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PEERS, PARENTS AND ATTITUDES ABOUT SCHOOL

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Peers, Parents, and Attitudes about School*

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Abstract

Educational attitudes are an important component of adolescent development linked to long-term educational success and as a component of noncognitive skills. This study focuses on peer and parent roles in shaping adolescent attitude development. First, I explore the relationship between an adolescent and their friends' attitudes and whether this influence is heterogeneous. Second, I ask whether parents can moderate the friend effect. I find that adolescents with poor attitudes and whose friends have particularly poor attitudes are especially at risk of developing low educational attitudes and that working with parents can serve as a channel to decrease the risk. (JEL C31, I21, Z13)

Keywords Skill Development, Attitudes, Peer Effects, Friendship Networks

1 Introduction

Adolescence is a time of increased social interaction while also a time that aspirations and beliefs remain sensitive. I study adolescent attitudes about school and future education and assess whether social influence has a role in shaping them and may serve as targets for intervention efforts. Attitudes in this study relate to an adolescent's attachment to their

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school, teachers, fellow students and their future collegiate hopes and desires. For some time it has been recognized that social influences can affect educational and life outcomes (Becker 1994; Akerlof 1997; Akerlof and Kranton 2002), but how peers and parents combine to causally effect skill development during adolescence has not received close attention.

Ability to succeed in life is now well recognized to include socio-emotional skills, hopes, and aspirations (Heckman, Humphries, and Kautz 2014; Heckman and Mosso 2014). Moreover, to a degree these can be shaped by environments and investments. Much attention has been paid to the key role of early life skill investments, especially by parents. Childhood appears the most sensitive time for investments to shift children onto positive trajectories. These are also thought to be dynamic complements with later investments, boosting their effectiveness (Heckman and Mosso 2014). To take advantage of this, however, requires understanding key channels of influence during adolescence that interact with skills and suggest continued targets for investments and interventions. Important for attempts to reduce inequality gaps is then to target mechanisms that support or hinder development during this time.

I contribute by assessing two sources of social influence, friends and parents, and focus on something quite malleable during adolescence, attitudes. First, I explore whether the attitudes of friends shape an adolescent's own-attitudes. I also explore whether friend attitude effects are constant or heterogeneous, meaning does the effect vary based on the level of friends' attitudes or the adolescent's position in the conditional distribution of attitudes. This will be important to policy if, for example, the attitudes of friends are only influential when sufficiently high or if the adolescent has sufficiently poor attitudes.

Studying attitudes is important in that attitudes, ability to get along with others, goal setting, and more have been broadly considered a part of noncognitive skills that support later life success (Lipnevich, Gjicali, and Krumm 2016; Heckman and Kautz 2014). In psychology, attitudes are a key predictor in the theory of planned behavior and descriptive evidence consistently points toward a positive association between attitudes and educational outcomes (Lipnevich, Gjicali, and Krumm 2016). For noncognitive skills in general, there is evidence of a substantial causal effect on outcomes such as wages, education, and risky behaviors (Heckman and Mosso 2014). Also, attitudes may have an immediate impact as experimental evidence indicates students appear to choose effort not only by extrinsic rewards but also by intrinsic motivation (Koch, Nafziger, and Nielsen 2015).

Second, I contribute by testing whether parental educational expectations and investments can moderate the influence of peers, thereby suggesting one channel for intervention efforts to build on. In light of the difficulty in establishing a link between parental action and youth outcomes in survey data, this focus is necessarily narrow. In light of suggestions that the influence of parental action is very weak, this represents an important contribution.[1]

There is a relatively large literature in peer effects studying a variety of outcomes. One branch of this literature has focused on whether higher-level peer groupings—such as the school-grade or classroom level—have reduced form effects on test scores or grade point average (GPA), risky behaviors, and later life education outcomes.[2]. Another has focused on friends using friendship nominations in survey data and the estimation of structural parameters. These studies have also explored peer effects on GPA, risky behaviors, and later life education outcomes.[3]

While the literature on peer effects is quite large, less attention has been paid to whether, and when, peer influence partly shapes underlying attitudes and skills and whether parental investments can interact with this process. One exception is by Bifulco, Fletcher, and Ross (2011). They study the reduced form peer effects from an adolescent's cohort peers parents' education on post-secondary outcomes. In an extension, they find no evidence that the cohort composition of college educated mothers bears influence on a number of attitude variables. I turn the focus on friends and the joint role of parental investments in shaping attitudes.

1. See Avvisati, Besbas, and Guyon (2011) for a review.

2. See Anelli and Peri (2016), Bifulco et al. (2014), Black, Devereux, and Salvanes (2013), and Sacerdote (2014). Results are somewhat mixed for school performance but point consistently point toward behavioral effects.

3. See Calvó–Armengol, Patacchini, and Zenou (2009), Fortin and Yazbeck (2015), Goldsmith-Pinkham and Imbens (2013), Hsieh and Lee (2016), Lin (2010, 2015), and Patachini, Rainone, and Zenou (2016, 2016). Results have pointed toward sizable effects across outcomes even after dealing with bias from possible endogenous network formation.

To empirically test for friend effects on attitudes and interaction effects between friends and parents, I use data from the National Longitudinal Study of Adolescent to Adult Health (Add Health).[4] Add Health provides best friend nominations for each adolescent allowing the construction of school friendship networks.

Identification of peer effects, especially from friends, can be complicated by simultaneity, unobserved shared environments, and friend selection. With network data, Bramoullé, Djebbari, and Fortin (2009) establish conditions whereby the characteristics of friends of friends, or those two links away, can be used as instruments for the simultaneity bias. For unobserved shared environments, the Add Health design allows controlling for school fixed effects, capturing shared environments up to those common at the school level.

Endogenous network formation still threatens identification through peer group selection bias. To address this, I use a two-step procedure, estimating a network formation model developed by Graham (2017) in a first step. In the second step, I implement a recently developed semiparametric estimator in the outcome equation, using information from the network formation model to correct for bias from the network endogeneity (Johnsson and Moon 2015). This approach allows for an unobservable, individual fixed effect in the choice of friendship between two dyads (adolescents) that is also correlated with attitudes. I do not find strong evidence for bias from allowing for endogenous network formation and subsequently focus on models that assume exogenous network formation.

Identification of parental expectations and investments is also complicated by unobservables. However, Bun and Harrison (2018) and Nizalova and Murtazashvili (2016) develop conditions under which I can interpret the interaction term between friend attitudes and

4. This research uses data from Add Health, a program project designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan Harris, and funded by a grant P01-HD31921 from the Eunice Kennedy Shriver National Institute of Child Health and Human Development, with cooperative funding from 17 other agencies. Special acknowledgment is due Ronald R. Rindfuss and Barbara Entwisle for assistance in the original design. Persons interested in obtaining Data Files from Add Health should contact Add Health, The University of North Carolina at Chapel Hill, Carolina Population Center, 206 W. Franklin Street, Chapel Hill, NC 27516-2524 (addhealth_contracts@unc.edu). No direct support was received from grant P01-HD31921 for this analysis. This research did not receive any specific grant from funding agencies in public, commercial, or not-for-profit sectors.

the parent variable as a causal effect even when the key parent variable is endogenous. I discuss these conditions and the interaction result in section 6. As the moderating effect is the primary concern for the parental analysis, I focus the discussion on it.

In summary of the results, I find that average friend attitudes about school have a strong, positive relationship with own-attitudes. An adolescent's social circle of friends in school, contribute to their development. I also find that this effect is heterogeneous. Friends with worse attitudes are the friends who exert the strongest influence, while adolescents with conditionally lower attitudes are more effected by their friends. Thus, the adolescents we are potentially the most worried about, may be those in danger of the worst social interaction effects in terms of attitude development. Results from the interaction of parental educational expectations and friend attitudes, however, suggest that parents can reduce bad influence from friends. One possible intervention, then, is to work with parents on their educational attitudes and transmission of expectations in the home, as an approach to avert downward spirals in attitudes about school between an adolescent and their friends.

2 Attitudes, Skills, and Social Influence

Into adolescence, there is evidence noncognitive skills in general continue to develop (Kautz and Zanoni 2014; Heckman and Mosso 2014) and, while attitudes can become set at some point, during this time they remain shapeable (Lipnevich, Gjicali, and Krumm 2016). There is not much causal evidence, however, on what processes continue to shape these skills. Thus, I focus narrowly on one part of skill and belief development, attitudes, and study the social processes determining them.

An essential role for social processes in skill and belief development, is supported by evidence from the psychological literature and within economics by social identity theory. During adolescence, social relationships outside of the home take on increased significance for development (Bagwell and Schmidt 2013; Mak, Fosco, and Feinberg 2018) and the combination of parent and friend relationships become key determinants (Zhang et al. 2018).

In identity theory, norm transmission from social groups generates conforming influences by telling a person how to act in order to belong (Akerlof and Kranton 2000). Investments into a stock of identity also serve an important role, determining the strength of identity influence (Bénabou and Tirole 2011). When social identities are highly relevant, they theoretically act to increase the immediate utility weight from social group incentives and reduce the weight on personal preferences (Akerlof and Kranton 2002).[5] Given the evidence in the psychological literature on the growing importance of friendships during adolescence and the key role of relevant social identities in economic theory, an adolescent's social circle of friends are prime suspects as potential contributors to the formation of attitudes about school.[6] Groupings at higher levels, such as the grade, may miss this if identity is too weak to motivate a conforming effect.

Parents too may take an active role in attempting to influence their children. However, parental influence has proven difficult to untangle from unobservable effects and it has been debated whether it is of much effect apart from more permanent background influences (Avvisati, Besbas, and Guyon 2011). The literature on early childhood investments distinctly does find that parental action is highly important (Heckman and Mosso 2014). Yet, to what extent and how parental action influences development into adolescence remains an important question along with the joint influence of parents and outside social groups.

In economics, the joint role of peers and parents has only recently begun to be studied. Fruehwirth (2016) explores whether peers' parents' education creates spillovers in kindergarten. She finds these exist and that teacher practices are responsive to the students' parental education. Avvisati et al. (2014) study a field experiment among Parisian middle schools that attempted to increase parental involvement and attitudes about the school. Children of

5. This is a point supported by experimental evidence showing primed social identities can immediately shift patience, risk-aversion, and effort (Benjamin, Choi, and Strickland 2010; Chen and Chen 2011; Hoff and Pandey 2006; Afridi, Li, and Ren 2015).

6. I will use peer and friend interchangeably in this paper, with the definition that peer groups are friend groups for the purposes of this study.

treated families experienced improved academic and behavioral outcomes that spilled over to untreated children in the classroom. I add to the literature by testing whether boosting parents' attitudes about education might be a viable strategy to mitigate negative influence from social circles outside the home.

3 Data, Variables, and the Adjacency Matrix

3.1 The Data

I use data from Add Health. Add Health provides in-depth information on adolescents and school networks. The data collection design is a nationally representative sample of high schools, with over 90,000 students initially interviewed. The in-school survey asked respondents to nominate their 5 best male friends and 5 best female friends, allowing the construction of school friendship networks. The first wave was collected during the 1994-96 school year. A subset of this sample consisting of just over 20,000 respondents was selected for an in-home survey. This survey provides much greater detail on an adolescents activities, behaviors, outcomes, and parents. The in-home subsample, however, does not provide information on all students within a school except for the saturated sample.

The saturated sample is of sixteen schools, where all students in the school were selected for the in-home interview. Of these schools, two were large schools with one mostly white and in a mid-sized town, and the other ethnically diverse and in a major metropolitan area. The remaining schools were scattered between rural and urban areas, some public and some private. Between the in-school and in-home survey a number of the respondents cannot be correctly linked because of missing data in the peer nominations. Add Health re-collected the school friendship nominations for the saturated schools in May of 1995, which re-gains many of the lost observations and places these friendship nominations closer to the actual dates of the in-home survey (occurred from May 1995–December 1995).[7] I select this sample,

7. All questions in the home survey related to schooling or other activities refer the respondent to answer

with the May friendship nominations, to explore the impact of both peers and parents on schooling attitudes.

3.2 Variables

I construct a measure of attitudes about school and future education from multiple measures using factor analysis. The variables, or measures, used in the factor analysis are scale type questions and consist of the following set: how much a respondent reports a desire to go to college, how likely they think it is they will go to college, whether they feel a part of their current school, are happy at their current school, feel that their teachers are fair, and feel close to people at their school. Factor analysis maps the relation of a set of measures to potential underlying latent variables that explain the measures. The linear measurement equation with j measures and M_j the j-th indicator and a set of p latent factors $\mathbf{F}_p$ is

$$M_j = \sum_{p=1}^{p} F_p \alpha_{jp} + \eta_j. \tag{1}$$

The error term, η_j, allows each equation to be measured with error. The factor loadings are α_{jp}. I find that all attitude measures load strongly on a single factor, thus I extract one factor that is a normalized predicted score based on the factor loadings from each measure and call this the attitudes about school scale, or just attitudes. I provide further information, summary statistics for each measure, and results from the factor analysis in appendix section A.

I first focus on peer effects in attitudes and then turn in a subsequent section to whether parents can have a moderating effect on peer influence. Here, I focus on a scale for parental educational expectations and on one for activity investments with the adolescent. For educational expectations, Add Health asks the adolescent to report on a one-five scale (one is low, five is high) how disappointed their mother would be if they do not graduate from college

for the 1994-1995 school year explicitly. The initial friendship nomination collection occurred towards the beginning of the 1994-1995 school year.

and another for failure to graduate from high school. These questions are repeated for the father. From these, I form multiple versions of an expectations scale. The primary scale sums the answers for all four variable (two mother, two father). However, the high school disappointment questions contain very little variation, with most reporting high disappointment, so, I create another version from only the college variables. Additionally, few of the mother variables are missing but many of the father variables are missing. Thus, I form a third scale from only the mother responses summed over high school and college disappointment. Finally, I consider only the response for mother's college disappointment.

Activity investments are formed by summing over a serious of questions regarding whether the adolescent had done a number of activities, such as played a sport, talked about school work, etc., during the past four weeks with their mother. The questions repeat for the father and I take the sum over both. A full list is available in appendix table B1. Again, I also consider the scale only for activities with the mother. I standardize all scales to mean zero and standard deviation of one. Summary statistics for these are reported in appendix table B2.[8]

The remainder of the variables cover controls for characteristics and environments that may influence the outcomes or network formation through homophily (Jackson 2011). These controls are the Add Health Peabody Picture Vocabulary test (ability control), parental education, an indicator for a single parent household, the number of siblings in the home, gender, ethnicity, and grade level in school (which may also capture maturity effects). Picture vocabulary test scores, normalized to mean zero and a standard deviation of one, are included as a proxy for ability, because ability may lead to selection of peers with similar abilities. Parental education, in this study, refers to the highest level of parental education in the household. It proxies socio-economic status or simply the information available to the adolescent on the returns to education. Additionally, the indicator for a single parent

8. Standardization is pre-analytic sample, thus the mean is not always zero. This is especially true for the combined mother father scales; however, the mother only scales are closer to zero. This is likely a result of more fathers not being in the home, with the fathers who are in the home selected on more positive expectations and investments.

household and the number of siblings in the home are included to capture more information about the family background.

3.3 The Adjacency Matrix

Add Health asked respondents for up to ten friendship nominations from which the school friend networks can be constructed as a spatial weights adjacency matrix (**G**). In the saturated sample prior to deletion of observations with missing data, only 12 adolescents out of approximately 3600 nominated friends for all 10 slots. In the final sample, only two have nominated all 10 slots and 21 adolescents nominate 9 slots. Thus, it does not appear that the cap limit on nominations is not a problem for the choice of self-identified peers. I use friendship nominations to define the links in the matrix. The spatial weights matrix is defined as a block-diagonal, row-normalized directed graph.[9] Each school network enters on the diagonal with zeros elsewhere.

Some respondents have all friendship nomination slots missing. I drop these observations to avoid row entries that contain all zeros in the spatial weights matrix and also drop those with missing values in the variables. In the final sample construction, each individual has sent at least one link and receives at least one, and the sample size is 2,216 adolescents.[10]

3.4 Summary Statistics

In table 1, I report the summary statistics for the variables with the initial sample, after deletion of missing data, the analysis sample after construction of the directed graph spatial weights matrix, and the analysis sample for the later extension to parental moderating effects. For the majority of variables, the summary statistics remain consistent across the samples. With listwise deletion of missing observations (column 3), very little changes, though average attitudes and picture vocabulary test scores do slightly increase. With the dropping of isolated

9. All rows sum to one.

10. When deleting observations with missing friendship nominations, one school is lost leaving 15 schools total.

observations for the analytic samples (column 5) attitudes and test scores increase to 0.086 and 0.129. Both attitudes and test scores are normalized to approximately mean zero and a standard deviation of one thus positive values indicate above average. This implies that deleted isolated adolescents from the directed graph construction have lower attitudes and lower verbal reasoning skills. Demographically, the compositional changes are minor. The largest changes are among black adolescents who fall from a 15 to a near 12 percent share and Hispanics who fall from a 20 to a near 18 percent share.

The last two columns show summary statistics for the main variables in the parental moderating effects analysis sample. The drop in observations here occurs because of missing in the added parental variables. The composition of the sample, however, is not effected. I report the summary statistics for the key parental variables of the extended analysis in appendix table B2.

This study is focused on friend effects and parental moderating effects. As a basic check, I explored regressions for attitudes with the basic control set and school fixed effects post-listwise deletion of missing and post-deletion of the isolated adolescents. The results were quite similar overall except for the association between attitudes and being black. In this case, the estimate falls from positive to near zero, suggesting that black adolescents who lacked friendship nominations had the strongest association with attitudes among blacks. Therefore, I consider the results to follow as conditional on being linked within the larger school network.

For the controls, the highest education level of the parents remains stable over the samples at around 13.6 years of education. Single parent homes account for about a quarter of the sample and the number of siblings in the home averages about 1.5 across the sub-sets of the data. Half of the sample is female and this does not change from the initial sample. Ethnicity/race indicators for Hispanic, Asian, black, and white are included with white used as the reference group in the analysis. Close to half the sample is white, with Asians near a 15 percent share, and black and Hispanic adolescents making up the rest. Average school

Table 1: Summary Statistics

	Pre-Deletion of Missing		Post-Deletion of Missing		Post-Deletion of Isolated		Extension Parental Analysis	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Attitudes	0.000	0.875	0.011	0.864	0.086	0.833	0.101	0.829
Pic Voc Test Scores	-0.000	1.000	0.029	0.976	0.129	0.939	0.135	0.932
Highest Parental Edu	13.530	2.756	13.547	2.742	13.664	2.726	13.693	2.731
Single Parent Household	0.275	0.447	0.274	0.446	0.259	0.438	0.220	0.414
Number of Siblings	1.479	1.227	1.493	1.209	1.513	1.189	1.516	1.165
Female	0.489	0.500	0.497	0.500	0.494	0.500	0.510	0.500
Hispanic	0.204	0.403	0.198	0.399	0.182	0.386	0.180	0.385
Asian	0.147	0.354	0.138	0.345	0.154	0.361	0.149	0.356
Black	0.151	0.358	0.151	0.358	0.118	0.322	0.120	0.325
School Grade	10.182	1.497	10.157	1.487	10.170	1.438	10.137	1.445
Observations	Varies Max = 3702		3222		2216		2045	

grade level is the tenth which remains consistent over the sub-samples.

4 Empirical Model and Identification

4.1 Empirical Model

Begin first with a basic model of peer effects. There are $s = 1, ..., \bar{s}$ school networks and n_s adolescents in a school with $N = \sum_{s=1}^{\bar{s}} n_s$ the total sample size. Let $\mathbf{Y}$ be an $N \times 1$ vector of attitudes, $\mathbf{X}$ an $N \times k$ matrix of the control variables,[11], and $\mathbf{G}$ the adjacency matrix from friendship nominations. The baseline specification is

$$\mathbf{Y} = \mathbf{l}\kappa_s + \lambda\mathbf{GY} + \mathbf{X}\beta_1 + \mathbf{GX}\beta_2 + \epsilon. \tag{2}$$

$\mathbf{l}$ is a vector of ones and κ_s the school intercept and ϵ_s is an i.i.d error component. λ is the endogenous social interaction effect—network effect—that captures the simultaneous peer effect from friend attitudes. Because $\mathbf{G}$ is row-normalized, $\mathbf{GY}$ returns the average of friend attitudes, and because the friendship nominations are unique to each individual, average

11. The parental expectation and investment variables are not added until the parents section.

friend attitudes are individual specific. Likewise, $\mathbf{GX}$ returns friend averages for each control variable. β_1 is the $k \times 1$ vector of own-coefficients and β_2 is the $k \times 1$ vector of coefficients for the average of control variables among one's friends.

In the spatial econometrics literature, this model is known as the spatial Durbin model (SDM) (Elhorst 2014; Lesage and Pace 2009). Additionally, the error term can be modeled as an autoregressive process controlling for the correlation in the residuals between neighboring units. In the peer effects model of equation 2, the error term is adjusted to $\mathbf{u} = \rho_0 \mathbf{Gu} + \epsilon$, where ρ_0 is the parameter denoting correlation in the errors between an adolescent and their friends and can be estimated using a concentrated likelihood approach (Elhorst 2014; Lesage and Pace 2009).[12] Elhorst (2014) dubs this the general nesting model (GNS), because it nests multiple forms of correlation in the network. One can restrict certain parameters to zero to obtain, for example, the spatial error model (SEM) with $\lambda = 0$ and $\rho \neq 0$ or the spatial autoregressive model (SAR) with $\mathbf{GX}$ omitted and $\rho = 0$. Estimation can proceed with a concentrated maximum likelihood (ML) method under the assumption that $\epsilon \sim N(0, \sigma^2)$.[13] Also, a two stage least squares (2SLS) approach can be taken with the characteristics of 2nd order links used as instruments. I discuss this further in the next section (4.2).

The peer effects literature distinguishes between social interaction effects through $\mathbf{GY}$ and contextual effects through $\mathbf{GX}$ (Sacerdote 2014). In the absence of social interaction effects, global spill-overs through the network do not exist but local spillovers from contextual effects may (Elhorst 2014; Epple and Romano 2011). For example, an adolescent's friends parents education may have some impact on the adolescent's attitudes simply from being around the parents even if the friend's attitudes do not directly impact them. In this paper, I control for contextual effects but I am directly interested in the structural parameter λ. That is I am interested in assessing whether changes in attitudes spread across the network creating social multipliers. This effect may arise, for example, if there are strong conformity effects, whereby an adolescent conforms to the typical attitudes they find among their friends.

12. Or, by a GMM approach.
13. ML estimation of spatial models is well presented in Elhorst (2014) and Lesage and Pace (2009).

4.2 Identifying Peer Effects with Friendship Network Data

A number of concerns exist for the identification of peer effects. Simultaneity from including the weighted average of peer outcomes introduces linear dependence between peer outcomes and peer characteristics. Manski (1993) dubs this the "reflection problem". The effect of peer average outcomes (the endogenous effect) and peer contextual effects cannot be separately identified. Network data, however, can break the linear dependence between peer outcomes and peer characteristics. Variation in the interaction groups is critical. With greater variation in the peer means, identification is stronger (Lee 2007). In network data, average peer outcomes and characteristics are specific to the individual. Bramoullé, Djebbari, and Fortin (2009) formally show that the "reflection problem" is solved in the presence of second order peers linked to first order peers but not to the individual.[14] Extending to control for correlated effects requires the existence of third order peers for identification to hold.[15] However, this all assumes exogenous network formation.

Key to the method in Bramoullé, Djebbari, and Fortin (2009) is that peers of peers characteristics ($\mathbf{G}^2\mathbf{X}$) can serve as instruments to identify the social interaction effect (λ) under the assumption of exogenous network formation. An important point to bear in mind, is that the simultaneity bias is separate from potential friend selection bias. One can use the peers of peers characteristics in a 2SLS or a control function manner to correct for the simultaneity bias. Similarly, controlling for the spatial correlation in the errors between friends (ρ_0) may capture some of this bias as well. Lee, Liu, and Lin (2010) even suggest that if there are omitted variables related to self-selection into friend groups including this error correlation may reduce some of the resulting bias. Even in the presence of exogenous network formation it is important to deal with bias that arises from the simultaneity. Also, as can be seen in any standard textbook derivation of simultaneity bias, it can be difficult to provide a prediction on the sign of the bias. That sign will depend on the correlation between ϵ and the reduced

14. There are specific network structure conditions under which identification fails. See Bramoullé, Djebbari, and Fortin (2009) for details.

15. I have checked my data for each school and these conditions hold.

form error term for $\mathbf{GY}$ along with the signs and magnitudes of the structural parameters. It may not, then, be entirely surprising to find the social interaction effect increases after isolating an exogenous effect.

Correlated effects from shared environments and friend group selection are additional threats to the identification of peer effects (Advani and Malde 2018; Epple and Romano 2011). To control for shared environments, I include school fixed effects. Friend selection, or endogenous network formation, represents a particularly difficult challenge. The primary example is that of homophily bias. An adolescent selects their friends based on some shared, unobserved characteristics, such as ability, and this characteristic is also correlated with attitudes about school. The result is that individual and peer attitudes will be correlated even if there is no true effect. A benefit of the Add Health data is that I can include a rich set of controls that may capture this selection bias.

Nonetheless, unobservables could still cause $\mathbf{G}$ to be endogenous. To deal with this, I turn to a recently developed estimator for peer effects by Johnsson and Moon (2015). This is a semiparametric control function approach, which estimates a first step network formation model developed in Graham (2017) and then uses information from the first step to estimate peer effects controlling for endogenous network formation. No outside instruments are needed, because natural exclusion restrictions are created between the link formation regressors and regressors in the outcome equation. As I detail in appendix section C, this occurs because the link formation regressors are dyad specific and of a non-linear form. This non-linearity is the absolute value from the difference in two dyads observable characteristics and derives from a theory of homophily in link formation. The exclusion of these variables is a feature shared by previous approaches that estimate a network formation model followed by a model of peer effects (Goldsmith-Pinkham and Imbens 2013; Hsieh and Lee 2016).

Johnsson and Moon (2015) improve in a number of ways on previous attempts in the literature to handle bias from peer selection. First, they develop an estimator that is more computationally tractable than previous methods. Second, they do not impose a normality assumption in the joint distribution of the errors, rather their approach is flexible. Third, they derive asymptotic results. Furthermore, the network formation model by Graham (2017) allows unobserved heterogeneity in the link formation model of arbitrary correlation, relaxing the stronger random effect restrictions necessary in previous applied studies. Thus, network endogeneity in the model by Johnsson and Moon (2015) is generated by an individual specific fixed effect in the model of friendship choice that is correlated with ϵ in equation 2.

Just as one includes observable covariates to control for homophily bias, estimating and then controlling for this fixed effect captures peer selection bias as far as that bias runs through dyad invariant[16] unobservables. For example, if an adolescent's ability is unobserved and fixed—at the time of the linking choices I study—and correlated with their link choices and attitudes, then peer effect estimates will be biased. The Johnsson and Moon (2015) approach corrects for this network endogeneity. I present further details on this estimation approach in appendix section C.

5 Results: Friend Attitudes

5.1 Baseline Estimates

Table 2 is focused on the estimates for the effect of friend average attitudes on own-attitudes. The goal is to answer whether there are social interaction effects in schooling attitudes. The first four columns report the results from the maximum likelihood estimation of the SAR, SDM, SEM, and GNS models. I did check the LR tests in each of these models against omitting school fixed effects and always found including them provided a better fit of the data, thus all specifications reported contain school fixed effects. The last four columns report results from 2SLS with the full set of peers of peers average control variables used as instruments for peer attitudes and with a restricted set based only on peers of peers average highest parental education in the home and average grade level. These two had stronger

16. Similar to time-invariant in a panel data context

associations with peer attitudes and restricting the instrument set to them provides stronger instruments. The last two columns report results from the method by Johnsson and Moon (2015) to deal with endogenous network formation.

In column 1, the SAR model omits the peer contextual effects ($\mathbf{GX}$). Testing it against the SDM, which includes the contextual effects, indicates that the SDM is a better fit of the data (LR $\chi = 29.91$) and the Wald test of joint significance of $\mathbf{GX}$ rejects the null that they are jointly equal to zero ($F = 30.07$). The point estimates for λ, the effect of peer attitudes, are both similar and near 0.20 standard deviations of the attitudes index.[17] These suggest that multiplier effects are indeed present in attitudes. Multiplier effects mean that when a change in attitudes occurs from a change in x, or possibly a program-intervention, effects will be magnified because of the social interaction effect. Solving for the reduced form of equation 2, one obtains a multiplier of $1/(1 - \lambda)$.[18] For example, if a program manages to improve adolescent attitudes by 0.2 standard deviations on the scale then because of the feedback loop between the peers the individual will actually improve by 0.25 standard deviations. The results, though, from these models may not correct for simultaneity bias much less selection bias.

Before turning to the GNS, I first explore the SEM, omitting peer attitudes but controlling for correlation between an adolescent's residual and their friends' (ρ_0). The error correlation is positive and strongly significant. This correlation could arise for reasons other than omitted peer attitudes, but comparing it to columns (1) and (2) does indicate that peer attitudes capture much of the correlation in the errors.

In the GNS model of column 4, I add peer attitudes back and continue to control for the error correlation. Here, and compared to the SDM, I find that the effect of peer attitudes actually increases and the error correlation is negative and marginally significant (10% level). Although, it may appear striking that $\hat{\rho}_0$ is negative it has not been uncommon to find

17. The average of peer average attitudes is 0.629. For a one standard deviation increase in peer average attitudes the effect on average is about 0.129 increase in attitudes. Based on the analysis sample standard deviation in attitudes this translates to an increase of 0.10 standard deviations in an individual's own-attitudes.

18. It is $1/(1 - \lambda\mathbf{G})$, but $\mathbf{G}$ is row-normalized to unity.

Table 2: Attitudes Model

	(1) SAR	(2) SDM	(3) SEM	(4) GNS	(5) 2SLS Full-Z	(6) 2SLS R-Z	(7) CFA-Semip Full-Z	(8) CFA-Semip R-Z
Peer Attitudes ($\hat{\lambda}$)	0.230***	0.218***		0.335***	0.474**	0.541**	0.456**	0.505**
	(0.024)	(0.024)		(0.069)	(0.203)	(0.224)	(0.203)	(0.224)
Peer Error Corr ($\hat{\rho}_0$)			0.217***	-0.133*				
			(0.025)	(0.079)				
Avg. Peer Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Likelihood	-2561.617	-2546.662	-2547.717	-2545.814				
First Stage F					3.934	16.254		
Over-ID P-Value					0.057	0.888		

Note: A $N = 2216$. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses.
B Each specification includes the full set of controls and school fixed effects. Average peer controls are **GX**.
C Full-Z uses the entire set of $\mathbf{G}^2\mathbf{X}$ instruments as IVs.
D R-Z restricts the IVs to the highest parental education and grade level of the peers of peers.

this among friends' residuals in studies that have explored GPA and risky behaviors (Lin 2010, 2015). One might first suspect negative peer selection on attitudes, but negative error correlation only implies negative selection, if it captures correlation from omitted variables in the friendship selection process. However, this not necessarily the case. It could also capture correlation due to simultaneity bias. The direction of this bias is difficult to predict ex-ante. Overall, the implication is that the SAR and SDM models underestimate the peer attitude effect on own-attitudes.

Columns 5-6 report results from using 2SLS with peers of peers characteristics as instruments. Assuming exogeneity of the network ($\mathbf{G}$), this approach corrects for simultaneity bias though is less efficient than the ML results. In column 5, I use the average for peers of peers from each control variable in $\mathbf{X}$ as the instrument set ($\mathbf{G}^2\mathbf{X}$). The point estimate for peer attitudes is large and significant—near a 0.34 standard deviation shift on the attitudes index for a standard deviation shift in peer average attitudes. Concerning, however, is that the first-stage F test for instrument strength is only 3.934, suggesting they lack relevance. Also, the over-identification test has a p-value of 0.057, raising doubts about the exogeneity of the instruments. In column 6, I restrict the instrument set based on two instruments which had stronger associations with peer average attitudes in the first-stage. Those are the peers of peers average highest parental education level in the home and average grade level. Here, the point estimate increases slightly to 0.541. Instrument strength greatly improves with the first-stage F at 16.254 and the over-identification test is now easily past with a p-value of 0.888. Correcting for simultaneity bias suggests that the attitudes of friends exert strong influence on an adolescent's own-attitudes about school.

Finally, in columns 7-8, I relax the assumption of an exogenous network and use the method by Johnsson and Moon (2015) to control for endogenous network formation. In column 7, I use the full set of peers of peers instruments corrected for endogenous network formation, as described in appendix section 4.2, and in column 8, I restrict the instrument set as before. The results are very similar to the standard 2SLS approach. Comparing columns 5 and 7 and columns 6 and 8 the point estimate for peer attitudes slightly decreases but not by a significant amount. After controlling for endogenous network formation, I still find that a standard deviation increase in friend attitudes increases own-attitudes by approximately 0.32 standard deviations. Thus, among friends attitudes about school are contagious.

5.2 Heterogeneous Peer Effects

The previous section indicates that friend attitudes are strongly related with own-attitudes. Next, I explore whether this effect is heterogeneous. First, I explore whether the effect of friends' attitudes varies non-linearly—by adding polynomials in the peer attitudes—and on an adolescent's unobservables. Second, I explore whether the effect of friends' attitudes varies based on an adolescent's conditional position in the distribution of attitudes.

To accomplish these objectives, I take the control function (CF) approach,[19] using the reduced form residuals as a control variable in the attitudes specification. This approach is more amenable to the goals of this section than 2SLS. To solidify what I am estimating, I first discuss the method.

Given the structural equation in 2 and a matrix $\mathbf{Z} = [\mathbf{X} \;\; \mathbf{GX} \;\; \mathbf{G}^2\mathbf{X}]$, with $\mathbf{G}^2\mathbf{X}$ the

19. Not the semiparametric CFA method incorporating endogenous network formation. Results from that were not different from the standard 2SLS, so I do not return to it.

excluded variables,[20] the reduced form for friend attitudes is

$$\mathbf{GY} = \mathbf{Z}\pi + v_2. \tag{3}$$

With standard assumptions on instrument exclusion and relevance, one can obtain the same result as in 2SLS by controlling for $\hat{v}_2$ in equation 2 (Wooldridge 2015). The specification becomes

$$\mathbf{Y} = \mathbf{l}\kappa_s + \lambda\mathbf{GY} + \mathbf{X}\beta_1 + \mathbf{GX}\beta_2 + \rho_1 v_2 + e, \tag{4}$$

with the $E(v_2 e) = 0$ and $E(\mathbf{GY}e) = 0$. Because v_2 is not observed, replace it with $\hat{v}_2$ and estimate by ordinary least squares.[21] I am interested in possible non-linear effects in friend attitudes, so I modify equation 4 by adding polynomials of $\mathbf{GY}$. The CF approach does not require multiple reduced form equations as in a standard 2SLS, but it does require a stricter assumption that (ϵ, v) be independent of $\mathbf{Z}$ (Wooldridge 2007). Thus, the CF method has the advantage of being more parsimonious, albeit with added assumptions.

The CF method also easily allows estimating a random coefficients model. Replace λ with $g = \lambda + v_1$, an unobserved random variable that may be correlated with ϵ, where $\lambda = E(g)$ and the $E(v_1) = 0$. It may be the case that the effect of friend attitudes varies based on unobservables that lead to higher or lower average friend attitudes. In this case, equation 2 becomes

$$\mathbf{Y} = \mathbf{l}\kappa_s + \mathbf{X}\beta_1 + \mathbf{GX}\beta_2 + \lambda\mathbf{GY} + \gamma_1 v_1\mathbf{GY} + \rho_1 v_2 + e. \tag{5}$$

To estimate with the CF method, we must assume that the covariance between peer attitudes and v_1 does not depend on $\mathbf{Z}$, both ϵ and v_1 are linearly related to v_2, and that (ϵ, v_1, v_2) are independent of $\mathbf{Z}$ (Wooldridge 2015). Under these conditions, the random coefficients model is estimated by replacing $v_1\mathbf{GY}$ with $\hat{v}_2\mathbf{GY}$ in equation 5. In the results to follow, I maintain the restricted instrument set as noted in section 5.1.

20. Restrict to a subset as needed.

21. Standard errors need to be bootstrapped to correct for the generated regressor

In table 3, I report the results for exploring non-linear effects in columns 1 and 2 and the random coefficients model in column 3 and 4. Non-linear effects are present up to a cubic term in peer attitudes. Including a fourth order term (column 2), returns a near zero estimate on the coefficient and results in the cubic term losing significance. Focusing on the cubic specification in column 1, the effect from peer attitudes remains positive but the effect decreases quite rapidly as average peer attitudes increase above zero.[22] In appendix figure E1, I plot the average marginal effects over a range of average peer attitudes. The effect quickly dips after crossing zero for the average of the peers' attitudes. Thus, peer attitude effects are strongest when peers' attitudes are lower.

Table 3: Heterogeneity in the Effect of Peer Attitudes

	(1)	(2)	(3)	(4)
Peer Attitudes	0.582***	0.576**	0.528**	0.581**
	(0.224)	(0.234)	(0.248)	(0.234)
$(PeerAttitudes)^2$	-0.133***	-0.141**		-0.110
	(0.032)	(0.058)		(0.111)
$(PeerAttitudes)^3$	-0.041**	-0.033		-0.042**
	(0.021)	(0.036)		(0.021)
$(PeerAttitudes)^4$		0.005		
		(0.022)		
$\hat{v_2}$	-0.252	-0.254	-0.261	-0.254
	(0.225)	(0.236)	(0.248)	(0.230)
$\hat{v_2}$ × Peer Attitudes			-0.105***	-0.028
			(0.029)	(0.130)
Joint Test (p-val)	0.000	0.001	0.001	0.532,0.077

Note: [A]$N = 2216$. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses.
[B]Each specification includes the full set of controls, average peer controls, and school fixed effects.
[C]The joint test in columns 1 and 2 is the Wald test for joint significance of the polynomial terms.
[D]The joint test in column 3 is that of $\hat{v}$ and it's interaction.
[E]The joint tests in column 4 are $\hat{v}$ and it's interaction and the polynomials.

In column 3, I turn to the random coefficient model. While $\hat{v}_2$ is negative,[23] it is not significant, but the interaction term is both negative and significant. This implies that when the average attitudes among friends are higher for unobservable reasons they are less

22. Recall the attitudes index stretches over positive and negative values.
23. Similar to the peer error correlation in the GNS model.

influential. Conversely, when they are lower for unobservable reasons they are more influential. Column 4 includes both the polynomials in friend attitudes and the interaction with $\hat{v}_2$. The coefficient on the interaction moves towards zero and is no longer significant. For the polynomial terms, the square of peer attitudes is not significant but its point estimate is similar to column 1 and the 3rd order polynomial remains robust. It appears that much of the unobserved variation in the effect of peer attitudes is explained by the non-linearity. The overall evidence here points toward a substantial amount of heterogeneity in the peer attitude effect that suggests peers with the poorest attitudes have the greatest effect.

My second objective is to explore for heterogeneous effects based on an adolescent's conditional position in the distribution of attitudes. To do this, I use the CF method with conditional quantile regressions as developed by Imbens and Newey (2009). The quantile regression with the control function is

$$\mathbf{Y} = \mathbf{l}\kappa_s(q) + \lambda(q)\mathbf{GY} + \mathbf{X}\beta_1(q) + \mathbf{GX}\beta_2(q) + \rho_1(q)v_2 + e(q), \tag{6}$$

at each quantile q. Again, replacing v_2 with $\hat{v}_2$, I estimate equation 6 over conditional quantiles of the attitudes index. I re-do this procedure adding the interaction between $v_1\mathbf{GY}$ to again allow the peer effect to vary on the reduced form unobservables.[24]

Figure 1 contains the results for the conditional quantile regressions. The left panel for the standard control function approach and the right panel for the random coefficients model. Both plot the effect of peer attitudes from the 0.1 to the 0.9 conditional quantiles of attitudes. The trend is downward, beginning high and dropping towards zero for adolescents who have conditionally higher attitudes. The standard CF method in the left panel does indicate a turn back upwards after the 0.8 conditional quantile, but the random coefficients model in the right panel indicates a consistent downward trend. Put differently, adolescents who have

24. Because the polynomials in peer attitudes and the interaction with $\hat{v}_2$ appear to capture the same variation in the social interaction effect, I only report the quantile regressions excluding and including the interaction term. Results not shown with the polynomials returned a very similar picture to the right panel of figure 1.

conditionally lower attitudes appear to be more effected by their friends.

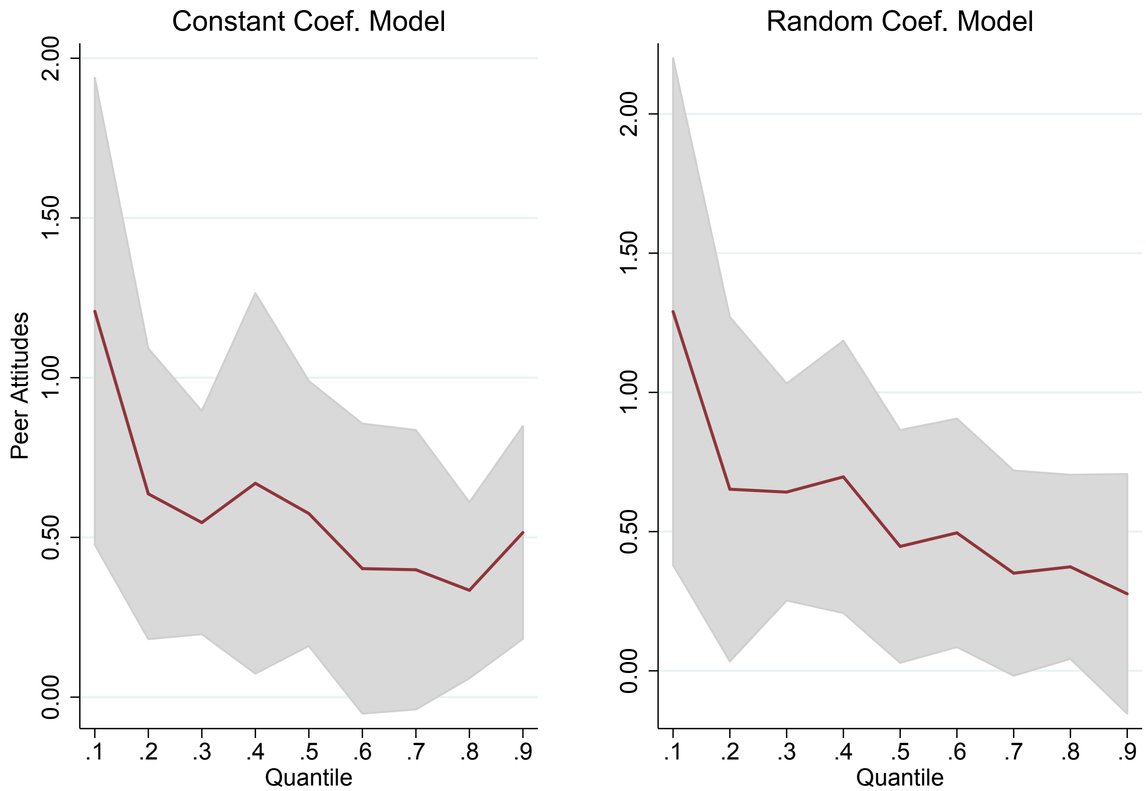

Figure 1: Quantile Regression The Effect of Peer Attitudes (90% CI)

There is substantial heterogeneity in the effect friends' attitudes have on an adolescent. Combined it suggests that when friends have worse attitudes they have a greater impact and that when an adolescent has conditionally worse attitudes they are more susceptible to their friends' attitudes. Indeed, an adolescent who has poor attitudes about school and whose social circle does as well is the one who schools, communities, families, and policy-makers may be the most concerned about. The evidence here indicates this concern is well founded and that interventions should carefully take into account the adolescents' friends.

5.3 Link Misspecification

Bias from measurement error in the network is non-classical, potentially positive or negative (Advani and Malde 2018; Chandrasekhar and Lewis 2011). One concern is missing data in the peer outcomes from simply not observing a portion of the school-friends. To this end, I used the saturated sample from Add Health that includes all network sampled adolescents in the in-home sample. However, links may be misspecified if non-friends indeed have direct influence. Also, a number of links are lost in the sample construction. I consider two sensitivity tests. In the first, I re-estimate the models with the undirected graph to regain some of the observations lost during sample construction. In the second, I implement a simulation similar to Patachini, Rainone, and Zenou (2016) and explore results as I add links to the network.

The undirected graph assumes friendship reciprocity. If someone nominates you as a friend, then both that person and you receive a link in the adjacency matrix. As a result, some observations are regained ($N = 2790$) that were dropped because of missing friendship nominations in the directed graph. A concern is that some links are induced where they do not exist. The results, reported in table D1 in appendix section D, are highly consistent with those found above. Some point estimates are larger but the confidence intervals generally overlap with the point estimates from the directed graph. In the ML estimation, the likelihood values are smaller, indicating the undirected graph provides a poorer fit of the data compared to the directed graph. This is also consistent with what Lin (2010) finds when focusing on GPA. Thus, I stick with the directed graph that makes no assumption on the presence of links where they are not nominated. The primary takeaway from this analysis is that the conclusions remain the same as those from the directed graph.

If non-friends (NF), individuals not named by the adolescent, actually do exert direct influence, then links are misclassified. The identification of the parameter estimate for $\mathbf{GY}$ depends on excluding peers of peers (PoP) characteristics from the outcome equation. Because of clustering within networks, it is more likely that a PoP bears direct influence on an adolescent than those further away. I implement a simulation to explore the consequences of misspecified links, reporting results in table 4.

In the simulation, I randomly change a percentage (q) of NF within a school to direct peers, do this for every school, and cycle the percentage from 0 to 1 in 0.05 increments. At each increment of q, I allow a percentage (p) of the added links to be from PoP. Holding at q, I cycle p from 0 to 1 in 0.05 increments. For instance, at $q = 0.20$ the percentage of PoP links changed to friend status is pq and the percentage of non-friend, non-PoP is $(1-p)q$. The resulting grid is 21×21. At each p, q grid point, I re-draw the network 100 times re-estimating the 2SLS model on each draw.[25]

The addition of links that are far away in network distance from an adolescent (∼PoP) should add noise to the estimates, if these people do not exert influence. I expect, in this case, the confidence intervals to become much wider. In general, as the percentage of added links from PoP increases the total number of added links falls, because the number of PoP is less than the remaining non-friends. We may expect more stable estimates when at higher percentages of PoP, or wildly different estimates from the baseline if true links between an adolescent and a PoP existed, violating the exclusion restriction. Additionally, as the percentage of added links grows large and the percentage of PoP small, then many links are induced that may not exist. In this case, I expect the point estimates to fall towards zero with wide confidence intervals, if indeed these links do not transmit direct influence. In a sense, this provides a test of whether the results from nominated friends appear from some mechanical feature of the estimation methods and the network design.

In table 4, the effect from peer attitudes shrinks and becomes insignificant for addition of NF that are not PoP and the point estimates also quickly fall. As the percentage of added links is composed of a greater share of PoP, the point estimates remain closer to the original. They become significant again when the majority of added links are from PoP. When 100% of added links (bottom row in the table) are drawn from PoP the point estimates are more stable, similar to those in table 2, and are significant at every q percentage. This is also

25. Standard errors are drawn by the process described in Patachini, Rainone, and Zenou (2016) and allow for within and between sample variance. At a gridpoint i, $\sigma_i = \sqrt{(1/100)\sum_{j=1}^{100}\sigma_{ij}^2 + (1/100)\sum_{j=1}^{100}(\lambda_{ij} - \bar{\lambda}_i)^2}$. σ_{ij}^2 is the variance estimated at a gridpoint i for repetition j. Likewise, λ_{ij} is the social interaction effect at repetition j.

Table 4: Simulating Links from Non-Friends

$NF_{0\to1}$	5%	15%	30%	50%	70%	90%
% that are PoP						
0%	(-0.51)0.35 (1.22)	(-0.81)0.27 (1.34)	(-1.77)-0.08 (1.61)	(-2.79)-0.37 (2.05)	(-4.10)-0.81 (2.49)	(-6.70)-2.15 (2.40)
5%	(-0.33)0.48 (1.29)	(-0.86)0.24 (1.35)	(-1.52)0.08 (1.69)	(-2.55)-0.21 (2.14)	(-3.86)-0.64 (2.58)	(-6.38)-1.77 (2.83)
15%	(-0.42)0.42 (1.26)	(-0.77)0.31 (1.38)	(-1.39)0.13 (1.64)	(-2.14)0.08 (2.29)	(-3.75)-0.72 (2.31)	(-5.50)-1.61 (2.28)
30%	(-0.25)0.46 (1.18)	(-0.72)0.27 (1.25)	(-1.19)0.16 (1.51)	(-1.95)0.02 (1.98)	(-2.99)-0.54 (1.91)	(-4.51)-1.05 (2.42)
50%	(-0.18)0.52 (1.23)	(-0.56)0.32 (1.20)	(-1.03)0.15 (1.34)	(-1.63)-0.02 (1.58)	(-2.10)-0.01 (2.08)	(-2.64)-0.16 (2.32)
70%	(0.02)0.69 (1.35)	(-0.47)0.34 (1.15)	(-0.70)0.31 (1.32)	(-0.88)0.31 (1.50)	(-1.18)0.28 (1.75)	(-1.70)0.05 (1.81)
90%	(0.24)0.80 (1.35)	(0.05)0.71 (1.36)	(-0.20)0.55 (1.29)	(-0.36)0.54 (1.43)	(-0.39)0.49 (1.38)	(-0.43)0.60 (1.63)
95%	(0.28)0.76 (1.24)	(0.19)0.77 (1.35)	(0.05)0.71 (1.37)	(0.02)0.77 (1.52)	(-0.02)0.78 (1.58)	(-0.09)0.78 (1.65)
100%	(0.12)0.46 (0.80)	(0.10)0.45 (0.80)	(0.14)0.51 (0.87)	(0.14)0.51 (0.88)	(0.22)0.61 (1.01)	(0.25)0.65 (1.04)

Note: Each table cell reports the lower and upper bounds of the 90% confidence interval in parentheses and the mean of λ estimates at a p, q point ((lower bound 90%) mean (upper bound 90%)). All specifications include the full set of controls and average peer controls defined previously.

true at 95%, 90%, and 70% of PoP changed to friends up to 50%, 15%, and 5% respectively of non-friends converted to friends. Thus, as links are added that are at a distance greater than PoP, many more links are induced and the estimated social interaction effect becomes less stable and more noisy. This is consistent with the expectation outlined above. When the share of added links is primarily from PoP, the estimates are more closely aligned with original estimates and maintain significance at high proportions. These results support the use of nominated friends as peers and suggest that adding links to PoP does not change the conclusions.[26]

6 Results: Parental Moderating Effects

The goal of this section is to study whether parents may be able to moderate the influence an adolescent experiences from their friends' attitudes. Parental investments are important to the development of noncognitive skills during early childhood (Heckman and Mosso 2014), but less attention has been focused on the parental role in continued development during adolescence. As social ties outside the home become more important, parents may be able to counteract influence towards worse attitudes by increasing the transmission of attitudes about

26. When the PoP draw is very high, this pushes the peers of peers instruments to those who were previously at a 3rd order distance. When the PoP draw is low, the peers of peers instruments potentially derive from those quite far away in the orginal network, thereby likely creating very weak instruments.

school in the home. In this case, programs targeted at improving an adolescent's engagement with their school, ambitions, and academic goals can begin by working with parents.

The specification of interest is now

$$\mathbf{Y} = \mathbf{l}\kappa_s + \lambda_0 \mathbf{GYd} + \lambda_1 \mathbf{GY} + \lambda_2 \mathbf{d} + \mathbf{X}\beta_1 + \mathbf{GX}\beta_2 + \rho_1 v_2 + e, \tag{7}$$

where $\mathbf{d}$ is the parental variable and the interaction term coefficient is the effect of interest.[27] The presence of a negative effect on the interaction will indicate that parents can moderate the influence of peer attitudes. Clearly, any parental variable in survey data will likely be endogenous. However, there are conditions under which the interaction effect (λ_0) can be identified even when λ_2 cannot be. First, based on the result in Nizalova and Murtazashvili (2016) λ_0 is identified if friend attitudes are independent of $(\mathbf{d}, e)$ or that $E(e|\mathbf{d}, \mathbf{GY}) = E(e|\mathbf{d})$. Independence between $\mathbf{GY}$ and e holds if the assumptions of the CF method hold, but independence between $\mathbf{GY}$ and $\mathbf{d}$ is unlikely. However, the conditional argument will hold if controlling for $\hat{v}_2$ indeed isolates exogenous variation in friend attitudes.

Second, we can take a 2SLS approach adding an interaction between $\mathbf{d}$ and an instrument. After exploring instrument strength with the addition of new parental variables, I restricted the peers of peers instrument set to only the average of the highest parental education in the home. Call this PoP_{pedu}. The interacted instrument is $\mathbf{d}PoP_{pedu}$. Of course, this is cleanest when $\mathbf{d}$ is exogenous, but based on the results in Bun and Harrison (2018) this interacted instrument can be exogenous under certain conditions. One, $E(\mathbf{d}\epsilon|PoP_{pedu}) = E(\mathbf{d}, \epsilon)$, meaning the covariance between the key parent variable and attitude unobservables does not vary with the peers of peers average parental education. And, two, that either PoP_{pedu} is independent of the key parental variable or a only a linear function of it. While parents may be aware of the education of other parents in the school, I control for the direct friends' parental education and the school fixed effect to reduce any dependence between PoP_{pedu} and $\mathbf{d}$.

The two sets of parental variables I focus on are the adolescent's perceptions of parental

27. $\mathbf{Gd}$ can be, and is, included among the peer averages.

educational expectations and adolescent self-reports on activities the parents have done with them. As described in the data section, I form multiple indexes out of these sets. Adding these indexes also resulted in losing some additional observations. The sample size is now $2,045$. For each index, I explore both the CF method and the 2SLS method with an added interacted instrument. If the conditions for each outlined above hold, then the estimate of λ_0 can be interpreted as a causal effect even though λ_2 is biased.

Table 5 presents the results for the full parental expectations scale in panel A and the college only scale in panel B. The inclusion of the new parental variables weakens the significance of the peer attitude effect, but the coefficient estimate is nearly identical with that estimated in the baseline results. Column 1 omits the interaction effect but in both panels, shows that parental expectations are highly correlated with attitudes.[28] This association, of course, is only descriptive.

Columns 2-3 add the interaction term of interest. With the CF method in column 2, the interaction estimate is negative and statistically significant (5% level) in both the full scale and the college only scale. If the conditions outlined above hold, then this suggests that increasing parental education expectations can moderate the influence of friend attitudes. Turning to column 3 and the 2SLS approach, the estimated interaction effect is very similar to the counterpart in column 2. The 2SLS estimate, however, is much less efficient with standard errors that more than quadruple. This stems from the addition of a reduced form equation for the interaction that is not present in the CF method. Statistical significance is lost but the point estimates remain consistent with those in column 2, pointing towards the presence of a moderating effect.

The descriptive statistics for parental expectations, reported in appendix table B2, indicate that average parental expectations are higher in the analytic sample than in the full sample.[29] The mother only scales (full and college) are much more robust to conditioning on the analytic

28. I omit the coefficient estimate for average friend parents' expectations but it was near zero and never significant in any specification.

29. The scales were normalized pre-conditioning on the analytic sample. Thus any mean that differs from zero results from a change based on lost observations.

Table 5: Parental Educational Expectations and Peer Effects

	CF		2SLS
	(1)	(2)	(3)
Panel A: Expectations Scale			
Peer Att. X Par. Expect		-0.070**	-0.063
		(0.029)	(0.137)
Peer Attitudes ($\hat{\lambda}$)	0.538*	0.540	0.540*
	(0.322)	(0.334)	(0.290)
Parental Edu. Expect.	0.196***	0.206***	0.204***
	(0.042)	(0.043)	(0.044)
$\hat{v}$	-0.248	-0.248	
	(0.323)	(0.335)	
First Stage F—**GY** EQ:		23.61	8.70
First Stage F—Interaction EQ:			17.14
Panel B: College (only) Scale			
Peer Att. X Par. College Expect.		-0.066**	-0.105
		(0.027)	(0.131)
Peer Attitudes ($\hat{\lambda}$)	0.525	0.512	0.503
	(0.358)	(0.370)	(0.315)
Parental College Expect.	0.204***	0.212***	0.217***
	(0.037)	(0.036)	(0.039)
$\hat{v}$	-0.248	-0.239	
	(0.360)	(0.371)	
First Stage F—**GY** EQ:		21.07	8.34
First Stage F—Interaction EQ:			23.59

Note: [A] $N = 2045$. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses.
[B] Each specification includes the full set of controls, average peer controls, and school fixed effects.
[C] The instrument is restricted to average peers of peers parental education (PoP_{pedu}).
[D] CF standard error estimates are calculated with 500 bootstrap replications.
[E] 2SLS adds an interaction between PoP_{pedu} and the parental expectations variable of interest.

sample. In the Add Health data, mother's are more likely to be present in the home than father's and based on the summary statistics are not selected into the analytic sample based on their educational expectations. Thus, in table 6 I focus on the expectation scales based on the mother reports.

Mothers' educational expectations remain positively associated with attitudes (column 1) and the interaction effect with friend attitudes remains negative (columns 2-3). With the CF method, the interaction effect size is similar to that found with the scale including father reports. Significance is weaker in panel A—the high school plus college scale—but remains at the 5% level in panel B, the college only scale. Turning to the 2SLS approach, this time the coefficient estimate increases in magnitude (panel A and B), becoming more negative, and is significant (10% panel A and 5% panel B). The standard errors again increase as expected and the confidence interval overlaps with the point estimate from the CF method. The overall evidence focusing on the mother's expectations are clearer and indicate that as they transmit higher expectations they moderate peer influence.

Table 6: Mother's Educational Expectations and Peer Effects

	CF		2SLS
	(1)	(2)	(3)
Panel A: Mother's Expectations			
Peer Att. X Mom Edu. Expect		-0.054*	-0.290*
		(0.028)	(0.170)
Peer Attitudes ($\hat{\lambda}$)	0.551	0.549	0.542*
	(0.382)	(0.337)	(0.289)
Mom Edu. Expect.	0.107***	0.115***	0.147***
	(0.024)	(0.024)	(0.032)
$\hat{v}$	-0.254	-0.260	
	(0.381)	(0.340)	
First Stage F—**GY** EQ:		24.02	8.68
First Stage F—Interaction EQ:			6.49
Panel B: Mother's College Expect.			
Peer Att. X Mom Coll. Expect		-0.054**	-0.221**
		(0.027)	(0.112)
Peer Attitudes ($\hat{\lambda}$)	0.519	0.500	0.440
	(0.437)	(0.343)	(0.314)
Mom Coll. Expect.	0.140***	0.146***	0.165***
	(0.029)	(0.025)	(0.028)
$\hat{v}$	-0.234	-0.227	
	(0.439)	(0.344)	
First Stage F—**GY** EQ:		20.30	7.71
First Stage F—Interaction EQ:			21.29

Note: [A]$N = 2045$. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses.
[B]2SLS adds an interaction between PoP_{pedu} and the mother's expectations variable of interest.
[C]All other notes from table 5 apply.

In table 7, I explore parental activity investments in place of educational expectations. It may be that just parental time and engagement with their adolescent can moderate the influence of friend attitudes. The evidence in table 7, however, is not consistent with this hypothesis. The association between parental (mother) activity investments and attitudes is positive but the interaction effect is never significant. In the CF method, the interaction is negative but closer to zero than the expectation coefficient estimates. In the 2SLS approach, the interaction turns positive and remains insignificant.

Table 7: Parental Activity Investments and Peer Effects

	CF		2SLS
	(1)	(2)	(3)
Panel A: Parental Activity Invest.			
Peer Att. X Par. Invest.		-0.038	0.100
		(0.025)	(0.097)
Peer Attitudes ($\hat{\lambda}$)	0.605*	0.607**	0.600**
	(0.331)	(0.295)	(0.276)
Parental Invest.	0.130***	0.137***	0.111***
	(0.021)	(0.022)	(0.028)
$\hat{v}$	-0.309	-0.309*	
	(0.332)	(0.296)	
First Stage F—**GY** EQ:		28.22	10.05
First Stage F—Interaction EQ:			24.10
Panel B: Mother's Activity Invest.			
Peer Att. X Mom Invest.		-0.019	0.027
		(0.028)	(0.107)
Peer Attitudes ($\hat{\lambda}$)	0.602*	0.557**	0.600**
	(0.337)	(0.258)	(0.278)
Mom Invest.	0.120***	0.125***	0.116***
	(0.020)	(0.021)	(0.026)
$\hat{v}$	-0.301	-0.255	
	(0.338)	(0.259)	
First Stage F—**GY** EQ:		27.30	10.60
First Stage F—Interaction EQ:			29.67

Note: [A] $N = 2045$. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses.
[B] 2SLS adds an interaction between PoP_{pedu} and the parent investment variable of interest.
[C] All other notes from table 5 apply.

From the results in table 7, I cannot conclude that only parental educational expectations moderate friend influence, but it does suggest that not all parental action has the same effect. It appears that the transmission of attitudes about education by the parents is most effective at moderating the transmission of attitudes by friends compared to time and engagement with the adolescent. In a model of identity, groups form ideal behaviors that generate conforming effects by transmission of norms Akerlof and Kranton (2000, 2002). If parental expectations capture in-home educational norms, then it is reasonable that this is where we would find the strongest moderating effect. Other parental actions are likely important to the formation of attitudes, but it is the in-home norms that likely compete the most with norms in an adolescent's in-school social circle.

A direction that interventions can take is to work with parents on their attitudes or norms. A recent field experiment among disadvantaged Parisian middle schools studied by Avvisati et al. (2014) provides an excellent example. Treated parents were invited to the school for multiple sessions that aimed to improve parental attitudes about the school and help the parents build better techniques to support their children academically. The authors' find strong evidence that the program was successful, especially for improving behavioral outcomes. While that study does not speak to moderating effects, it does suggest that working with parents can be effective. My study shows that, in the US, parents are relevant to the influence social circles have on an adolescent's attitudes about school. It suggests that interventions such as that studied by Avvisati et al. (2014) have scope to be expanded and targeted to environments where social interaction effects likely build poor attitudes.

7 Conclusion

Bad influence from peers at school has long been a concern for parents of adolescents along with whether they can remain effective in protecting their teenagers from such influence. Skills and beliefs remain malleable during adolescence. One particular area bad influence may create long-term consequences is by impacting the development of these skills and beliefs. Educational attitudes are important in their own right. They have long-term implications for educational attainment (Lipnevich, Gjicali, and Krumm 2016), and in general, noncognitive skills have a causal impact on many long-term outcomes (Heckman and Mosso 2014).

Social ties outside of the home become more important during adolescence (Bagwell and Schmidt 2013; Mak, Fosco, and Feinberg 2018). The combination of friend and parent influence may be important to development. In economic theory, groups with the strongest influence relate to the groups most relevant to a person's identity and with whom one shares the greatest identity investments (Akerlof and Kranton 2000, 2002; Bénabou and Tirole 2011). In that regard, close friends and parents are likely the most relevant relationships to explore for conforming influences that shape adolescent attitudes.

In this paper, I have focused on a component of noncognitive skills, attitudes about school and future education, and on the relationship between an adolescent and their friends' attitudes. Furthermore, I explored whether parental transmission of educational expectations and parental activities with the adolescent can moderate the influence of friends on attitudes. The results imply friendship circles can influence the formation of attitudes. Also, I find that parents can have a moderating role, mitigating the overall influence friends can exert.

Empirical identification of friend attitude effects is complicated by the presence of simultaneity bias, shared environments, and endogenous network formation. Add Health provides friendship nominations, allowing the construction of school friendship networks. With this information, I use the structure of the network to correct for simultaneity bias,[30] control for shared environments up to the school level, and implement a new estimator accounting for the network formation process by Johnsson and Moon (2015). I do not find evidence for substantial bias from the network formation process but do find that once correcting for simultaneity[31] the effect from average friend attitudes rises and remains highly significant.

I also find that attitude peer effects are heterogeneous. As friends' attitudes decrease, they exert greater influence. Moreover, I find that when an adolescent is at a lower point in the conditional distribution of attitudes, friend attitudes have a greater effect on them. Adolescents who already have poor attitudes and who are surrounded by friends with poor attitudes stand to be the most influenced by their friends.

This is concerning on the one hand as they may be caught in a very bad equilibrium, but on the other hand, suggests that if interventions can successfully raise attitudes among those with poor attitudes, then those adolescents will improve the attitudes of those linked to them

30. Peers of peers instruments.

31. And, measurement error too since I am instrumenting for average peer attitudes.

but not treated. Of course, once attitudes about school become sufficiently high then the peer effects exerted drop off and little in the way of spillovers will continue to be generated, or worse, further increases in attitudes could actually have negative spillovers. The implication is that policy need only promote attitudes where attitudes are likely to be poor.

Empirical identification of a parental effect is also complicated by the presence of unobservables. The primary coefficient of interest for the purposes of this study is the interaction term between key parental variables—expectations and investments—and average friend attitudes. Based on the results in Bun and Harrison (2018) and Nizalova and Murtazashvili (2016) I discuss conditions under which the interaction term can still be identified in the CF method and the 2SLS approach even when lacking an instrument for the key parental variable. I find parental expectations, especially driven by mothers, have moderating effects on the friend attitude effect. I do not find this to be true for parental activity investments, suggesting for attitudes it may be the attitude norm on education set in the home that matters. This result also suggests that working with parents is one possible channel for interventions to consider when hoping to improve adolescent attitudes about their school and their future education. This may be especially useful among adolescents at-risk of poor educational attitudes from poor environments.

There is still much to discover about the processes shaping skills during adolescence. Attitudes represent only one component of a broad set of skills and beliefs that are malleable. The point at which these skills become set is also unknown, with current research implicitly suggesting that at some point it is too late to intervene (Sampson 2016). But, as Sampson (2016) discusses, whether this is true is not well understood and the current implication could be damaging without further research.

In this study, I show attitudes are continuing to develop during adolescence and that friends and parents are important to this process. As social identity and social ties become increasingly important during the adolescent years, successful interventions will need to take these into account. Early childhood interventions are highly important, but so too may be adolescent interventions targeted on the right mechanisms.

Appendix: Supplementary Materials

A Details on Variable Construction for Key Measures

Own-attitudes about school is constructed as an index normalized to mean zero and a standard deviation of one using factor analysis. A set of scale-type questions related to how much a respondent reports a desire to go to college, how likely they think it is they will go to college, whether they feel apart of their current school, are happy at their current school, feel that their teachers are fair, and feel close to people at their school forms the index. Tables A1 and A2 contain summary statistics and information on the factor analysis. The factor analysis is conducted on the full sample post-listwise deletion of missing observations in the variables included for the factor analysis ($N = 3596$). Table A1 shows that all of the variables range from one to five The scales are coded such that ones relate to the lowest report for a variable and fives the highest. Table A2 shows that all variables load strongly onto a single factor and only one factor in the analysis has an eigenvalue greater than one—the common cut-off rule for considering a factor as potentially relevant. Additionally, table A2 reports the factor scores used to generate an index out of these variables that I use as a proxy for attitudes about schooling.

Table 8: Summary Statistics for Variables Used in Factor Analysis

	Mean	SD	Min	Max	N
How Likely Variables					
Desire for College	4.30	1.12	1	5	3596
How Likely College	4.01	1.22	1	5	3596
Agree/Disagree					
Feel Part of School	3.81	1.04	1	5	3596
Happy to be at School	3.71	1.09	1	5	3596
Feel Teachers are Fair	3.52	1.05	1	5	3596
Feel Close to People at School	3.73	1.00	1	5	3596

Table 9: Factor Analysis: Factor Loadings and Eigenvalues

	Factor Loadings	Uniqueness
How Likely Variables		
Desire for College	0.532	0.717
How Likely College	0.537	0.712
Agree/Disagree		
Feel Part of School	0.681	0.537
Happy to be at School	0.616	0.621
Feel Teachers are Fair	0.356	0.873
Feel Close to People at School	0.579	0.665
Factor Eigenvalue	1.88	

B Key Parental Variables

Table B1: List of Variables for Measures Parent Expectations and Activity Investments

	EDU Expectations Scale		Mother's EDU Expectations		Activity Investments	
	Scale A	Scale B	Scale A	Scale B	Scale A	Scale B
Variable Preface					Which of these have you done... with your mother (past 4 weeks)...	
Scale Variable 1	Mother's disappointment if do not graduate college	Mother's disappointment if do not graduate college	Mother's disappointment if do not graduate college	Mother's disappointment if do not graduate college	gone shopping	*only Mother variables*
Scale Variable 2	Mother's disappointment if do not graduate HS		Mother's disappointment if do not graduate HS		played a sport	
Scale Variable 3	Father's disappointment if do not graduate college	Father's disappointment if do not graduate college			religous service or event	
Scale Variable 4	Father's disappointment if do not graduate HS				talked about someone you're dating	
Scale Variable 5					movie, play, museum, etc.	
Scale Variable 6					talked about personal problem	
Scale Variable 7					had a serious argument	
Scale Variable 8					talked about school work/grades	
Scale Variable 9					worked on a project for school	
Scale Variable 10					talked about other school activites	
					Repeats for fathers	
Answer Format	Likert (1-5; low–high)	Likert (1-5; low–high)	Likert (1-5; low–high)	Likert (1-5; low-high)	Yes, No	
Scale Format	Sum then standardized	Sum then standardized	Sum then standardized	Standardized	Sum then standardized	

Note: See the in-home, wave I, section 16 "relation with parents" Add Health codebook.

Table B2: Summary Stats for Parental Variables

	Mean	SD	Min	Max
Parental Edu. Expect.	15.395	4.850	2.000	20.000
Parental Edu. Expect. (z)	0.174	0.943	-2.430	1.069
Parental Coll. Expect.	7.013	2.754	1.000	10.000
Parental Coll. Expect. (z)	0.124	0.982	-2.020	1.189
Mom Edu. Expect	8.666	1.831	2.000	10.000
Mom Edu. Expect. (z)	-0.020	1.011	-3.699	0.716
Mom Coll. Expect	3.937	1.276	1.000	5.000
Mom Coll. Expect. (z)	-0.037	1.020	-2.384	0.813
Parental Invest.	6.350	3.374	0.000	19.000
Parental Invest. (z)	0.149	1.000	-1.733	3.897
Mother Invest.	4.042	1.992	0.000	10.000
Mother Invest. (z)	0.054	0.997	-1.969	3.036

Note: $N = 2045$. All summary statistics are from the analysis sample post-deletion of missing and post-deletion of isolated adolescents in the network. Standardized scores (z) were calculated pre-deletion of data thus the current mean is not always zero.

C Semi-Parametric Control Function Approach with Endogenous Network Formation

The instrument matrix is $\mathbf{Z} = [\mathbf{X}\ \ \mathbf{GX}\ \ \mathbf{G}^2\mathbf{X}]$.[32] For $\mathbf{Z}$ to be a valid instrument matrix, the assumption that $\mathbb{E}[\mathbf{Z}'\epsilon] = 0$ must hold. However, as noted above, unobserved characteristics that impact network formation and outcomes will correlate $\mathbf{G}$ with ϵ violating this assumption. Johnsson and Moon (2015) approach aims to restore the validity of $\mathbf{G}^2\mathbf{X}$ as instruments for the simultaneity that are free of selection bias.

Links form between adolescent dyads following

$$D_{ij,N} = \mathbb{1}(T_{ij}'\gamma + A_i + A_j - u_{ij} \geq 0).$$

$D_{ij,N}$ takes the value of 1 if a link exists for the i,jth dyad and 0 otherwise. T_{ij} represents a matrix of $t_{ij} = |x_i - x_j|$ variables that capture the difference between each of the observable characteristics of each adolescent in the dyad. Every variable in $\mathbf{X}$ can be included here, but as will be described below the set had to be restricted for some schools. γ is the coefficient vector for homophily taste in friend selection and $\gamma < 0$ implies a taste for homophily in link formation for the observable covariates. In a slight abuse of notation, redefining n and N, there are $n = \binom{N}{2}$ dyads, where N is the number of observations in a network.[33] u_{ij} is an idiosyncratic shock, and it is assumed that $u_{ij} \perp (\mathbf{X}, \mathbf{A}, \epsilon)$.[34]

A_i and A_j generate endogeneity between dyad unobserved heterogeneity in link formation and outcomes. An important contribution of Graham (2017) is the development of estimation techniques for this model, allowing the unobserved heterogeneity to be of arbitrary correlation rather than the stronger restriction of random effects in Goldsmith-Pinkham and Imbens (2013). This model of network formation does not admit interdependence based on network

32. One can restrict $\mathbf{G}^2\mathbf{X}$ to a subset of $\mathbf{X}$ as needed for the purpose of instrument strength.
33. This model applies to a single network, thus I will run the model for each school separately and then stack up the results for $\hat{A}_i$.
34. Johnsson and Moon (2015) assume the undirected graph but the approach is valid for the directed graph as well.

structure (e.g. transitivity: impact of shared links on linking decision). Graham (2015, 2017) show that with a single observation of the network we cannot identify network structure covariates in the link formation model including unobserved heterogeneity, as both homophily and transitivity lead to clusters.[35] What we can do is estimate network formation controlling for homophily and unobserved fixed effects and then obtain an estimate of this unobserved heterogeneity determinant.

An estimate of A_i can be used to correct the bias from endogenous network links, if attitudes are influenced by unobservables that also make the adolescent a better or worse linking partner to select. An example case is a student who has traits that make them popular and that also influence attitudes. Higher ability may make a student more or less popular to select based on, for example, whether other students share their ability (homophily), desire to be linked to someone of higher ability, or desires to not be linked with anyone of a particularly high ability. The goal is to obtain $\hat{A}_i$ in a first step and control for it in the second using a non-parametric sieve basis—which allows a flexible functional form between ϵ and A_i—in the two stage least square (2SLS) estimation of peer effects. Because the link formation regressors are dyad specific and of a non-linear form, there are natural exclusion restrictions created between the link formation regressors and regressors in the outcome equation. No outside instruments are required.

Estimates of $\hat{A}_i$ are obtained from a logit following the joint maximum likelihood estimator developed in Graham (2017) of $D_{ij,N}$ with dyad specific regressors. This particular dyadic model is designed to be run on a single network. I run the network formation model separately by school-network, stack up the estimates of A_i from each into a single vector, and then return to the block-diagonal adjacency matrix for the second step. This did require adjusting the indicator covariates by school because some schools, for example, had no observations for Hispanic ethnicity and so on.

Given an estimate for A_i, Johnsson and Moon (2015) define the $\mathbb{E}[\epsilon_i|A_i] = h(A_i)$ where

35. A recent development by Graham (2016) provides a method to incorporate both but requires four periods of network observations.

$h(A_i)$ is an unknown function to be approximated by a sieve estimator. They consider multiple versions of the sieve estimator of which I adopt the polynomial.[36] The estimated sieve basis is $\hat{\mathbf{Q}} = \left[A_i^0 \;\; A_i^1 \;\; ... \;\; A_i^{K_N}\right]$, where K_N is the degree of the polynomial. I choose $K_N = 6$.[37] Finally, the outcome equation is rewritten as

$$\mathbf{Y} = \mathbf{C}\theta + \hat{\mathbf{Q}}\alpha + \epsilon + H(A) - \hat{\mathbf{Q}}\alpha,$$

where $\mathbf{C} = [\mathbf{GY} \;\; \mathbf{X} \;\; \mathbf{GX}]$ and $\theta = [\lambda \quad \beta_1 \quad \beta_2]'$. Define $M = I - \hat{\mathbf{Q}}(\hat{\mathbf{Q}}'\hat{\mathbf{Q}})^{-1}\hat{\mathbf{Q}}'$ with I the identity matrix. Johnsson and Moon (2015) show that the 2SLS estimator controlling for the fixed effect individual heterogeneity in link formation and restoring peers of peers characteristics to valid instruments is[38]

$$\hat{\theta} = \left(\mathbf{C}'M\mathbf{Z}\left(\mathbf{Z}'M\mathbf{Z}\right)^{-1}\mathbf{Z}'M\mathbf{C}\right)^{-1}\mathbf{C}M\mathbf{Z}\left(\mathbf{Z}'M\mathbf{Z}'\right)^{-1}\mathbf{Z}'M\mathbf{Y}. \tag{8}$$

36. I also tested the cosine sieve basis but it did not change the results.

37. Monte carlo results suggest that peer effect estimates are more precise with $K_N = 6$ (Johnsson and Moon 2015).

38. See Johnsson and Moon (2015) for derivation of asymptotic results and formulas for variance estimation.

D Friend Attitude Effects and the Undirected Graph

Table D1: Attitudes Model with the Undirected Graph

	(1) SAR	(2) SDM	(3) SEM	(4) GNS	(5) 2SLS Full-Z	(6) 2SLS R-Z	(7) CFA-Semip Full-Z	(8) CFA-Semip R-Z
Peer Attitudes ($\hat{\lambda}$)	0.217***	0.205***		0.553***	0.886***	0.913***	0.791***	0.853***
	(0.022)	(0.022)		(0.033)	(0.233)	(0.289)	(0.233)	(0.292)
Peer Error Corr ($\hat{\rho}$)			0.202***	-0.410***				
			(0.022)	(0.042)				
Likelihood	-3281.768	-3268.736	-3270.806	-3250.390	-3414.909	-3431.327		
First Stage F					3.712	12.256		
Over-ID P-Value					0.479	0.586		

Note: [A] $N = 2790$. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses.
[B] Each specification includes the full set of controls and school fixed effects. Average peer controls are $\mathbf{GX}$.
[C] Full-Z uses the entire set of $\mathbf{G}^2\mathbf{X}$ instruments as IVs.
[D] R-Z restricts the IVs to the highest parental education and grade level of the peers of peers.

E Nonlinear Peer Effects

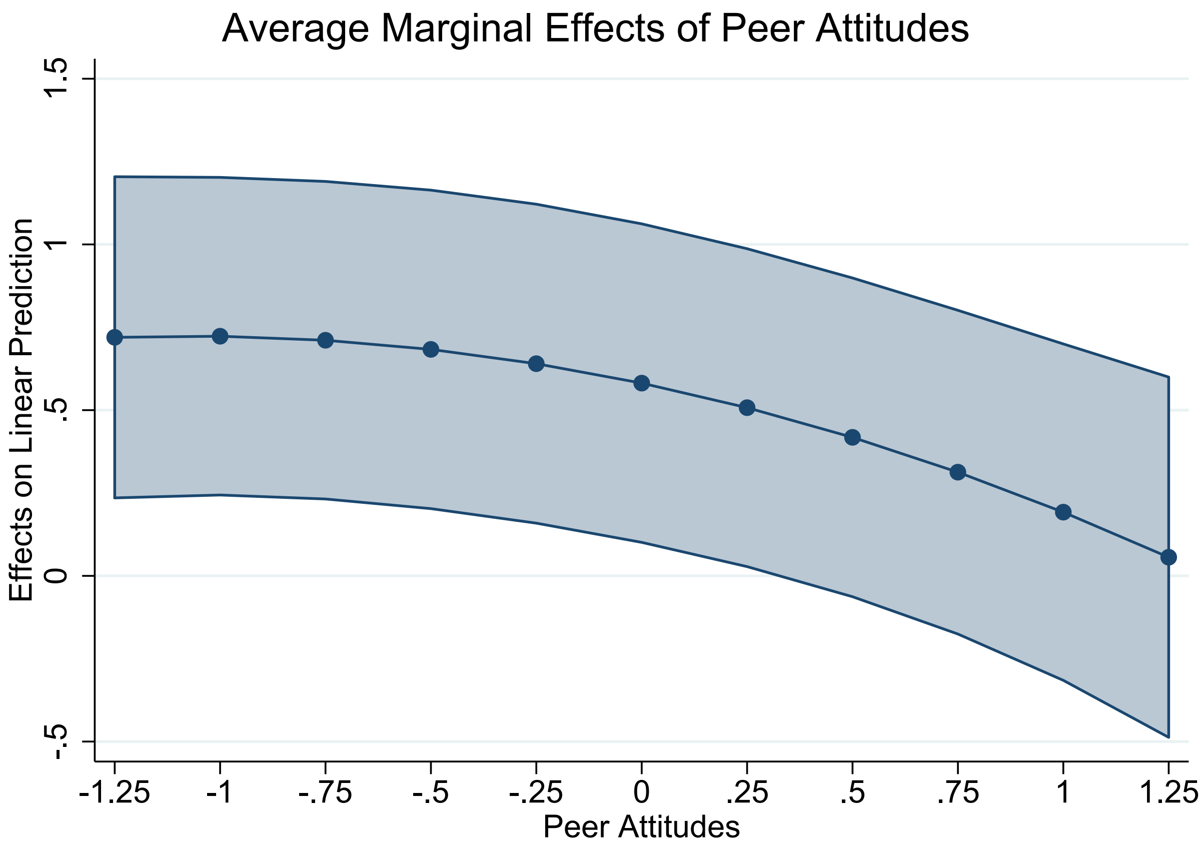

Figure E1: Nonlinear Effect of Peer Attitudes on Own-Attitudes (2nd and 3rd order polynomials)

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