ranking of the respondent's age in the school-grade. Column 3 controls for additional individual-level predetermined covariates, including number of siblings, mother's age at the student's birth, birth weight, height, and indicators for whether the mother was born in US, the father was born in US, the parents are Catholic, Baptist, the student was born in US, was breastfed, is mentally retarded, and has diabilibity. Column 4 controls for additional individual-level SES controls, including family income, mother's years of schooling, father's years of schooling, and indicators for whether the mother lives in the household and whether the father lives in the household. Column 5 controls for cohort-level means of the additional SES controls in Column 4. The instrument is age distance. The confidence intervals are constructed based on standard errors clustered at the school level.

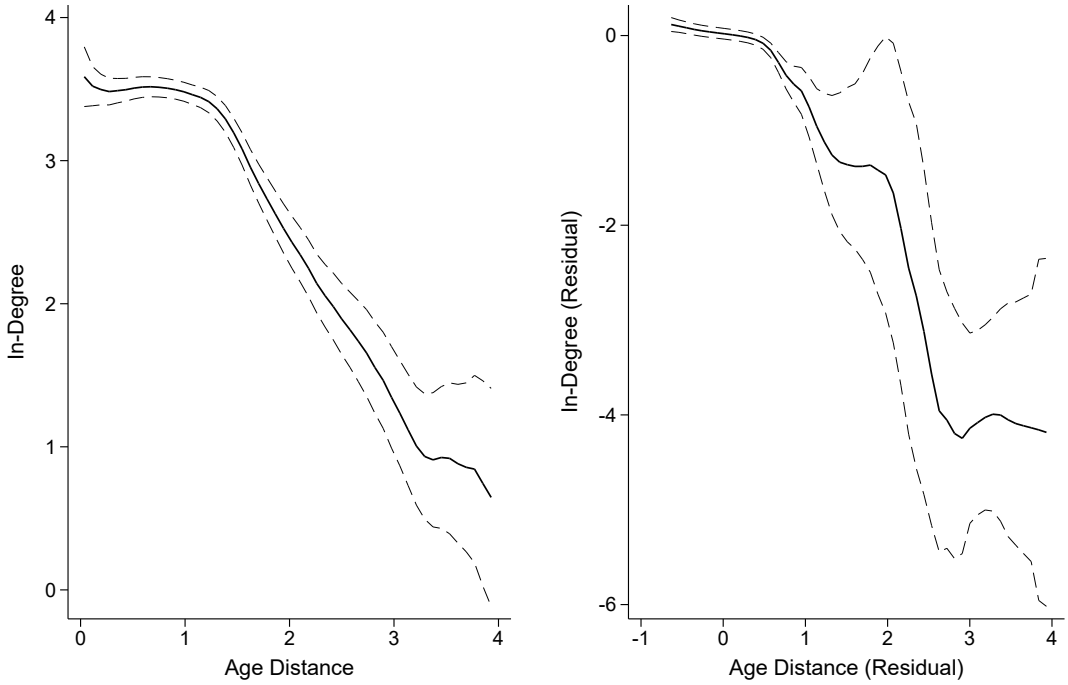
Online Appendix to

Party On: The Labor Market Returns to Social Networks In Adolescence

Adriana Lleras-Muney, Matthew Miller, Shuyang Sheng, and Veronica Sovero

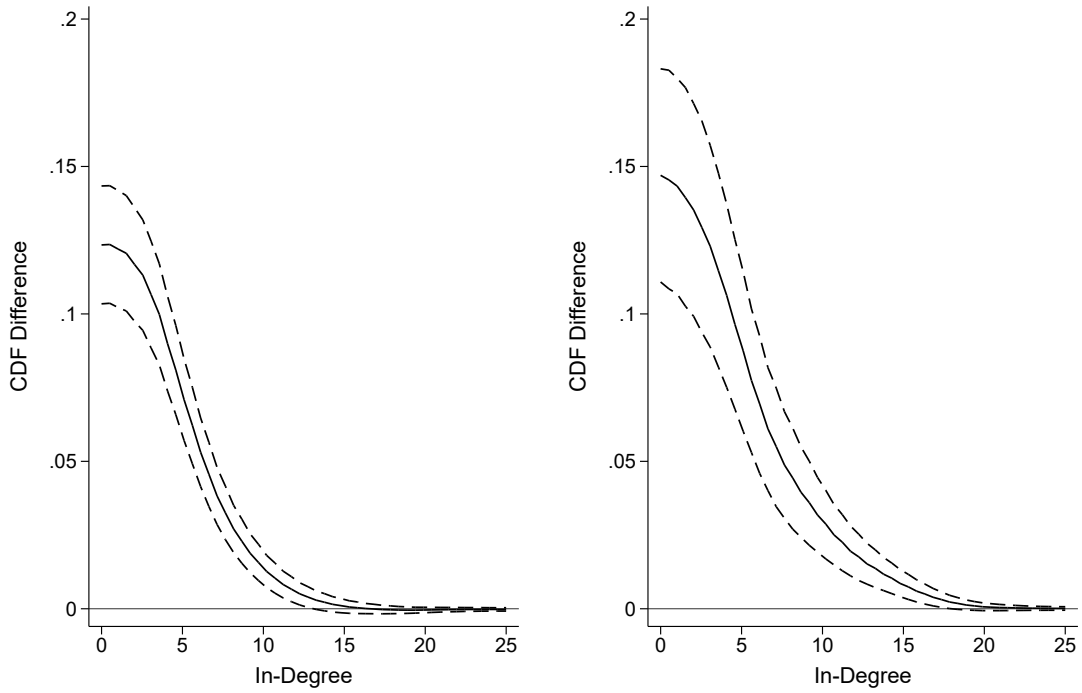
A Additional Figures and Tables

Figure A.1: Friendships and Homophily in Age: Nonparametric Plots



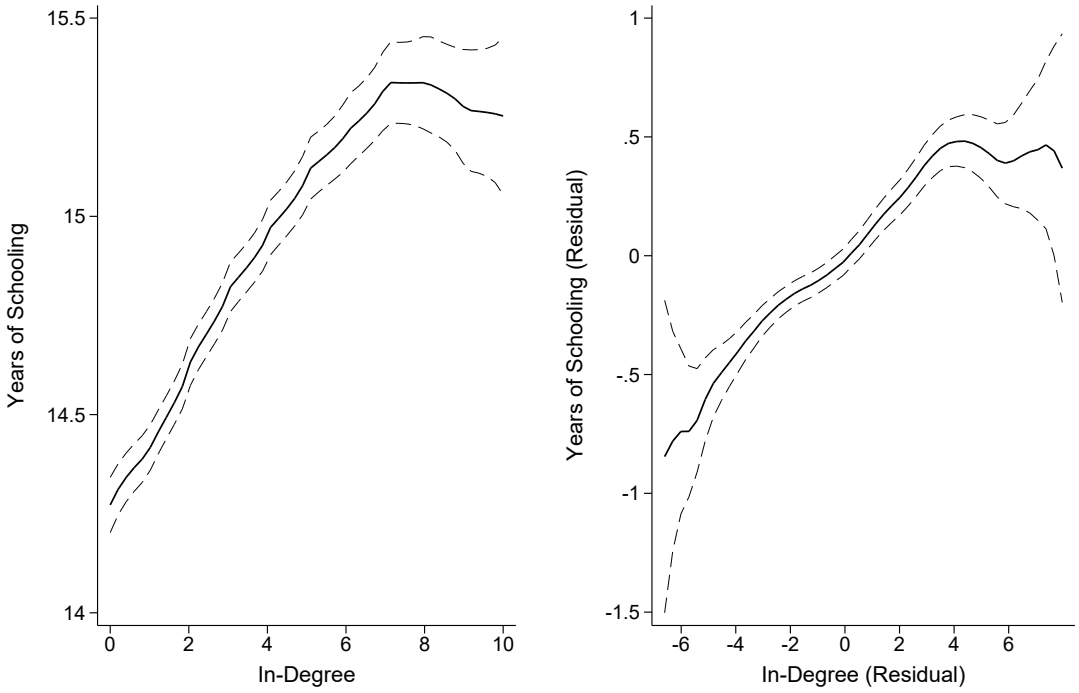
Note: Add Health restricted-use data. Local polynomial nonparametric plots and 95% confidence intervals of grade in-degree on age distance. The left plot uses the original variables. The right plot uses their residuals after removing individual characteristics (age, IQ, and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects.

Figure A.2: Difference in Friendship CDF by Age Distance



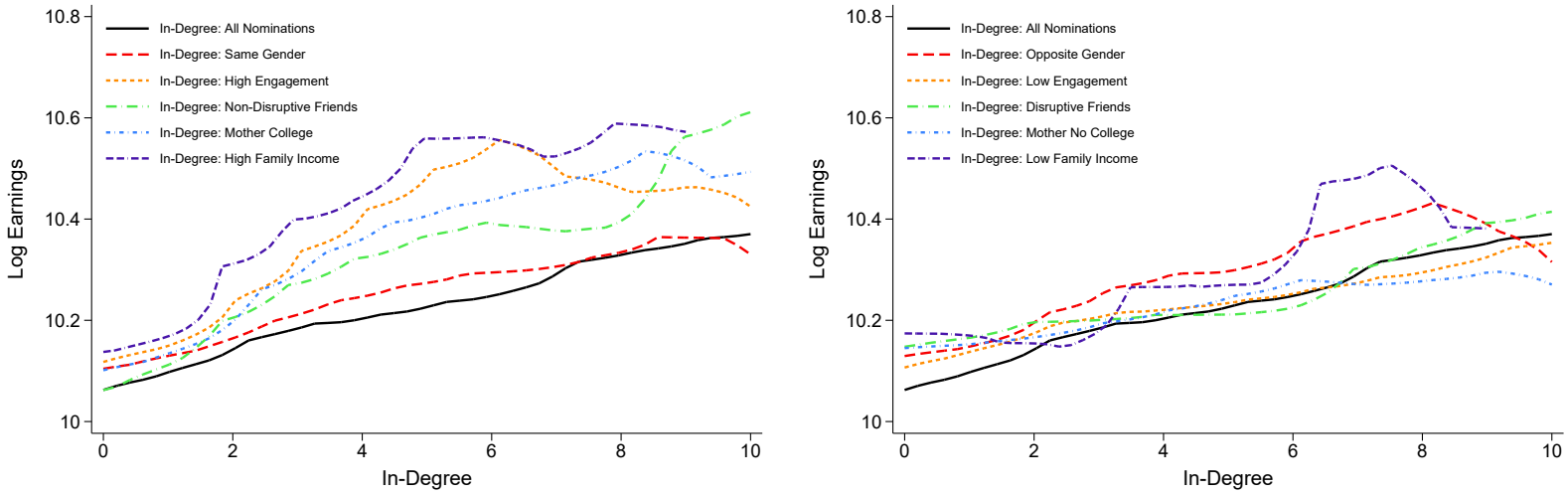
Note: Add Health restricted-use data. Estimated difference in the CDF of grade in-degree as age distance increases by one unit. Dashed lines are 95% confidence intervals. To be specific about the estimation procedure, let X represent grade in-degree and Z age distance. We estimate the CDF difference $\mathbb{E}[1\{X \leq x\}|Z = z'] - \mathbb{E}[1\{X \leq x\}|Z = z]$ for all x and $z' \geq z$ by regressing the indicator variable $1\{X \leq x\}$ on Z. The coefficient of Z provides an estimate of the CDF difference by one unit increase in Z. The left plot does not include any covariates. The right plot controls for individual characteristics (age, IQ, and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects.

Figure A.3: Education and Friendships



Note: Add Health restricted-use data. Local polynomial nonparametric plots and 95% confidence intervals of years of schooling on grade in-degree. The left plot uses the original variables. The right plot uses their residuals after removing individual characteristics (age, IQ, and indicators for whether the student is extrovert, female and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects.

Figure A.4: Log Earnings and Friendship Measures



Note: Add Health restricted-use data. Local polynomial nonparametric plots of log earnings on various network measures. In both the left and right figures, the solid line includes all the friendships nominated by students in the same school-grade. The red long-dashed lines restrict to friendships nominated by students in the same (opposite) gender. The orange short-dashed lines restrict to high(low)-engagement nominations (nominations that the nominator reports doing at least three (at most two) out of the five listed activities with the nominated friend). The green long-dash-dotted lines restrict to friendships nominated by (non-)disruptive students. The blue short-dash-dotted lines restrict to friendships nominated by students with mothers who are (not) college educated. The purple double-dash-dotted lines restrict to friendships nominated by students from high(low)-income families (above (below) median).

Table A.1: Variation in Age Distance: An Illustrating Example

Cohort	Person	Age	Cohort-Mean Age	Age Distance	Cohort-Mean Age Distance
Cohort 1	1	14	13.5	0.75	0.67
	2	13.5	13.5	0.5	0.67
	3	13	13.5	0.75	0.67
Cohort 2	1	13.8	13.5	0.45	0.4
	2	13.5	13.5	0.3	0.4
	3	13.2	13.5	0.45	0.4

Note: We compute the average distance of a person to all their peers in their cohort excluding themselves. For example, for person 1 in cohort 1, their distance to person 2 is 0.5 and to person 3 is 1, so the average distance is 0.75.

Table A.2: Sample Variation in Age Distance

	SD
Age Distance	0.435
Residual After School FE	0.400
Residual After School FE + Mean Age	0.400
Residual After School FE + Mean Age + Age	0.205
Residual After School FE + Full Controls	0.202
Residual After School FE + Grade FE	0.399
Residual After School FE + Grade FE + Age	0.214
Residual After School FE + Grade FE + Full Controls	0.200
Observations	10,605

Note: Add Health restricted-use data. Standard deviations in the residuals of age distance after removing a variety of controls. Mean Age refers to the average age of all the students in a school-grade. Full Controls include individual characteristics (age, IQ, and indicators for whether the student is extrovert, female, and white) and cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white).

Table A.3: Testing for Instrument Validity: Individual Tests

	Age Distance
The Dependent Variable is	
Mother's Years of Schooling	-0.0642
	(0.1437)
Father's Years of Schooling	-0.0175
	(0.1009)
Mother Born in US	-0.0119
	(0.0260)
Father Born in US	-0.0224
	(0.0138)
Catholic	0.0114
	(0.0176)
Baptist	-0.0256
	(0.0178)
Mother's Age at Respondent's Birth	-0.1676
	(0.2476)
Number of Siblings	0.0999
	(0.0961)
Born in US	-0.0041
	(0.0233)
Birth Weight	0.0513
	(0.0555)
Breastfed	0.0221
	(0.0198)
Height	-0.1614
	(0.1616)
Mentally Retarded	-0.0000
	(0.0019)
Disability	0.0005
	(0.0029)
Observations	10,605

Note: Add Health restricted-use data. Each row presents an OLS regression of the specified dependent variable on age distance, controlling for individual characteristics (age, IQ, and indicators for whether the student is extrovert, female and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Standard errors in parentheses are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Testing for Instrument Validity: Joint Tests

	(1) Log Earnings	(2) Log Earnings	(3) Age Distance
Mother's Years of Schooling		0.0143***	-0.0004
		(0.0046)	(0.0013)
Father's Years of Schooling		0.0138**	0.0002
		(0.0060)	(0.0011)
Mother Born in US		-0.0518	0.0006
		(0.0330)	(0.0115)
Father Born in US		-0.0772*	-0.0096
		(0.0424)	(0.0068)
Catholic		0.0645***	0.0007
		(0.0216)	(0.0053)
Baptist		-0.0171	-0.0072
		(0.0280)	(0.0059)
Mother's Age at Respondent's Birth		-0.0000	-0.0004
		(0.0020)	(0.0004)
Number of Siblings		0.0128*	0.0026
		(0.0068)	(0.0022)
Born in US		-0.1577***	0.0033
		(0.0410)	(0.0148)
Birth Weight		0.0193**	0.0017
		(0.0079)	(0.0015)
Breastfed		-0.0292	0.0046
		(0.0224)	(0.0043)
Height		0.0030	-0.0007
		(0.0029)	(0.0006)
Mentally Retarded		-0.4339	-0.0094
		(0.3464)	(0.0327)
Disability		-0.1970	0.0019
		(0.1370)	(0.0192)
F-stat of Predetermined Characteristics		6.790	0.904
P-value		0.000	0.556
R^2	0.059	0.066	0.753
Observations	10,605	10,605	10,605

Note: Add Health restricted-use data. The dependent variable in Columns 1 and 2 is the log annual earnings. The dependent variable in Column 3 is age distance. All specifications include individual characteristics (age, IQ, and indicators for whether the student is extrovert, female and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Standard errors in parentheses are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: First-Stage Estimates for Pairwise Friendship Nominations

	(1) Probit	(2) Probit	(3) Probit
Pairwise Age Distance	-0.0699***	-0.0343***	
	(0.0031)	(0.0051)	
Pairwise Age Distance Squared		-0.0176***	
		(0.0022)	
Pairwise Age Distance: Older Sender			-0.1017***
			(0.0046)
Pairwise Age Distance: Younger Sender			-0.0160***
			(0.0042)
Receiver Age	-0.0417***	-0.0424***	-0.0844***
	(0.0035)	(0.0036)	(0.0059)
Mean Age	0.0636	0.0656	0.0994
	(0.0658)	(0.0657)	(0.0652)
Mean of Dep. Var.	0.011	0.011	0.011
LR-stat of Homophily Measures	516.798	594.731	531.939
P-value	0.000	0.000	0.000
Observations	21,918,404	21,918,404	21,918,404

Note: Add Health restricted-use data. The estimation sample includes all the pairwise combinations of students in the in-home survey within the same school-grade. The dependent variable is an indicator for whether student i nominates student j as a friend. Pairwise age distance is constructed by taking the absolute value of the age distance between student i (sender) and student j (receiver). Pairwise age distance to older (younger) sender is equal to pairwise age distance if the sender is older (younger) than the receiver and 0 otherwise. Additional covariates include receiver's characteristics (IQ and indicators for whether the student is extrovert, female and white), cohort-level characteristics (mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Standard errors in parentheses are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Log Earnings on Age Distance: Reduced-Form Results

	Log Earnings	Log Earnings	Log Earnings
Age Distance	-0.1708***	-0.2908***	
	(0.0571)	(0.1042)	
Age Distance Squared		0.0359	
		(0.0315)	
Age Distance to Older Peers			-0.4134**
			(0.1823)
Age Distance to Younger Peers			0.0373
			(0.1131)
Age	-0.0474	-0.0358	-0.2643**
	(0.0376)	(0.0373)	(0.1216)
Mean Age	0.0644	0.0687	0.1743
	(0.1143)	(0.1165)	(0.1495)
F-stat of Homophily Measures	8.942	6.428	4.931
P-value	0.003	0.002	0.009
R^2	0.054	0.054	0.054
Observations	10,605	10,605	10,605

Note: Add Health restricted-use data. Age distance refers to the average age distance to other students in the same school-grade. Age distance to older (younger) peers refers to the average age distance to other students in the same school-grade who are older (younger) than the respondent. Additional covariates include individual characteristics (IQ and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Standard errors in parentheses are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Covariance of Education and Friendships

Panel A: Covariance Matrix			Panel B: Inverse of Covariance Matrix		
	Years of Schooling	In-Degree		Years of Schooling	In-Degree
Years of Schooling	3.3532		Years of Schooling	0.3055	
In-Degree	0.8296	8.6717	In-Degree	-0.0292	0.1181

Note: In-degree refers to the number of friendships nominated by other students in the same school-grade. Both years of schooling and in-degree are the residuals after controlling for individual characteristics (age, IQ, and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects.

Table A.8: Labor Market Returns to Friendships: Various Friendship Measures

	(1) In-Degree	(2) Out-Degree	(3) Reciprocated Degree	(4) Network Size
OLS	0.0245	0.0146	0.0392	0.0183
95% CI	[0.0177, 0.0312]	[0.0064, 0.0227]	[0.0261, 0.0522]	[0.0123, 0.0243]
IV	[0.0926, 0.1367]	[0.1246, 0.1840]	[0.2007, 0.2964]	[0.0722, 0.1067]
95% CI	[0.0075, 0.2242]	[0.0114, 0.3022]	[0.0149, 0.4898]	[0.0067, 0.1742]
Observations	10,605	10,605	10,605	10,605

Note: Add Health restricted-use data. The dependent variable is the log annual earnings. All friendship measures restrict to nominations within the same school-grade. In-degree refers to the number of friendships nominated by other students. Out-degree refers to the number of friendships that the respondent nominates. Reciprocated degree refers to the number of friendships that both nominate. Network size refers to the number of friendships that either one nominates. All specifications include individual characteristics (age, IQ, and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. The instrument is age distance. The confidence intervals are constructed based on standard errors clustered at the school level.

Table A.9: Robustness Check: Bullying

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV
In-Degree	[0.0926, 0.1367]	[0.0913, 0.1347]	[0.0923, 0.1356]	[0.0930, 0.1363]	[0.0923, 0.1351]
95% CI	[0.0075, 0.2242]	[0.0051, 0.2235]	[0.0036, 0.2268]	[0.0063, 0.2255]	[0.0029, 0.2270]
Additional Individual Controls	N	Get Along w Others	Part of School	Safe in School	All 3 Measures
Observations	10,605	10,605	10,605	10,605	10,605

Note: Add Health restricted-use data. The dependent variable is the log annual earnings. In-degree refers to the number of friendships nominated by other students in the same school-grade. All specifications include individual characteristics (age, IQ, and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Column 2 controls for an indicator for whether the student gets along with other students. Column 3 controls for an indicator for whether the student feels like he/she is part of the school. Column 4 controls for an indicator for whether the student feels safe in the school. Column 5 controls for all the three indicators in Columns 2-4. The confidence intervals are constructed based on standard errors clustered at the school level.

Table A.10: Labor Market Returns to Friendships in Various Subsamples: OLS Estimates

	(1) Log Earnings	(2) Log Earnings	(3) Log Earnings	(4) Log Earnings	(5) Log Earnings	(6) Log Earnings	(7) Log Earnings	(8) Log Earnings
Years of Schooling	0.0758***	0.1301***	0.0924***	0.1063***	0.1104***	0.1050***	0.1027***	0.0859***
	(0.0080)	(0.0077)	(0.0083)	(0.0102)	(0.0117)	(0.0081)	(0.0060)	(0.0163)
In-Degree	0.0240***	0.0239***	0.0221***	0.0255***	0.0191***	0.0263***	0.0237***	0.0292**
	(0.0053)	(0.0041)	(0.0045)	(0.0063)	(0.0058)	(0.0041)	(0.0035)	(0.0128)
Subsample	Male	Female	High Family Income	Low Family Income	Mother College	Mother No College	Native	Immigrant
R^2	0.063	0.096	0.080	0.102	0.082	0.111	0.101	0.097
Observations	5,059	5,546	4,342	3,768	3,933	5,347	9,774	831

Note: Add Health restricted-use data. In-degree refers to the number of friendships nominated by other students in the same school-grade. Additional covariates include individual characteristics (age, IQ, and indicators for whether the student is extrovert, female and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Standard errors in parentheses are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: The Effect of Social Activities on Friendships, and Cognitive and Health Outcomes

	(1) In-Degree	(2) GPA	(3) Job Cognitive Score	(4) Depression	(5) Healthy
Years of Schooling			0.0620***	-0.0119***	0.0408***
			(0.0031)	(0.0020)	(0.0026)
Very Hard Study Effort	0.3352***	0.3671***	0.0983***	-0.0353***	0.1079***
	(0.1121)	(0.0295)	(0.0181)	(0.0104)	(0.0186)
Some Study Effort	0.5040***	0.1646***	0.0735***	-0.0255**	0.0632***
	(0.1039)	(0.0270)	(0.0156)	(0.0113)	(0.0181)
Frequently Hang with Friends	0.9035***	-0.0084	-0.0330*	-0.0215*	0.0727***
	(0.1178)	(0.0354)	(0.0186)	(0.0112)	(0.0184)
Sometimes Hang with Friends	0.6947***	0.0405	-0.0169	-0.0284**	0.0578***
	(0.1077)	(0.0318)	(0.0209)	(0.0122)	(0.0170)
Frequently Drink	0.4353***	-0.1996***	-0.0224*	0.0257**	-0.0259*
	(0.1199)	(0.0281)	(0.0134)	(0.0104)	(0.0151)
Sometimes Drink	0.3519***	-0.1050***	-0.0158	0.0212***	-0.0243**
	(0.0767)	(0.0221)	(0.0119)	(0.0072)	(0.0118)
IQ	0.0148***	0.0122***	0.0017***	0.0014***	0.0003
	(0.0024)	(0.0010)	(0.0005)	(0.0003)	(0.0004)
Extrovert	0.3960***	0.0075	0.0283*	-0.0123	0.0251**
	(0.0777)	(0.0185)	(0.0145)	(0.0074)	(0.0121)
Mean of Dep. Var.	3.385	2.851	2.668	0.145	0.590
R^2	0.046	0.127	0.123	0.039	0.043
Observations	10,205	7,008	5,754	10,204	10,205

Note: Add Health restricted-use data. The dependent variable in Column 2 is the GPA of the respondent in Wave 2. The dependent variable in Columns 3 is the index of cognitive skills required by the respondent's occupation that is constructed from O*NET data. The dependent variable in Column 4 is an indicator for whether the respondent has ever been diagnosed with depression (Wave 4). The dependent variable in Column 5 is an indicator for whether the respondent's self-reported health status in Wave 4 is excellent or very good. Additional covariates include individual characteristics (age, indicators for whether the student is female and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Standard errors in parentheses are clustered at the school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Labor Market Returns to Friendships: OLS Estimates

	(1) Log Earnings	(2) Log Earnings	(3) Log Earnings	(4) Log Earnings	(5) Log Earnings	(6) Log Earnings
Years of Schooling	0.1175***	0.1064***	0.1219***	0.1125***	0.1099***	0.1030***
	(0.0068)	(0.0059)	(0.0060)	(0.0059)	(0.0060)	(0.0058)
In-Degree	0.0153***	0.0145***	0.0211***	0.0219***	0.0229***	0.0245***
	(0.0034)	(0.0033)	(0.0034)	(0.0035)	(0.0035)	(0.0034)
Endowments	N	Y	Y	Y	Y	Y
Individual Covariates	N	N	Y	Y	Y	Y
Cohort Means	N	N	N	Y	Y	Y
Grade FE	N	N	N	N	Y	Y
School FE	N	N	N	N	N	Y
R^2	0.065	0.070	0.117	0.125	0.127	0.098
Observations	10,605	10,605	10,605	10,605	10,605	10,605

Note: Add Health restricted-use data. In-degree refers to the number of friendships nominated by other students in the same school-grade. Endowments include IQ and an indicator for whether the student is extrovert. Individual Covariates include age and indicators for whether the student is female and white. Cohort Means include mean age, mean IQ, fraction extrovert, fraction female, and fraction white. Standard errors in parentheses are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Covariance Matrix of Network Measures

	School In-Degree	Grade In-Degree	Grade In-Degree (High Engagement)
School In-Degree	12.250		
Grade In-Degree	9.507	8.672	
Grade In-Degree (High Engagement)	2.499	2.281	1.363

Note: Add Health restricted-use data. The variance-covariance matrix is calculated using the residuals of the variables after removing individual characteristics (IQ, age, and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean IQ, mean age, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects.

Table A.14: Labor Market Returns to Friendships of Various Types: OLS Estimates

	(1) Log Earnings	(2) Log Earnings	(3) Log Earnings	(4) Log Earnings	(5) Log Earnings	(6) Log Earnings
Years of Schooling	0.1030***	0.1027***	0.1029***	0.1013***	0.1025***	0.1029***
	(0.0058)	(0.0058)	(0.0058)	(0.0059)	(0.0060)	(0.0058)
In-Degree: All Nominations	0.0245***					
	(0.0034)					
In-Degree: Same Gender		0.0344***				
		(0.0048)				
In-Degree: Opposite Gender		0.0149***				
		(0.0053)				
In-Degree: High Engagement			0.0401***			
			(0.0078)			
In-Degree: Low Engagement			0.0189***			
			(0.0047)			
In-Degree: Non-Disruptive Friends				0.0373***		
				(0.0049)		
In-Degree: Disruptive Friends				0.0101		
				(0.0064)		
In-Degree: Mother College					0.0290***	
					(0.0072)	
In-Degree: Mother No College					0.0260***	
					(0.0045)	
In-Degree: Missing Mother Education					-0.0018	
					(0.0160)	
In-Degree: High Family Income						0.0474***
						(0.0093)
In-Degree: Low Family Income						0.0342*
						(0.0174)
In-Degree: Missing Family Income						0.0186***
						(0.0044)
R^2	0.098	0.098	0.098	0.099	0.098	0.098
Observations	10,605	10,605	10,605	10,605	10,605	10,605

Note: Add Health restricted-use data. Column 2 separates friendships nominated by students in the same (opposite) gender. Column 3 separates nominations of high (low) engagement (nominations that the nominator reports doing three or more out of the five listed activities with the nominated friend). Column 4 separates friendships nominated by (non-)disruptive students. Column 5 separates friendships nominated by students with (without) college-educated mothers. Column 6 separates friendships nominated by students with family income above (below) median. All specifications include individual characteristics (age, IQ, and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Standard errors in parentheses are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.15: First-Stage Results for Friendships of Various Types

	(1) In-Degree	(2) In-Degree	(3) In-Degree	(4) In-Degree	(5) In-Degree
Age Distance	-0.6239***	-0.3580***	-0.6443***	-0.4980***	-0.1941***
	(0.0707)	(0.0420)	(0.0665)	(0.0631)	(0.0353)
Age	0.1294**	0.1255***	0.1880***	0.1348***	0.0615**
	(0.0560)	(0.0304)	(0.0501)	(0.0400)	(0.0235)
Mean Age	-0.0928	-0.1111	-0.3320**	-0.1198	-0.1679**
	(0.1167)	(0.0685)	(0.1561)	(0.1209)	(0.0691)
Who Nominates?	Same Gender	High Engagement	Non-Disruptive	Mother College	High Family Income
Mean of Dep. Var.	2.103	0.906	1.800	1.250	0.464
F-stat of Instrument	77.905	72.556	93.841	62.221	30.284
P-value	0.000	0.000	0.000	0.000	0.000
R^2	0.043	0.030	0.039	0.036	0.014
Observations	10,605	10,605	10,605	10,605	10,605

Note: Add Health restricted-use data. The dependent variable in Column 1 is the number of friendships nominated by students in the same gender. The dependent variable in Column 2 is the number of high-engagement nominations (nominations that the nominator reports doing three out of the five listed activities with the nominated friend). The dependent variable in Column 3 is the number of friendships nominated by non-disruptive students. The dependent variable in Column 4 is the number of friendships nominated by students with college-educated mothers. The dependent variable in Column 5 is the number of friendships nominated by students with family income above median. Additional covariates include individual characteristics (IQ and indicators for whether the student is extrovert, female, and white), cohort-level characteristics (mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Standard errors in parentheses are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16: Why Do Adolescent Friendships Matter for Labor Market Outcomes? Social Mechanisms

	(1) Work	(2) Repetitive	(3) Supervisory	(4) Job Social Score	(5) Friends (W4)	(6) Marry	(7) Extrovert (W4)
In-Degree (W1)	0.0049***	-0.0091***	0.0025	0.0124***	0.0682***	0.0034**	0.0092***
	(0.0013)	(0.0014)	(0.0015)	(0.0025)	(0.0093)	(0.0017)	(0.0015)
Years of Schooling	0.0235***	-0.0338***	0.0050*	0.0662***	0.1841***	0.0046*	0.0069***
	(0.0023)	(0.0024)	(0.0030)	(0.0041)	(0.0173)	(0.0026)	(0.0025)
IQ	-0.0002	-0.0016***	-0.0003	0.0006	0.0051**	-0.0008*	-0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0025)	(0.0004)	(0.0005)
Extrovert (W2)	-0.0070	-0.0032	0.0135	0.0427**	0.1255**	0.0309***	0.1694***
	(0.0084)	(0.0107)	(0.0097)	(0.0180)	(0.0613)	(0.0116)	(0.0121)
Mean of Dep. Var.	0.809	0.314	0.362	2.890	4.726	0.491	0.364
R^2	0.027	0.044	0.012	0.085	0.047	0.035	0.034
Observations	11,590	11,442	11,442	5,982	10,469	10,599	10,599

Note: Add Health restricted-use data. W1 stands for Wave I, etc. OLS estimates are reported. The dependent variable in Column 1 is an indicator for whether the respondent is currently working for at least ten hours a week. The dependent variable in Column 2 is an indicator for whether the respondent's job tasks are repetitive. The dependent variable in Column 3 is an indicator for whether the respondent has a supervisory role at their current or previous job. The dependent variable in Columns 4 is the index of social skills required by the respondent's occupation that is constructed from O*NET data. The dependent variable in Column 5 is the number of friends reported in Wave 4. The dependent variable in Column 6 is an indicator for whether the respondent has ever been married (Wave 4). The dependent variable in Column 7 is an indicator for whether the respondent's extroversion index in Wave 4 is 15 and above. In-degree refers to the number of friendships nominated by students in the same school-grade. Additional covariates include individual characteristics (age, and indicators for whether the student is female and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Standard errors in parentheses are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17: Why Do Adolescent Friendships Matter for Labor Market Outcomes? Cognitive and Other Mechanisms

	(1) GPA	(2) Skip School	(3) Suspension	(4) Job Cognitive Score	(5) Depression	(6) Healthy
In-Degree	0.0273***	-0.0040***	-0.0105***	0.0091***	-0.0034***	0.0100***
	(0.0028)	(0.0014)	(0.0017)	(0.0017)	(0.0010)	(0.0016)
Years of Schooling				0.0615***	-0.0119***	0.0408***
				(0.0030)	(0.0020)	(0.0027)
IQ	0.0114***	-0.0013***	-0.0027***	0.0015***	0.0014***	0.0001
	(0.0010)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)
Extrovert	-0.0286*	0.0509***	0.0515***	0.0192	-0.0093	0.0140
	(0.0169)	(0.0087)	(0.0101)	(0.0148)	(0.0072)	(0.0120)
Mean of Dep. Var.	2.839	0.274	0.244	2.663	0.144	0.587
R^2	0.097	0.050	0.071	0.122	0.036	0.041
Observations	7,303	10,468	10,594	5,982	10,604	10,605

Note: Add Health restricted-use data. OLS estimates are reported. The dependent variable in Column 1 is the GPA of the respondent in Wave 2. The dependent variable in Column 2 is an indicator for whether the respondent has skipped school for at least one full day without an excuse during the school year (Wave 1). The dependent varaible in Column 3 is an indicator for whether the respondent has ever received an out-of-school suspension from school (Wave 1). The dependent variable in Columns 4 is the index of cognitive skills required by the respondent's occupation that is constructed from O*NET data. The dependent variable in Column 5 is an indicator for whether the respondent has ever been diagnosed with depression (Wave 4). The dependent variable in Column 6 is an indicator for whether the respondent's self-reported health status in Wave 4 is excellent or very good. In-degree refers to the number of students in the same school-grade who nominate the respondent as a friend in Wave 1. Additional covariates include individual characteristics (age, and indicators for whether the student is female and white), cohort-level characteristics (mean age, mean IQ, fraction extrovert, fraction female, and fraction white), grade fixed effects, and school fixed effects. Standard errors in parentheses are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B A Model of Friendship Formation, Education and Earnings

We now present a simple model of how individuals decide to invest in educational and social connections and what ultimately determines their education, friendships and earnings. In the model, each individual i decides how to allocate their time (which we normalize to one) between hours of studying (H_i), socializing (S_i), and leisure ($L_i = 1 - H_i - S_i$). Studying increases education (denoted by E_i), whereas socializing increases the number of friends (denoted by F_i). Both E_i and F_i raise earnings. Any remaining time is devoted to pure leisure (L_i), which represents time spent on solo activities such as watching television or sleeping and has no labor market returns.

Following Card (1999), we assume the individual's utility is determined by consumption, which is determined by log earnings (Y)[29] and leisure (U) (which is split into social and non-social leisure time), and can be written as

$$Y(E_i, F_i, X_i, \epsilon_i) + U(S_i, L_i, X_i, \upsilon_i, \omega_i). \tag{B.1}$$

The log earnings $Y(E_i, F_i, X_i, \epsilon_i) \equiv Y_i(E_i, F_i)$ depends on education (E_i), friendships (F_i), observed characteristics (X_i) such as gender, IQ or sociability, and unobserved characteristics that affect earnings (ϵ_i) such as competence, motivation, etc. The utility from socializing and other forms of leisure $U(S_i, L_i, X_i, \upsilon_i) \equiv U_i(S_i, L_i)$ depends on the time one spends socializing (S_i) and doing solo leisure activities (L_i), one's type of endowment (X_i), and one's unobserved preferences for socializing (υ_i) and for leisure (ω_i).[30] The cost (or disutility) of studying ($C(H_i, X_i, \upsilon_i, \omega_i)$) is netted from $U(S_i, L_i, X_i, \upsilon_i, \omega_i)$, so this utility term can be positive or negative.

Although the model is static, observations and decisions are realized with a certain timing. At the beginning of the schooling period, each student i observes their characteristics and the characteristics of their peers $X = (X_1, \ldots, X_n)$, as well as everyone's utility preferences $\upsilon = (\upsilon_1, \ldots, \upsilon_n)$ and $\omega = (\omega_1, \ldots, \omega_n)$. Then they decide how much time to spend on studying H_i and socializing S_i. A student's education E_i and friendships F_i are realized at the end of the schooling period. After the schooling period, students enter the labor market, ϵ_i is realized, and they receive log earnings $Y(E_i, F_i, X_i, \epsilon_i)$.

[29] We assume that all earnings are consumed. We abstract from saving and borrowing considerations in this paper because we observe earnings in the data only once.

[30] Given that we have two choice variables S_i and L_i, we consider errors in both. If we specified the utility function fully, it would have two terms (one for the utility of socializing and one for the utility of leisure) each of which might contain some unobservable determinants.

Given X, υ and ω, an individual's expected utility from the choices H_i and S_i is given by

$$\mathbb{E}[Y(E_i, F_i, X_i, \epsilon_i)|X, \upsilon, \omega] + U(S_i, 1 - H_i - S_i, X_i, \upsilon_i, \omega_i). \tag{B.2}$$

We assume that the expected value of log earnings takes the form $\mathbb{E}[Y(E_i, F_i, X_i, \epsilon_i)|X, \upsilon, \omega] = Y(\mathbb{E}[E_i|X, \upsilon, \omega], \mathbb{E}[F_i|X, \upsilon, \omega], X_i, \mathbb{E}[\epsilon_i|X, \upsilon, \omega])$, that is, the expected log earnings is a function of i's expected education, expected friendships, observable characteristics, and expected labor market shocks. This is satisfied by the standard specification in the literature that log earnings is a linear function of education, friendships and other traits

$$Y(E_i, F_i, X_i, \epsilon_i) = r_e E_i + r_f F_i + \beta' X_i + \epsilon_i, \tag{B.3}$$

where r_e represents the returns to education, r_f represents the returns to friendships, and β captures the effects of the observed characteristics of i.[31]

We assume that X_i is independent of ϵ_i, υ_i and ω_i for all i, but we allow ϵ_i to be correlated with υ_i and ω_i, potentially making education E_i and friendships F_i in this equation endogenous (correlated with the error term). We also assume that conditional on (X, υ, ω), ϵ_i does not depend on time spent studying H_i and socializing S_i. In other words, the amounts of time spent studying and socializing while growing up have no direct effect on adult earnings: they affect earnings only through their effects on education and friendships.[32]

Production of education and friendships.

Education E_i and friendships F_i depend on initial endowments and on the time individuals allocate to each activity.

Friendship formation. We assume i becomes a friend of j if they spend time together (they socialize), and they like each other (they derive nonnegative utility from the friendship). If individuals i and j spend S_i and S_j amounts of time socializing, then i and j become friends ($F_{ij} = 1$) following

$$F_{ij} = \{g(S_i, S_j, X_i, X_j) + \eta_{ij} \geq 0\}, \tag{B.4}$$

where $g(S_i, S_j, X_i, X_j)$ represents the deterministic latent utility of becoming friends and η_{ij} represents an unobservable preference shock in friendship formation that is independent

[31] More general specifications can also be considered. For example, we can add an interaction between education and networks, that is, $Y(E_i, F_i, X_i, \epsilon_i) = r_e E_i + r_f F_i + r_{e \cdot f} E_i \times F_i + \beta' X_i + \epsilon_i$, provided that the production of E_i and F_i are conditionally independent given X, υ, and ω, which is satisfied given the production functions specified below.

[32] More explicitly, we are assuming that socializing, a form of leisure, increases one's utility but it does not directly affect earnings, except through its effect on one's network and education, and similarly for studying. The exclusion of H_i and S_i from Y_i will turn out to be a crucial assumption later on for our IVs to be valid.

of X, υ, and ω. For example, individuals i and j might become friends because they were together during a particularly good or bad event. The likelihood that i and j become friends, $\Pr(F_{ij} = 1|S_i, S_j, X_i, X_j) \equiv p_{ij}(S_i, S_j)$, depends on how much time they spend socializing S_i and S_j.[33] We assume that both i and j have to spend time socializing together ($S_i > 0$ and $S_j > 0$) for them to have a non-zero probability of becoming friends. Thus the production of friendships requires coordination with others – you cannot "party alone." We assume that if people study together they are socializing part of the time, and studying part of the time.[34]

Conditional on socializing S_i and S_j, the likelihood of becoming friends also depends on the individual and shared characteristics of i and j (X_i and X_j). This feature captures the empirical finding that individuals tend to form friendships with other individuals with whom they share similar characteristics, often referred to as homophily. Individual i's total number of friends F_i is given by $F_i = \sum_{j \neq i} F_{ij}$,where F_{ij} is the indicator for whether i and j are friends.

Education. The production of education is standard. If individual i spends a certain amount of time H_i studying, their education is given by

$$E_i = a(H_i, X_i, X_{-i}) + \xi_i, \tag{B.5}$$

where $a(H_i, X_i, X_{-i}) \equiv a_i(H_i)$ represents the deterministic educational output, and ξ_i is an unobservable shock that is assumed to be independent of X, υ, and ω. For example, individuals could suffer unexpected health shocks (such as getting the flu) that affect their ability to attend school or study. Thus in addition to studying, the production of education depends on the observed characteristics of i (X_i) (which include their cognitive skills, social skills, and other characteristics, most importantly the school they attend), and on the characteristics of their peers $X_{-i} = (X_j, j \neq i)$. This specification allows for (exogenous) peer effects in education, namely, the possibility that individuals learn faster (or slower) depending on the characteristics of their classroom peers. Note however that even in the absence of peers, individuals can obtain education.

[33] This model is similar in spirit to the dyadic network formation models with individual fixed effects (Graham, 2017), where the time spent socializing S_i and S_j act as the individual fixed effects.

[34] We assume that even when people study together that time can be split into socializing time and studying time. This is of course a simplification. The results are qualitatively similar if we write a more realistic model where there are four activities possible including "studying together". However, this model is more complicated and less intuitive so we present the simpler version here.

How do individuals decide how much to study and socialize? Best response functions and equilibrium.

Given information (X, υ, ω), individual i chooses H_i and S_i in order to maximize their *expected* utility in (B.2). Recall that the expected value of log earnings is a function of i's expected education, expected number of friends, observable characteristics, and expected labor market shocks. For individual i, the expected number of friends depends on the time she spends socializing and the amount of time others spend socializing. In particular, the expected number of friends is of the form $\mathbb{E}[F_i|X, \upsilon, \omega] = \sum_{j \neq i} p_{ij}(S_i, S_j)$. The expected education depends on the time i spent studying and takes the form $\mathbb{E}[E_i|X, \upsilon, \omega] = a_i(H_i)$. Let $\partial Y_i/\partial E_i$ and $\partial Y_i/\partial F_i$ represent the derivatives of $Y_i(E_i, F_i)$ with respective to E_i and F_i evaluated at $E_i = a_i(H_i)$ and $F_i = \sum_{j \neq i} p_{ij}(S_i, S_j)$.

Given the actions S_j of other individuals $j \neq i$, the optimal amounts of studying H_i and socializing S_i satisfy the first-order conditions

$$\frac{\partial U_i}{\partial L_i}(S_i, 1 - H_i - S_i) = \frac{\partial Y_i}{\partial E_i}\frac{\partial a_i}{\partial H_i}(H_i) \tag{B.6}$$

$$\frac{\partial U_i}{\partial L_i}(S_i, 1 - H_i - S_i) = \frac{\partial U_i}{\partial S_i}(S_i, 1 - H_i - S_i) + \frac{\partial Y_i}{\partial F_i}\sum_{j \neq i}\frac{\partial p_{ij}}{\partial S_i}(S_i, S_j). \tag{B.7}$$

The optimal amount of studying equates the marginal utility with the marginal cost of studying. The marginal cost of studying is the utility loss due to one less unit of leisure (the left-hand side of (B.6)). The marginal benefit from studying (the right-hand side of (B.6)) is the additional earnings from studying one more unit of time. Similarly, the optimal amount of socializing equates the marginal utility with the marginal cost of socializing. The marginal cost of socializing is also the utility loss due to one less unit of leisure. The marginal benefit of socializing (the right-hand side of (B.7)) has two terms. The first term is the direct utility individuals derive from socializing one more unit of time. The second term comes from the additional earnings individuals get when they socialize and accumulate friendships.

Assume that the marginal utilities from socializing and leisure are both diminishing.[35] Monotonicity implies that their inverse functions exist. Let $I_i^S(\cdot, L_i)$ and $I_i^L(\cdot, S_i)$ denote the inverse of the marginal utility functions $\partial U_i(\cdot, L_i)/\partial S_i$ and $\partial U_i(S_i, \cdot)/\partial L_i$ with respect to S_i and L_i respectively. Then, under the standard Inada conditions,[36] we can derive the optimal

[35] Specifically we assume that the marginal utility from socializing $\partial U_i/\partial S_i$ is decreasing in S_i ($\partial^2 U_i/\partial S_i^2 < 0$), and similarly for the marginal utility from leisure $\partial U_i/\partial L_i$ ($\partial^2 U_i/\partial L_i^2 < 0$).

[36] We assume that $\lim_{S_i \to 0} \frac{\partial U_i}{\partial S_i}(S_i, L_i) = \infty$, $\lim_{L_i \to 0} \frac{\partial U_i}{\partial L_i}(S_i, L_i) = \infty$, and $\lim_{H_i \to 0} \frac{\partial a_i}{\partial H_i}(H_i) = \infty$.

H_i and S_i as an interior solution to

$$S_i = I_i^S \left(\frac{\partial Y_i}{\partial E_i} \frac{\partial a_i}{\partial H_i}(H_i) - \frac{\partial Y_i}{\partial F_i} \sum_{j \neq i} \frac{\partial p_{ij}}{\partial S_i}(S_i, S_j), 1 - H_i - S_i \right) \tag{B.8}$$

$$H_i = 1 - S_i - I_i^L \left(\frac{\partial Y_i}{\partial E_i} \frac{\partial a_i}{\partial H_i}(H_i), S_i \right). \tag{B.9}$$

Because the right-hand sides of (B.8) and (B.9) are both continuous functions of H_i and S_i, by Brouwer's fixed-point theorem, there exists at least one solution to equations (B.8)-(B.9). In general, there may be multiple solutions.[37]

The optimal amount of socializing depends on the decisions of others to socialize; thus, equations (B.8)-(B.9) correspond to the "best response function" of a given individual, who takes others' actions as given. A Nash equilibrium is a profile of actions (H_i^*, S_i^*), $i = 1, \ldots, n$, that satisfies (B.8)-(B.9) for all $i = 1, \ldots, n$. The best response of socializing in a Nash equilibrium is given by

$$S_i^* = I_i^S \left(\frac{\partial Y_i^*}{\partial E_i} \frac{\partial a_i}{\partial H_i}(H_i^*) - \frac{\partial Y_i^*}{\partial F_i} \sum_{j \neq i} \frac{\partial p_{ij}}{\partial S_i}(S_i^*, S_j^*), 1 - H_i^* - S_i^* \right), \tag{B.10}$$

where $\partial Y_i^* / \partial E_i$ and $\partial Y_i^* / \partial F_i$ represent the derivatives of $Y_i(E_i, F_i)$ with respect to E_i and F_i evaluated at $E_i = a_i(H_i^*)$ and $F_i = \sum_{j \neq i} p_{ij}(S_i^*, S_j^*)$. This equation states that the optimal amounts of socializing of students in a school are jointly determined by the returns to schooling, the returns to friendships, schooling inputs and productivity, homophily with peers, and their initial endowments and preferences. Due to the coordination effects, the social investment of a student is no longer unilaterally determined by that student: it also depends on the investments and endowments of the peers.

B.1 Implications.

We now investigate a few properties of the model that are useful for the empirical analysis.

Proposition B.1. *Assume that the marginal product of studying is positive ($\partial a_i / \partial H_i > 0$) and the labor market returns to education are positive ($\partial Y_i / \partial E_i > 0$). If there are no labor market returns to friendships ($\partial Y_i / \partial F_i = 0$), then in an OLS regression of log earnings on socializing, the coefficient on socializing will be negative when education and friendships are*

[37] In the most general form of the model – without imposing the Inada conditions, there can be multiple equilibria in the model. Intuitively, there can be situations where no one ever parties because no one else is partying, or where everyone parties all the time, because everyone else is partying. We can also obtain multiple interior solutions where individuals both study and socialize in partial amounts.

not controlled for.

Proof. See Appendix B.2.1. If there are no returns to friendships ($\partial Y_i/\partial F_i = 0$), then the optimal amount of socializing becomes

$$S_i^* = I_i^S \left(\frac{\partial Y_i^*}{\partial E_i} \frac{\partial a_i}{\partial H_i}(H_i^*), 1 - H_i^* - S_i^* \right). \tag{B.11}$$

In this case, individuals still socialize ($S_i^* > 0$), but socializing would have non-positive returns in the labor market because it is pure leisure. □

Proposition B.2. *If we estimate the earnings equation by OLS, then the estimated returns to education and friendships will be biased. Without further assumptions, the directions of the biases in the OLS estimates of returns to education and friendships are ambiguous.*

Proof. See Appendix B.2.2. In the model, both education and friendships can be correlated with the error term because tastes for leisure and for socializing are unobserved. If we estimate the earnings equation by OLS, then the estimated returns to education and friendships will be biased. This proposition states that ex-ante, it is not possible to assign the direction of the bias. The bias can be upward or downward, depending on, for example, whether the taste for socializing leans more toward productive activities like studying or working together or pure leisure like drinking or partying. □

Proposition B.3. *Suppose that Assumption B.2 is satisfied. Increasing an individual's homophily level has ambiguous predictions on socializing and on the number of friends. But the level of homophily will in general affect the equilibrium level of socializing and the number of friends an individual has.*

Proof. See Appendix B.2.3. Without coordination effects, the model predicts that individuals that are more similar to each other are more likely to be friends. However, the effect of increasing homophily on the number of friends is theoretically ambiguous because of coordination effects. For example, suppose that a boy is placed in a cohort with only girls. Compare him to another boy placed in a cohort with only boys. If girls socialize more than boys, then the boy placed in the girls-only cohort may still want to socialize more because it is more productive to socialize in this group and he might make more friends as a result, despite the gender difference. Therefore, the effect of homophily on social outcomes (socializing and number of friends) is an empirical question. Nevertheless, the theory also predicts that unless the direct impact of social distance is exactly offset by the coordination effects, the effect of homophily on social outcomes will not be zero. □

Proposition B.4. *Suppose that Assumptions B.3-B.5 are satisfied. The effect of an individual's cognitive and social endowments (X_i) on socializing and thus on friendships is theoretically ambiguous. The same is true for studying and education.*

Proof. See Appendix B.2.4. One might expect that individuals reinforce their initial endowments – social people socialize and make friends, smart people study – but that is not necessarily the case. If we assume that individuals with large social skills are not better students (social endowments do not affect studying productivity), then individuals with social skills will spend more time socializing and less time studying. Consequently, they accumulate more friends and less education. But if social endowments affect studying productivity – for example if people study together, then the predictions will not hold. Similarly, whether or not smart students socialize more depends on their socializing and studying productivity. If the marginal productivity of socializing is increasing in intelligence and large enough to induce a reduction in studying time, then high-IQ students can accumulate more friends. □

B.2 Proofs

B.2.1 Proposition B.1

Proof of Proposition B.1. Recall that the expected log earnings is

$$\mathbb{E}[Y_i|X,\upsilon,\omega] \;=\; Y(a_i(1-S_i-L_i),\sum_j p_{ij}(S_i,S_j),X_i,\mathbb{E}[\epsilon_i|X,\upsilon,\omega]).$$

Suppose there are no social returns ($\partial Y_i/\partial F_i = 0$). Under the assumption that the education returns are positive ($\partial Y_i/\partial E_i > 0$) and the marginal product of studying is positive ($\partial a_i(H_i)/\partial H_i > 0$), the derivative of the expected log earnings with respect to S_i is negative

$$\frac{\partial \mathbb{E}[Y_i|X,\upsilon,\omega]}{\partial S_i} = -\frac{\partial Y_i}{\partial E_i}\frac{\partial a_i}{\partial H_i}(1-S_i-L_i) < 0.$$

In other words, when there are no returns to socializing then a student who socializes relatively more will study less, attain a lower level of education, and have lower expected log earnings. □

B.2.2 Proposition B.2

Proof of Proposition B.2. Write the OLS regression of log earnings on education E_i, friendships F_i, and other traits X_i as

$$Y_i = r'K_i + \beta' X_i + \epsilon_i, \tag{B.12}$$

where $K_i = (E_i, F_i)'$ represents the vector of education and friendships and $r = (r_e, r_f)'$ represents the vector of returns to education and friendships. Assume that $\mathbb{E}(\epsilon_i) = 0$. The endogeneity of K_i and exogeneity of X_i mean that $\mathbb{E}[K_i\epsilon_i] \neq 0$ and $\mathbb{E}[X_i\epsilon_i] = 0$.

The OLS estimator of r is given by

$$\hat{r} = (\sum_{i=1}^{n} \tilde{K}_i K_i')^{-1} \sum_{i=1}^{n} \tilde{K}_i Y_i,$$

where $\tilde{K}_i = K_i - (\sum_{i=1}^{n} K_i X_i')(\sum_{i=1}^{n} X_i X_i')^{-1} X_i$ is the residual of K_i after partialing out X_i. Because $\sum_{i=1}^{n} \tilde{K}_i X_i' = 0$ we can derive $\hat{r} - r = (\sum_{i=1}^{n} \tilde{K}_i K_i')^{-1} \sum_{i=1}^{n} \tilde{K}_i \epsilon_i$. By the law of large numbers and the exogeneity of X_i ($\mathbb{E}[X_i\epsilon_i] = 0$), we obtain

$$\hat{r} - r \xrightarrow{p} (\mathbb{E}[K_i K_i'] - \mathbb{E}[K_i X_i']\mathbb{E}[X_i X_i']^{-1}\mathbb{E}[X_i K_i'])^{-1}\mathbb{E}[K_i\epsilon_i]$$

as $n \to \infty$. Because $\mathbb{E}[K_i\epsilon_i] \neq 0$ due to the endogeneity of K_i, the right-hand side is nonzero, leading to a bias in the OLS estimator $\hat{r}$.

The bias in $\hat{r}$ depends on both the correlation between K_i and ϵ_i ($\mathbb{E}[K_i\epsilon_i]$) and the inverse of the matrix

$$\mathbb{E}[K_i K_i'] - \mathbb{E}[K_i X_i']\mathbb{E}[X_i X_i']^{-1}\mathbb{E}[X_i K_i']. \tag{B.13}$$

Notice that because this matrix is positive definite,[38] so is its inverse. Unlike the case with a single endogenous variable, unless matrix (B.13) is diagonal, the OLS bias in r_f does not necessarily have the same sign as the correlation between friendships and the error term ϵ_i, and the same for r_e. Without knowledge about matrix (B.13), even if the correlations between education, friendships and ϵ_i are known, the OLS biases in the returns to education and friendships are ambiguous. □

Discussion: OLS bias in our sample Observe that matrix (B.13) involves the observables K_i and X_i only. In a given dataset this matrix can be estimated. In our Add Health data, we find that the off-diagonal elements in the inverse of matrix (B.13) are relatively small compared with the diagonal elements (Table A.7).[39] This suggests that the OLS biases in the returns to education and friendships are mostly determined by their correlations with ϵ_i. In particular, a positive (negative) correlation between friendships and ϵ_i will lead to an

[38] This is because $\mathbb{E}[K_i K_i'] - \mathbb{E}[K_i X_i']\mathbb{E}[X_i X_i']^{-1}\mathbb{E}[X_i K_i'] = \mathbb{E}[(K_i - \mathbb{E}[K_i X_i']\mathbb{E}[X_i X_i']^{-1} X_i)(K_i - \mathbb{E}[K_i X_i']\mathbb{E}[X_i X_i']^{-1} X_i)']$.

[39] The off-diagonal elements in the inverse matrix are determined by the correlation between education and friendships. If conditional on other covariates, education and friendships are positively (negatively) correlated, then we expect the off-diagonal elements in the inverse of the matrix (B.13) to be negative (positive). In our data, we find that education and friendships are positively correlated, controlling for other covariates, and the off-diagonal elements in the inverse of the matrix (B.13) are indeed negative.

upward (downward) bias in the returns to friendships.

The number of friends can be correlated with ϵ_i for a number of reasons. For example, because the number of friends depends on socializing, which in turn depends on the unobserved preference for socializing υ_i, if υ_i is correlated with ϵ_i, so is the number of friends.

To speculate on the direction of the correlation between friendships and ϵ_i through υ_i, we show in a lemma that socializing is increasing in the unobserved preference for socializing.

Assumption B.1. *(i) The marginal utility from socializing is increasing in υ_i ($\partial^2 U_i/\partial S_i \partial \upsilon_i > 0$), that is, students with higher υ_i enjoy more utility from each unit of socializing. (ii) The marginal utility from leisure does not depend on socializing nor υ_i ($\partial^2 U_i/\partial L_i \partial S_i = 0$ and $\partial^2 U_i/\partial L_i \partial \upsilon_i = 0$). (iii) The marginal product from socializing (or studying) is diminishing in socializing (or studying) ($\partial^2 p_{ij}/\partial S_i^2 < 0$ and $\partial^2 a_i/\partial H_i^2 < 0$). (iv) The labor market returns to education and friendships are positive constants ($\partial Y_i/\partial E_i = r_e > 0$ and $\partial Y_i/\partial F_i = r_f > 0$).*

Lemma B.1. *Under Assumption B.1, the optimal amount of socializing S_i^* is increasing in υ_i.*

Proof. Suppose that the change of υ_i does not trigger any change in the equilibrium so that $\frac{\partial S_j^*}{\partial \upsilon_i} = 0$, for all $j \neq i$. Taking the derivative of both sides of (B.6) and (B.7) evaluated at optimal (H_i^*, S_i^*), $i = 1, \ldots, n$, with respect to υ_i, we obtain

$$\frac{\partial^2 U_i}{\partial L_i^2}(S_i^*, L_i^*)\frac{\partial L_i^*}{\partial \upsilon_i} = r_e \frac{\partial^2 a_i}{\partial H_i^2}(H_i^*)\frac{\partial H_i^*}{\partial \upsilon_i} \tag{B.14}$$

$$\frac{\partial^2 U_i}{\partial L_i^2}(S_i^*, L_i^*)\frac{\partial L_i^*}{\partial \upsilon_i} = \frac{\partial^2 U_i}{\partial S_i \partial \upsilon_i}(S_i^*, L_i^*) + \left(\frac{\partial^2 U_i}{\partial S_i^2}(S_i^*, L_i^*) + r_f \sum_{j \neq i} \frac{\partial^2 p_{ij}}{\partial S_i^2}(S_i^*, S_j^*)\right)\frac{\partial S_i^*}{\partial \upsilon_i} \tag{B.15}$$

where we have used $\partial^2 U_i/\partial L_i \partial S_i = 0$, $\partial^2 U_i/\partial L_i \partial \upsilon_i = 0$, $\partial Y_i/\partial E_i = r_e$, and $\partial Y_i/\partial F_i = r_f$ by Assumption B.1(ii) and (iv), and the fact that a_i does not depend on υ_i. Recall that $\partial^2 U_i/\partial L_i^2 < 0$ and $\partial^2 U_i/\partial S_i^2 < 0$. Under Assumption B.1(i) and (iii), we have $\partial^2 U_i/\partial S_i \partial \upsilon_i > 0$, $\partial^2 p_{ij}/\partial S_i^2 < 0$, and $\partial^2 a_i/\partial H_i^2 < 0$. Suppose that $\partial S_i^*/\partial \upsilon_i \leq 0$. Equations (B.14) and (B.15) imply that $\partial L_i^*/\partial \upsilon_i < 0$ and $\partial H_i^*/\partial \upsilon_i < 0$. This contradicts the setup that $H_i^* + S_i^* + L_i^* = 1$: the amounts of time spent on studying, socializing, and leisure cannot all decrease in υ_i because they sum up to 1. We conclude that $\partial S_i^*/\partial \upsilon_i > 0$. □

From the lemma, socializing is increasing in υ_i. Because the number of friends is increasing in the time spent socializing, we therefore expect that the number of friends is positively (negatively) correlated with ϵ_i if υ_i and ϵ_i are positively (negatively) correlated.

For example, unobserved communication skills in υ_i may contribute to more friends and better labor market performance, resulting in a positive correlation between friendships and ϵ_i. This will yield an upward bias in the social returns. On the other hand, if unobserved tastes for socializing in υ_i are in favor of leisure and counterproductive on the labor market, then we expect a negative correlation between friendships and ϵ_i, yielding a downward bias in the social returns. Overall, the OLS bias in the social returns can be ambiguous, depending on whether the positive or negative correlation dominates.

B.2.3 Proposition B.3

To prove Proposition B.3, let $d_{ij} = d(X_i, X_j)$ denote the social distance between students i and j, and assume that the linking probability $p_{ij}(S_i, S_j)$ depends on social distance d_{ij}. We examine the impact of a change in social distance d_{ij}, by changing j's characteristics (X_j), on i's time spent socializing and studying and on later friendships and education.

To speculate on the impacts of social distance, we make additional assumptions on the utility and production functions.

Assumption B.2. *(i) The marginal product of socializing is decreasing in social distance ($\partial^2 p_{ij}/\partial S_i \partial d_{ij} < 0$), that is, students with higher social distance to peers make fewer friends from each unit of socializing. (ii) The marginal utility from leisure does not depend on socializing ($\partial^2 U_i/\partial L_i \partial S_i = 0$). The marginal product of studying does not depend on social distance ($\partial^2 a_i/\partial H_i \partial d_{ij} = 0$).*[40] *(iii) The marginal product from socializing (or studying) is diminishing in socializing (or studying) ($\partial^2 p_{ij}/\partial S_i^2 < 0$ and $\partial^2 a_i/\partial H_i^2 < 0$). The marginal product from socializing is increasing in peer's socializing ($\partial^2 p_{ij}/\partial S_i \partial S_j > 0$). (iv) The labor market returns to education and friendships are positive constants ($\partial Y_i/\partial E_i = r_e > 0$ and $\partial Y_i/\partial F_i = r_f > 0$).*

Proof of Proposition B.3. Suppose that the change of d_{ij} (due to the change in X_j) does not trigger any change in the equilibrium so that $\partial S_k^*/\partial d_{ij} = 0$, for all $k \neq i, j$. Taking the derivatives of both sides of (B.6) and (B.7) evaluated at optimal (H_i^*, S_i^*), $i = 1, \ldots, n$, with respect to d_{ij}, we obtain

$$\begin{aligned}
\frac{\partial^2 U_i}{\partial L_i^2}(S_i^*, L_i^*)\frac{\partial L_i^*}{\partial d_{ij}} &= r_e \frac{\partial^2 a_i}{\partial H_i^2}(H_i^*)\frac{\partial H_i^*}{\partial d_{ij}} \qquad \text{(B.16)}\\
\frac{\partial^2 U_i}{\partial L_i^2}(S_i^*, L_i^*)\frac{\partial L_i^*}{\partial d_{ij}} &= r_f \frac{\partial^2 p_{ij}}{\partial S_i \partial d_{ij}}(S_i^*, S_j^*) + \left(\frac{\partial^2 U_i}{\partial S_i^2}(S_i^*, L_i^*) + r_f \sum_{k \neq i} \frac{\partial^2 p_{ik}}{\partial S_i^2}(S_i^*, S_k^*)\right)\frac{\partial S_i^*}{\partial d_{ij}}
\end{aligned}$$

[40] This assumption is imposed for simplicity and can be relaxed. For example, if we assume $\partial^2 p_{ij}/\partial S_i \partial d_{ij} < \partial^2 a_i/\partial H_i \partial d_{ij} < 0$, we can derive similar results on S_i^*, though with more ambiguity.

$$+r_f \frac{\partial^2 p_{ij}}{\partial S_i \partial S_j}(S_i^*, S_j^*) \frac{\partial S_j^*}{\partial d_{ij}}, \tag{B.17}$$

where we have used $\partial^2 U_i/\partial L_i \partial S_i = 0$, $\partial^2 a_i/\partial H_i \partial d_{ij} = 0$, $\partial Y_i/\partial E_i = r_e$, and $\partial Y_i/\partial F_i = r_f$ by Assumption B.2(ii) and (iv), and the fact that U_i and p_{ik} (for $k \neq i, j$) do not depend on d_{ij}. Note that the presence of the term $\partial S_j^*/\partial d_{ij}$ in equation (B.17) is because S_j^* depends on the social distance d_{ij} and j's characteristics X_j.

We start with the special case where we ignore the effect on S_j^* and assume that $\partial S_j^*/\partial d_{ij} = 0$. Recall that $\partial^2 U_i/\partial L_i^2 < 0$ and $\partial^2 U_i/\partial S_i^2 < 0$. Under Assumption B.2(i) and (iii), we have $\partial^2 p_{ij}/\partial S_i \partial d_{ij} < 0$, $\partial^2 p_{ik}/\partial S_i^2 < 0$ (for $k \neq i$) and $\partial^2 a_i/\partial H_i^2 < 0$. Suppose that $\partial S_i^*/\partial d_{ij} \geq 0$. Equations (B.17) and (B.16) then imply that $\partial L_i^*/\partial d_{ij} > 0$ and $\partial H_i^*/\partial d_{ij} > 0$. This contradicts the setup $H_i^* + S_i^* + L_i^* = 1$: the amounts of time spent on studying, socializing, and leisure cannot all increase in d_{ij} because they sum up to 1. We conclude that $\partial S_i^*/\partial d_{ij} < 0$, that is, socializing is decreasing in social distance d_{ij}. Moreover, from equation (B.16) we can see that $\partial L_i^*/\partial d_{ij}$ and $\partial H_i^*/\partial d_{ij}$ have the same sign. Because $\partial S_i^*/\partial d_{ij} < 0$, we thus derive that $\partial H_i^*/\partial d_{ij} > 0$ and $\partial L_i^*/\partial d_{ij} > 0$. In sum, if the impact of social distance d_{ij} on j's time spent socializing is ignored, an increase in social distance d_{ij} leads i to socialize less and study more.

In general, we have $\partial S_j^*/\partial d_{ij} \neq 0$, that is, social distance d_{ij} affects j's time spent socializing. If we know $\partial S_j^*/\partial d_{ij} \leq 0$, by $\partial^2 p_{ij}/\partial S_i \partial S_j > 0$ (Assumption B.2(iii)) and the same reasoning as above, we can derive $\partial S_i^*/\partial d_{ij} < 0$ and $\partial H_i^*/\partial d_{ij} > 0$. However, the change in X_j may lead to an increase in j's time spent socializing ($\partial S_j^*/\partial d_{ij} > 0$). In this case, the sign of $\partial S_i^*/\partial d_{ij}$ becomes ambiguous, as does the sign of $\partial H_i^*/\partial d_{ij}$. In other words, because the impact of social distance d_{ij} (through j's characteristics X_j) on j's time spent socializing is ambiguous, we cannot predict its impact on i's time spent socializing and studying.

Even though the signs of $\partial S_i^*/\partial d_{ij}$ and $\partial H_i^*/\partial d_{ij}$ are ambiguous, from equations (B.16) and (B.17) we can derive that $\partial S_i^*/\partial d_{ij} \neq 0$ and $\partial H_i^*/\partial d_{ij} \neq 0$, that is, a change in social distance d_{ij} affects i's time spent socializing and studying. To see this, suppose that $\partial S_i^*/\partial d_{ij} = 0$. Under Assumption B.2(i), (iii) and (iv), in general we have $r_e \partial^2 p_{ij}/\partial S_i \partial d_{ij} + r_f \partial^2 p_{ij}/\partial S_i \partial S_j \cdot \partial S_j^*/\partial d_{ij} \neq 0$, so for equations (B.16) and (B.17) to hold, we must have $\partial H_i^*/\partial d_{ij} \neq 0$ and $\partial L_i^*/\partial d_{ij} \neq 0$. Note that equation (B.16) implies that $\partial H_i^*/\partial d_{ij}$ and $\partial L_i^*/\partial d_{ij}$ have the same sign. This implies that $\partial(H_i^* + L_i^*)/\partial d_{ij} \neq 0$, which contradicts $\partial S_i^*/\partial d_{ij} = 0$ because $H_i^* + S_i^* + L_i^* = 1$. Moreover, because $\partial S_i^*/\partial d_{ij} \neq 0$ implies that the sum $H_i^* + L_i^*$ must change, and $\partial H_i^*/\partial d_{ij}$ and $\partial L_i^*/\partial d_{ij}$ have the same sign, we can further derive that $\partial H_i^*/\partial d_{ij} \neq 0$. To sum up, we have proved that $\partial S_i^*/\partial d_{ij} \neq 0$ and $\partial H_i^*/\partial d_{ij} \neq 0$, that is, social distance d_{ij} has nonzero effects on socializing and studying.

Finally, because the expected number of friends and expected education depend on time spent socializing and studying ($\mathbb{E}[F_i|X, \upsilon, \omega] = \sum_{j \neq i} p_{ij}(S_i, S_j)$ and $\mathbb{E}[E_i|X, \upsilon, \omega] = a_i(H_i)$), a change in social distance d_{ij} would in general affect friendships and education, through the change in socializing and studying. However, because the impacts of social distance d_{ij} on socializing and studying are ambiguous, so are its impacts on friendships and education. □

B.2.4 Proposition B.4

In this section, we investigate the roles of individual endowments such as IQ and extroversion on socializing, studying and their friendship and education outcomes. For convenience, we write $X_i = (X_{i,1}, X_{i,-1})$, where $X_{i,1}$ represents the endowment under investigation (e.g., IQ and extroversion) and $X_{i,-1}$ represents the remaining observed characteristics. Assume that $X_{i,1}$ does not directly affect i's social distance to peers.

To speculate on the roles of IQ and extroversion, we make additional assumptions on the utility and production functions. In particular, we impose Assumptions B.3 and B.4 when $X_{i,1}$ represents IQ and impose Assumptions B.3 and B.5 when $X_{i,1}$ represents extroversion.

Assumption B.3. *(i) The marginal utility from leisure does not depend on socializing nor endowment $X_{i,1}$ ($\partial^2 U_i/\partial L_i \partial S_i = 0$ and $\partial^2 U_i/\partial L_i \partial X_{i,1} = 0$). (ii) The marginal product from socializing (or studying) is diminishing in socializing (or studying) ($\partial^2 p_{ij}/\partial S_i^2 < 0$ and $\partial^2 a_i/\partial H_i^2 < 0$). (iii) The labor market returns to education and friendships are positive constants ($\partial Y_i/\partial E_i = r_e > 0$ and $\partial Y_i/\partial F_i = r_f > 0$).*

Assumption B.4 (IQ)**.** *The marginal product of studying is increasing in IQ ($\partial^2 a_i/\partial H_i \partial X_{i,1} > 0$), that is, students with higher IQ attain higher levels of education from each unit of studying.*

Assumption B.5 (Extroversion)**.** *(i) The marginal product of socializing is increasing in the magnitude of extroversion ($\partial^2 p_{ij}/\partial S_i \partial X_{i,1} > 0$), that is, students who are more extroverted make more friends from each unit of socializing. The marginal utility from socializing is also increasing in the magnitude of extroversion ($\partial^2 U_i/\partial S_i \partial X_{i,1} > 0$). (ii) The marginal product of studying does not depend on the the magnitude of extroversion ($\partial^2 a_i/\partial H_i \partial X_{i,1} = 0$).*

Proof of Proposition B.4. Because $X_{i,1}$ does not directly affect i's social distance to peer j, under the assumption that the equilibrium effects are negligible, we obtain $\partial S_j^*/\partial X_{i,1} = 0$ for $j \neq i$, that is, i's endowment does not affect j's socializing. Taking the derivatives of both sides of (B.6) and (B.7) evaluated at optimal (H_i^*, S_i^*), $i = 1, \ldots, n$, with respect to

$X_{i,1}$, we obtain

$$\frac{\partial^2 U_i}{\partial L_i^2}(S_i^*, L_i^*)\frac{\partial L_i^*}{\partial X_{i,1}} = r_e \frac{\partial^2 a_i}{\partial H_i \partial X_{i,1}}(H_i^*) + r_e \frac{\partial^2 a_i}{\partial H_i^2}(H_i^*)\frac{\partial H_i^*}{\partial X_{i,1}} \tag{B.18}$$

$$\begin{aligned}\frac{\partial^2 U_i}{\partial L_i^2}(S_i^*, L_i^*)\frac{\partial L_i^*}{\partial X_{i,1}} &= \frac{\partial^2 U_i}{\partial S_i \partial X_{i,1}}(S_i^*, L_i^*) + r_f \frac{\partial^2 p_{ij}}{\partial S_i \partial X_{i,1}}(S_i^*, S_j^*) \\ &\quad + \left(\frac{\partial^2 U_i}{\partial S_i^2}(S_i^*, L_i^*) + r_f \sum_{j \neq i} \frac{\partial^2 p_{ij}}{\partial S_i^2}(S_i^*, S_j^*)\right)\frac{\partial S_i^*}{\partial X_{i,1}}\end{aligned} \tag{B.19}$$

where we have used $\partial^2 U_i/\partial L_i \partial S_i = 0$, $\partial^2 U_i/\partial L_i \partial X_{i,1} = 0$, $\partial Y_i/\partial E_i = r_e$, and $\partial Y_i/\partial F_i = r_f$ by Assumption B.3(i) and (iii).

IQ. We first consider the scenario where $X_{i,1}$ represents IQ. If we assume that

$$\frac{\partial^2 U_i}{\partial S_i \partial X_{i,1}}(S_i^*, L_i^*) + r_f \frac{\partial^2 p_{ij}}{\partial S_i \partial X_{i,1}}(S_i^*, S_j^*) \leq 0, \tag{B.20}$$

which represents the case where students with higher IQ are less efficient in socializing, then we can derive that $\partial H_i^*/\partial X_{i,1} > 0$ and $\partial S_i^*/\partial X_{i,1} < 0$, that is, smarter students study more and socialize less. To see this, suppose that $\partial H_i^*/\partial X_{i,1} \leq 0$. Recall that $\partial^2 U_i/\partial L_i^2 < 0$ and $\partial^2 U_i/\partial S_i^2 < 0$. Under Assumptions B.3(ii) and B.4, we have $\partial^2 p_{ij}/\partial S_i^2 < 0$, $\partial^2 a_i/\partial H_i^2 < 0$, and $\partial^2 a_i/\partial H_i \partial X_{i,1} > 0$. If $\partial H_i^*/\partial X_{i,1} \leq 0$, equations (B.18) and (B.19) then imply that $\partial L_i^*/\partial X_{i,1} < 0$ and $\partial S_i^*/\partial X_{i,1} < 0$. This contradicts the setup $H_i^* + S_i^* + L_i^* = 1$: the amounts of time spent on studying, socializing, and leisure cannot all decrease in $X_{i,1}$ because they sum up to 1. We conclude that $\partial H_i^*/\partial X_{i,1} > 0$, that is, studying is increasing in IQ. Moreover, suppose that $\partial S_i^*/\partial X_{i,1} \geq 0$. From equation (B.19) we derive that $\partial L_i^*/\partial d_{ij} > 0$, which again contradicts the setup that $H_i^* + S_i^* + L_i^* = 1$. In sum, if condition (B.20) is satisfied, smarter students spend more time studying and less time socializing. This is in line with the idea of "nerdy" students who are not popular and prefer to spend their time studying.

In general, without condition (B.20), the roles of IQ on socializing and studying become ambiguous. For example, if

$$0 < \frac{\partial^2 U_i}{\partial S_i \partial X_{i,1}}(S_i^*, L_i^*) + r_f \frac{\partial^2 p_{ij}}{\partial S_i \partial X_{i,1}}(S_i^*, S_j^*) < r_e \frac{\partial^2 a_i}{\partial H_i \partial X_{i,1}}(H_i^*),$$

following similar reasoning we can derive $\partial H_i^*/\partial X_{i,1} > 0$ and $\partial L_i^*/\partial X_{i,1} < 0$, but the sign of

$\partial S_i^*/\partial X_{i,1}$ is ambiguous. More interesting, if

$$\frac{\partial^2 U_i}{\partial S_i \partial X_{i,1}}(S_i^*, L_i^*) + r_f \frac{\partial^2 p_{ij}}{\partial S_i \partial X_{i,1}}(S_i^*, S_j^*) > r_e \frac{\partial^2 a_i}{\partial H_i \partial X_{i,1}}(H_i^*),$$

we can derive that $\partial S_i^*/\partial X_{i,1} > 0$ and $\partial L_i^*/\partial X_{i,1} < 0$, but the sign of $\partial H_i^*/\partial X_{i,1}$ is ambiguous. This is the case where smarter students are relatively more efficient in socializing than studying: they enjoy more utility from one unit of socializing or are more productive in making friends. It is reasonable that these students socialize more by resting less, though it is unclear whether they study less as well.

Because the roles of IQ on socializing and studying are in general ambiguous, so are its roles on their friendships and education.

Extroversion. Next, we turn to the scenario where $X_{i,n}$ represents extroversion. Unlike IQ, the roles of extroversion are predictable. In particular, we can show that $\partial S_i^*/\partial X_{i,1} > 0$, $\partial H_i^*/\partial X_{i,1} < 0$, and $\partial L_i^*/\partial X_{i,1} < 0$, that is, students who are more extroverted socialize more, study less, and have less leisure. To see this, note that under Assumptions B.3(ii) and B.5(i) and (ii), we have $\partial^2 p_{ij}/\partial S_i^2 < 0$, $\partial^2 a_i/\partial H_i^2 < 0$, $\partial^2 U_i/\partial S_i \partial X_{i,1} > 0$, $\partial^2 p_{ij}/\partial S_i \partial X_{i,1} > 0$, and $\partial^2 a_i/\partial H_i \partial X_{i,1} = 0$. Suppose that $\partial S_i^*/\partial X_{i,1} \leq 0$. Equations (B.18) and (B.19) then imply that $\partial L_i^*/\partial X_{i,1} < 0$ and $\partial H_i^*/\partial X_{i,1} < 0$. This contradicts the setup $H_i^* + S_i^* + L_i^* = 1$: the amounts of time spent on studying, socializing, and leisure cannot all decrease in $X_{i,1}$ because they sum up to 1. We conclude that $\partial S_i^*/\partial X_{i,1} > 0$, that is, socializing is increasing in the magnitude of extroversion. Moreover, from equation (B.18) we can see that $\partial L_i^*/\partial X_{i,1}$ and $\partial H_i^*/\partial X_{i,1}$ have the same sign. Because $\partial S_i^*/\partial X_{i,1} > 0$, we thus derive that $\partial H_i^*/\partial X_{i,1} < 0$ and $\partial L_i^*/\partial X_{i,1} < 0$. In sum, more extroverted students spend more time socializing and less time studying and resting.

Based on the roles of extroversion on time allocation, we expect that students who are more extroverted make more friends and attain lower levels of education. □

C Pairwise Instruments

An alternative approach to constructing an individual-level instrument is through a pairwise regression of friendship nominations. Specifically, we run a Probit regression of whether i normalizes j as a friend on pairwise homophily measures between i and j (such as age distance). We also control for $i's$ characteristics (X_i), the mean characteristics in $i's$ school-grade ($\bar{X}_{gs}$), grade fixed effects (α_g), and school fixed effects (λ_s). In particular, the Probit

regression of friendship nominations has the specification

$$\Pr(F_{ij} = 1) = \Phi(\beta_0 + \beta_1' d_{ij} + \beta_2' X_i + \beta_3' \bar{X}_{gs} + \alpha_g + \lambda_s),$$

where d_{ij} represents the pairwise homophily measures between i and j, and Φ represents the cdf of standard normal distribution. To run this regression, we use the pairwise sample that consists of all the pairs of individuals being in the same school and same grade. From the pairwise regression, we obtain the predicted value of friendship nomination for each pair of i and j ($\hat{\Pr}(F_{ij} = 1)$). The instrument for i's friendship nominations is then given by the sum of the predicted friendship nominations toward i, that is, $\sum_{j \in c} \hat{\Pr}(F_{ij} = 1)$, where the sum is over all j in i's school-grade.

Compared with the average homophily measures, using the predicted number of friends as an instrument can be more efficient. Following Newey and McFadden (1994) and Wooldridge (2010) we derive that under homoscedasticity in the log earnings equation, an efficient instrument for the number of friends takes the form of the predicted number of friends. Using the predicted number of friends as an instrument instead of a regressor in the second stage is also in line with what Angrist and Pischke (2009, Section 4.6) suggested to avoid a forbidden regression in the case of a nonlinear first stage.

D Indices of Cognitive and Social Skills from the O*NET

We use data from the O*NET to construct the indices of cognitive and social skills.[41] We construct the indices as follows.

Cognitive skills score. From the O*NET we observe whether an occupation requires the following cognitive abilities: Category Flexibility; Deductive Reasoning; Flexibility of Closure; Fluency of Ideas; Inductive Reasoning; Information Ordering; Mathematical Reasoning; Memorization; Number Facility; Oral Comprehension; Oral Expression; Originality; Perceptual Speed; Problem Sensitivity; Selective Attention; Spatial Orientation; Speed of Closure; Time Sharing; Visualization; Written Comprehension; and Written Expression. For each occupation the O*NET reports the level of the skill that is needed. A higher level indicates that the occupation requires a greater amount of that skill. To compute the cognitive score for an occupation, we take the average of the levels of these cognitive skills that O*NET reports are needed for that particular occupation.

Social skills score. From the O*NET we observe whether an occupation requires the following social skills: Coordination; Instructing; Negotiation; Persuasion; Service Orien-

[41] The data can be found from https://www.onetonline.org/.

tation; Social Perceptiveness; Assisting and Caring for Others; Coaching and Developing Others; Communicating with Persons Outside Organization; Communicating with Supervisors, Peers or Subordinates; Coordinating the Work and Activities of Others; Developing and Building Teams; Establishing and Maintaining Interpersonal Relationships; Guiding, Directing and Motivating Subordinates; Interpreting the Meaning of Information for Others; Performing Administrative Activities; Performing for or Working Directly with the Public; Provide Consultation and Advice to Others; Resolving Conflicts and Negotiating with Others; Selling or Influencing Others; Staffing Organizational Units; Training and Teaching Others. For each occupation the O*NET reports the level of the skill that is needed. A higher level indicates that the occupation requires a greater amount of that skill. To compute the social score for an occupation, we take the average of the levels of these social skills that are needed in the occupation.

E STATA Code: Bound Estimates and Confidence Intervals

```
* Set the significance level
clear mata
mata alpha = 0.05

* Estimate the bounds by two-step GMM
xtivreg2 ln_earn_upper (in_grade=$iv) $xi $mean g2-g7 if insample, fe gmm cl(sid)
mata bu = st_matrix("e(b)")'
mata Vu = st_matrix("e(V)")
xtivreg2 ln_earn_lower (in_grade=$iv) $xi $mean g2-g7 if insample, fe gmm cl(sid)
mata bl = st_matrix("e(b)")'
mata Vl = st_matrix("e(V)")

* Construct the bound estimates and standard errors
mata nb = rows(bu)                /* number of parameters      */
mata b_set = J(nb, 2, 0)          /* bound estimates           */
mata se_set = J(nb, 2, 0)         /* standard errors           */
mata d = J(nb, 1, 0)              /* widths of identified sets */
mata se_max = J(nb, 1, 0)         /* maximum of s.e.           */
mata for (i=1; i<=nb; i++){
    b_set[i,1] = bl[i,1] * (bu[i,1] > bl[i,1]) +       ///
                 bu[i,1] * (bu[i,1] < bl[i,1])
    b_set[i,2] = bu[i,1] * (bu[i,1] > bl[i,1]) +       ///
                 bl[i,1] * (bu[i,1] < bl[i,1])
```

```
    se_set[i,1] = Vl[i,i]^0.5 * (bu[i,1] > bl[i,1]) +  ///
                  Vu[i,i]^0.5 * (bu[i,1] < bl[i,1])
    se_set[i,2] = Vu[i,i]^0.5 * (bu[i,1] > bl[i,1]) +  ///
                  Vl[i,i]^0.5 * (bu[i,1] < bl[i,1])
    d[i,1] = b_set[i,2] - b_set[i,1]
    se_max[i,1] = se_set[i,1] * (se_set[i,1] > se_set[i,2]) +  ///
                  se_set[i,2] * (se_set[i,1] < se_set[i,2])
}

* Calculate the critical values in Imbens and Manski (2004)
mata c = J(nb, 1, 0)
mata c0 = invnormal(1 - alpha/2)     /* initial value of c */
mata void cfun(todo, c, d, se, alpha, f, g, H){
    f = (normal(c + d/se) - normal(-c) - (1 - alpha)) ^ 2
}
mata CV = optimize_init()
mata optimize_init_which(CV, "min")
mata optimize_init_evaluator(CV, &cfun())
mata optimize_init_params(CV, c0)
mata optimize_init_argument(CV, 3, alpha)
mata for (i=1; i<=nb; i++){
    optimize_init_argument(CV, 1, d[i,1])
    optimize_init_argument(CV, 2, se_max[i,1])
    c[i,1] = optimize(CV)
}

* Construct the confidence interval in Imbens and Manski (2004)
mata ci = J(nb, 2, 0)
mata for (i=1; i<=nb; i++){
    ci[i,1] = b_set[i,1] - c[i,1] * se_set[i,1]
    ci[i,2] = b_set[i,2] + c[i,1] * se_set[i,2]
}
mata round(b_set[1,.], 0.0001)   /* bounds               */
mata round(ci[1,.], 0.0001)      /* confidence interval  */
```