NBER WORKING PAPER SERIES

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Working Paper 21418
http://www.nber.org/papers/w21418

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2015

This work has been made possible by generous funding provided by NSF, SSHRC, the Mellon Foundation, and the Spencer Foundation. Lori Scafidi, George Orlov and Zinaida Folton provided research assistance. We have benefited from comments made during seminars at McMaster University, Cornell PAM, and UCLA. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 21418
July 2015
JEL No. H0,I20,J0

ABSTRACT

We develop and estimate an equilibrium model of study time choices of students on a social network. We examine how network structure interacts with student characteristics to affect academic achievement. Due to data limitations, few papers examine the mechanisms through which peer effects operate. The model is designed to exploit unique data collected in the Berea Panel Study. Study time data allow us to quantify an intuitive mechanism for social interactions: the cost of own study time may depend on friend study time. Social network data allow study time choices and resulting academic achievement to be embedded in an equilibrium framework. We find friend study time strongly affects own study time, and, therefore, student achievement. Not taking into account equilibrium behavior would drastically understate the effect of peers. Sorting on friend characteristics appears important in explaining variation across students in study time and achievement, and determines the aggregate achievement level.

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1 Introduction

Peer effects are widely believed to be important for determining academic achievement. Most of the existing research in this context has focused on establishing a causal link between peer characteristics and academic outcomes in an effort to provide evidence about whether peers matter.[1] However, though crucial for policymaking, empirical evidence on specific mechanisms generating peer effects is very limited. In this paper we exploit unique data on college students from the Berea Panel Study (BPS) to provide some of the first evidence about how peer effects are generated in an academic setting. We consider the intuitively appealing mechanism that a student's study effort is influenced by her peers. We focus on what is likely the most relevant set of peers in our higher education context, a student's friends.[2]

The goal of this paper is to move beyond a demonstration that peer effects exist and pursue some of the next steps necessary to understand how they are generated. One step is to provide evidence about a mechanism underlying peer influences in our context. This is in the spirit of Manski (2000), who stresses that, in order to understand correlations between own and peer outcomes, it is important to clearly define mechanisms and to directly measure them. Motivated by recent research which has hypothesized that student effort is likely to be an input that is readily influenced by peers in the short run (Stinebrickner and Stinebrickner (2006), Calvó-Armengol et al. (2009), Fruehwirth (2013), and De Giorgi and Pellizzari (2014)), we focus on study time as an explicit mechanism through which peer effects could arise in the first year of college.[3]

[1] See Epple and Romano (2011) for a survey of this extensive literature.

[2] Often due to data limitations, peer definitions are commonly taken to be all other students within an observable administrative unit like a classroom, dormitory, or platoon. These units are inherently of interest when the key policy question regards an administrative choice regarding their composition, for example, classroom tracking or platoon assignment(Gamoran and Hallinan (1995), Hanushek and Woessmann (2006), Carrell et al. (2009), Fu and Mehta (2014)). However, recent research has recognized that, in many contexts, the relevant social network of peers is not well-represented as disjoint, complete (e.g., students within a classroom interact with all other students in that classroom, and no students outside that classroom) networks corresponding to administrative groups. Rather, individuals are better modeled as interacting with each other in a (typically sparse) social network that is not revealed directly from administrative groupings (Brock and Durlauf (2001a), Brock and Durlauf (2001b), Conley and Udry (2001), Calvó-Armengol et al. (2009), Weinberg (2009), Conley and Udry (2010), Weinberg (2013), Carrell et al. (2013)). From the standpoint of establishing whether peers matter, it is less than ideal that the peer group under study is often dictated by issues related to data availability rather than by a researcher's priors about which type of peers are likely to be most important.

[3] For a non-education (financial) example of research which is interested in understanding why

Another step forward involves investigating the role social networks play in the propagation of peer effects. General equilibrium effects may be key. Not only might student i's study time be influenced by i's peers, but i's peers' study time may be influenced by i. Moreover, these types of feedback effects could work indirectly through students in the social network who are not directly connected to student i. In general, the distribution of feedback effects depends on three interrelated components. First, the graph describing links in a social network, which we refer to as the "network structure," may be important in and of itself (Jackson and Yariv (2011)). Second, students with different characteristics may differ in how much they are affected by their peers.[4] Third, students may form links based on these characteristics; in particular, students may link to others with similar characteristics, i.e., the network may exhibit "homophily." Put together, the network structure and the specific manner in which heterogeneous students are arranged on the network may determine how changes in behavior propagate throughout the network and affect equilibrium outcomes.[5]

To take these important next steps, we move away from black box regressions in which individuals' outcomes are related to the characteristics or outcomes of peers and estimate an equilibrium model of study time choice and resulting grade determination conditional on a social network. Estimating such a model entails substantial data challenges. First, including an explicit mechanism requires student-level data measuring an important input in the production of human capital through which peer effects can be transmitted. Study time is a natural candidate, but, because collecting reliable time-use information is very difficult in annual surveys, available data sources typically do not contain information of this type.[6] Second, equilibrium outcomes de-

peer effects exist, see Bursztyn et al. (2014). Richards-Shubik (2014) separates supply and demand mechanisms in a model of sexual initiation.

[4]Sacerdote (2011) discusses, for example, heterogeneity in the effect of mean peer ability in determining one's own academic achievement.

[5]There is a literature on spatial autoregressive models which posits econometric models relating one's own outcomes to the outcomes and characteristics of one's peers, and then solves for equilibrium outcomes. See Pinkse et al. (2002) and Lee (2004), for example.

[6]Typically, the object of interest will be how much a respondent studies over an entire academic period (semester or year). Measurement error will be present in answers to retrospective questions which attempt to elicit study amounts over the entire period. An alternative is to elicit information over a shorter, recent period using a time diary. However, the amount a person studied in the shorter period will be a noisy measure of how much the person studied over the entire academic period. The difficulty of finding current surveys that provide information about study time can be seen in the work of Babcock and Marks (2011), whose goal is to detail changes in the amount of time spent studying over the last several decades.

pend on the entire social network, necessitating data characterizing the full set of peer connections as well as data on characteristics that likely determine study time choices. Among existing sources of social network data, perhaps only one, the National Longitudinal Survey of Adolescent Health (Add-Health), could potentially provide a full view of an entire social network in an educational setting where academic outcomes and student characteristics are also observed. Unfortunately, because the Add-Health dataset has a central focus on adolescent health and risk-related behaviors, it does not contain information about time spent studying. Thus, to the best of our knowledge, there is no existing a data source that is able to both characterize an entire social network of students and provide direct evidence about a central input in the grade production function that likely plays an important role in peer transmission.[7]

Our project is made possible by unique data from the Berea Panel Study (BPS) that were collected specifically to overcome these current data limitations. To characterize the entire social network, the BPS design involves surveying full cohorts of students. The BPS is also unique in its high frequency of contact with students, allowing, in each year, the collection of eight time-use diaries and the multiple measures of friendships which we use to define peers. We combine these survey data with administrative data that include pre-college characteristics and college grades.

We develop our model to exploit these unique data. The model consists of two time periods. The social network is known in the beginning of each period. Subsequently, all students in the social network simultaneously choose their study time to maximize human capital, net the cost of studying. A student's cost of studying depends on her own study time and friend study time, e.g., it may be more fun to study if your friends are studying, or the opportunity cost of studying may be higher if your friends are out having fun. Cost functions are allowed to be heterogeneous across students. How much human capital is produced depends on a student's own study time and may also be heterogeneous across students, conditional on own study time. Social interactions are generated because students take into account that friend study time may affect one's own cost of studying.

In the present work, we take the network as given. The tractability gained by this approach allows us to make significant progress on the question of how students affect

[7] Sacerdote (2011) discusses several papers studying how peer ability may affect one's own achievement. However, these papers typically do not examine explicit mechanisms through which peer ability may be transmitted. See De Giorgi and Pellizzari (2014) and Tincani (2014) for exceptions.

each other, given the entire social network. We show there exists a unique equilibrium in the period study-time game for any social network. There is a growing literature studying peer effects that has focused on modeling the formation of social networks, an important and notoriously difficult problem (see Christakis et al. (2010), Mele (2013), Badev (2013), de Paula et al. (2014), Hsieh and Lee (2015), or Sheng (2014)). Because we do not model how friendships are formed, we limit our counterfactual exercises to examine fully-specified networks of interest. Though our approach takes the network as given, its virtue is that for reasonable parameter values it can accommodate any combination of network structure and student characteristics – no matter the network size or how complicated the nature of interconnectedness is within the network.

The tractability of our approach also allows us to provide some of the first empirical evidence about how homophily, the tendency for individuals to have links to others with similar characteristics, impacts outcomes. As Golub and Jackson (2012) note, despite a large amount of work documenting the existence of homophily and a smaller literature examining its origins, the literature modeling the effect of homophily is in its infancy.[8] Golub and Jackson (2012) examine how homophily affects convergence of agents' beliefs in a social learning model where beliefs are updated based upon information from neighbors.[9] In their model, results are driven by the link patterns that arise when an agent is more likely to have links with others in her own group (who have similar information sets) than with agents belonging to different groups. Our model's implications are also shaped by such patterns of network connections. In addition, our model allows students with differing characteristics to have heterogeneous best responses, or "reactiveness," to friend study time choices.

The previous studies most related to ours are perhaps those of Fruehwirth (2013), Calvó-Armengol et al. (2009), De Giorgi and Pellizzari (2014), and Tincani (2014), who stress the importance of equilibrium models of students' effort choices but lack our direct data on student effort. Fruehwirth (2013) and Calvó-Armengol et al. (2009) estimate parameters of their respective models, effectively identifying effort through residual variation in peer outcomes. De Giorgi and Pellizzari (2014) and Tincani

[8] Jackson (2008) provides a discussion of work documenting the existence of homophily; see Camargo et al. (2010) for a specific example. For theoretical models of homophily's origins see Currarini et al. (2009), Currarini et al. (2010), and Bramoullé et al. (2012). Badev (2013) allows for homophily in his empirical study of friendship formation and smoking behavior.

[9] Acemoglu et al. (2011) develop a theoretical model of social learning to study how network structure affects whether or not agents eventually learn the true state of the world.

(2014) test the implications of different theoretical models of social interactions using student achievement data.

Our objectives are to provide some of the first evidence about the mechanisms underlying peer effects and the role social interactions play in the determination of academic achievement. As such, we do not develop a novel approach to address the difficult endogeneity problems that have been the focus of much previous work.[10] However, the luxury of designing a survey specifically for the purposes of this paper allows us to collect data to mitigate the most salient endogeneity concerns. In a context where own and friend study time move together, our use of data on study time, typically an unobserved input, can help explain the co-movement between own and friend GPA. Although this may address endogeneity concerns about the determination of GPA, one may also be concerned about how the relationship between own and friend study time arises. Friendships may arise in part due to unobserved propensities to study. At the time of college entrance, we collect and utilize previously unavailable information about how much a student expects to study in college as well as how much she actually studied in high school. These variables detailing one's propensity to study have substantial content; both expected college study time and high school study time have strong correlations with study time in college. One prominent concern in this vein is that the relationship between own and friend study time is caused by preferences over course specialization. Although measures such as expected study time would likely inform us about these preferences, we collected transcript data to directly examine this concern. We also investigate additional channels wherein friend characteristics or friend study time, which may be determinants of friend human capital, directly affect one's own production of human capital. We find no evidence of such spillovers.

Our estimates provide strong evidence that friend study time has a substantial effect on one's own study time, which in turn is an important determinant of one's own achievement. We also find significant heterogeneity in reactiveness. That is, we estimate students to have different best response functions, i.e., they react differently

[10]Documenting the existence of peer effects requires addressing the well-known omitted variables (endogeneity) problem (or Manski (1993)'s "correlated unobservables") that will be present if peer groups are determined, in part, on the basis of unobservable student characteristics that also influence academic performance. To deal with this issue, researchers have often looked for situations where some subset of one's peers (e.g., one's college roommates (e.g., Sacerdote (2001)) are randomly assigned.

to changes in friend study time. This heterogeneity has equilibrium implications: we estimate that a student in the 75th percentile propensity to study who is paired with a student in the 75th percentile would study almost twice as much as a student in the 25th percentile who is paired with a student in the 25th percentile.

To characterize the importance of social interactions it is necessary to go beyond reporting our estimates of best response functions, to take into account the actual social network.[11] Therefore, we use our estimated model to further understand the importance of peers using two counterfactual exercises. First, we examine how the network structure, combined with homophilous sorting into friendships, affects the response to changes in friend study time. We exogenously increase (shock) the study time of each student and measure how study times and achievement change for other students in the social network. There is substantial heterogeneity in study time responses depending on which student is shocked, with larger impacts associated with more central students and students connected to more reactive peers. The specific manner in which students with different characteristics are arranged on the network is important for responses. The shock has a big impact when the shocked student is directly connected to multiple reactive students, who then propagate the shock to their friends. However, the shock has a small impact when it is initially only passed through a less reactive student, who dampens it before passing it to the rest of the network. This exercise also provides a natural framework for quantifying the importance of general equilibrium effects. On average, general equilibrium responses, which take into account all feedback effects, produce a network-wide aggregate response that is 2.7 times larger than the partial equilibrium counterpart, which only measures the effect of the shock on immediate neighbors. This implies that peer effects may be much easier to detect when general equilibrium interactions are taken into account.

Second, because peer effects are a function not only of reactiveness but also who is friends with whom, we examine how achievement would differ if friend characteristics were identically distributed across students instead of being strongly correlated with one's own characteristics, or homophilous, as in the data. This exercise provides a natural comparison point from which we can assess the importance of homophily in friendships. On average, women, blacks, and students with higher than median high school GPAs have high propensities to study and tend, in the data, to sort into

[11] Kline and Tamer (2011) discuss the importance of distinguishing between estimates of technological parameters and the equilibrium effects of social interactions.

friendships with students similar to themselves. Therefore, these groups tend to see declines in their friends' propensities to study in the counterfactual.[12] This reduces the average of own study times for these groups by 0.20, 0.25, and 0.15 hours per day, respectively, corresponding to average reductions in achievement of about 0.05, 0.07, and 0.04 GPA points, respectively. Moreover, due to the estimated heterogeneity in best response functions and the lack of assortative matching in the counterfactual networks, these groups' losses are not offset by gains of their complements.

The remainder of this paper is organized as follows. Section 2 contains a description of the BPS data. Section 3 presents our model. Section 4 presents our empirical specification. Section 5 discusses our results and counterfactual exercises, and Section 6 concludes.

2 Data

The BPS is a longitudinal survey that was designed to provide detailed information about students' input choices and educational outcomes in college, and labor market outcomes in the early post-college period.[13] The BPS survey design involved collecting information about all students who entered Berea College, located in central Kentucky, in the fall of 2000 and the fall of 2001. Baseline surveys were conducted immediately before the start of first year classes and students were subsequently surveyed 10-12 times each year during school. As has been discussed in previous work that uses the BPS (e.g., Stinebrickner and Stinebrickner (2006), Stinebrickner and Stinebrickner (2013)), caution is appropriate when considering exactly how results from this case study would generalize to other specific institutions.

At the same time, from an academic standpoint, Berea has much in common with many four-year colleges. It operates under a standard liberal arts curriculum and the students at Berea are similar in academic quality to, for example, students at the University of Kentucky (Stinebrickner and Stinebrickner (2008)). In addition, earlier work found that academic decisions at Berea look very similar to decisions made elsewhere. For example, dropout rates are similar to those found elsewhere (for students from similar income backgrounds) and patterns of major-switching at Berea are similar in spirit to those found by Arcidiacono (2004) in a dataset representative

[12]See Hoxby (2000) for other evidence regarding the effects of having female peers.

[13]The BPS was designed and administered by Todd Stinebrickner and Ralph Stinebrickner.

of four-year college students. It is also worth noting that, not only does our focus on one school make it feasible to collect the multiple surveys each year that provide data more detailed in important dimensions than other existing surveys, but it also makes outcomes such as college grade performance more comparable across students.

Our study is made possible by three types of information that are available in the BPS. First, the BPS elicited each student's closest friends, four times each year. Our analysis utilizes friendship observations from the end of the first semester and the end of the second semester. The survey question for the end of the first semester is shown in Appendix A.1, and, while not shown, the survey question for the end of the second semester is similar. One motivation for using end-of-semester observations is that these survey questions have a full-semester flavor to them; they asked students to list the four people who had been their best friends that semester. Second, the BPS collected detailed time-use information eight times each year, using the twenty-four hour time diary shown in Appendix A.1. Finally, questions on the baseline survey reveal the number of hours that a student studied per week in high school and how much the student expects to study per week in college. The survey data are merged with detailed administrative data on race, sex, high school grade point average, college entrance exam scores, and college GPA in each semester.

This paper focuses on the freshman year for students in the 2001 entering cohort. We focus on students in this cohort because the survey contains more comprehensive friendship and time-use information for them. We focus on understanding grade outcomes during students' freshmen years for two primary reasons. First, as discussed more in Section 5.1, students tend to have similar course loads in their first year under the general liberal arts curriculum at Berea. Second, we are able to characterize the network most completely in the first year both because survey response rates are very high in the first year and because over 80% of friends reported by students in their freshman year are themselves freshmen.[14] These advantages tend to fade in subsequent years as friendships change (in part due to substantial dropout after the first year) and students' programs of study specialize.

[14]Approximately 88% of all entering students in the 2001 cohort completed our baseline survey, and response rates remained high for the eleven subsequent surveys that were administered during the freshman year.

2.1 Descriptive statistics

Our sample consists of 307 students who are each observed in the two semesters of their freshman year. Table 1 shows descriptive statistics of student characteristics. The first row in each of the six panels shows an overall sample average for the variable of interest described in the first column. Forty-four percent of students are male, 18% of students are black, the mean high school grade point average for the sample is 3.39, the mean combined score on the American College Test (ACT) is 23.26, and, on average, students studied 11.24 hours per week in high school and expect to study 24.96 hours per week in college. The subsequent rows in each panel show sample averages of the variable of interest in the first column for different groups. For example, the third panel shows that, on average, males have lower high school grade point averages than females (3.24 vs. 3.51) and blacks have lower high school grade point averages than nonblacks (3.14 vs. 3.45). The fifth panel shows that blacks studied more, on average, in high school than other students (15.29 vs. 10.36).[15]

Table 2 shows descriptive statistics of outcomes during the first year. The first rows of panels 1 and 2, respectively, show that, on average, students study 3.45 hours in the first semester and 3.48 hours in the second semester. The subsequent rows of the first two panels show that, on average, males study less than females, blacks study more than nonblacks, and students with above-median high school GPAs study more than students with below-median high school GPAs.[16] The first rows of panels 3 and 4, respectively, show that the average first semester GPA is 2.89 and the average second semester GPA is 2.93. The subsequent rows of the third and fourth panels show that males, blacks, and students with below-median high school GPAs all have lower average GPAs than their counterparts.[17]

Our main results define friendship as the union of reported links between two students that semester.[18] Table 3 summarizes friend data for those who have at least one friend in each semester, stratified by the same characteristics as in Table 1. The top panel shows that students have 3.3 friends on average. The mean masks

[15]The first two differences in means are significantly different at the 0.001 level. The averages of high school study time for blacks and nonblacks are significantly different at the 0.01 level.

[16]Pooling observations from both semesters, the first and last differences in means are significantly different at a 0.05 level and, given the relatively small number of black students, the middle difference in means is significant at a 0.10 level.

[17]Pooling observations from both semesters, all of these differences are significant at a 0.05 level.

[18]Two students are defined to be friends if either reports being friends with the other. We investigate alternative definitions of friendship in Appendix A.4.

considerable variation: the minimum number of friends is one, while the maximum is 10 friends. The second and third panels show that male and black students (and, therefore, female and nonblack students) sort strongly towards students with the same characteristics. For example, 74% of the friends of males are male, while only 18% of the friends of females are male. Similarly, 69% of the friends of blacks are black, while only 7% of the friends of nonblack students are black. In addition, the third panel shows that students with above-median high school GPAs have fewer black friends. The fourth and fifth panels show that male and black students have friends with lower incoming GPAs and lower combined ACT scores. The sixth and seventh panels show that males have friends who studied less in high school and expect to study less in college (compared to females), while blacks have friends who studied more in high school and expect to study more in college (compared to nonblacks).

The last panel of Table 3 describes friend study time. Consistent with own study time in Table 2, the first row shows that, on average, friend study time is 3.5 hours per day. The second and third rows of the last panel show that average friend study time is much lower for males than for females (3.16 vs. 3.76 hours per day).

Table 1: Own summary statistics

Variable	Group	N	Mean	SD	Min	q1	q2	q3	Max
(1) Male indicator	all	307	0.44	0.5	0	0	0	1	1
	given black	55	0.45	0.5	0	0	0	1	1
	given nonblack	252	0.43	0.5	0	0	0	1	1
	given above-med. HS GPA	155	0.33	0.47	0	0	0	1	1
	given below-med. HS GPA	152	0.55	0.5	0	0	1	1	1
(2) Black indicator	all	307	0.18	0.38	0	0	0	0	1
	given male	134	0.19	0.39	0	0	0	0	1
	given female	173	0.17	0.38	0	0	0	0	1
	given above-med. HS GPA	155	0.1	0.31	0	0	0	0	1
	given below-med. HS GPA	152	0.26	0.44	0	0	0	1	1
(3) HS GPA	all	307	3.39	0.47	1.68	3.09	3.5	3.8	4
	given male	134	3.24	0.51	1.68	2.9	3.21	3.7	4
	given female	173	3.51	0.4	2.13	3.3	3.6	3.85	4
	given black	55	3.14	0.46	2.24	2.78	3.1	3.52	4
	given nonblack	252	3.45	0.46	1.68	3.19	3.53	3.8	4
	given above-med. HS GPA	155	3.77	0.17	3.5	3.6	3.8	3.9	4
	given below-med. HS GPA	152	3	0.35	1.68	2.8	3.08	3.29	3.47
(4) ACT	all	307	23.26	3.61	14	21	23	26	33
	given male	134	22.54	3.77	14	20	23	25	31
	given female	173	23.82	3.39	17	21	24	26	33
	given black	55	19.91	2.51	14	18	20	21	25
	given nonblack	252	23.99	3.4	14	22	24	26	33
	given above-med. HS GPA	155	24.45	3.53	17	22	25	27	33
	given below-med. HS GPA	152	22.04	3.28	14	20	22	24	31
(5) HS study*	all	307	11.24	11.35	0	4	8	15	70
	given male	134	11.43	11.94	0	3.12	8	15	70
	given female	173	11.1	10.9	0	4	9	15	70
	given black	55	15.29	14	0	5	10.5	20	70
	given nonblack	252	10.36	10.51	0	3	7	14	70
	given above-med. HS GPA	155	10.66	10.44	0	4	8	14.5	70
	given below-med. HS GPA	152	11.84	12.21	0	3.38	8.25	15	70
(6) Expected study**	all	307	24.96	11.61	0	17	23	31	64
	given male	134	22.72	11.08	0.97	16	20.75	27.38	64
	given female	173	26.68	11.74	0	19	25.5	33	57.5
	given black	55	28.56	13.56	0	19	25	38.5	57.5
	given nonblack	252	24.17	11.01	0	17	22.5	30.62	64
	given above-med. HS GPA	155	25.18	10.47	0	18	23.5	32	56
	given below-med. HS GPA	152	24.72	12.69	0	16	22.25	30.12	64

* Hours per week spent studying during senior year of high school
** Expected study hours per week in college

Table 2: Own summary statistics for outcomes, by semester

Variable	Group	N	Mean	SD	Min	q1	q2	q3	Max
(1) Sem. 1 Own study*	all	296	3.45	1.67	0	2.33	3.29	4.5	10.33
	given male	129	3.16	1.76	0	2	2.92	4.09	8.66
	given female	167	3.67	1.56	0	2.62	3.38	4.62	10.33
	given black	53	3.8	1.63	0	2.84	3.67	4.78	8.33
	given nonblack	243	3.37	1.67	0	2.25	3.25	4.37	10.33
	given above-med. HS GPA	153	3.6	1.7	0	2.41	3.34	4.75	8.58
	given below-med. HS GPA a	143	3.28	1.61	0	2.25	3.22	4.04	10.33
(2) Sem. 2 Own study*	all	278	3.48	1.6	0	2.23	3.34	4.75	9
	given male	117	3.19	1.67	0	2	3	4.34	9
	given female	161	3.68	1.52	0	2.58	3.41	4.79	7.75
	given black	50	3.75	1.55	0	2.74	3.5	4.96	7.33
	given nonblack	228	3.42	1.6	0	2.17	3.33	4.67	9
	given above-med. HS GPA	145	3.69	1.47	0	2.66	3.67	4.83	7.92
	given below-med. HS GPA	133	3.25	1.7	0	2	3.08	4.38	9
(3) Sem. 1 GPA	all	307	2.89	0.78	0	2.49	3.06	3.46	4
	given male	134	2.72	0.8	0.3	2.17	2.8	3.29	4
	given female	173	3.02	0.74	0	2.66	3.13	3.55	4
	given black	55	2.42	0.78	0	1.82	2.57	2.84	4
	given nonblack	252	3	0.74	0.3	2.58	3.11	3.55	4
	given above-med. HS GPA	155	3.19	0.62	0.52	2.81	3.29	3.69	4
	given below-med. HS GPA	152	2.59	0.8	0	2	2.66	3.12	4
(4) Sem. 2 GPA	all	301	2.93	0.78	0	2.53	3.05	3.46	4
	given male	131	2.74	0.84	0	2.38	2.82	3.33	4
	given female	170	3.07	0.71	0.44	2.66	3.2	3.54	4
	given black	53	2.58	0.86	0.44	2.22	2.62	3.33	3.78
	given nonblack	248	3	0.75	0	2.58	3.08	3.5	4
	given above-med. HS GPA	155	3.21	0.66	0	2.82	3.36	3.74	4
	given below-med. HS GPA	146	2.63	0.79	0.26	2.15	2.66	3.24	4

*Note: Average hours per day spent studying during the semester (from time diaries).

Table 3: Average friend summary statistics, pooled over both semesters

Variable	Group	N	Mean	SD	Min	q1	q2	q3	Max
(1) Num. friends	all	614	3.31	1.58	1	2	3	4	10
	given male	268	3.22	1.59	1	2	3	4	10
	given female	346	3.38	1.57	1	2	3	4	9
	given black	110	3.21	1.35	1	2	3	4	7
	given nonblack	504	3.33	1.62	1	2	3	4	10
	given above-med. HS GPA	310	3.34	1.62	1	2	3	4	10
	given below-med. HS GPA	304	3.28	1.53	1	2	3	4	8
(2) Frac. male friends	all	614	0.43	0.39	0	0	0.33	0.75	1
	given male	268	0.74	0.31	0	0.5	0.82	1	1
	given not male	346	0.18	0.25	0	0	0	0.33	1
	given black	110	0.43	0.4	0	0	0.33	0.83	1
	given not black	504	0.42	0.39	0	0	0.33	0.75	1
	given above-med. HS GPA	310	0.35	0.38	0	0	0.25	0.67	1
	given below-med. HS GPA	304	0.5	0.39	0	0	0.5	1	1
(3) Frac. black friends	all	614	0.18	0.32	0	0	0	0.25	1
	given male	268	0.18	0.32	0	0	0	0.25	1
	given not male	346	0.17	0.33	0	0	0	0.2	1
	given black	110	0.69	0.38	0	0.43	1	1	1
	given not black	504	0.07	0.16	0	0	0	0	1
	given above-med. HS GPA	310	0.1	0.22	0	0	0	0	1
	given below-med. HS GPA	304	0.26	0.39	0	0	0	0.45	1
(4) Friend HS GPA	all	614	3.37	0.32	2.24	3.2	3.41	3.62	4
	given male	268	3.29	0.33	2.25	3.07	3.34	3.53	4
	given not male	346	3.44	0.29	2.24	3.29	3.46	3.64	4
	given black	110	3.18	0.34	2.25	2.96	3.19	3.41	4
	given not black	504	3.42	0.3	2.24	3.25	3.45	3.63	4
	given above-med. HS GPA	310	3.46	0.27	2.65	3.29	3.46	3.63	4
	given below-med. HS GPA	304	3.29	0.35	2.24	3.08	3.35	3.55	3.92
(5) Friend ACT	all	614	23.29	2.63	16	21.67	23.33	25	32
	given male	268	22.72	2.64	16.33	21	23	24.64	31
	given not male	346	23.74	2.54	16	22	23.67	25.5	32
	given black	110	21.2	2.53	16	19.33	21	22.5	29
	given not black	504	23.75	2.43	16.33	22.25	23.67	25.33	32
	given above-med. HS GPA	310	23.79	2.42	17.5	22.23	23.67	25.33	32
	given below-med. HS GPA	304	22.78	2.74	16	21	23	25	30
(6) Friend HS study	all	614	11.03	7.64	0	6	9.5	14.47	70
	given male	268	10.53	7.37	0.5	5.17	9	14	37.33
	given not male	346	11.41	7.83	0	6.5	9.79	14.6	70
	given black	110	14.62	7.31	2.5	9.18	13.92	18.75	37
	given not black	504	10.24	7.49	0	5.5	8.68	13.19	70
	given above-med. HS GPA	310	11.48	8.44	0.5	6	9.7	14	70
	given below-med. HS GPA	304	10.57	6.7	0	6	9.17	14.64	37.33
(7) Friend expected study	all	614	24.82	7.4	0	19.75	23.55	29.62	55
	given male	268	22.89	6.97	4.06	18.23	21.65	27.05	55
	given not male	346	26.33	7.38	0	21.02	25.06	31.38	52
	given black	110	28.05	8.53	12	21.35	28.9	33.79	51
	given not black	504	24.12	6.94	0	19.5	23	28.2	55
	given above-med. HS GPA	310	24.72	7.42	0	20	23.55	29.48	55
	given below-med. HS GPA	304	24.93	7.39	10.5	19.31	23.61	29.81	52
(8) Friend study*	all	614	3.5	1.72	0	2.47	3.26	4.28	11.93
	given male	268	3.16	1.49	0.5	2.21	3	3.88	8.46
	given not male	346	3.76	1.83	0	2.65	3.51	4.5	11.93
	given black	110	3.78	1.77	0.5	2.7	3.52	4.47	10.81
	given not black	504	3.44	1.7	0	2.4	3.2	4.24	11.93
	given above-med. HS GPA	310	3.64	1.79	0	2.56	3.36	4.41	11.93
	given below-med. HS GPA	304	3.36	1.64	0.5	2.36	3.17	4.13	10.81

*Note: Average hours per day friends spent studying during the semester (from friends' time diaries).

Table 4: Network characteristics

Friendship transitions		Correlations between own and avg. of friends	
Prob. friendship reported first semester but not second i.e. $\Pr\{A_2(i,j)=0 \mid A_1(i,j)=1\}$	0.51	Black	0.74
		Male	0.71
		HS GPA	0.23
Prob. second semester friendship is new i.e. $\Pr\{A_1(i,j)=0 \mid A_2(i,j)=1\}$	0.51	Combined ACT	0.31
		HS study time	0.23
		Expected study time	0.14

Table 4 shows other network characteristics. Both the probability that a first-semester friendship no longer exists in the second semester and the probability that a second-semester friendship was not present in the first semester are 0.51. Consistent with the findings from Table 3, the correlations in right side of the table shows substantial sorting on the basis of observable characteristics.

Table 5 presents descriptive OLS regression results predicting own study time (left column) and GPA (right column), pooling observations in the two semesters.[19] The study time regression shows evidence of significant partial correlations of one's own study time (computed as the average amount the student reports studying in the time diaries within a semester) with own sex, own high school GPA, and own high school study time. Of particular relevance for our analysis, one's own study time also has a significant positive partial correlation with friend study time (computed as the average over friends of their own study times). The GPA regression shows that own achievement has a significant positive partial correlation with being female, nonblack, and having above-median high school GPA. Own achievement also has a significant partial correlation with own study time.[20]

3 Model

Students are indexed by $i = 1, \ldots, N$ and time periods (semesters) by $t = 1, 2$. We denote the study time of student i in time period t as s_{it} and let S_t define a column vector collecting all students' study times during that period. We treat the adjacency

[19]Standard errors are clustered at the student level.

[20]In Section 5.1 we discuss modifying the specification in column (2) of Table 5 to include friend characteristics and friend study time. We find that own study time remains an important predictor of own achievement.

Table 5: Study time and GPA OLS regressions

	Dependent variable:	
	Own study	GPA
	(1)	(2)
Male	-0.369^{**}	-0.131^{*}
	(0.171)	(0.076)
Black	0.116	-0.225^{**}
	(0.214)	(0.109)
HS GPA	0.413^{**}	0.437^{***}
	(0.188)	(0.081)
ACT	-0.032	0.040^{***}
	(0.023)	(0.013)
HS study	0.043^{***}	0.001
	(0.008)	(0.004)
Expected study	-0.002	-0.006
	(0.009)	(0.003)
Friend study	0.166^{***}	
	(0.039)	
Own study		0.090^{***}
		(0.022)
Constant	1.915^{**}	0.417
	(0.759)	(0.362)
Observations	574	571
R^2	0.169	0.259
Clustered SE	student	student
Note:	*p<0.1; **p<0.05; ***p<0.01	

matrix representing the network of friendships as pre-determined; we discuss the implications of this assumption in Section 3.2. This matrix in period t, denoted A_t, has a main diagonal of zeros and an (i, j) entry of one if student i has j as a friend and zero otherwise.[21] The average study time of i's friends during period t is:

$$s_{-it} = \frac{\sum_{j=1}^{N} A_t(i,j) s_{jt}}{\sum_{j=1}^{N} A_t(i,j)}. \tag{1}$$

Taking into account their friends, students make decisions about how much to study in a particular semester by considering the costs and benefits of studying. The benefits of studying come from the accumulation of human capital. The production function for human capital, $y(\cdot)$, is:

$$y(s_{it}, \mu_{yi}) = \beta_1 + \beta_2 s_{it} + \mu_{yi}, \tag{2}$$

where μ_{yi} is an observable "human capital type" which allows the amount a person learns in school to vary across people, conditional on her own study level. As will be discussed in Section 4, in practice this type will be constructed using observable characteristics that have consistently been found to influence academic performance. We adopt a value-added formulation for the evolution of human capital, i.e., the human capital type is assumed to a sufficient statistic for the history of prior inputs.[22]

The cost of studying, $c(\cdot)$, is determined by:

$$c(s_{it}, s_{-it}, \mu_{si}) = \theta_1 s_{it} + \theta_2 \gamma(\mu_{si}) s_{it} + \frac{\theta_3 s_{it}}{s_{-it}^{\tau_s}} + \frac{\theta_4 \gamma(\mu_{si}) s_{it}}{s_{-it}^{\tau_s}} + \frac{\theta_5 s_{it}^2}{2 s_{-it}^{\tau_s}}, \tag{3}$$

where friend study time enters the cost function by reducing the cost of one's own studying, with curvature given by τ_s. It may be less arduous (or more fun) to study

[21] Other than its being full rank, we impose no restrictions on A_t. Though in our baseline empirical specification we use the union of reported links (i.e. $A_t(i, j) = 1$ if either i reports being friends with j, or vice versa), the model could also accommodate non-reciprocal links (i.e., i may link to j without j linking to i).

[22] We assume the human capital type is constant between the periods. It is feasible to extend our static framework to a dynamic one allowing the human capital type to evolve between periods. However, the benefits of doing this are mitigated by two facts: (1) each model period corresponds to a semester, which is shorter than the period typically considered when estimating value-added production functions in an educational context (see Hanushek (1979) and Todd and Wolpin (2003) for discussions of issues related to the estimation of education production functions), and (2) we study students during their freshman year, before they typically specialize in terms of course material, meaning second semester coursework does not build heavily on first semester coursework.

at the library when everyone else is at the library. Conversely, if all your friends are at the library, it may be less fun to stay in your dormitory room. The term μ_{si} is i's propensity to study, or "study type," which allows the disutility from studying (or utility from leisure) to vary across students, conditional on own and friend study levels. As will be discussed in Section 4, in practice this type will be constructed from observable characteristics reflecting one's propensity to study. Study types enter the model through the $\gamma(\cdot)$, defined as:

$$\gamma(\mu_{si}) = \frac{1}{\exp(\tau_{\mu,1}\mu_{si} + \tau_{\mu,2}\mu_{si}^2)}, \tag{4}$$

which allows the cost function to have intercepts and slopes that vary across people of different study types. We refer to $\gamma(\mu_{si})$ as the "effective study type." We do not include a fixed cost of studying because almost no students report zero study time over the semester.

With full knowledge of the A_t sequence and all students' human capital types $\{\mu_{yi}\}_{i=1}^N$ and study time types $\{\mu_{si}\}_{i=1}^N$, students simultaneously choose study times to maximize utility, which we assume to be separable across periods:[23]

$$u(s_{i1}, s_{i2}) = \left\{ \sum_{t=1}^{2} y(s_{it}, \mu_{yi}) - c(s_{it}, s_{-it}, \mu_{si}) \right\}. \tag{5}$$

3.1 Model Solution

The student can solve each period's problem separately because her decision problem is additively separable across time periods t.[24] Student i's best response to friend study time in t is given by:

$$s_{it} = \arg\max_{s} \{y(s, \mu_{yi}) - c(s, s_{-it}, \mu_{si})\}. \tag{6}$$

[23]As written, students choose a sequence of study times, knowing the sequence $\{A_1, A_2\}$. The alternative assumption, where students know only the adjacency matrix that period when choosing their study time and have to calculate expectations over the future, would have identical predictions in our model. See Section 3.1.

[24]If utility were nonlinear in semester achievement or the argument of the cost function were study time over the whole year, the problem would no longer be separable across time periods. We assume student utility is linear in achievement because non-linearity of utility in achievement would be difficult to separate from non-linearity in the cost function without functional form restrictions.

Differentiating (6) with respect to own study time gives $\frac{\partial y}{\partial s} = \frac{\partial c}{\partial s}$, i.e., the utility-maximizing study time equates the marginal return for increasing study time with the marginal cost. Expanding the optimality condition gives:

$$\beta_2 = \theta_1 + \theta_2 \gamma(\mu_{si}) + \theta_3 \frac{1}{s_{-it}^{\tau_s}} + \theta_4 \frac{\gamma(\mu_{si})}{s_{-it}^{\tau_s}} + \theta_5 \frac{s_{it}}{s_{-it}^{\tau_s}}.$$

Solving for own study time yields the best response function, which expresses student i's study time as a function of friend study time:

$$s_{it} = -\frac{\theta_3}{\theta_5} - \frac{\theta_4}{\theta_5}\gamma(\mu_{si}) + \frac{(\beta_2 - \theta_1)}{\theta_5} s_{-it}^{\tau_s} - \frac{\theta_2}{\theta_5}\gamma(\mu_{si}) s_{-it}^{\tau_s}. \tag{7}$$

Equation (3) shows that the term associated with θ_5 introduces curvature into the student's cost function. Equation (7) shows that this curvature is necessary for an interior equilibrium. If θ_5 were zero, the student's objective in Equation (6) would be linear in own study time and there would not exist an interior best response to friend study time. Equation (7) also shows that one of the preference parameters θ must be normalized. Therefore, we fix θ_5 equal to one, resulting in the final form of the student best response function:

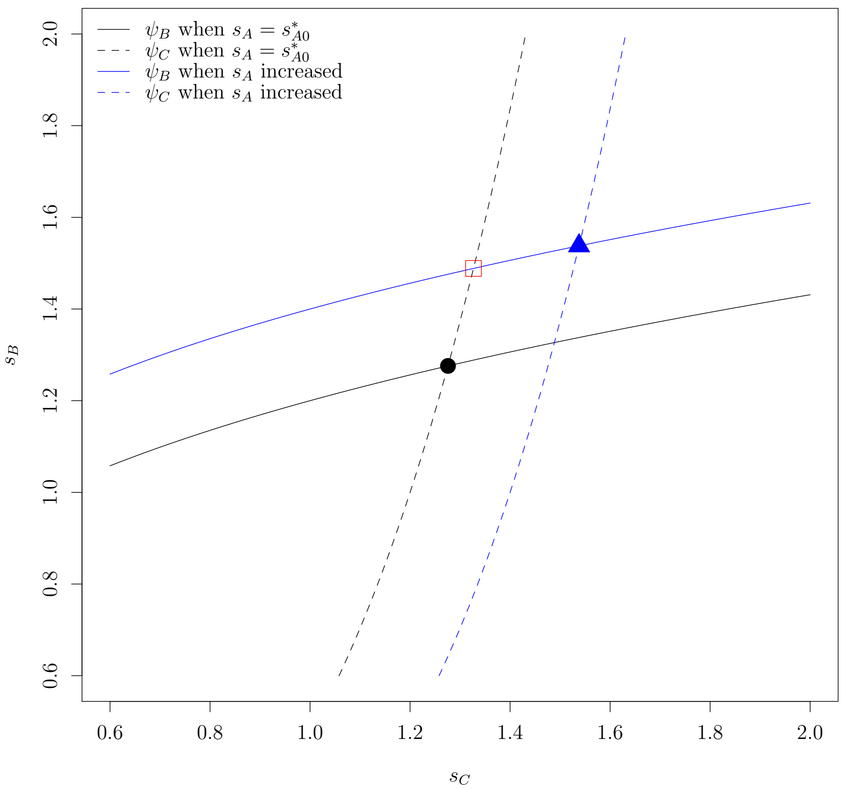
$$s_{it} = -\theta_3 - \theta_4 \gamma(\mu_{si}) + (\beta_2 - \theta_1) s_{-it}^{\tau_s} - \theta_2 \gamma(\mu_{si}) s_{-it}^{\tau_s} \equiv \psi(s_{-it}, \mu_{si}). \tag{8}$$

Note that best response functions depend on study type μ_{si}; when notationally convenient we suppress the study type and write the best response function as $\psi_i(s_{-it})$. Own study time is increasing linearly in the productivity of own study time β_2, and may also increase in own study type, μ_{si}, depending on θ_2 and θ_4. We restrict parameters to ensure that own study time is a weakly increasing and weakly concave function of friend study time.

As shown in Section 3.1.1, concave best response functions ensure existence of a unique equilibrium for the study time game.[25] As shown in equations (7) and (8), the separable form we adopted for the cost function has the benefit of producing a closed-form solution for the student best response function. We show in Appendix A.2 that concavity of the best response function would result from any cost function possessing the natural properties of being strictly convex in s_{it} and weakly concave in s_{-it} (i.e., $\tau_s \leq 1$).

[25] We compute the equilibrium by iterating best responses.

Figure 1: Partial versus general equilibrium effects resulting from an exogenous increase in s_A



3.1.1 Equilibrium

Definition 1 (Period Nash equilibrium)**.** *A pure strategy Nash equilibrium in study times* $S^* = [s^*_1, s^*_2, \cdots, s^*_N]'$ *satisfies* $s^*_i = \psi(s^*_{-i}, \mu_{si})$*, for* $i \in N$*, given adjacency matrix* A*.*

Claim 1. *Let* k *be the number of hours during the entire time period. There exists a unique pure strategy Nash equilibrium if* $\psi_i : R^N \mapsto R$ *are weakly concave and weakly increasing,* $\psi_i(0) > 0$*, and* $\psi_i(k) < k$ *for* $i \in N$*.*

Proof. See Appendix A.3. $\square$

Example 1. *Consider a network of three friends* (A, B, C)*, in which each student is directly connected to the others, at an initial equilibrium* $S^*_0 = (s^*_{A0}, s^*_{B0}, s^*_{C0})$*. To* *consider the effect of an exogenous increase to the study time of student A on the achievement of B, differentiate y_B with respect to s_A:*

$$\frac{\partial y_B}{\partial s_A} = \beta_2 \frac{\partial s_B}{\partial s_{-B}} \frac{\partial s_{-B}}{\partial s_A} = \beta_2 \frac{\partial s_B}{\partial s_{-B}} \frac{\partial(\frac{s_A}{2} + \frac{s_C}{2})}{\partial s_A} = \beta_2 \psi_B'(s_{-B}) \left(\frac{1}{2} + \frac{\psi_C'(s_{-C})}{4}\right).$$

To calculate the partial equilibrium effect, we can use the estimated best response and production functions to calculate how y_B changes due to a change in s_A, fixing $s_C = s_{C0}^*$. However, if $\psi_C'(s_{-C})$ is positive, which we estimate to be the case, this will understate the effect of increasing s_A because s_C will be higher in the new equilibrium. Figure 1 demonstrates the difference between partial and general equilibrium effects. First, consider the initial equilibrium characterized by the intersection of best responses of B and C, given $s_A = s_{A0}^*$ (black dot). The increase in s_A shifts ψ_B vertically for every s_C. The partial equilibrium effect on study time, represented by the vertical distance between the black dot and the red square, takes into account only this shift, ignoring the change in ψ_C. However, the change in s_A also shifts ψ_C horizontally. The general equilibrium effect, represented by the vertical distances between the black dot and the blue triangle, also takes into account this shift in ψ_C and is therefore larger.

3.2 Model discussion

There are two main implications of treating the adjacency matrix as pre-determined. First, if students sort into friendships based on expected benefits, a model of the friendship formation process could serve as the basis for a control function for unobservables affecting sorting (Chan (2015), Hsieh and Lee (2015), Badev (2013)). As discussed in the introduction and Section 5.1, the fact that we designed a survey specifically for this project allows us to take a direct approach by collecting data to address this endogeneity problem, mitigating our need to model friendship formation to derive such a control function. Second, because we do not model how friendships are formed, we must limit our counterfactual exercises to examine fully-specified social networks of interest.[26]

Our model allows for more variety in network interactions than typical approaches. Part of this is due to the nonlinearity in the model when τ_s is different from one. How-

[26]There is a growing literature modeling friendship choices (Badev (2013), de Paula et al. (2014), Mele (2013)), which typically abstracts from mechanisms underlying payoffs to friendship formation.

ever, even with $\tau_s = 1$, implying best response functions are linear in friend study time, we have more flexibility than the most commonly used social interactions models because their linear-in-means structure restricts the impact of friend averages to be common across students. In contrast, our framework allows a student's best response to s_{-it} to be heterogeneous across students, depending on study type. This heterogeneity interacts with the entire network graph represented in A_t and the distribution of study types across nodes to determine outcomes. The relevant sorting of students across nodes is not a simple form of homophily, wherein friends tend to have similar study types. Rather, it matters exactly how the different study types are arranged on the network graph (i.e., one's own study type, friends' study types, friends of friends' study types, etc.).

4 Estimation

The model provides a mapping from the adjacency matrix A_t and all the students' types $\{(\mu_{si}, \mu_{yi})\}_{i=1}^N$ to a unique equilibrium in study times for all students, S_t^*. The equilibrium study times S_t^* generate achievement in equilibrium y_{it}^* via the production function $y(s_i, \mu_{yi})$. The model is operationalized by parameterizing a student's types as linear combinations of observable characteristics collected in a vector x_i. This vector includes indicators for being black and being male along with high school GPA, combined ACT score, average hours per week of study time in high school, and expected hours of study time per week in college. Thus, we take $\mu_{si} = x_i'\omega_s$ and $\mu_{yi} = x_i'\omega_y$.[27] This allows us to express each student's equilibrium study time and achievement as a function of A_t and all students' characteristics, which we collect in a matrix X. Given the full set of parameters $\Gamma = (\beta_1, \beta_2, \theta_1, \theta_2, \theta_3, \theta_4, \omega_s, \omega_y, \tau_{\mu,1}, \tau_{\mu,2}, \tau_s)'$, we write these outcomes for individual i as

$$s_{it}^* = \psi(s_{-it}^*, \mu_{si}) = \delta_s(A_t, X; \Gamma)$$

and

$$y_{it}^* = y(s_{it}^*, \mu_{yi}) = \delta_y(A_t, X; \Gamma),$$

where s_{-it}^* is defined by applying equation (1) to S_t and A_t.

We estimate Γ by maximum likelihood, using data on achievement and study time.

[27] We set $\omega_{s,\text{HS GPA}} = 1$ to identify $\gamma(\cdot)$.

Our measure of achievement is the student's semester-level grade point average (GPA) measured on a four-point scale, denoted $\tilde{y}_{it}$. In our data there are approximately 7% of students who have a GPA of four and 1% who have a GPA of zero. Therefore we take a Tobit model approach to fitting GPA. We define latent GPA as $y^*_{it} + \epsilon_{it}$ where ϵ_{it} is a Gaussian measurement error, IID and independent from A and X. Thus our Tobit model with censoring at zero and four becomes:

$$\tilde{y}_{it} = \begin{cases} 4 & \text{if } y^*_{it} + \epsilon_{it} \geq 4 \\ 0 & \text{if } y^*_{it} + \epsilon_{it} \leq 0 \\ y^*_{it} + \epsilon_{it} & \text{otherwise.} \end{cases}$$

The GPA component of the likelihood function for individual i at time t is simply the likelihood for this Tobit model, with censoring at zero and four:

$$L^y_{it} = \Phi\left(\frac{0 - \delta_y(A_t, X; \Gamma)}{\sigma_\epsilon}\right)^{\mathbf{1}\{\tilde{y}_{it}=0\}} \times \left(1 - \Phi\left(\frac{4 - \delta_y(A_t, X; \Gamma)}{\sigma_\epsilon}\right)\right)^{\mathbf{1}\{\tilde{y}_{it}=4\}} \times \frac{1}{\sigma_\epsilon}\phi\left(\frac{\tilde{y}_{it} - \delta_y(A_t, X; \Gamma)}{\sigma_\epsilon}\right),$$

where Φ and ϕ denote the CDF and PDF, respectively, of the standard normal distribution.

The likelihood function also contains observations on study times. Our measures of s^*_{it} come from up to four within-semester reports of study time for each student in semester t. Each study time observation is a report of time the student spent studying in a 24-hour period. Study time report r for student i in semester t is denoted $\tilde{s}_{rit}$. We use R_{it} to denote the set of reports for student i in semester t. These study time observations are assumed to be noisy measures of s^*_{it}.[28] Approximately 5% of our study time observations are zero, therefore we use a Tobit model approach analogous to that for GPA. Defining latent study time as $s^*_{it} + \eta_{rit}$, reported study time is:

$$\tilde{s}_{rit} = \begin{cases} 0 & \text{if } s^*_{it} + \eta_{rit} \leq 0 \\ s^*_{it} + \eta_{rit} & \text{otherwise} \end{cases}$$

The contribution for student i, report r in semester t is:

$$L^s_{rit} = \Phi\left(\frac{0 - \delta_s(A_t, X; \Gamma)}{\sigma_\eta}\right)^{\mathbf{1}\{\tilde{s}_{rit}=0\}} \times \frac{1}{\sigma_\eta}\phi\left(\frac{\tilde{s}_{rit} - \delta_s(A_t, X; \Gamma)}{\sigma_\eta}\right).$$

[28] Stinebrickner and Stinebrickner (2004) document how reported study time varies within semesters.

We treat the ϵ and η measurement errors as jointly independent across students, semesters, and study time reports. The likelihood contribution for student i is therefore:

$$L_i = \left(\prod_t \prod_{r\in R_{it}} L^s_{rit}\right) \times \left(\prod_t L^y_{it}\right).$$

We note that our method of fitting the model to data is close to the approach of fitting $\delta_s(A_t, X; \Gamma)$ and $\delta_y(A_t, X; \Gamma)$ to observed study time and GPA, respectively, via least squares. We obtain qualitatively very similar results using least squares but prefer treatment, in particular, of observations with GPA=4 as a censored measure of achievement.

5 Estimation Results

Table 6 contains parameter estimates. The top panel contains the parameters that enter the human capital production function. The key parameter is the marginal product of own study time on achievement, β_2. The point estimate of 0.254 implies that increasing own study time by one hour per day increases achievement by about a quarter of a GPA point, ceteris paribus. Table 6 shows that students with high GPAs in high school and high ACT scores accumulate significantly more human capital, and black students accumulate significantly less human capital.

As can be seen in equation (8), the curvature in the best response function is given by τ_s, the exponent on s_{-it}. We estimated the model allowing τ_s to be in the set [0,1], nesting the standard assumption of a linear best response function (i.e., that τ_s=1).[29] However, because our estimation provided evidence that τ_s in equation (9) is indistinguishable from one, we re-estimated the model with τ_s=1.[30] Estimates of the parameters in the study cost function appear in the second panel of Table 6. It is perhaps easiest to interpret the study cost function parameters by substituting them into the best response function:

$$\widehat{\psi}(s_{-it}, \widehat{\mu}_{si}) = \{0.907 - 0.096\widehat{\gamma}(\widehat{\mu}_{si})\} + \{1.328 - 0.874\widehat{\gamma}(\widehat{\mu}_{si})\}\, s_{-it}. \tag{9}$$

The first bracketed term in equation (9) represents the intercept of the best response

[29]See Blume et al. (2015) for an extensive discussion of linear social interactions models.

[30]We note that we find values of τ_s that are distinguishable from one for some of our robustness check specifications, presented in Table 10 in Appendix A.4.

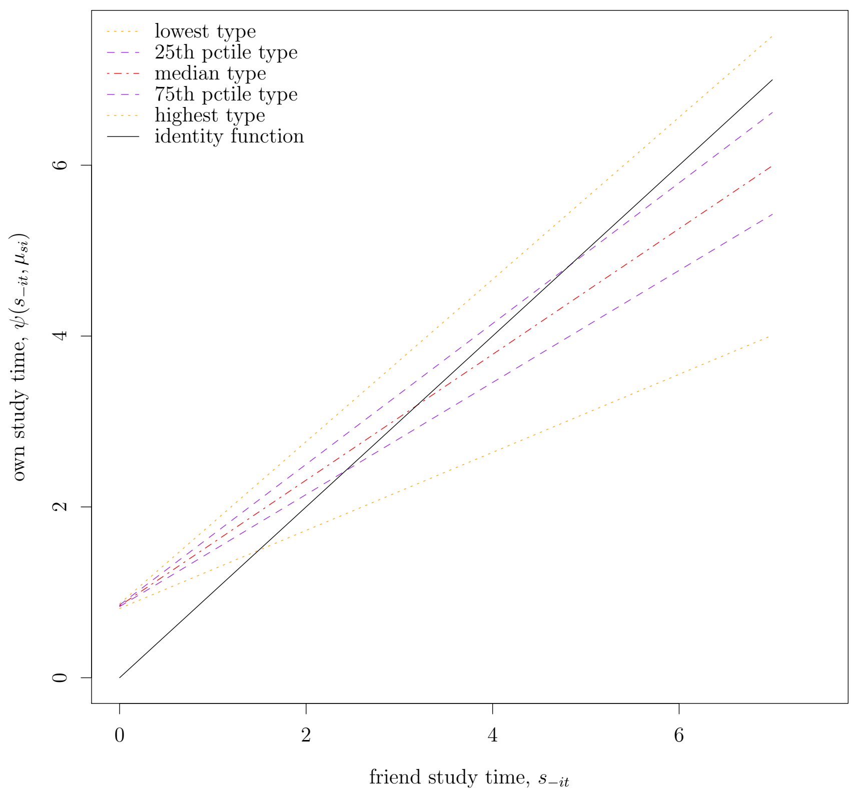
function for student i, that is how much this student would study even if her friends did not study at all. This term consists of $-\theta_1$ =0.907, the common component of the intercept across students, and $-0.096\widehat{\gamma}(\widehat{\mu_{si}})$, the component characterizing variation in the intercept across students. Likewise, the second bracketed term in equation (9) reveals the slope of the best response function, that is, *reactiveness*, or how a student's choice of study time depends on the study time of her friends. This terms consists of $(\beta_2 - \theta_1) = 1.328$, the common component of the slope across students, and $-0.874\widehat{\gamma}(\widehat{\mu_{si}})$, the component characterizing variation in the slope across students. With $\gamma(\mu_{si}) = \frac{1}{\exp(\tau_{\mu,1}\mu_{si}+\tau_{\mu,2}\mu_{si}^2)}$, the latter component in both the first and second bracketed terms depends on the estimated values of $\tau_{\mu,1} = 0.105$ and $\tau_{\mu,2} = -0.003$, which indicate that $\gamma(\cdot)$ is decreasing and convex in one's study type, μ_s. The latter component also depends on the value of one's study type, μ_s, which is determined by the cost function parameters ω_s. As seen at the end of Table 6, study type is increasing in high school GPA and high school study time, but is smaller for males.[31] Effective study types $\widehat{\gamma}(\widehat{\mu}_s)$ and human capital types $\widehat{\mu}_y$ are not very strongly correlated with a Pearson correlation coefficient of 0.106. This follows from the fact that high school study time is a strong determinant of study types, but, as we show later, not of human capital types.

To provide a better sense of the total effect of peer study effort in the best response functions, Figure 2 plots best response functions for the lowest (lower dotted orange line), 25th percentile (lower dashed purple line), median (dot-dashed red line), and 75th percentile (higher dashed purple line), and the highest (higher dotted orange line) effective study types, $\widehat{\gamma}(\widehat{\mu}_s)$. The table just below Figure 2 calculates equation (9) for each effective study type, presenting the type-specific intercept (i.e., the first bracketed term in equation (9)) in the top row and the coefficient on friend study time (i.e., the second bracketed term in equation (9)) in the bottom row. The first row shows that there is little heterogeneity in the intercepts of best response functions; the second row shows that reactiveness to peer study time is increasing in effective study type. It is important to note that, even for the lowest effective study type person (lower dotted orange line, or first column of the table), the effect of peer study time is positive. Combining the slope and intercept terms, one's optimal study choice

[31] Though black students study considerably more than nonblack students, the coefficient on being black is negative. This may be due to the fact that black students have much higher high school study levels, which are an important determinant of study type.

is increasing in study type. That is, the best response is always increasing in s_{-it} and is often very substantial.

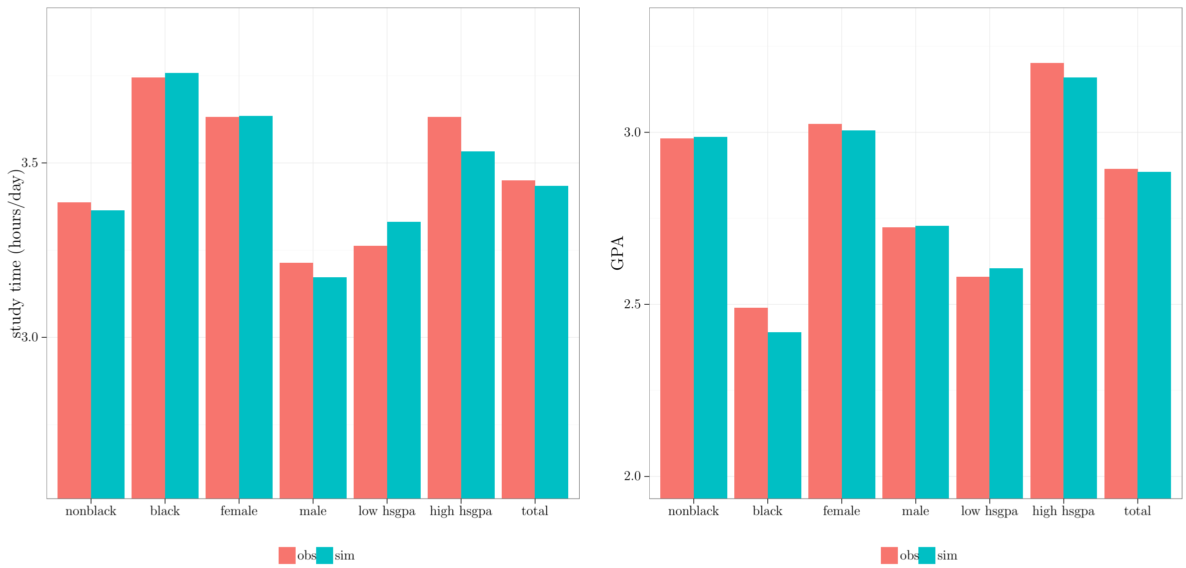
Figure 2: Estimated study best response functions for different effective study types $\widehat{\gamma}(\widehat{\mu}_s)$



Effective study type $\widehat{\gamma}(\widehat{\mu}_s)$:	Lowest	25th pctile	Median	75th pctile	Highest
Intercept	0.81	0.83	0.84	0.85	0.87
Coefficient on s_{-it}	0.46	0.66	0.74	0.82	0.95

In addition to describing individual heterogeneity in best response functions, Figure 2 provides evidence about the implications of this heterogeneity. To see this, note that the intersection of each best response function with the identity function indicates the equilibrium study outcome in a hypothetical scenario in which a student was friends with someone of the same effective study type. Therefore, by comparing where the different types' best response functions intersect the identity function (solid black line), we can identify equilibria when each student is matched with someone of her respective study type. When two 75th percentile effective study types are paired

Figure 3: Fit of mean study time (left) and GPA (right)



they would study almost 5 hours each, almost twice the amount two 25th percentile types would study when paired together. Our estimates indicate that the game exhibits a complementarity: In total, students may study more, and therefore produce more human capital, when matched by study type. That being said, whether or not students will take advantage of this complementarity depends on how they sort into friendships.

Figure 3 shows that the model closely fits mean observed study time (left panel) and GPA (right panel), both in total and by student characteristics.[32] Even though the relationship between own and friend study time is not explicitly targeted (i.e., friend study time does not explicitly enter the likelihood), the model also closely captures this relationship. Figure 4 plots own versus friend study time, for both the observed data (solid red line) and simulated outcomes (dashed blue line).[33]

[32]Model outcomes are simulated by first solving for equilibrium outcomes given $\widehat{\Gamma}$ and then applying IID measurement errors using the specification in Section 4.

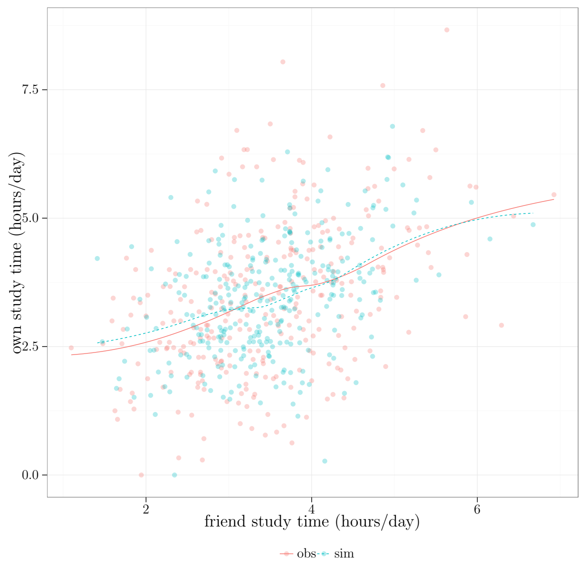
[33]The lines in the figure are fitted values from a local quadratic regression. For each value of friend study time the fit is computed using the closest 75% of the observations via weighted least squares, with weights proportional to $(1-(\text{distance}/\text{max. distance})^3)^3$). See stat_smooth in the R package ggplot2 for details (Wickham (2009), R Core Team (2015)).

Table 6: Parameter estimates

Parameter	Estimate	SE	Description
Production function: $y = \beta_1 + \beta_2 s_{it} + \mu_{yi}$			
β_1	-0.350	0.363	intercept
β_2	0.254	0.057	marginal product of own study time
$\omega_{y,\text{HS GPA}}$	0.470	0.072	coefficient on HS GPA on human capital type
$\omega_{y,\text{ACT}}$	0.047	0.010	coefficient on ACT on human capital type
$\omega_{y,\text{Black}}$	-0.213	0.089	coefficient on Black on human capital type
$\omega_{y,\text{Male}}$	-0.037	0.073	coefficient on Male on human capital type
$\omega_{y,\text{HS study}}$	-0.007	0.004	coefficient on HS study on human capital type
$\omega_{y,\text{expected study}}$	-0.005	0.003	coefficient on expected study on human capital type
Study cost function: $c = \theta_1 s_{it} + \theta_2 \gamma(\mu_{si}) s_{it} + \frac{\theta_3 s_{it}}{s_{-it}^{\tau_s}} + \frac{\theta_4 \gamma(\mu_{si}) s_{it}}{s_{-it}^{\tau_s}} + \frac{\theta_5 s_{it}^2}{2 s_{-it}^{\tau_s}}$			
θ_1	-1.074	0.088	study cost terms
θ_2	0.874	0.146	study cost terms
θ_3	-0.907	0.524	study cost terms
θ_4	0.096	0.828	study cost terms
τ_s	1.000	–	curvature on friend study time, fixed to 1*
$\tau_{\mu,1}$	0.105	0.035	linear term for study type
$\tau_{\mu,2}$	-0.003	0.002	quadratic term for study type
$\omega_{s,\text{HS GPA}}$	1.000	–	coefficient on HS GPA on study type, fixed to 1
$\omega_{s,\text{ACT}}$	-0.063	0.054	coefficient on ACT on study type
$\omega_{s,\text{Black}}$	-0.735	0.437	coefficient on Black on study type
$\omega_{s,\text{Male}}$	-1.065	0.474	coefficient on Male on study type
$\omega_{s,\text{HS study}}$	0.344	0.096	coefficient on HS study (hours/week) on study type
$\omega_{s,\text{expected study}}$	0.005	0.018	coefficient on expected study (hours/week) on study type
Shocks			
σ_ϵ	0.721	0.017	sd measurement error for human capital
σ_η	2.159	0.025	sd measurement error for study time

* See discussion in Section 5.

Figure 4: Fit of own study time against friend study time



5.1 Endogeneity and Identification

Our primary endogeneity concerns arise from the potential for the relationship between a student's study effort and that of her peers to be due, in part, to friendships being formed on the basis of unobservable propensities to study. We attempt to mitigate these concerns by taking advantage of our survey collection to obtain direct measures of students' propensities to study. Our baseline survey elicited information about: 1) how much a student expected to study in college and 2) how much a student studied in high school. These measures of the propensity to study clearly have content; they are strongly correlated with how much a student studies.[34] Further, the overall contribution of these two variables to the regression of study time on observable characteristics and friend study time reported in Table 5 column (1) is substantial, with their omission reducing R-squared from 0.169 to 0.087 (see Table 12 in the appendix). We stress a crucial feature of this information on study propensity: it describes a student's propensity to study at the time of entrance, immediately before students can be influenced by their friendships at Berea. It is possible that endogeneity concerns could arise from changes in propensity to study after entrance and induce friendship sorting. However, if this type of endogeneity were particularly

[34]Bivariate regressions of each of these variables predicting own study time have slope t-statistics of 3.104 and 7.931, for expected study and high school study, respectively.

problematic, we would expect the strength of the relationship between a student's study time and friend study time to increase over time. We find no evidence that the strength of partial correlations between own and friend study time increases across semesters.[35]

One prominent concern related to sorting on unobservable propensities to study is that the relationship between own and friend study time is caused by preferences over course specialization. For example, if students in science courses tend to study more and befriend students in their courses, there may be a spurious relationship between own and friend study time. Although measures such as expected study time would likely inform us about these preferences, we collected transcript data to directly examine this concern. We find that a version of the descriptive regression in Table 5, including both own and friend fraction of courses which are science, does not appreciably change the partial correlation between own and friend study time (0.166 vs. 0.160).[36] This may be due to the fact that, not only may students make friends with students outside classes, but the large majority of curriculum choices for freshman are required general or introductory classes. Thus, workloads are relatively homogeneous across all students.[37]

We have focused on a mechanism wherein friend study time may affect one's own study time, which in turn may affect one's human capital via a production function, equation (2). A broad set of alternative mechanisms involve peer human capital directly entering the achievement production technology. For example, friends with high human capital may provide quick and reliable answers to questions, or may know more about specific course requirements. Friends' human capital is composed of both incoming human capital and that acquired during college. Signals of these components may be provided by pre-college characteristics and friend study time, respectively. We investigate the potential importance of such mechanisms by examining partial correlations between these signals of friend human capital and a student's own GPA. Table 7 presents descriptive regressions where a student's own GPA is the outcome and columns contain different sets of conditioning information. In all cases,

[35]In regressions analogous to that in Table 5 column (1), broken down by semester, estimates of semester-specific partial correlations of friend study with own study are lower in the second semester but statistically indistinguishable from their analogs in the first semester.

[36]See Table 13 in the appendix.

[37]On average, students take about one additional course in their area of specialization per semester in their freshman year.

the student's own characteristics are included. The correlations evident in column (1) between students' own characteristics and their achievement are unsurprising and motivate our use of friend characteristics as signals of their incoming human capital. Column (2) adds friend characteristics as well as own and friend study time. Consistent with the results shown in Table 5, own study time is a significant predictor of achievement. Moving on to measures of friend human capital, there do not appear to be strong partial correlations between students' GPAs and signals of the incoming human capital of their friends. This leads us to conclude that mechanisms involving a direct role of friends' incoming human capital are not motivated in our application.

In contrast, friend study time helps predict own achievement: though the estimated coefficient on friend study time is less than half the coefficient on own study time in column (2), it is statistically different from zero.[38] This leaves open the possibility that both own and friend study time should enter the production function. Therefore, we consider an alternative to our baseline model where friend study time also directly enters the achievement production function. In particular, we estimate a specification that adds a term linear in s_{-it} to the production technology in equation (2). The estimated coefficient on friend study time is small and not significantly different from zero. Thus, we find no evidence of a direct role for peer study time in the achievement production function. We conjecture that the predictive power of peer study time in Table 7 could be due to its being a signal of own study time rather than arising from a role as an direct input in production.

5.2 Quantitative Findings

How much does it matter who your friends are? We conduct two counterfactual exercises using the estimated model to address this question. First, we characterize how students respond to changes in friend study time by exogenously increasing (shocking) the study time of each student and measuring how study times and achievement change for other students in the network. In addition to providing evidence about how network structure (A_t) and student characteristics jointly determine how students are affected by their peers, this exercise provides a natural framework for quantifying the

[38]The point estimate of the partial correlation between own study time and GPA is 0.090 when we exclude friend study time from the regression in column (2). The coefficients on own and friend study time remain essentially unchanged when we exclude measures of friend incoming human capital from the specification in column (2).

Table 7: Investigating alternative mechanisms

	Dependent variable:	
	GPA	
	(1)	(2)
Male	−0.156***	−0.115
	(0.060)	(0.086)
Black	−0.188**	−0.154
	(0.083)	(0.121)
HS GPA	0.493***	0.427***
	(0.067)	(0.069)
ACT	0.037***	0.039***
	(0.009)	(0.010)
HS study	0.004	0.001
	(0.003)	(0.003)
Expected study	−0.005**	−0.006**
	(0.003)	(0.003)
Own study		0.084***
		(0.019)
Frac. male friends		0.063
		(0.108)
Frac. black friends		−0.117
		(0.150)
Friend HS GPA		0.056
		(0.108)
Friend ACT		0.006
		(0.014)
Friend HS study		−0.003
		(0.004)
Friend expected study		0.007
		(0.004)
Friend study		0.039**
		(0.018)
Constant	0.561*	−0.134
	(0.290)	(0.501)
Observations	608	571
R^2	0.228	0.271
Note:	*p<0.1; **p<0.05; ***p<0.01	

importance of general equilibrium effects as well as the importance of heterogeneity in the effect of peers. Second, because peer effects are a function of not only how students respond to changes in peer inputs but also who is friends with whom, we examine how achievement would differ if, instead of sorting into friendships as in Table 4, students were randomly assigned friends. This exercise provides a natural comparison point from which we can assess the importance of homophily in friendships.

Throughout this section, we compare outcomes between baseline and counterfactual scenarios for achievement, own study time, and friend study time. We use s_{it}^{cf} and s_{it}^{baseline} to denote student i's study time in the counterfactual and baseline scenarios, respectively. We define the treatment effect on achievement for student i in period t as $\Delta_{it}^{y} \equiv y(s_{it}^{\text{cf}}, \mu_{yi}) - y(s_{it}^{\text{baseline}}, \mu_{yi})$. Treatment effects for own and friend study time are defined analogously.

5.2.1 Network structure, student characteristics, and the response to peer input changes

To provide quantitative evidence about how students respond to changes in peer study time, we estimate the impulse response to an impulse of increasing study effort. Specifically, we increase (shock) the study time of a single student by one hour per day in a particular semester and examine the responses of all other students in the network in that semester. We summarize our findings when we perform this exercise 614 times, once for each of the 307 students in each of the two semesters.

The averages in the first row of Table 8 show how the effect of the study shock varies with a student's distance from the shocked student. For example, to obtain the number in the second column we first compute, for each student j in each of the two semesters t, the mean response in achievement for all students who are one link away from j when j is shocked in semester t. Averaging this mean response over all students and semesters shows that, on average, students who are one link away from the shocked node have an achievement gain of 0.078. Similarly, the third, fourth, and fifth columns, respectively, show that, on average, students who are two links, three links, and four links away from the shocked node, respectively, have an achievement gain of 0.022, 0.006, and 0.002, respectively. The final column involves first computing, for each student j in each of the two semesters t, the *total* response in achievement, $\sum_{i \neq j} \Delta_{it}^{y}$, for all students (other than j) who are in the network when j is shocked in semester t. Averaging this total response over all students and semesters shows that, on average, the total effect of the shock is 0.52.

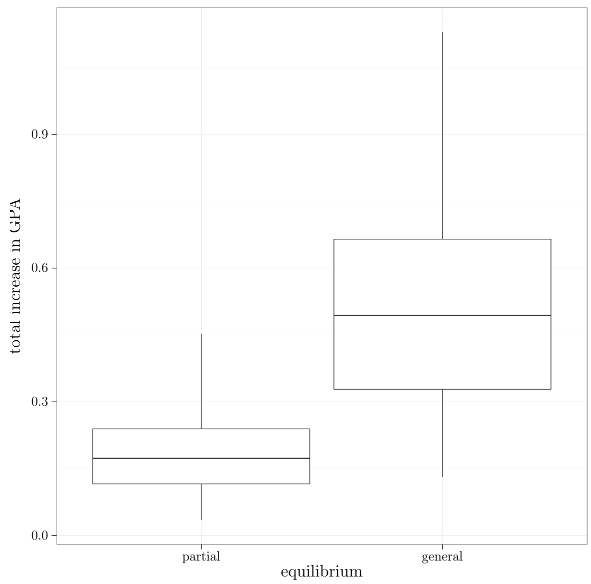
The general equilibrium effects in the first row take into account the full set of feedback effects in the network. In contrast, partial equilibrium effects, which are computed by calculating only the best response (as opposed to study time choices in the new equilibrium) for students directly connected to the shocked student, would take into account only how the exogenous shock to a node influences students who are directly linked to her. Thus, as illustrated by Figure 1, general equilibrium effects will be larger than the partial equilibrium effects that are frequently computed in the peer effects literature. To quantify the importance of this difference, the second row of Table 8 shows the partial equilibrium effects. The average effect on students who are one link away from the shocked node is about 1/4 smaller under partial equilibrium than general equilibrium (0.059 vs. 0.078), while, by definition, the effect on the (typically) large number of students who are two or more links away from the shocked node is zero in the partial equilibrium case. The last column shows that, on average, the total response of the shock is only 0.19 GPA points. Therefore, if we considered only partial equilibrium effects we would, on average, understate the achievement response by 64%. Thus, our results suggest it may be much easier to find evidence of social interactions when general equilibrium effects are taken into account.

Table 8: Average change in achievement (GPA points)

	Avg. effect, by distance from shocked node					Total
Dist. from shocked node	0	1	2	3	4	response
General equilibrium	0.254	0.078	0.022	0.006	0.002	0.52
Partial equilibrium	0.254	0.059	0.000	0.000	0.000	0.19

In addition to computing the average value of the total response $\sum_{i \neq j} \Delta_{it}^{y}$ over each student j who is shocked in each of the two semesters t, we can examine how much this total varies depending on which j is shocked in t. The Box and Whisker plot in Figure 5 shows that the total response in achievement varies substantially depending on which student is shocked. For example, under the general equilibrium case, the first quartile, median, and third quartile of the total increase in GPA are 0.33, 0.49, and 0.66, respectively. To get a better sense of what drives the heterogeneity in achievement gains by which node is shocked, the left panel of Figure 6 shows the relationship between the centrality of the shocked node and the total GPA response,

Figure 5: Distribution of partial versus general equilibrium effects across students



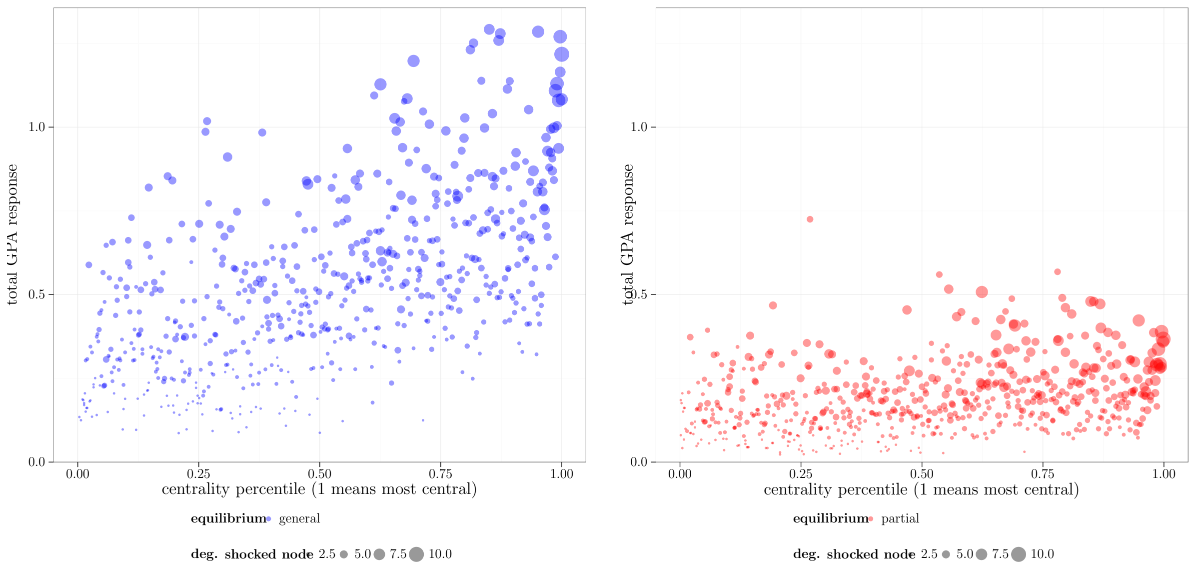
taking into account general equilibrium effects.[39] As before, this calculation excludes the mechanical gain in achievement experienced by the shocked node. Each dot records the total GPA response (y-axis) in the economy by the percentile centrality that semester, or by how central the shocked node is (x-axis). The size of each (blue) dot shows the degree (i.e., number of friends) of the shocked node. Larger dots are concentrated at the top-right, and smaller ones at the bottom-left, i.e., students with more friends tend to have higher centrality indices. Intuitively, because the effects of effort changes are stronger the closer students are, the total response is higher when the shocked node is more centrally located.[40] The right panel of Figure 6 plots partial equilibrium effects (red dots). We can see here that, though shocked nodes have the same degree (dot sizes), the average response is not as strongly increasing in centrality of the shocked node. This is the case because the general equilibrium effects play a larger role the more densely connected the shocked node is to the rest of the network.

Figure 6 evinces variation in the total GPA response (i.e., the y-axis) to shocking

[39] We use what is called a "closeness" centrality measure given by the reciprocal of the sum of shortest distances between that node and every other node in the graph. Average distance to others for unconnected nodes is set to the number of nodes (Csardi and Nepusz (2006), Freeman (1979)).

[40] The notion that certain students may disproportionately affect other students is related to the concept of a "key player," studied in Ballester et al. (2006).

Figure 6: Total GPA response, by centrality of shocked node



different students who are similarly central (i.e., the x-axis) and who also have the same number of friends (i.e., dot sizes). We use two examples to illustrate how the structure of the social network interacts with the distribution of best response functions, which depend on student characteristics, to determine how changes in students' actions affect other students.

The left panel of Figure 7a shows the subgraph containing students within three degrees of the student whose shock creates the largest total GPA response. The right panel shows the subgraph containing students within three degrees of the student whose shock creates the smallest total GPA response.[41] The total responses correspond to the ends of the whiskers shown in the right panel of Figure 5. In each case, the shocked student is denoted by a red star. Squares represent males and circles represent females. Shapes corresponding to black students are shaded and those corresponding to nonblacks are unshaded. The area for the circle or square representing a student other than the shocked student is proportional to the slope of that student's best response function (similar to those presented in the second column of the table just below Figure 2). Both subgraphs show homophilous sorting based on the characteristics which affect best response functions – black students tend to be friends with other black students (and nonblacks with nonblacks), males tend to be

[41]These responses take into account general equilibrium effects.

friends with males (and females with females); in general, students with steeper best response functions tend to be friends with each other.

The link structures of the subgraphs are very different. The shocked student in the left panel has six friends while the shocked student in the right panel has only one friend. The number of students within three degrees of the shocked student is also much larger (39 vs. 12).[42]

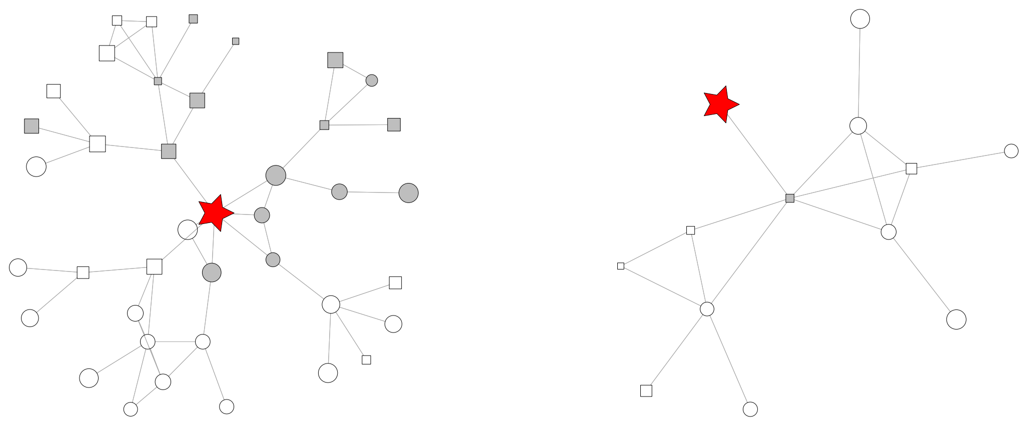
These statistics computed purely from network structure do not tell the whole story. In addition to the structure of links, how the heterogeneous students are arranged on the network matters a great deal. The friends of the shocked student in the left panel have steeper best response functions than the friend of the shocked student in the right panel. In the right panel, the shock is immediately dampened by being passed through the student's only, nonresponsive friend.

Figure 7b shows the analogous plot where the area of the shape is now proportional to the achievement gain for that student. The effect of the shock dies off in the same pattern illustrated by the first row of Table 8, that is, shapes further from the star tend to be smaller. Friends of the shocked student in the left subgraph gain much more than the friend of the shocked student in the right subgraph. Due to the much steeper best response functions of the shocked student's friends, the impulse dies out much less quickly in the left subgraph. Indeed, the gains for students who are two links from the shocked student in the left subgraph are about the same magnitude as the gain for the student directly connected to the shocked student in the right subgraph. This persistence comes from both the steeper best response functions of direct friends of the shocked student and the fact that many of them are also connected to each other, further augmenting the effects of the shock through feedback. Although the average slope of best response functions is similar between the subgraphs, 0.759 in the left vs. 0.698 in the right, there is a big difference in the average amount gained due to the specific manner in which students are arranged on the network (0.030 vs. 0.001 GPA points). Naturally, when combined with the much larger number of students in the left subgraph, the total response is 1.29 GPA points, compared with 0.087 GPA points for the right subgraph. This implies the effectiveness of policies targeting students may depend critically on how they fit into the arrangement of the social network.

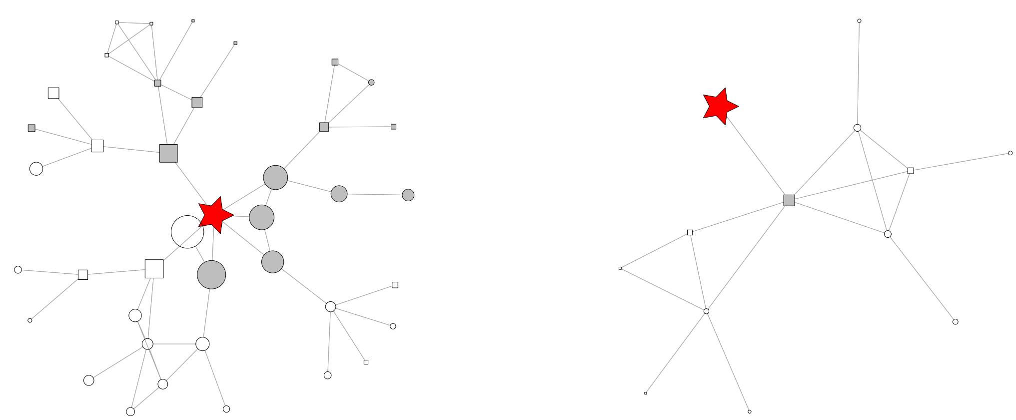
[42] We limit this illustration to students within three degrees based on the first row of Table 8, which shows the total impact dies off quite quickly in distance from the shocked student.

Figure 7: Subgraphs corresponding to students producing the largest and smallest total GPA responses

(a) Slope of best response functions for students within three degrees of the student producing largest total response when shocked (left) and smallest total response when shocked (right)



(b) Gain in achievement for students within three degrees of the student producing largest total response when shocked (left) and smallest total response when shocked (right)



Note: Red star indicates shocked student, males are square (females are circles), blacks are shaded (nonblacks are unshaded), and area of squares and circles is proportional to outcome of interest for corresponding students (i.e., (a) slope of best response function or (b) gain in achievement from shocking starred student)

5.2.2 The effect of sorting into friendships

Peer effects manifest through a combination of how students respond to the input choices of others, which was examined in Section 5.2.1, and who is friends with whom (i.e., sorting into friendships), which may exhibit homophily. Therefore, to provide further evidence about the importance of peers, we compare achievement under the baseline social network with achievement under a counterfactual where friends are homogeneously distributed across students. In this counterfactual, for semester t, we essentially maintain the marginal distribution of friends per student observed in the data, but replace reported links with random draws from the entire sample of students. We then form a counterfactual symmetrized A matrix in the same manner as it was formed for the real data in Section 2. Repeating this process 300 times for each of the two semesters produces 300 pairs of simulated adjacency matrices.[43] Appendix Table 14 presents correlations between students' own characteristics and the average characteristics of their friends in both the baseline and across the simulated counterfactual networks, illustrating that the range of correlations across the simulated counterfactual matrices is quite small.

Table 9 summarizes changes in model outcomes between the baseline and counterfactual, averaged over all 300 simulated networks. Achievement is measured in GPA points and study times are in hours per day. The first column shows the average change in study time, across all students and all simulated networks, that results from moving to homogeneous (i.e., randomly assigned) friends. The first row shows that, on average, moving to this counterfactual would reduce own study time by 0.10 hours. Intuitively, students who, in reality (i.e., under the baseline), have friends with strong propensities to study are most harmed by the move to a homogeneous distribution because this makes them much more likely to have lower study type friends than in the baseline. This explains why females, blacks, and students with above-median high school GPAs, who tend to be high study types and are seen in Table 4 to often have friends with high-study-type characteristics under the baseline, see own study time fall by 0.20, 0.25, and 0.15 hours, respectively. Conversely, males, who have less studious peers under the baseline, tend to study more when friends are homogenized.

[43] For example, in the first semester the algorithm starts with IID draws of counterfactual "friends per student" from the empirical marginal distribution of friends per student in A_1, divided by two and rounded to the nearest integer because A_1 has been union-symmetrized. The number of directed links per student is set to the student's "friends per student" draw. Directed links are IID draws from the whole set of other students.

However, importantly, the estimated complementarities, which arise due to the heterogeneity in best response functions combined with sorting into friendships based on effective study type, imply that the gains of lower study types are smaller than the losses of the higher study types. This explains the overall decrease in own study time. Removing the sorting in the manner of our experiment does not merely re-allocate output, but also lowers total output. Accordingly, the standard deviation of own study time drops by 29%. A similar story drives both the overall results and the stratified results associated with changes in friend study time in the second column of Table 9.

The third column of Table 9 shows the average change in achievement across all students and all simulated networks that result from the changes in study time found in the first column. The first row shows that, on average, moving to the counterfactual would reduce achievement by 0.02 GPA points. However, as expected given the findings of study time, the declines are largest for black students, female students, and students with above-median high school GPAs. As before, the losses to these groups are not offset by the gains to other groups. Homogenizing the distribution of friends' characteristics would increase the baseline GPA gap between nonblack and black students of 0.5 GPA points by 14%, reduce the baseline GPA gap between female and male students of 0.31 GPA points by almost 20%, and reduce the baseline GPA gap between students with above-median and below-median high school GPAs of 0.60 GPA points by 7%. Overall, homogenizing friends would reduce the standard deviation of achievement by 5%. Figure 8 illustrates the range of average achievement over all of the simulations, providing the 2.5th and 97.5th percentiles. Only the group with below-median high school GPAs has an interval that contains zero, reinforcing the finding that sorting significantly affects student achievement.

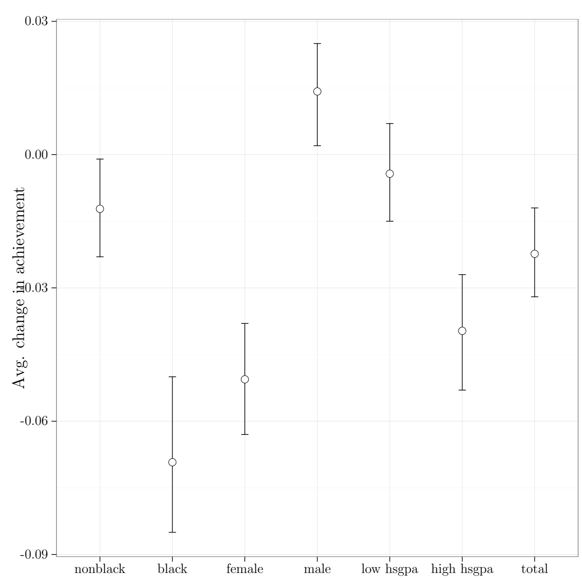
In an attempt to put our results in a broader context, we take advantage of our longitudinal data to provide a back-of-the-envelope calculation about how graduation rates might change under the counterfactual.[44] Our data allow us to estimate the mapping between first year achievement and the probability that a student graduates

[44]Another advantage of mapping human capital to graduation rates is that this relationship is arguably invariant to general equilibrium effects on the relationship between human capital and achievement that may result from large changes in achievement. For example, suppose course grades were curved upwards in response to a policy change that reduced average human capital. In this scenario, average GPA might not change despite their being a lower aggregate level of achievement, while graduation rates would likely be lower if they were a function of human capital, not GPA.

Table 9: Average changes for study time (hours), achievement (GPA points), and predicted probability of graduation resulting from counterfactual homogeneous distribution of friend characteristics, across simulated networks

	Own study time	Friend study time	Achievement	Prob. Graduate
	(1)	(2)	(3)	(4)
Total	-0.10	-0.09	-0.02	-0.006
Nonblack	-0.07	-0.04	-0.01	-0.001
Black	-0.25	-0.36	-0.07	-0.029
Female	-0.20	-0.25	-0.05	-0.016
Male	0.05	0.12	0.01	0.008
Below-med. HS GPA	-0.03	0.02	0.00	-0.001
Above-med. HS GPA	-0.15	-0.20	-0.04	-0.010

Figure 8: Effect of homogenizing friends on average achievement (GPA points), across simulated networks



from college within ten years of starting.[45] Column (4) of Table 9 shows the average change in the graduation probability over all students and all simulated networks. The share of students graduating would fall slightly (about half a percentage point) under the counterfactual assignment of friends. However, as expected given our previous results, there are non-trivial differences in the effects across groups. For example, while the share of female students graduating would decrease by 1.6 percentage points, the share of male students graduating would increase by almost one percentage point. While the share of black students graduating would decrease by 2.9 percentage points, the share of nonblack students graduating would essentially remain the same. These changes are not trivial when compared to the size of other effects in the literature. For example, Belley and Lochner (2007) find that moving from the lowest to highest income quartile would increase college graduation rates by 10 percentage points.[46]

Finally, Figure 9 illustrates how the change in achievement arising under the counterfactual varies across students within particular observable groups, for one pair of simulated adjacency matrices (one for each semester). The figure plots the CDF for the change in achievement by race and sex. Over three quarters of black women (dotted red line) and about 60% of nonblack women (solid red line) would have lower achievement if friends were randomly assigned. The median black male (dotted blue line) would not experience a change in achievement if friends were randomly assigned, while most nonblack males (solid blue line) would gain. Our results show that, not only does there exist substantial heterogeneity in the response to the counterfactual across observable groups, there also exists heterogeneity in the response within these observable groups.

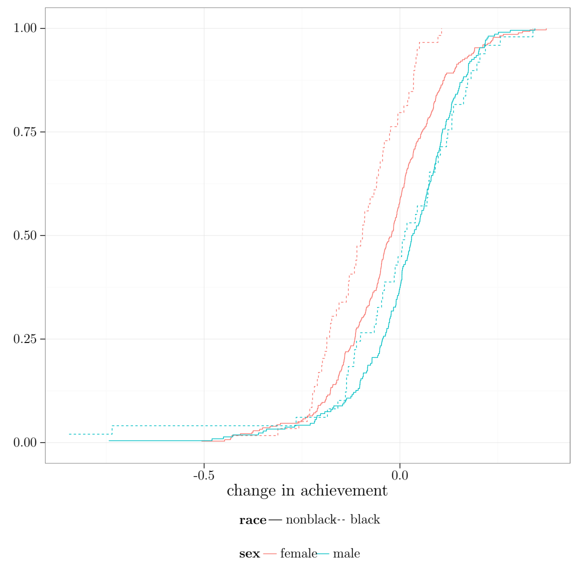
6 Conclusion

This paper presents an equilibrium model of student study time choices and the production of achievement. Social interactions are present because costs of study time for a student depend on the study times of that student's peers. We estimate this model and provide evidence that this mechanism is important in the production of academic achievement. Our approach was made possible by three key features of the

[45] Details of these calculations are in Appendix A.6.

[46] Intervals of the type shown in Figure 8 do not contain zero for females, males, blacks and the full sample.

Figure 9: Changes in achievement (GPA points), by group



BPS: direct measurements of study time, credible measurements of a social network for a cohort of Berea students, and unusually rich measures of ability and propensity to study. We use the structural model to examine counterfactuals that are informative about the role of network feedback effects and sorting in peer characteristics. Heterogeneity in student characteristics and how students are interconnected determine the distribution of responses to changes in a student's study time. Our results indicate that general equilibrium effects mediated by the whole social network are quantitatively important in determining the responses of network-wide study time and achievement to shocks in study time. In addition, our results indicate that homophily, or sorting in peers' characteristics, plays an important role in the production of achievement.

In this paper we investigate the importance of well-motivated and intuitively plausible mechanisms underlying peer effects in our context. We do not claim nor expect that these are the only mechanisms underlying influences across peers. Thus an examination of other mechanisms potentially underlying peer effects in higher education is an important direction for future work. In particular, mechanisms in settings like advanced classes could easily differ from those most relevant for the freshman year general classes that we study in the current paper. The panel nature of the BPS allows us the potential to investigate the importance of joint production of achievement in advanced classes. In particular, the time-use information and administrative records of class and major choices in the BPS data would be well-suited to such an investigation.

A major area for future work is the development of better methodology for measuring entire social networks, building upon the robustness exercises studying alternative definitions of friendships conducted in Appendix A.4. These exercises show that general equilibrium contributions to outcomes were substantial across four ways of measuring networks, but, as expected, there are some differences in the results obtained using directed and undirected networks. Future work investigating the sources of these differences could substantially improve our understanding of how to properly specify networks and best measure them in education settings. A more complete analysis of the role of measurement error in link reporting and how to best utilize longitudinal data on network connections is also potentially very valuable in many other applications of social network models (Comola and Fafchamps (2013)).

A Data

A.1 Survey questions

Figure 10: Time diary question

Survey #5 (Please complete both sides of this sheet) CPO 1971 (3)

Question A.

Reminders: Be sure to put an arrow (-->) next to the time that it is right now. And label this arrow with the words **YESTERDAY** and **START**.

Beginning with the **What were you doing** box next to the arrow, fill in your activities starting 24 hours ago (yesterday) and ending right before you began completing this survey.

Please use the 13 words listed in BOLD on the right of this page to describe your activities.

Time Period	What were you doing?	Time Period	What were you doing?
MORNING		EVENING	
6:00 AM		6:00 PM	
6:20 AM		6:20 PM	
6:40 AM		6:40 PM	
7:00 AM		7:00 PM	
7:20 AM		7:20 PM	
7:40 AM		7:40 PM	
8:00 AM		8:00 PM	
8:20 AM		8:20 PM	
8:40 AM		8:40 PM	
9:00 AM		9:00 PM	
9:20 AM		9:20 PM	
9:40 AM		9:40 PM	
10:00 AM		10:00 PM	
10:20 AM		10:20 PM	
10:40 AM		10:40 PM	
11:00 AM		11:00 PM	
11:20 AM		11:20 PM	
11:40 AM		11:40 PM	
AFTERNOON		NIGHT	
12:00 noon		12:00 midnight	
12:20 PM		12:20 AM	
12:40 PM		12:40 AM	
1:00 PM		1:00 AM	
1:20 PM		1:20 AM	
1:40 PM		1:40 AM	
2:00 PM		2:00 AM	
2:20 PM		2:20 AM	
2:40 PM		2:40 AM	
3:00 PM		3:00 AM	
3:20 PM		3:20 AM	
3:40 PM		3:40 AM	
4:00 PM		4:00 AM	
4:20 PM		4:20 AM	
4:40 PM		4:40 AM	
5:00 PM		5:00 AM	
5:20 PM		5:20 AM	
5:40 PM		5:40 AM	

LIST OF WORDS in bold

In Class
Attending class, attending labs, attending required class sessions

Studying (Outside of class time)
(refer to **pg 2** for more details)

Athletics
(Intercollegiate or Intramural - games or practice)

Clubs

Exercising

Recreation
(reading which is unrelated to courses, listening to music, watching movie, spending time with friends, etc.)

Shopping

Eating

Sleeping

Partying

Personal

Working (in Labor position)

Other
(Please describe on your sheet)

Figure 11: Friends question

Question K. Please write down the **first and last names** of the four people that have been your best friends at Berea College during **this fall term (2001)** . That is, write down the names of the four people with whom you have been spending the most time during the fall term. Also please mention how many hours per week you spend with each person and how many hours you spend studying or talking about classes with each person. (6

Please include your boyfriend/girlfriend or husband/wife if they are among your four best friends.
Also include your roommate if he/she is among your four best friends.
Place a check next to the name of your boyfriend/girlfriend or husband/wife.

Four best friends	Hours spent with this person in a typical week	Hours spent with this person studying /talking about classes in a typical week
1. ______________________	________	________
2. ______________________	________	________
3. ______________________	________	________
4. ______________________	________	________

Current Roommate: (Your roommate should be listed above also if he/she is one of four best friends.)

______________________ ________ ________

Question L. How would you describe your relationship with your roommate during **Fall term**? **Circle one.**
1. Good friends, spent a lot of time together.
2. Got along OK, but didn't spend much time together.
3. Didn't get along very well.
4. Had significant conflicts.
5. Did not have a roommate.

Question M. 1) Since the start of the fall term, did your father lose his job without being able to find a similarly paying replacement job? **Note**: Please answer NO if your father did not lose his job, lost his job but found a similarly paying new job, did not work at a job for pay, you do not know the status of your father , or your father is deceased.

Yes **No** **Not applicable**

2) Since the start of the fall term did your mother lose her job without being able to find a similarly paying replacement job? Note: Please refer to the **Note** in part 1) of this question.

Yes **No** **Not applicable**

Question N. Have you encountered any academic difficulties during the **fall term**? Circle one. **Yes** **No**

If you have encountered academic difficulties during the **fall term**, please circle the people that you discussed these problems with? Also indicate whether each circled item was helpful or not in providing encouragement.

1. Parents	helpful	not helpful
2. Family members other than parents	helpful	not helpful
3. Friends at Berea	helpful	not helpful
4. Friends not at Berea	helpful	not helpful
5. Counselors, Advisers, or Teachers at Berea	helpful	not helpful
6. Former high school or elementary teachers	helpful	not helpful
7. Other (describe) ________________	helpful	not helpful

A.2 Concavity of best response function

The optimal choice of study time for the period game solves the function $G(s, s_{-i}) = \frac{\partial c}{\partial s} - \beta_2 = 0$. To find how s varies with friend study time, use the Implicit Function Theorem:

$$\frac{\partial s}{\partial s_{-i}} = -\frac{\frac{\partial G}{\partial s_{-i}}}{\frac{\partial G}{\partial s}} = -\frac{\frac{\partial^2 c}{\partial s \partial s_{-i}}}{\frac{\partial^2 c}{\partial s^2}}.$$

If friend study time decreases the cost of increasing one's own study time, the numerator is positive. If the cost of studying is convex in own study time, the denominator is negative, meaning the overall sign is positive. Moreover, if friend study time enters $c(\cdots)$ in a weakly concave manner, e.g., $\tau_s \leq 1$, the numerator is weakly smaller in absolute value for larger values of s_{-i}, i.e. study time is weakly concave in friend study time.

A.3 Proof of existence and uniqueness of equilibrium

Claim 2. *Let k be the number of hours during the entire time period. There exists a unique pure strategy Nash equilibrium if $\psi_i : R^N \mapsto R$ are weakly concave and weakly increasing, $\psi_i(0) > 0$, and $\psi_i(k) < k$ for $i \in N$.*

Proof. Define $\mathbf{S} = [0, k]^N$, i.e. a compact and convex set. Define a function Ψ:

$$\Psi : \mathbf{S} \mapsto \mathbf{S} = \begin{bmatrix} \psi_1(x_{-1}) \\ \psi_2(x_{-2}) \\ \vdots \\ \psi_N(x_{-N}) \end{bmatrix}.$$

Existence: $\Psi(\cdot)$ is a continuous self map on the compact set $\mathbf{S}$, so an equilibrium exists by Brouwer's Fixed Point Theorem.

Uniqueness: If $\Psi(\cdot)$ is strictly concave and weakly increasing we can apply Kennan (2001). Next, consider the case where $\Psi(\cdot)$ is linear, in which case we can prove

$\Psi(\cdot)$ is a contraction. Write the linear form of $\Psi(\cdot)$ as

$$\Psi(X) = \begin{bmatrix} \alpha_{11} + \alpha_{21} x_{-1} \\ \alpha_{12} + \alpha_{22} x_{-2} \\ \vdots \\ \alpha_{1N} + \alpha_{2N} x_{-N} \end{bmatrix},$$

where, by assumption, $\max_{i \in N}\{\alpha_{2i}\} < 1$. Let distance be calculated according to the taxicab distance, i.e. $d(X_1, X_2) = \sum_{g \in N} |X_{1g} - X_{2g}|$ for $X_1, X_2 \in \mathbf{S}$. The Contraction Mapping Theorem holds if $d(\Psi(X_1), \Psi(X_2)) \leq \delta d(X_1, X_2)$, for $\delta \in (0, 1)$. Calculating this for the special case where Ψ is a linear map, we have

$$d(\Psi(X_1), \Psi(X_2)) = \sum_{i \in N} \alpha_{2i} |X_1 - X_2| \leq \max_{i \in N}\{\alpha_{2i}\} |X_1 - X_2| < d(X_1, X_2),$$

i.e. the condition for the Contraction Mapping Theorem is satisfied, where $\delta = \max_{i \in N}\{\alpha_{2i}\} \in (0, 1)$. □

A.4 Robustness to specification of adjacency matrix

Recall that our baseline social network is defined using a union approach: $A_t(i, j) = 1$ if either i or j report a friendship in the last social network survey of semester t, resulting in a symmetric adjacency matrix. We believe this to be the most reasonable definition of friendships given the mechanism we investigate, but friendships could be defined in other ways as well. In these robustness exercises, we consider alternate definitions of A_t using directed links so $A_t(i, j) = 1$ only if i reports a friendship with j in the last social network survey of semester t. Denote the directed adjacency matrix in period t as $\tilde{A}_t$. In addition, we exploit our repeated measurements of friendships by constructing networks for the second semester that uses information in the first semester network. We compute a "never lose friends" network for the second semester by replacing zeros in A_2 with ones if the corresponding link is present in A_1; we use this two-survey approach for both the undirected and directed networks. Table 10 contains parameter estimates for different specifications of the adjacency matrix. It is organized by column as follows:

1. Symmetrized: This is our baseline specification, where $A_t(i, j) = \max\{\tilde{A}_t(i, j), \tilde{A}_t(j, i)\}$
2. Asymmetric: $A_t(i, j) = \tilde{A}_t(i, j)$

3. Asymmetric, never lose friends: $A_t(i,j) = \max_{t' \leq t}\{\tilde{A}_{t'}(i,j)\}$

4. Symmetrized, never lose friends: $A_t(i,j) = \max_{t' \leq t}\{\max\{\tilde{A}_{t'}(i,j), \tilde{A}_{t'}(j,i)\}\}$

The most restrictive definition of friendship is the directed (asymmetric) one (column (2)), the most inclusive is the symmetrized version where there is no friendship destruction (column (4)). The top part of the table presents parameter estimates.

Table 10: Parameter estimates for different specifications of the adjacency matrix A

Parameter	Symmetrized A (baseline) (1)	Asymmetric A (2)	Asymmetric A (never lose a friend) (3)	Symmetrized A (never lose a friend) (4)
Production function				
β_1	-0.350	-0.385	-0.685	-0.488
β_2	0.254	0.140	0.269	0.320
$\omega_{y,\text{HS GPA}}$	0.470	0.469	0.548	0.496
$\omega_{y,\text{ACT}}$	0.047	0.063	0.041	0.037
$\omega_{y,\text{Black}}$	-0.213	-0.169	-0.165	-0.223
$\omega_{y,\text{Male}}$	-0.037	-0.034	-0.025	-0.044
$\omega_{y,\text{HS study}}$	-0.007	0.002	-0.006	-0.007
$\omega_{y,\text{expected study}}$	-0.005	-0.005	-0.001	-0.005
Study cost function				
θ_1	-1.074	-1.854	-1.413	-1.323
θ_2	0.874	1.054	1.137	1.112
θ_3	-0.907	-0.735	-1.480	-1.927
θ_4	0.096	0.418	0.551	1.472
τ_s	1	0.683	0.955	0.992
$\tau_{\mu,1}$	0.105	0.147	0.042	0.061
$\tau_{\mu,2}$	-0.003	-0.006	-0.001	-0.002
$\omega_{s,\text{HS GPA}}$	1	1	1	1
$\omega_{s,\text{ACT}}$	-0.063	-0.080	-0.094	-0.061
$\omega_{s,\text{Black}}$	-0.735	-0.194	-1.436	-0.727
$\omega_{s,\text{Male}}$	-1.065	-1.300	-1.359	-0.476
$\omega_{s,\text{HS study}}$	0.344	0.301	0.562	0.315
$\omega_{s,\text{expected study}}$	0.005	-0.016	-0.006	0.019
Shocks				
σ_ϵ	0.721	0.689	0.773	0.764
σ_η	2.159	2.125	2.180	2.173

Table 11 shows the impulse response function from Table 8, supplemented with those computed for the other specifications of the adjacency matrix. The gains from considering general equilibrium effects for students one link from the shocked node are non-trivial, but do differ between scenarios, ranging from 18% for the asymmetric friends scenario (2) to 33% in the scenario considering the symmetrized adjacency matrix where there is no friend destruction (4).

Table 11: Avg. change in achievement by distance from shocked node, for different specifications of the adjacency matrix

	Distance from shocked node				
(1) Baseline (Symmetrized)	0	1	2	3	4
Partial equilibrium	0.254	0.059	0.000	0.000	0.000
General equilibrium	0.254	0.078	0.022	0.006	0.002
(2) Asymmetric	0	1	2	3	4
Partial equilibrium	0.140	0.041	0.000	0.000	0.000
General equilibrium	0.140	0.047	0.015	0.005	0.001
(3) Asymmetric, never lose	0	1	2	3	4
Partial equilibrium	0.269	0.056	0.000	0.000	0.000
General equilibrium	0.269	0.068	0.017	0.005	0.001
(4) Symmetric, never lose	0	1	2	3	4
Partial equilibrium	0.320	0.060	0.000	0.000	0.000
General equilibrium	0.320	0.080	0.019	0.005	0.001

A.5 Additional tables

Table 12: Study time regressions controlling for different sets of characteristics, pooled over both semesters

	Dependent variable:			
	Own study			
	(1)	(2)	(3)	(4)
Male	-0.369^{***}	-0.328^{**}	-0.391^{***}	
	(0.136)	(0.140)	(0.135)	
Black	0.116	0.333^{*}	0.324^{*}	
	(0.186)	(0.192)	(0.172)	
HS GPA	0.413^{***}	0.392^{**}		
	(0.149)	(0.156)		
ACT	-0.032	-0.029		
	(0.021)	(0.022)		
HS study	0.043^{***}			
	(0.006)			
Expected study	-0.002			
	(0.006)			
Friends study	0.166^{***}	0.198^{***}	0.202^{***}	0.228^{***}
	(0.037)	(0.039)	(0.039)	(0.038)
Constant	1.915^{***}	2.167^{***}	2.850^{***}	2.648^{***}
	(0.671)	(0.679)	(0.172)	(0.152)
Observations	574	574	574	574
R^2	0.169	0.087	0.076	0.058
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 14 presents correlations between students' own characteristics and the average characteristics of their friends. The first column shows that the correlations in our baseline networks (i.e., in the data) are substantial. The second column shows that the average correlation over all of the simulated counterfactual adjacency matrices is, by construction, nearly zero. The third and fourth columns illustrate that the range

Table 13: Study time regressions, pooled over both semesters

	Dependent variable:	
	Own study	
	(1)	(2)
Male	-0.369^{***}	-0.365^{***}
	(0.136)	(0.137)
Black	0.116	0.115
	(0.186)	(0.187)
HS GPA	0.413^{***}	0.389^{***}
	(0.149)	(0.150)
ACT	-0.032	-0.034
	(0.021)	(0.021)
HS study	0.043^{***}	0.041^{***}
	(0.006)	(0.006)
Expected study	-0.002	-0.002
	(0.006)	(0.006)
Own share science courses		0.349
		(0.390)
Friend study	0.166^{***}	0.157^{***}
	(0.037)	(0.038)
Avg. friend share science courses		0.880
		(0.562)
Constant	1.915^{***}	1.873^{***}
	(0.671)	(0.684)
Observations	574	574
R^2	0.169	0.176
Note:	*p<0.1; **p<0.05; ***p<0.01	

of correlations across the simulated counterfactual matrices is quite small, providing the 2.5th and 97.5th percentiles.

Table 14: Characteristics of baseline and counterfactual social networks

	Baseline (1)	Avg. simulated (2)	2.5 pctile (3)	97.5 pctile (4)
Avg. number of friends	3.309	3.389	3.240	3.522
Own and avg. friends' correlations				
Black	0.736	-0.004	-0.111	0.103
Male	0.712	-0.006	-0.113	0.105
HS GPA	0.234	-0.004	-0.107	0.088
ACT	0.307	-0.003	-0.101	0.105
HS study	0.233	-0.004	-0.101	0.097
Expected study	0.139	-0.001	-0.117	0.104

A.6 Graduation rates

In an attempt to relate student human capital to graduation outcomes, Table 15 shows the results of a probit of graduating within ten years of starting college on first year achievement. Column (1) shows the results of a probit of graduating on the estimated human capital type $\widehat{\mu}_y$ and average model achievement during the first two semesters of college.[47] Column (2) runs a similar probit, substituting student characteristics in for estimated human capital type. Both statistical models show a strong link between performance during the first year and whether or not a student graduates from college within ten years of starting. The results in the fourth column of Table 9 are calculated using the covariates in the first column; the results are very similar when we to use those in the second column instead.

[47]Note that this specification is consistent with the separable manner in which human capital type and own study time enter the human capital production function.

Table 15: Probit of graduating on average of first year achievement

	Dependent variable:	
	Graduate	
	(1)	(2)
$\widehat{\mu}_y$	-0.063	
	(0.458)	
Black		0.417
		(0.275)
Male		-0.303
		(0.205)
HS GPA		0.309
		(0.391)
ACT		-0.051
		(0.041)
HS study		-0.013
		(0.008)
Expected study		0.003
		(0.009)
Avg. achievement$^{\heartsuit}$	1.249^{***}	1.309^{*}
	(0.444)	(0.672)
Constant	-2.772^{***}	-2.799^{***}
	(0.578)	(0.900)
Observations	307	307
Log Likelihood	-154.725	-146.111
Akaike Inf. Crit.	315.451	308.221

Note: *p<0.1; **p<0.05; ***p<0.01

$^{\heartsuit}$: Average of model achievement across both semesters

We use the estimated coefficients and model achievement given a social network to predict the probability of graduation for each student in that social network. Then, for each of our 300 simulated pairs of networks, we can compare the predicted probability of graduation for each student under the baseline network to the predicted probability of graduation after achievement has changed under the simulated counterfactual network. Averaging the difference in predicted probabilities (between the baseline and counterfactual) across all students produces the change in predicted graduation rates for the simulated network pair.

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