Social Interactions in College Choice: The Interplay of Information, Preferences, Social Norms, and Individual Characteristics in Predicting College Choice

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Abstract:
This research examines the extent to which college decisions among adolescents depend on the decisions of their peers. The goals of this paper are to (1) establish the importance of high school classmates' decisions to enroll in college on individual college enrollment choices and (2) examine the mechanisms that underlie high school classmate influence on individual college choices. I address these questions by exploiting two unique features of the recently collected Texas Higher Education Opportunity Project (THEOP) survey data that potentially allow the identification of the mechanism through which peer social interactions operate. This survey collects information on student-reported preferences for specific colleges and student-reported information channels about college.
I use instrumental variables to combat the well known "reflection problem" in the social interactions literature. Results indicate that students who attend high school with 10% more classmates who go on to attend college are eight percentage points more likely to themselves attend college. I also find that students who have "unpopular" preferences for specific colleges are less likely to attend their preferred college, suggesting the importance of social norms in shaping college choices. These results have implications for broad types of policy interventions to increase college enrollment among disadvantaged groups. In particular, policies that shape student preferences are predicted to "spillover" on the decisions of their classmates.

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Introduction

This paper examines whether interdependent choices, called *social interactions* in the economics literature (Brock and Durlauf 2001a,b, Manski 2000), can help explain the dramatic differences found in college choices across individuals with similar characteristics. The basic question is whether college decisions among adolescents depend on the decisions of their peers. Does the fact that many students in an individual's reference group plan to go to college (or a particular college) affect an individual's college plans? There is some evidence that peers' decisions affect college enrollment (e.g. Fletcher 2006), but the mechanism in unknown. On the one hand, peers' decisions could change an individual's information regarding college, through *expectations interactions* (Manski 2000). Expectations interactions can occur in the context of college choice when students share information about internet searches, campus visits, etc. and alter the perceived costs and benefits of college. On the other hand, peers' decisions could change social norms within schools regarding which choices are socially valued (e.g. enroll in college, enroll in a specific college such as Texas A & M) and which choices are not (e.g. enroll in an out-of-state college, join the work force after high school graduation), though *preference interactions* (Manski 2000). In the present paper, I concentrate on expectations interactions and preference interactions through specific channels. I focus on expectations interactions via the sharing of information about college within a school. I constrain preference interactions to be the influence on individual preferences of the preferences of his/her reference group.

The results indicate that students who attend high school with 10% more classmates who go on to attend college are eight percentage points more likely to attend college. I also find evidence that the preferences of classmates influence individual college choices, even controlling for alternative mechanisms such as information acquisition and the school environment. In particular, results show that students who have "unpopular" preferences for specific colleges are less likely to attend their preferred college, suggesting the importance of social norms in shaping college choices.

Background

In their seminal economic analysis of adolescent college enrollment decisions, Manski and Wise (1983) suggest five factors that are most important in determining enrollment: (1) academic aptitude, (2) family income, (3) cost and aid, (4) quality of high school and decisions of peers,[1] and (5) labor market conditions. This list of important factors has been used in decades of research of college enrollment by economists and other educational researchers (Rouse 1994, Cameron and Heckman 1998, Avery and Hoxby 2004). A casual examination of past and recent economic research on the question of college enrollment, however, also indicates that one listed factor is noticeably missing from most subsequent analysis—the decisions of peers.

The decisions of peers is an intuitively important, but relatively understudied, determinant of many adolescent choices. In recent related research peer choices have been shown to be an important determinant of adolescent decisions to pursue several risky behaviors during high school. For example, Fletcher (forthcoming) examines the decision to initiate premarital sex by adolescents and reports results that suggest large reductions in school-level sexual initiation from interventions that decrease the chances of initiation for high risk adolescents. In related work, Gaviria and Raphael (2001) report that social interactions appear to partially account for adolescent decisions to pursue other risky behaviors including drug, cigarette, and alcohol use.[2] Cipollone and Rosolia (2003) find social interactions in educational attainment for Italian students and Bobonis and Finan (2005) report similar findings for Mexican students.

While the social interactions framework has been applied to many adolescent behaviors, there is little research that examines social interactions in college choices.[3] This is problematic because social interactions have the potential of partially explaining why minority students do not enroll in college at the same rates as majority students as well as partially explain the variation in college-going rates across the US. Additionally, the presence of social interactions suggests specific types of policies that may be used

[1] Although Manksi and Wise list the quality of high school and decisions of peers as one factor, they should likely be considered two distinct and important factors in determining college enrollment.
[2] Powell et al (2003) also finds peer effects in youth smoking behaviors.
[3] While several papers examine social interactions *during* college (Sacerdote 2001, Foster 2006, Ward 2004), I am only aware of one paper (Fletcher 2006) that examines the transition from high school to college.

most effectively in changing adolescent choices. For example, the presence of social interactions implies that policies that change the behavior of a few individuals in a school will have “spillover effects” on the behaviors of other individuals. This has particular relevance for recent programs in Texas, such as the Longhorn Scholars Program, which is targeted at a few top graduates in poor high schools. This type of scholarship could—through social interactions—increase both the likelihood of attending college for an individual disadvantaged student as well as increase the chances that other students in the same school consider college a viable choice. Finding social interactions in college decisions is also relevant in the school choice debate. Allowing school choice can dramatically change the composition of both “good” and “bad” schools. Since school composition differences are amplified in the presence of social interactions, those students “left behind” in bad schools after school choice programs are implemented would be more likely to think that college is unreachable, partly because they would likely have few classmates who plan on enrolling.

To the author’s knowledge, no researchers have been able to uncover the mechanism of social interactions due to the extreme data requirements. One of the most important data limitations (from non-experimental data) is that most datasets contain only data on *outcomes* for members of a reference group (e.g. classmates in a high school). This limits the social interactions to being a “black box.” Without additional information on *why* individuals make the decisions we see in the data, researchers are left with assessing the correlation between individual and group level outcomes, which is itself fraught with difficulty (Manski 1993, 2000, Blume and Durlauf 2006). Two of the benefits of the data used in the present paper are the availability of student reports of college preferences before college decisions were made as well as sources of information about college. I will use this usually unavailable information in the data to attempt to look inside the black box of social interactions.

Finding evidence of a mechanism for social interactions is important because the various types of interactions imply different policies. If information interactions are a mechanism through which students are making choices similar to their peers, then interventions that inform students as to the costs and benefits of attending colleges and the attributes of particular colleges could help increase college enrollment for some students. Further, the increase in information for one student will increase the information for other students through the information interactions. In contrast, significant preference interactions among students imply that different types of policies would be more efficacious. For example, an intervention on groups who set the norms within schools of whether it is "cool" to aspire to attend college or which college is "right" to attend could have significant indirect effects on other students.

Data

This paper will use the newly available Texas Higher Education Opportunity Project (THEOP) data.[4] The THEOP data is a multi-year study that began in fall 2000. In addition to gathering administrative data from 10 colleges and universities in Texas, the centerpiece of the study is a two-cohort longitudinal survey of sophomores and seniors who were enrolled in Texas public schools in spring 2002. This paper will focus on the senior cohort. The baseline survey (Wave 1) was conducted on a stratified random sample of 105 public high schools in the state of Texas and consists of 13,803 seniors. The baseline survey asked students about their course taking and grades, experiences with guidance counselors, college perceptions, future plans and demographic information, including race, family background, and household structure. Seniors were asked a battery of questions about college preferences, the colleges applied to, and plans to attend college. A random sample of 5,836 respondents from the senior cohort were re-interviewed (Wave 2) one year after graduating from high school to ascertain primary post-secondary school activity, military enlistment, labor force participation, etc.[5] They are being re-interviewed (Wave 3) during spring 2006, when a large majority of those who attended college are juniors and seniors.

This paper uses the combined Wave 1 and Wave 2 data to examine whether individuals make similar college decisions as their peers, and, if so, why. In particular, in addition to examining whether social interactions are present in college choices, I will use two unique features of the THEOP survey data to more deeply examine *why* the social interactions are occurring. First, the high school seniors were asked to provide the names

[4] Complete information can be found at http://www.texastop10.princeton.edu/index.html
[5] A public version of the data is available at http://opr.princeton.edu/archive

of the colleges that they prefer to attend. Second, the students were asked how they received information about college—parents, friends, guidance counselors, etc. I will use these data to attempt to examine the importance of the two principal types of social interactions—*preference interactions* and *expectations interactions* (Manski 2000).

While the focus of the paper is necessarily on the 5,836 individuals who were followed in Wave 2 and have information on college outcomes, this paper also uses the Wave 1 survey to construct various aspects of each individual's environment using information from individuals who were not followed in Wave 2 but nonetheless provide details on preferences for college, information acquisition for college, and other school-level characteristics.

As noted above, the sample size starts at 5,836 individuals. Since several variables will be created at the school-level for each senior class within each school, I drop sixteen individuals who are sampled in schools with fewer than ten other students. Unfortunately, non-response for gender and race forces the deletion of almost six hundred individuals so that 5,224 individuals remain. Another one hundred and fifty individuals are dropped because of unreported grades during high school and sixty-six individuals are dropped due to other missing variables. I use single-imputation methods to estimate mother's education level for six hundred individuals, leaving a sample size of 5,029 (86% of original sample). Summary statistics are presented in Table 1 below. Over 75% of the individuals in the sample report some post-secondary experience[6] by Wave 2; 43% of those who attended college enrolled in their preferred school. Other variables of interest in the survey include gender (46% male), race (39% white, 19% black, 27% Hispanic, and 11% "other" race), and number of siblings. Unfortunately, there is relatively little information in the survey that captures family resources (e.g. income) at the individual level, so mother's education attainment is used as an indicator of income. To partially capture information about college, individuals report the number of their friends who plan to enroll in college following high school[7] and whether they discussed college with a guidance counselor. There are also specific variables regarding

[6] This includes vocational, technical, or trade school, and those who have taken courses from a university or college for academic credit. For brevity, I refer to all these institutions as "college" throughout the paper.
[7] The dataset does not contain information on each individual's number of friends, so this measure could conflate popularity with peer quality.

the Texas Top 10% rule,[8] including whether a friend or a guidance counselor discussed the rule with the individual.

At the school level, many types of information are available. I include enrollment, the proportion male, the proportion Hispanic, the proportion black, and the proportion who are economically disadvantaged. I also aggregate individual-level information to the school level to measure additional school characteristics. I include the proportion of the senior class whose friends discussed the Top 10% plan, the proportion whose guidance counselor discussed the Top 10% plan, the proportion who discussed college with the guidance counselor, and average parental education level. Additionally, the THEOP data contains measures of the distance from each high school to each college in the state, which allows inclusion of an important set of variables that are related to college decisions by adolescents but often neglected in previous research.[9] Finally, in addition to the variables above that relate to college-going norms, the number of each individual's classmates who share his/her preference for specific colleges as well as the number of classmates who report different preferences for individual colleges are calculated.

Methodology

I examine two questions in this research paper: (1) Is there evidence of social interactions in college enrollment decisions? (2) If so, what is the mechanism behind the social interactions? For the first question, I follow most research on examining social interactions (Manski 2000, Gaviria and Raphael 2001, Fletcher 2006, forthcoming) and use the following framework:

$$Y = c + X\beta + \overline{X}\delta + \alpha\overline{Y} + \varepsilon \qquad (1)$$

where Y is the outcome (e.g. college enrollment), X is a vector of individual and family characteristics, $\overline{X}$ is a vector of peer characteristics, $\overline{Y}$ is the average incidence of Y in the school,[10] and ε is a random component independent across individuals. In the

[8] Briefly, the Texas Top 10% rule guarantees automatic admission to the public colleges in the state of Texas for students who graduate in the top decile of their high school class.
[9] Fletcher (2006) and Turley (2006) are recent exceptions.
[10] To deal with the issue of timing of decisions within peer groups, the assumption is made that individuals are responding to expectations of their peers' choices rather than the actual peer choices, and these

language of Manski (1993, 2000), $\overline{X}$ are contextual/exogenous variables, and $\overline{Y}$ is an endogenous variable. To estimate the model, $\overline{X}$ and $\overline{Y}$ are replaced with their sample analogs (the average college enrollment of students in each school).[11] Following Gaviria and Raphael (2001), the model is expanded to include school characteristics to avoid spurious estimates of social effects due to common school-level unobservables that affect both the individuals and their peers.

$$Y_{is} = c + X_{is}\beta + \overline{X_{-is}}\delta + W_s\phi + \alpha\overline{Y_{-is}} + \varepsilon_{is} \qquad (2)$$

Here Y_{is} is the probability that student *i* in school *s* will enroll in college; X_{is} is a vector of family and individual characteristics, $\overline{X_{-is}}$ is a vector of average characteristics of students in school *s* excluding individual i , W_s is a vector of school characteristics, and $\overline{Y_{-is}}$ is the proportion of the individual's classmates who enroll in college (excluding individual *i*). This model will be estimated with standard OLS and probit regression analyses. Because more than one student is sampled within the same school, the estimation will allow the errors in the outcomes of students within the same school to be correlated using techniques in the STATA software package (i.e. the "cluster" and "robust" commands).[12]

As Manski (1993, 2000) points out, the types of social effects estimated from (2) imply different policy interventions. If δ is estimated to be non-zero, this is consistent with role model effects or resource effects from the environment (Durlauf 2004). For example, individuals whose classmates' parents are highly educated may be more likely to have high achievement. One interpretation of this relationship is that the classmates' parents serve as role models for other children in the school. These types of effects do not, however, indicate that there will be collective gains from changing the composition of the student body through busing or other reallocation of students. While reorganizing

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expectations are rational (Brock and Durlauf 2001). With the assumption of rational expectations, the use of peers' actual choices is appropriate.

[11] Hoxby (1999) and Gaviria and Raphael (2001) also uses sample averages. This method will be unbiased but imprecise (with large standard errors) because of the classical measurement error introduced (Hoxby 1999).

[12] "Robust" performs the Huber/White/sandwich estimate of variance (White 1980). "Cluster" allows individuals within the cluster (school) to not be treated as independent observations during estimation (Williams 2000).

students will have *distributional* effects across schools, the overall level of college enrollment will remain unchanged.[13] In contrast, if α is estimated to be greater than zero, this is consistent with a positive social interaction—that choices are interdependent. This implies that an intervention on a subset of students will have indirect effects on students who do not receive the intervention. Similarly, reallocating students across schools can lead to an overall increase in college enrollment. Additionally, this type of social interaction might explain some of the current large variation across high schools in observed college choices.

Once the importance of social interactions is established for college enrollment, I will utilize the college preference and information data available in the THEOP dataset to examine *why* social interactions are present. As described above, I calculate the number of students in each high school with the same preferences (and different preferences) for particular colleges as each individual in the data. I will use this information to examine whether having classmates with similar preferences for specific colleges increases the likelihood of an individual enrolling in any college and enrolling in his/her preferred college. Then, in further analysis I will include the variables from the data which detail the avenues through which individuals report receiving information about college (friends, guidance counselors, etc). Finding evidence of how social interactions affect college choice will allow consideration of the types of policies that might be most effective in increasing enrollment for disadvantaged and minority students.

Finally, this last analysis on the effects of classmates' preferences on individual college choices will also allow the use of school fixed effects to examine the robustness of the baseline results. School fixed effects can be employed because the proportion of classmates who have the same preferences within a high school varies within high school—in contrast, school fixed effects cannot be used in the more general examination of the evidence of "black box" social interactions in college enrollment presented in the

[13] This implication relies on the linear specification for role model effects. If this specification was incorrect and role model effects exhibited non-linear or threshold effects, there could be aggregate benefits from reallocating students to schools to exploit the benefits of the non-linear effects (Hoxby 2000).

next section because the regressor of interest (i.e. the proportion of classmates who attend college) does not vary within high schools.[14]

Empirical Results I: Evidence of Social Interactions

In order to overcome the difficulty of disentangling different types of social effects—the so called "reflection problem" (Manski 1993, 2000)—I use two instruments. The reflection problem occurs because individual outcomes affect group outcomes and vice-versa. Without instrumental variables, in most contexts researchers are unable to properly identify whether social interactions are present or must make extremely restrictive assumptions (Blume and Durlauf 2005, Durlauf 2004).[15] Following Fletcher (2006), I use the school-level proportion of males and the average number of older siblings of classmates in each school as instruments. To be valid, these variables must meet several criteria: (1) the individual level characteristic predicts individual behavior (2) the school-level peer characteristic does not predict *individual* behavior[16] and (3) the school-level peer characteristic must predict *school-level* behavior. Gender seems a likely candidate for an instrument. The intuition is that being male is negatively related to enrolling in college but the proportion of males in a school has no direct effect on an individual's decision to attend college. Stated another way, a student in a high school with a sixty percent male enrollment will, ceteris paribus, have peers who go to college at a lower rate than a student in a high school with forty percent male enrollment. This arguably exogenous difference in exposure of college-going peers will allow identification of a social interactions effect.[17] A similar intuitive argument holds for the average number of older siblings of classmates. Individuals with older siblings are less likely to enroll in college (conditional on family resources, etc) due to the budget constraints faced by families. However, the average number of older siblings of an

[14]An exception to this is the use of longitudinal data to examine within-school differences over time of the proportion of high school students who enroll in college.
[15] For example, Gaviria and Raphael (2001) assume that one type of social effect ("contextual" or "exogenous" effects) does not exist in order to estimate social interactions in several risky behaviors. Many other researchers make no distinction between the two types of social effects, which confounds their results.
[16] The instrument must be uncorrelated with unobservable characteristics that predict the individual outcomes. In practice, this criterion must be assumed rather than tested.
[17] This identification strategy is related to Hoxby (2000). She uses idiosyncratic changes in gender and racial composition over time to identify peer effects in student achievement.

individual's classmates is assumed to not affect the individual's college enrollment probability and only affect the proportion of an individual's classmates who attend college. Linear probability models of college enrollment are presented in Table 2.[18]

Column 1 presents a basic set of individual and school-level characteristics to predict college enrollment. Even though this sample is taken only from the student population of Texas, the results are uncontroversial and consistent with previous research. Grade point average and maternal education are positively related to college enrollment. Female students are four percentage points more likely to attend college than their white and male counterparts. There are racial differences in college enrollment, with black and individuals of "other race" more likely than similar white students to attend college, but Hispanic students are four percentage points less likely to attend college than whites (p-value<0.14). At the school level, high school size is positively associated with college enrollment, and the proportion of economically disadvantaged students in the school is negatively related to college enrollment.

Column 2 includes peer characteristics for each student, measured at the school level. As expected, very few previous results change. The exceptions are that several school-level characteristics from column 1 decrease in importance and statistical significance. Once peer characteristics are controlled for, black students are now over six percentage points more likely to attend college and Hispanic students are now almost six percentage points less likely to attend college than white students with similar characteristics.[19] Additionally, the distance to the nearest college is not statistically significant.[20] Finally, the average educational level of classmates' mothers is positively related to individual decisions to attend college. This is suggestive evidence of traditional peer effects (i.e. contextual effects) (e.g. McEwan 2003).

[18] All results show robust standard errors to account for the heteroskedasticity introduced from using linear estimation methods on a binary outcome. Probit regression specifications yield very similar results, which are available from the author.
[19] Controlling for immigrant status reduces the coefficient for Hispanic students to 4.5 percentage points.
[20] The "distance" variable measures the miles to the nearest college from the high school rather than the individual's residence. I have standardized it for ease of interpretation. Including distance in miles and distance in miles squared instead of the standardized distance measure does not change the results, and these variables are not statistically significant at conventional levels. The unreported results do suggest, though, that distance decreases college attendance probabilities at an increasing rate.

In Columns 3 and 4, I present two-stage least square regression results to examine whether there is evidence of social interactions—that individual outcomes are intertwined with the decisions of peers. Using the proportion of male students in each high school and average number of older siblings of classmates as instruments for the percentage of peers enrolling in college, the results show evidence of social interactions in college enrollment decisions. While the F-statistic is a little low (i.e. less than 10), the over-identification test is unable to reject the validity of the instruments. Taken at face value, the results imply that if the proportion of an individual's classmates who enroll in college increases by ten percentage points, the probability that the individual enrolls in college increases by eight percentage points. I also follow Gaviria and Raphael (2001) and Fletcher (forthcoming) and examine the likely bias due to the endogeneity of the peer group by examining the results separately by residential mobility (results in the appendix). I find no evidence that more mobile students are biasing upward the estimated social interactions coefficient. In fact, I find evidence that the immobile students have a larger estimated endogenous social effect of college enrollment. Finally, in the appendix I present results stratified by race that suggest that black students have higher returns to increasing peer college enrollment than white students.

Empirical Results II: Mechanisms of Social Interactions

In this section, I examine the importance of social norms and information within high schools for determining both college enrollment and specific college choice. In order to pursue this goal, I create several variables from the Wave I data that measure the preferences of each individual's classmates for college, including how many classmates prefer the same college as the individual and how many classmates prefer other colleges than each individual.[21]

In Table 3, I examine the importance of social norms for students who report having a preference for a specific college during their senior year. Multinomial logistic regression analysis is used to examine the determinants of the following outcomes: (1) not enrolled in college (2) enrolled in non-preferred college and (3) enrolled in preferred college. For each student, the proportions of his classmates who also report the same

[21] In practice, 1/3 of the sample does not list a preferred college. These individuals are dropped from this section of the analysis because of the inability to examine whether they enrolled in their preferred school.

college preference or a different college preference are included as additional covariates in the analysis.[22] All coefficients are interpreted relative to the omitted category of enrolling in the preferred college; robust p-values are included in parentheses.

I find strong evidence consistent with social norms being an important determinant of college selection. Students in high schools where their classmates contradict their own college preference are more likely to enroll in a non-preferred college. Likewise, students in high schools with classmates who prefer the same college are more likely to attend their preferred college. Several additional findings are also interesting. An individual's grade point average increases the chances of enrollment in his/her preferred college. Black and Hispanic students are more likely to attend a non-preferred college than white students, and I find no gender differential in enrolling in an individual's preferred college. Thus, I find that an individual's classmates' preferences about specific colleges are important predictors of individual college choices, which is consistent with notions of social norms within schools affecting classmates' college choices.

In Table 4, I examine whether information about college determines college enrollment for students. In column 1, I find that the increasing the number of friends with college plans increases an individual's probability of attending college by almost ten percentage points. Unfortunately, there are multiple possible reasons for this correlation, such as peer effects through information sharing or social norms of going to college, so there does not appear to be a straightforward interpretation of this result. There is suggestive evidence that counselors who provide direct information about college increase the probability an individual enrolls in college (p-value=0.11), but it may be the case that counselors only discuss college opportunities with students who are already likely to attend. To examine more specific topics of conversation about college, in column 2 I add variables to represent whether the Texas Top 10% Plan was discussed by friends or guidance counselors. Again, I find that students who report having discussions about college are more likely to attend college. To access more indirect information flows within schools, in column 3 I add variables that represent the proportion of

[22] See Niu et al. (Forthcoming) for evidence that preferences for college selectivity differ across racial groups.

individuals in each school who report discussing the Texas Top 10% Plan with their counselors and peers (excluding the individual). Interestingly, conditional on speaking directly to guidance counselors and friends about the Top 10% Plan, individuals who are in schools with high proportions of discussions about the Top 10% Plan are more likely to attend college.[23] Thus, I find evidence of both direct and indirect channels though which information appears to affect the college enrollment choices of adolescents.

Finally, in Table 5, I include variables that measure social norms as well as different sources of information for the students in the same school. I also incorporate a school fixed-effects approach in order to eliminate common unobserved factors at the school-level and endogeneity of school (Arcidiacono and Nicholson 2005).[24] To ease the computational burden of performing multinomial logistic regression with fixed effects, I instead report the findings of a logistic regression analysis on the sample of students who attended any college (preferred or non-preferred) employing school-level fixed effects. As mentioned above, school fixed effects still allows within-school differences in exposure to peer preferences for colleges because the measure of social norms is whether the individual has classmates who prefer attending the same college or a difference college. For example, consider a school size of 3 students where students 1 and 2 prefer attending the University of Texas-Austin and student 3 prefers attending Texas A & M. For students 1 and 2, the proportion of their classmates who prefer the same college is

[23] In unreported results, I examine whether the variables I use to capture information are correlated with whether the individuals attend their preferred college and find no evidence. Results available upon request.

[24] The selection issue in the present paper is somewhat different than other research that examines the influence of classmates on behaviors—for example, by regressing an individual's propensity to smoke on the proportion of classmates who smoke. In the present paper, the presence of a classmate who prefers attending Harvard (potentially indicating a "good" high school) is treated in the same way as the presence of a classmate who prefers attending a community college or no college (potentially indicating a "bad" high school). That is, a student who prefers to attend the University of Texas-Austin is penalized in the same way with the presence of each classmate (Harvard or Community College) in that the students' preferences are different from each other. Thus, the potential endogeneity of the variables "Same Preferences" and "Different Preferences" are more difficult to ascertain. If parents select high schools for their children based on the similarity in preferences with other students, then the variables are clearly endogenous in the specification. However, if parents select high schools based on 'quality,' it is not clear that observable measures of school quality are correlated to similarity in preferred college. In fact, the correlation between mother's education and the proportion of classmates with the same college preference is *negative*. This likely reflects the fact that the measurement of the proportion of classmates with the same college preference is high in schools that send all their students to Harvard *and* in schools that send all their students to a local community college.

50% and for student 3, the proportion of his classmates who prefer the same college is 0%.

In column 1, the outcome is whether the student attended his or her preferred college, and the sample contains only those students who attended college (preferred and non-preferred). The results indicate that, controlling for fixed school-level factors, a student in a school with a 1% larger shared college preference with his/her peers has 20% greater odds of attending his/her preferred college. Likewise, a student in a school with a 1% larger dissimilarity with peer preferences for a specific college has a 5% reduction in the odds of attending his/her preferred college. We also see that information does not seem to matter in the sample of students who attend *some* college (preferred and non-preferred).

Discussion

Past attempts to detect social interactions in applied economic research have been shown to be incomplete for several reasons. First, the difficulty of disentangling different types of social effects has called into question the results in most research of this type prior to the early 1990's (Manski 1993, 2000, Brock and Durlauf 2001a, 2001b). This difficulty continues to be problematic in current research. This paper follows current practice (Fletcher 2006, Gaviria and Raphael 2001) and uses instrumental variables to disentangle the types of social effects and identify whether social interactions are present in college choices by adolescents. Second, proper attention to the endogeneity of an individual's peer group has been shown to dramatically change estimates of social interactions in previous literature (Evans et al. 1992). While I am not able to utilize random assignment to schools to fully address endogeneity bias, I follow several researchers (Raphael and Gaviria 2001, Fletcher 2006) and examine the magnitude of the potential endogeneity bias by examining results separately by residential mobility. Although this measure is not perfect, I find no evidence of endogeneity bias in the results and additional work is necessary to fully examine this important issue.[25] Finally, in much research, group-level factors are usually not sufficiently controlled for in the analysis

[25] A related, but separate, issue is sample selection. By the 12th grade, a relatively large number of students have already dropped out of high school and are not represented in my sample. Thus, the results should not be applied to attempting to understand the importance of social influences on the educational decisions of dropouts.

(Blume and Durlauf 2005). This problem is ubiquitous and allows skeptics to speculate on omitted variables that could lead to spurious results in the present setting. Unfortunately, there is no cure-all for this problem, but I am able to take advantage of a relatively rich set of control variables (including geographic distance to college and several school-level characteristics) that allows added confidence in the results.

Conclusion

In this paper, I find evidence that social norms within high schools influence adolescent college choices. These results are robust to including variables meant to capture an alternative mechanism for social interactions—information interactions or social learning. Importantly, I find that classmates' preferences for specific colleges have consequences for individual choices. Individuals who prefer an "unpopular" college are less likely to enroll in their preferred college than individuals with classmates who agree on what colleges are most preferred.

I also present findings that suggest that information about college increases an individual's propensity to enroll in college. In addition to presenting evidence that direct communication with guidance counselors and friends increases the probability of college enrollment, I find evidence that *indirect* communication about colleges (i.e. not information gathered through friends and counselors) is an important determinant of individual college choice; conditional on a student's own information gathering, those students whose classmates also gather information about college are more likely to enroll in college.

While the current paper has found several important determinants of college choice that are not usually examined, several future avenues of research remain. This paper has used a broad definition of college; future research should examine the social and informational determinants of the type of college attended. Further, the use of additional data sets to confirm the results in the present paper is necessary.

Finding convincing evidence of the role of social influences on individual choice is an extremely challenging enterprise. Confronting issues of endogeneity bias, non-identification of parameters of interest, and omitted variable bias is necessary in many areas of research, though arguably unusually problematic in efforts to uncover evidence of social interactions. This paper confronts each difficulty and finds robust evidence of social interactions in college choices for adolescents. The magnitude of the findings is also important; a ten percentage increase in classmates' college enrollment is found to increase individual college enrollment by eight percentage points. This effect is quite robust across specifications and is comparable to increasing an individual's grade point average by 1/2 of a point or increasing maternal education by over six years. Coupled with the overall finding of positive social interactions in college enrollment, I find evidence that social norms *and* informational exchange help determine college choices. Thus, it appears that interventions that change the informational available to a subset of individuals in a high school could affect the college choices of all individuals in that high school. Additionally, I find suggestive evidence that shifting the social norms within high school toward valuing college enrollment and specific colleges could have multiplier effects across the entire student body. One interesting intervention would implement a policy that influences the preferences of a subset of students within a high school—possibly the most popular students—and evaluate whether the choices of untreated students change in response.

Evidence of social interactions in college choices opens up many new avenues of potential education interventions that could have significant aggregate impacts. While additional research is needed to examine the robustness of the findings presented here, pursing this new direction of policy interventions would provide complementary evidence of the necessity to consider social influences on adolescent choices when crafting policies.

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Table 1
Summary Statistics
THEOP Data, Wave I and II
5,029 Observations

Variable	Wave	Mean	Std. Dev.	Min	Max
Individual-Level Variables					
College	2	0.76	0.43	0	1
Enrolled in Preferred College (3805 obs)	2	0.43	0.49	0	1
Grade Point Average	1	3.13	0.67	1	4
Male	1	0.46	0.5	0	1
White	1	0.39	0.49	0	1
Black	1	0.18	0.39	0	1
Hispanic	1	0.27	0.45	0	1
Other Race	1	0.11	0.31	0	1
Sibling	1	0.66	0.48	0	1
Mother Education (Imputed)	1	13.79	2.85	0	19
Number of Friends who Plan on College	1	3.72	0.63	1	4
Friend Told About Top 10%	1	0.18	0.39	0	1
Guidance Counselor Discussed Colleg	1	0.72	0.45	0	1
Guidance Counselor Told About Top 10%	1	0.27	0.45	0	1
% Same College Preference	1	4.67	7.3	0	35.9
% Different College Preference	1	4.71	7.11	0	36.8
School-Level Variables					
Log (Enrollment)	1	7.53	0.75	4	8.5
Feeder School	1	0.06	0.24	0	1
Affluent School	1	0.25	0.43	0	1
Poor School	1	0.08	0.28	0	1
Longhorn/Century School	1	0.19	0.4	0	1
Number of Students Sampled	1	314	206	12	727
% Economic Disadvantage	1	33.47	23.1	0.9	93.8
% Enroll in College	2	74.57	11.81	0	100
% Male	1	47.19	4.78	20	70
% Hispanic	1	29.07	27.43	0	89.3
% With Siblings	1	68.43	7.63	33	100
% Friend Told Top 10%	1	16.18	7.49	0	44.1
% Discuss with Guidance	1	71.32	12.17	31	100
% Guidance Told Top 10%	1	23.56	10.57	0	62.5
Distance to Nearest College (Miles)[26]	1	6.66	8.13	0.54	60.2
Average Mother Education	1	15.76	2.3	12.5	26.6

[26] This variable is the minimum of three variables: distance to nearest 4 year public university, distance to nearest 2 year college, and distance to nearest private university.

Table 2
Determinants of College Enrollment
Individual, School, and Social Predictors

	LPM	LPM	2SLS	First Stage
Sample	Full	Full	Full	Full
Column	1	2	3	3
Grade Point Average	0.143	0.143	0.141	0.268
	(0.000)**	(0.000)**	(0.000)**	(0.196)
Male	-0.041	-0.042	-0.045	0.493
	(0.001)**	(0.001)**	(0.000)**	(0.028)*
Black	0.044	0.064	0.061	0.506
	(0.036)*	(0.004)**	(0.005)**	(0.133)
Hispanic	-0.041	-0.052	-0.052	-0.032
	(0.138)	(0.056)+	(0.050)+	(0.918)
Other Race	0.043	0.048	0.049	-0.218
	(0.010)*	(0.003)**	(0.002)**	(0.724)
Number of Older Siblings	-0.016	-0.016	-0.015	-0.113
	(0.000)**	(0.000)**	(0.000)**	(0.118)
Mother's Education	0.013	0.013	0.012	0.060
	(0.000)**	(0.000)**	(0.000)**	(0.141)
School-Level Variables				
Log (Enrollment)	0.031	0.026	-0.002	2.639
	(0.014)*	(0.094)+	(0.801)	(0.057)+
% Economically Disadvantaged	-0.002	-0.003	-0.001	-0.290
	(0.000)**	(0.006)**	(0.241)	(0.022)*
Mean Mother's Education		0.008	0.004	2.860
		(0.004)**	(0.008)**	(0.000)**
% Black		-0.000	-0.000	0.103
		(0.476)	(0.580)	(0.150)
% Hispanic		0.001	0.001	0.052
		(0.265)	(0.001)**	(0.627)
Distance to Nearest College		0.005	-0.001	1.125
		(0.601)	(0.818)	(0.164)
% Male				0.220
				(0.122)
% With Siblings				-12.818
				(0.001)**
% College			0.008	
			(0.000)**	
Constant	0.009	-0.066	-0.462	30.071
	(0.941)	(0.658)	(0.000)**	(0.039)*
Observations	5095	5095	5095	5095
R-squared	0.112	0.116		0.577
F-Statistic			6.177	
J-Statistic p-value			0.478	
			0.035	

+ significant at 10% * significant at 5% ** significant at 1%
Robust p values in parentheses

Table 3
Multinomial Logistic Regression Analysis of Social Norms for College
(Omitted Category=Preferred College Enrollment)

Outcome	No College	Non-Preferred College
Sample	Reported Preference	Reported Preference
Column	1	2
% with Same Preference	-0.011	-0.018
	(0.029)*	(0.025)*
% With Different Preference	-0.002	0.005
	(0.000)**	(0.000)**
Grade Point Average	-0.089	-0.066
	(0.000)**	(0.000)**
Male	0.015	0.002
	(0.174)	(0.891)
Black	-0.014	0.057
	(0.425)	(0.037)*
Hispanic	0.034	0.128
	(0.037)*	(0.000)**
Other Race	-0.035	0.139
	(0.123)	(0.000)**
Sibling	0.015	0.019
	(0.209)	(0.287)
Mother's Education	-0.008	-0.004
	(0.000)**	(0.284)
School-Level Variables		
Log (Enrollment)	-0.026	-0.007
	(0.006)**	(0.647)
% Economically Disadvantaged	0.002	-0.002
	(0.000)**	(0.053)
Mean Mother's Education	-0.010	0.005
	(0.000)**	(0.236)
% Black	0.000	0.004
	(0.695)	(0.000)**
% Hispanic	-0.001	0.002
	(0.069)	(0.077)
Constant	0.682	-0.087
	(0.000)**	(0.608)
Observations	3587	
R-squared	.075	

+ significant at 10% * significant at 5% ** significant at 1%
Robust p values in parentheses

Table 4
Informational Determinants of College Enrollment

Outcome	College	College	College
Sample	Full	Full	Full
Column	1	2	3
Grade Point Average	0.133	0.124	0.125
	(0.000)**	(0.000)**	(0.000)**
Male	-0.035	-0.032	-0.032
	(0.003)**	(0.009)**	(0.008)**
Black	0.055	0.055	0.054
	(0.013)*	(0.011)*	(0.013)*
Hispanic	-0.042	-0.042	-0.042
	(0.121)	(0.112)	(0.110)
Other Race	0.052	0.042	0.040
	(0.002)**	(0.008)**	(0.008)**
Sibling	-0.032	-0.028	-0.028
	(0.012)*	(0.029)*	(0.028)*
Mother's Education	0.012	0.012	0.011
	(0.000)**	(0.000)**	(0.000)**
Guidance Counselor Provided College Info	0.023	0.015	0.015
	(0.112)	(0.304)	(0.307)
Number of Friends with College Plans	0.094	0.089	0.088
	(0.000)**	(0.000)**	(0.000)**
Guidance Discussed Top 10 Plan		0.081	0.077
		(0.000)**	(0.000)**
Friends Discussed Top 10 Plan		0.084	0.079
		(0.000)**	(0.000)**
School-Level Variables			
Log (Enrollment)	0.023	0.019	0.001
	(0.112)	(0.176)	(0.963)
% Economically Disadvantaged	-0.003	-0.003	-0.003
	(0.010)**	(0.008)**	(0.014)*
Mean Mother's Education	0.008	0.008	0.009
	(0.002)**	(0.002)**	(0.001)**
% Black	-0.000	-0.000	-0.000
	(0.502)	(0.495)	(0.631)
% Hispanic	0.001	0.001	0.001
	(0.378)	(0.348)	(0.199)
% Guidance Provided College Info	0.001	0.000	-0.001
	(0.369)	(0.642)	(0.504)
% Friends Discussed Top 10			0.004
			(0.006)**
% Guidance Discussed Top 10			0.002
			(0.026)*
Constant	-0.430	-0.352	-0.307
	(0.021)*	(0.050)*	(0.077)
Observations	5029	5029	5029
R-squared	0.131	0.140	0.142

\+ significant at 10% * significant at 5% ** significant at 1%
Robust p values in parentheses

Table 5
Logit Regression Analysis with School Fixed Effects

Outcome	Attend Preferred School
Sample	Attended College
Column	1
% with Same Preference	1.218
	(0.000)**
% With Different Preference	0.964
	(0.000)**
Grade Point Average	1.622
	(0.000)**
Male	0.992
	(0.924)
Black	0.858
	(0.239)
Hispanic	0.524
	(0.000)**
Other Race	0.616
	(0.000)**
Sibling	0.907
	(0.231)
Mother's Education	1.018
	(0.248)
Friend Told about Top 10	1.205
	(0.079)
Guidance Told about Top 10	1.181
	(0.080)
Number of Friends with College Plans	1.082
	(0.346)
Guidance Told about College	0.912
	(0.331)
Observations	3013
Schools	87

+ significant at 10%   * significant at 5%   ** significant at 1%
Robust p values in parentheses

Appendix:

Table 1A
Social Interactions in College Enrollment
2SLS Results Separated by Mobility

Sample	2SLS Full	First Stage Full	2SLS Immobile	First Stage	2SLS Mobile	First Stage
Column	1	2	3	4	5	6
% College	0.008		0.010		0.008	
	(0.000)**		(0.000)**		(0.000)**	
Grade Point Average	0.141	0.268	0.138	-0.274	0.136	0.646
	(0.000)**	(0.196)	(0.000)**	(0.324)	(0.000)**	(0.037)*
Male	-0.045	0.493	-0.063	0.334	-0.034	0.570
	(0.000)**	(0.028)*	(0.000)**	(0.343)	(0.017)*	(0.018)*
Black	0.061	0.506	0.014	0.455	0.101	0.447
	(0.005)**	(0.133)	(0.664)	(0.486)	(0.000)**	(0.226)
Hispanic	-0.052	-0.032	-0.074	-0.450	-0.032	0.193
	(0.050)+	(0.918)	(0.015)*	(0.280)	(0.315)	(0.683)
Other Race	0.049	-0.218	-0.003	-0.547	0.091	-0.161
	(0.002)**	(0.724)	(0.907)	(0.399)	(0.000)**	(0.811)
Number of Siblings	-0.015	-0.113	-0.011	-0.143	-0.016	-0.102
	(0.000)**	(0.118)	(0.038)*	(0.217)	(0.001)**	(0.275)
Mother's Education	0.012	0.060	0.015	0.056	0.008	0.063
	(0.000)**	(0.141)	(0.000)**	(0.440)	(0.001)**	(0.246)
School-Level Variables						
Log (Enrollment)	-0.002	2.639	-0.025	3.363	0.010	2.120
	(0.801)	(0.057)+	(0.052)+	(0.020)*	(0.312)	(0.121)
% Econ Disadvantaged	-0.001	-0.290	-0.001	-0.236	-0.001	-0.327
	(0.241)	(0.022)*	(0.452)	(0.058)+	(0.284)	(0.012)*
Mean Mother's Education	0.004	2.860	0.001	2.726	0.005	2.944
	(0.008)**	(0.000)**	(0.482)	(0.000)**	(0.011)*	(0.001)**
% Black	-0.000	0.103	0.000	0.082	-0.001	0.118
	(0.580)	(0.150)	(0.584)	(0.224)	(0.231)	(0.119)
% Hispanic	0.001	0.052	0.002	0.025	0.001	0.070
	(0.001)**	(0.627)	(0.005)**	(0.810)	(0.147)	(0.523)
Distance to Nearest College	-0.001	1.125	-0.005	1.410	-0.005	0.804
	(0.818)	(0.164)	(0.439)	(0.047)*	(0.434)	(0.395)
% Male		0.220		0.192		0.244
		(0.122)		(0.176)		(0.095)+
Mean Number of Siblings		-12.818		-12.875		-12.674
		(0.001)**		(0.000)**		(0.003)**
Constant	-0.462	30.071	-0.374	29.378	-0.516	30.440
	(0.000)**	(0.039)*	(0.005)**	(0.048)*	(0.000)**	(0.040)*
Observations	5095	5095	2112	2112	2983	2983
R-Squared		0.577		0.527		0.613
F-Statistic		6.177		6.877		5.488
J-Statistic p-value	0.478		0.731		0.312	

+ significant at 10% * significant at 5% ** significant at 1%
Robust p values in parentheses

Table 2A
Social Interactions in College Enrollment
2SLS Results Separated by Race

Sample Column	2SLS White	1st Stage	2SLS Black	1st Stage	2SLS Hispanic	1st Stage	2SLS Other Race	1st Stage
% College	0.006		0.015		0.008		0.001	
	(0.070)+		(0.028)*		(0.026)*		(0.850)	
Grade Point Average	0.130	-0.388	0.102	0.206	0.166	0.401	0.138	1.057
	(0.000)**	(0.119)	(0.000)**	(0.594)	(0.000)**	(0.306)	(0.000)**	(0.031)*
Male	-0.053	0.911	-0.013	-0.029	-0.063	0.657	-0.044	-0.830
	(0.000)**	(0.009)**	(0.663)	(0.944)	(0.008)**	(0.078)+	(0.210)	(0.061)+
Number of Siblings	-0.018	-0.100	-0.014	0.007	-0.010	-0.222	-0.021	-0.058
	(0.001)**	(0.389)	(0.061)+	(0.939)	(0.150)	(0.057)+	(0.069)+	(0.693)
Mother's Education	0.022	0.088	0.018	0.151	0.005	0.043	0.004	-0.084
	(0.000)**	(0.408)	(0.007)**	(0.112)	(0.167)	(0.447)	(0.396)	(0.234)
School-Level Variables								
Log (Enrollment)	0.019	5.417	0.018	3.135	-0.015	0.537	0.024	3.118
	(0.393)	(0.001)**	(0.548)	(0.031)*	(0.545)	(0.810)	(0.392)	(0.007)**
% Econ Disadvantaged	-0.001	-0.073	0.005	-0.352	-0.001	-0.391	-0.005	-0.312
	(0.378)	(0.617)	(0.074)+	(0.002)**	(0.506)	(0.004)**	(0.106)	(0.047)*
Mean Mother's Education	0.001	1.958	-0.002	2.261	0.005	2.991	0.023	3.700
	(0.817)	(0.019)*	(0.707)	(0.008)**	(0.251)	(0.039)*	(0.000)**	(0.000)**
% Black	0.000	-0.145	-0.001	0.113	-0.002	0.250	0.002	0.031
	(0.734)	(0.149)	(0.203)	(0.035)*	(0.035)*	(0.089)+	(0.226)	(0.751)
% Hispanic	0.000	-0.233	-0.001	0.096	0.002	0.204	0.002	0.001
	(0.764)	(0.115)	(0.389)	(0.304)	(0.062)+	(0.060)+	(0.185)	(0.994)
Dist to Nearest College	0.016	1.685	0.012	0.733	-0.013	0.136	0.024	0.935
	(0.241)	(0.046)*	(0.492)	(0.627)	(0.358)	(0.920)	(0.407)	(0.310)
% Male		0.296		-0.112		0.317		0.133
		(0.031)*		(0.487)		(0.199)		(0.387)
Mean Number of Siblings		-9.330		-10.526		-13.149		-14.800
		(0.009)**		(0.022)*		(0.092)+		(0.000)**
Constant	-0.475	17.207	-1.057	46.286	-0.368	35.334	-0.175	23.241
	(0.018)*	(0.233)	(0.013)*	(0.009)**	(0.220)	(0.127)	(0.662)	(0.172)
Observations	1983	1983	925	925	1386	1386	536	536
R-Squared		0.541		0.615		0.446		0.736
F-Statistic		5.511		4.400		1.606		7.183
J-Statistic p-value	0.988		0.653		0.063		0.644	

+ significant at 10% * significant at 5% ** significant at 1%
Robust p values in parentheses

Table 3A
Multinomial Logistic Regression Analysis of Social Norms for College
"No College" Omitted

Outcome	No College	Non-Preferred College	Preferred College
Sample	Reported Preference	Reported Preference	Reported Preference
Column		1	2
% with Same Preference		-0.018	0.029
		(0.025)*	(0.000)**
% With Different Preference		0.005	-0.003
		(0.000)**	(0.002)**
Grade Point Average	(Omitted)	-0.066	0.155
		(0.000)**	(0.000)**
Male		0.002	-0.018
		(0.891)	(0.329)
Black		0.057	-0.042
		(0.037)*	(0.134)
Hispanic		0.128	-0.162
		(0.000)**	(0.000)**
Other Race		0.139	-0.104
		(0.000)**	(0.001)**
Sibling		0.019	-0.034
		(0.287)	(0.066)
Mother's Education		-0.004	0.011
		(0.284)	(0.001)**
School-Level Variables			
Log (Enrollment)		-0.007	0.034
		(0.647)	(0.040)*
% Economically Disadvantaged		-0.002	-0.000
		(0.053)	(0.690)
Mean Mother's Education		0.005	0.005
		(0.236)	(0.292)
% Black		0.004	-0.005
		(0.000)**	(0.000)**
% Hispanic		0.002	-0.001
		(0.077)	(0.536)
Constant		-0.087	-0.596
		(0.608)	(0.001)**
Observations	3587		
R-squared	.075		

+ significant at 10% * significant at 5% ** significant at 1%
Robust p values in parentheses