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Abstract

This paper examines academic peer effects in college. Unique new data from the Berea Panel Study allow us to focus on a mechanism wherein a student's peers affect her achievement by changing her study effort. Although the potential relevance of this mechanism has been recognized, data limitations have made it difficult to provide direct evidence about its importance. We find that a student's freshman grade point average is affected by the amount her peers studied in high school, suggesting the importance of this mechanism. Using time diary information, we confirm that college study time is actually being affected.

Keywords: Peer effects; Time use; Higher education; Mechanisms

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1 Introduction

1.1 Background

A large body of research documents that peers affect academic achievement, which has important implications for both the level and degree of academic inequality (Epple and Romano 2011; Sacerdote 2014). Understanding the causes of peer effects is crucial for the design of effective policy (Epple and Romano 2011).

Unfortunately, there is little direct evidence about the channels through which peer effects arise. Notably, while it is recognized that in many educational contexts a student's peers might have an influence by affecting the student's effort (see, e.g., Cooley Fruehwirth 2013), virtually no direct evidence exists about the empirical importance of this "effort" channel. This lack of evidence can largely be attributed to a lack of ideal data. Researchers typically take advantage of administrative data to estimate reduced-form models that relate the academic performance of a student to predetermined characteristics of her peers (see, e.g., Imberman et al. 2012). In this framework, providing evidence about the importance of the effort channel requires access to a predetermined characteristic of peers that likely influences the student's effort. Further, confirming that a particular peer characteristic is indeed operating by influencing effort requires a researcher to observe time-use information about the student. Then, it is problematic that: 1) predetermined peer characteristics, such as high school grade point average (GPA) and college entrance exam scores, that are typically available in administrative data do not necessarily operate primarily through the effort channel and 2) time-use data are not available in administrative data.

This paper provides some of the first direct empirical evidence about the importance of the peer effort channel in the higher education context. We do this by answering the following questions. First, do peers have an affect on grades by influencing study time? Second, how pervasive is this potential channel? That is, do we find evidence that this channel is important both when we define a student's peer group to be her randomly assigned roommate and when we define a student's peer group to be her close friends, which, though not randomly assigned, may be the more relevant peer group for affecting academic outcomes?

Our analysis is made possible by unique data that we collected as part of the Berea Panel

Study (BPS) in order to address the two data requirements described above. With respect to the first data requirement, we used the BPS to collect information about a predetermined peer characteristic that is most likely related to the effort channel: how much the peer studied in high school. We often refer to this information as the peer's *study propensity*. With respect to the second data requirement, we administered time diaries eight times over the course of an academic year. Our analysis also benefits from being able to examine two different types of peer groups. To the best of our knowledge, no other data source contains information on both randomly assigned peers (e.g., roommates) and detailed friendship surveys.

1.2 Mechanisms Underlying Peer Effects

To describe the mechanism of interest, we begin by splitting the determinants of a student's achievement into two parts: 1) a student's own effort and 2) all other inputs. Our focus is on peer effects generated by changes in a student's own effort, which we refer to as as operating through the "effort channel." The potential importance of the effort channel is motivated by the traditional view that human capital, which in our education context may be measured by academic achievement, is produced by investments, which in our education context would naturally include time spent studying, or effort (Ben-Porath 1967). The effort channel may be particularly important in the higher education context that we study in this paper. Academic outcomes of interest, for example, freshman grades, are often of a short-run nature. In the short-run, it may be easier for certain types of peers, such as close friends or roommates, to influence a student's own effort than to influence her ability, which is likely to be one of the main determinants in the "all other inputs" category.[1]

While the effort channel is the conjectured mechanism underlying academic peer effects in many recent papers, prior empirical approaches have been forced to deal with the reality that a student's effort is typically not directly observed. One approach posits effort as an input to achievement and then uses achievement data to test implications of input (i.e., effort) changes that would be generated under different models of social interactions (see, e.g., Calvó-Armengol et al. 2009; Cooley Fruehwirth 2013; De Giorgi and Pellizzari 2014; Tincani

[1]Roughly speaking, one might think of ability as all individual attributes at a point in time that determine how well a person performs at a given level of effort.

2016). A closely related approach examines a higher-level mechanism that is not labeled as "effort", per se, but which is conjectured to ultimately affect a student's achievement by changing her effort. For example, Murphy and Weinhardt (2016) find that a student's earlier academic rank (which depends on the quality of her peers) affects both her own achievement and self-confidence, which they measure using a survey instrument. They then conjecture that self-confidence affects a student's own academic achievement by affecting her effort choice.

The contribution of this paper comes from the fact that the unique data in the BPS allow us to provide direct evidence about the effort channel. To emphasize the uniqueness of our contribution, we note that, to the best of our knowledge, there are only two other papers that provide any type of direct evidence about the effort channel. Lavy and Schlosser (2011) use a survey administered in the middle of the school year to study gender-based peer effects using non-randomly-assigned classrooms; they use as their measure of effort how much time students spent doing their homework. Feld and Zölitz (2017) examine whether information about how much a student studied for one particular class, obtained from a survey that the student completed at the end of the semester to assess her teacher, is related to the prior academic achievement of the students assigned (randomly) to her course section.[2]

1.3 Approach and Overview of Results

We begin by defining a student's peer group to be her randomly assigned roommate. Randomly assigned roommates have been studied extensively because of well-known problems that exist if the observed characteristics of a student's peers are related to unobserved deter-

[2]Characterizing a student's study effort over a particular period (e.g., a full semester or a full year) using a single survey, as in Lavy and Schlosser (2011) and Feld and Zölitz (2017), is known to be difficult; answers to retrospective questions about time spent studying over the full period are likely to contain substantial (potentially non-classical) measurement error, while a single time diary is likely to accurately measure study time for a particular day (or week) but cannot ascertain how much sampling variation in study time exists across different days (or weeks). As such, from the standpoint of documenting whether a student's effort may respond to particular types of peers, a primary contribution of our paper comes from the collection of multiple time diaries, with Stinebrickner and Stinebrickner (2004) showing that averaging over several daily study measurements can greatly mitigate concerns about sampling variation in study time across days. A second contribution relative to past research comes from our unique ability to characterize peers using a measure of prior study effort (how much a peer studied in high school), although, given the prior discussion, we believe that it is prudent to note that it was necessary to collect this information using a retrospective question.

minants of her academic performance. Our results using roommates provide evidence that the effort mechanism is of importance. We find clear evidence that a student's academic achievement, as measured by her freshman grade point average, is affected by her roommate's propensity to study (i.e., how much her roommate studied in high school). Further, using our time-use information, we are able to provide direct evidence that the student's study time is actually being affected.

While the clear causal interpretation afforded by randomly assigned roommates is certainly appealing, naturally occurring peer groups are also of obvious interest.[3] We supplement our roommate analysis by taking advantage of survey questions that ask students to name their best friends in each semester. Our results for friend-based peer groups are strikingly consistent with those for roommate-based peer groups. Having friends with higher propensities to study is predictive of receiving higher freshman grades. Moreover, friend study propensity is a very strong predictor of own study time. Our results from friendship groups make a useful contribution, as they serve to bolster our evidence that time use is an important mechanism. We discuss in the results section how our unique study propensity data may help mitigate potential endogeneity concerns.

2 Data and Measures

The Berea Panel Study is a longitudinal survey that followed students at Berea College, a liberal arts college in central Kentucky, from college entrance through the early stages of their careers. Berea College has a unique history. It was one of the first schools in the American south to educate blacks and whites on an equal basis and now focuses on providing educational opportunities to students from low-income families. However, the findings from our study are pertinent to other university contexts, given that Berea College operates a rather standard liberal arts curriculum and its students are of similar quality to those at the state's large public university, the University of Kentucky (Stinebrickner and Stinebrickner

[3] This interest has motivated a body of recent work examining peer effects that operate via friendships (see, e.g., Fletcher and Ross 2012; Card and Giuliano 2013; Yakusheva and Fletcher 2015; Daw et al. 2015). For recent applications featuring randomly assigned, non-roommate peer groups, see, e.g., Murphy (Forthcoming) and Booij et al. (2017).

2008b).

We examine students who entered Berea College in the fall of 2001, 88% of whom participated in the BPS. We focus on the first year of college largely because this is the only year in which students have randomly assigned roommates. We discuss below the additional criteria determining the analytical samples for our two peer group measures. In the next three subsections, we describe the unique data that we utilize to provide direct evidence about the importance of the effort mechanism.

2.1 Measures Related to Effort

Of central importance for our paper's objective is unique information about effort. Most obviously, providing direct evidence about the effort mechanism requires access to information about a predetermined characteristic of peers that may have an influence through the effort channel. If the effort channel tends to matter because, for example, peers who are predisposed (at the time of college entrance) to study a substantial amount may act as good role models, then it is natural to attempt to measure something about this propensity to study. Our peer propensity measure is how much the peer studied per week in high school, which was elicited the day before classes began. To the best of our knowledge, the BPS is unique in providing this type of information. More readily available from administrative data are academic measures such as a student's high school GPA or college entrance exam scores. However, the fact that these types of variables may largely be measuring factors related to what one may think of as "ability" makes them less than ideal for our purposes.

Given access to our peer study propensity measures, the obvious starting point for our analysis is to examine whether a student's grades depend on the study propensities of her peers. A finding that this were the case would suggest that the effort channel is of importance, i.e., that the grade increase occurs because the student's study effort is being influenced by her peers. However, collecting time-use information allows us to provide direct evidence that this is the case. Our time-use information is collected using the 24-hour time diary shown in Appendix B. We compute a student's study time in each of the two semesters by averaging across the (up to four) 24-hour time diaries that were completed by the student in that semester.

2.2 Characterizing Peers

We use data on two types of peers: roommates and friends. We take advantage of the fact that, although students were permitted to request a roommate, two-thirds of students did not do so. Students who did not request a roommate were randomly assigned one of the same sex, unconditional of all other characteristics, using a random assignment option on Berea's digital administrative system, BANNER. There was no roommate preference questionnaire, meaning that students were not asked what types of roommates they would like. According to the administrator in charge of room assignments, the rationale for not having such a questionnaire for this cohort was that students had been found to misreport certain behaviors, such as smoking, when such a questionnaire had been used in the past. As expected, as we discuss in Section 4.2, we find no evidence that own and roommate characteristics (other than sex) are correlated.

Second, we examine data on friends. At the end of each semester, students were asked to name their four best friends that semester; we define two students to be friends if either student named the other.[4] The number of friends ranges from one to ten, with a mean of 3.31 and standard deviation of 1.58 friends.

We note that our primary objective for using two different measures of peers is not to determine whether roommates have a larger or smaller influence than friends, but, rather, to provide some evidence about the pervasiveness of the effort channel. Given this objective, it is natural to use all available observations when examining results for a particular peer measure. However, as we describe in Section 4.4, our results change very little when we restrict our samples to contain the same observations.

2.3 Other Measures

Our academic achievement outcome is a student's semester-specific GPA, on a four-point scale, which we obtain from the administrative data. Our data also include student's demographic information, such as sex and whether the student is Black, and other administrative

[4] It is worth noting that a student's peer group under the roommate definition is typically not a subset of the student's peer group under the friend definition because the majority of roommates are not named as friends.

variables, such as high school GPA (also measured on a four-point scale).

3 Analytic Strategy

For each of our definitions of peer groups (i.e., the student's randomly assigned roommate or the student's friends), we start by using OLS to estimate the following regression model of student i's achievement during semester t, GPA_{it}, on own and peer characteristics:[5]

$$\text{GPA}_{it} = \beta_0 + \beta_1 x_i^{\text{own}} + \beta_2 x_{it}^{\text{peer}} + \epsilon_{it}^{\text{GPA}}. \tag{1}$$

The vector x_i^{own} contains predetermined own characteristics, e.g., a student's own race and high school GPA. The vector x_{it}^{peer} contains predetermined peer characteristics, which are computed by averaging x_{jt}^{own} for student(s) j who are peers of i in semester t. We pool observations over the two freshman semesters and we cluster standard errors at the student level. Note that a student's roommate is constant across semesters but her friends, and therefore, x_{it}^{peer}, may differ between semesters.

Of particular interest is β_2, which represents the role of peer characteristics in grade determination. We note that, as is standard in this type of peer framework, interpretation can be complicated by the fact that β_2 will capture not only the effect of the measured peer characteristics x_{it}^{peer}, but also the effect of any unobserved peer characteristics that are correlated with x_{it}^{peer}. To be concrete, in our context it would be natural to wonder whether an observed effect of how much peers studied in high school on grades arises primarily because of this peer study propensity measure per se, or because peers who studied more in high school are different in other ways that influence grades.

In our context, some confidence that a grade effect is coming from the amount that peers studied in high school per se can be obtained by directly examining whether this peer characteristic influences the most obvious input associated with the effort channel—a student's study time in college. To do this, for each of our definitions of peer groups, we

[5] Very few GPA observations were at the boundaries of zero or four. In the roommate sample, 1% of the observations had a GPA of zero and 5% had a GPA of four; these numbers are, respectively, 0.003% and 5% in the friend sample.

estimate an OLS regression of student i's average semester-t study time, Study_{it}, on own and peer characteristics:[6]

$$\text{Study}_{it} = \delta_0 + \delta_1 x_i^{\text{own}} + \delta_2 x_{it}^{\text{peer}} + \epsilon_{it}^{\text{Study}}, \tag{2}$$

again pooling over freshman semesters t and clustering standard errors at the student level. It is important to stress that, regardless of whether an observed effect of how much peers studied in high school on grades arises primarily because of this peer study propensity measure per se, eq. (2) represents an important contribution because it represents a direct examination of our notion that, in the short-run, peers may have an important effect by influencing time-use.

Another strength of our data is that we have repeated friendship surveys. Thus, we also use between-semester variation in friendships to estimate a differenced version of eq. (2). This specification differences out permanent characteristics that may be related to sorting into friendships.

4 Results

4.1 Descriptive Statistics

Table 1 contains descriptive statistics for the sample in which peer groups are defined to be students' randomly assigned roommates (left panel) and the sample in which peer groups are defined to be students' friends (right panel).[7] The top four rows in each panel summarize a student's own characteristics, where "High school (HS) study" is our study propensity measure. The next four rows in each panel summarize the characteristics of a student's peers. For example, "Peer black" is an indicator for having a black roommate and the fraction of a student's friends who are black, in the left and right panels, respectively. The last two rows in each panel summarize own semester-specific GPA and college study time (in hours per day). While not necessary for our analyses, the characteristics of students, their

[6]In both the roommate and friend samples, 1% of the observations had an average study time of zero.

[7]There are fewer observations in the left panel because not all students had randomly assigned roommates.

peers, and academic outcomes are very similar between panels.

[Table 1 about here.]

4.2 Checking the Random Assignment of Roommates

[Table 2 about here.]

Table 2 shows results from regressions of each of a student's characteristics on the same characteristic of their roommate and their sex. When we regress HS study on roommate HS study and sex (column (1)), the coefficient on roommate HS study has a p-value of 0.30. The analogous p-values are 0.60 and 0.15 when we replace "HS study" with "Black" and "HS GPA", respectively (columns (2) and (3), respectively). The results of these checks do not provide reason to doubt the randomness of the computerized random assignment procedure for roommates.

4.3 Results Defining Peers as Roommates

[Table 3 about here.]

We first examine results where we define a student's peer group to be her randomly assigned roommate. Column (1) of Table 3 uses eq. (1) to explore how a student's GPA co-varies with the types of variables typically available to researchers in administrative data, such as sex, race, and high school GPA. Although own race and own high school GPA have significant partial correlations with college GPA, neither roommate race nor roommate high school GPA is significantly related to college GPA. Results are similar when we also include own and roommate combined ACT scores.[8]

Column (2) adds our measures of own study propensity and roommate study propensity to the specification in column (1). Roommate high school study time has a significant, positive effect on own college GPA. If a student's roommate had studied ten more hours per week in high school, which corresponds roughly to a one-standard-deviation increase,

[8] The coefficient on roommate combined ACT when added to the specification in column (1) has a p-value of 0.20.

her GPA would increase by 0.108 points (p-value of 0.018). Thus, column (2) provides clear evidence that a student's academic performance is influenced by the study propensity of her peer. In prior work, Stinebrickner and Stinebrickner (2008a) find evidence that study time is a productive input to academic achievement. This, combined with our finding that roommate high school *study time* affects achievement (column (2)) suggests that the peer effect found for grade performance arises because of changes in a student's own study time. We are able to examine this mechanism directly by taking advantage of measures of study effort obtained from time diaries. Column (3) presents results from a regression of own study time on own characteristics and roommate characteristics (i.e., eq. (2)). Consistent with academic peer effects operating through time-use, column (3) shows that roommate high school study time has a significant, positive effect on own study time. If a student's roommate had studied ten more hours a week in high school, corresponding to an increase of roughly one standard deviation, her study time would increase by 0.225 hours per day (p-value of 0.023).[9]

To examine potential nonlinearities, we also estimated eqs. (1) and (2) after stratifying the sample based on whether a student's own high school GPA is above or below the median and after stratifying the sample based on whether a student's own high school study time is above or below the median. In results not shown here, the point estimates of the effects of roommate characteristics on own GPA and study time are similar across the subsamples, and none of the estimated effects of roommate characteristics are significantly different across the subsamples.

4.4 Results Defining Peers as Friends

[Table 4 about here.]

Table 4 presents results from our analysis where a student's peer group is defined to be her friends. The results in Table 4 are remarkably similar to those in Table 3. Column (1)

[9] In terms of the various components of time-use, our focus on own study time is motivated by previous work from the BPS that showed that other potential inputs in the production of grades (e.g., sleeping, partying, and class attendance) tend to remain largely unchanged at Berea when outside factors, such as whether a roommate brought a videogame, influence how much a student studies (Stinebrickner and Stinebrickner 2008a).

shows that, as was the case when defining peer groups using roommates, we would not have found peer effects for college GPA when using the types of variables typically available to researchers in administrative data.[10] However, as was also the case with roommates, column (2) shows that how much friends studied in high school has a significant, positive partial correlation with college GPA.[11] If a student's friends had, on average, studied ten additional hours a week in high school, her predicted GPA would increase by 0.0865 points (p-value of 0.048).[12]

As in the roommate analysis, we next directly examine our proposed effort mechanism by examining whether a student's effort relates to the study propensity of her peers. Column (3) presents results from a regression of own study time on own characteristics and friend characteristics. Both the own study propensity measure and the friend study propensity measure have significant, positive partial correlations with how much students study. If a student's friends had, on average, studied ten additional hours a week in high school, her predicted study time would increase by 0.407 hours per day (p-value of 0.0001).[13]

Friend-based peer groups, though obviously of interest, are not randomly assigned. The standard endogeneity concern is that the observable characteristics of a student's peers may be correlated with unobserved characteristics of the student. In particular, in this context, the relevant concern might be that motivated students, who may be predisposed to exert substantial effort into obtaining good grades, may tend to become friends. Such a concern would suggest that the unobserved variable of relevance in this context might be a student's propensity to study at the time of college entrance. Of course, our analysis to this point has largely been focused on this measure. Thus, our novel study propensity data play two, distinct, roles in our analysis: they allow us to explore the effort mechanism and they may also help address potential endogeneity concerns. While we believe that this approach

[10] Results are similar when we also include combined ACT score. The coefficient on friend combined ACT score, when added to the specification in column (1), has a p-value of 0.517.

[11] We lose about 30 observations of students with missing study time data that semester when we restrict the sample to be common across columns (1)-(3). This reduces the estimated coefficient on friend study propensity.

[12] The point estimate is similar, 0.0729, when we restrict the sample to students with randomly assigned roommates.

[13] The point estimate is similar, 0.318, when we restrict the sample to students with randomly assigned roommates.

to tackling endogeneity concerns is appealing from a scientific standpoint, some caution is warranted when viewing the friendship results.

While it is, in general, important to be cautious when interpreting friendship results as causal in nature, consider the scenario where the problematic correlation arose due to fixed, person-specific attributes. Here, a finding that the estimates in column (3) of Table 4 were similar to those obtained using an estimator that differenced out fixed, person-specific attributes would provide evidence consistent with the notion that this type of correlation was not problematic.[14] To this end, taking advantage of our having collected two semesters of friendship data, column (4) shows results from a regression of the between-semester change in study time on between-semester changes in friend characteristics (i.e., a first-differenced version of eq. (2)). We find that a ten-hour increase in friend high school study time would increase own predicted study time by 0.411 hours per day (p-value of 0.004), a coefficient that is strikingly similar to that in column (3).[15] The results could be similar across columns (3) and (4) either because the aforementioned correlations did not exist to begin with or because our study propensity measure helped remove the correlations. Evidence consistent with the latter comes from an additional finding that the estimated coefficient on own high school study time increases by 30% when friends high school study time is removed as a regressor. Nonetheless, while these results suggest that it might be productive for future survey efforts to explore the benefits of collecting data related to students' propensities to study, we continue to believe it prudent to be cautious in interpreting the results from our friends-based analysis.

[14] This is similar to an assumption made in Hanushek et al. (2003), which uses fixed effects. Alternatively, one could use economic theory to motivate a particular measure of the unobserved determinant underlying endogeneity concerns (see, e.g., Rivkin 2001).

[15] Prior research has found that fixed effects models of grade performance may difference out important cross-sectional variation in inputs. In fact, Stinebrickner and Stinebrickner (2008a) obtain a *negative* estimate of study time on achievement when using fixed effects, in contrast to their positive estimate when using instrumental variables. Unsurprisingly, then, we do not find a significant effect on academic achievement when we regress changes in GPA on changes in friend characteristics.

5 Discussion

Despite the substantial policy relevance and implications for the distribution of academic achievement (Epple and Romano 2011), there is sparse direct evidence about the mechanisms underlying academic peer effects. We use college freshmen in the Berea Panel Study to study effort, a particularly salient mechanism that may underlie academic peer effects.

Our results using roommates are simple and compelling. A student's freshman grades are clearly affected by how much her roommate studied in high school, suggesting that the effort mechanism may be important. This is confirmed by taking advantage of our time-use data, where we find that the study propensity of a student's randomly assigned roommate at the time of college entrance does affect her own study effort during college.

From our roommate analysis alone, it is not easy to discern exactly why one's peers (in this case, roommate) might influence effort. One possibility is simply that non-studious roommates create distractions in the room, making it hard to study. However, another possibility is that roommates change the costs and benefits of studying: it may be more fun to go to the library if a roommate is also studying and it may be more costly to go the library if the opportunity arises to join the roommate in a fun, non-study activity. To see the importance of differentiating between these explanations, note that the importance of the second possibility would suggest that the effort channel may be quite widespread, arising not only due to roommates but also likely, for example, from non-roommate friends on campus (who would largely not exercise their influence through the mechanical distraction possibility).

Consistent with the effort channel being of quite widespread importance, our results for friend-based peer groups are strikingly consistent with those for roommate-based peer groups. Having friends who studied more in high school is predictive of receiving higher freshman grades. Moreover, the amount that friends studied in high school is a very strong predictor of own study time.

In terms of caveats, perhaps the most obvious reason that one should be cautious when thinking about exactly how the results found here would generalize to other environments is that our data come from a single school. Additionally, the importance of the effort mechanism could vary with the age of the students being studied. For example, perhaps outside-of-class study effort can be influenced more easily (or matters more) at a college than in an elementary school. Nonetheless, the direct evidence about the effort mechanism in our paper makes an important contribution, by supporting recent research recognizing the central role effort may play in generating academic peer effects.

A Appendix

B Time Diary Question

[Figure 1 about here.]

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Table 1: Descriptive statistics for pooled data used in roommate and friend analyses

Variable	Roommate data Mean	Std. Dev.	n	Friend data Mean	Std. Dev.	n
Male	0.477	0.500	348	0.436	0.497	614
Black	0.152	0.360	348	0.179	0.384	614
HS GPA	3.374	0.485	348	3.390	0.471	614
HS study (hours/week)	11.349	9.942	348	11.243	11.348	614
Peer male	0.477	0.500	348	0.425	0.393	614
Peer black	0.132	0.339	348	0.177	0.324	614
Peer HS GPA	3.368	0.468	348	3.374	0.320	614
Peer HS study (hours/week)	10.231	9.194	348	11.028	7.637	614
GPA	2.852	0.819	348	2.909	0.781	608
Own study (hours/day)	3.396	1.646	326	3.461	1.632	574

Notes: Own study is the average over study reports that semester.

Table 2: Regressions of own characteristic on roommate characteristic and sex

	Own characteristic		
	HS Study	Black	HS GPA
	(1)	(2)	(3)
Roommate HS Study (hours/week)	0.0835		
	(0.0810)		
Roommate Black		-0.0408	
		(0.0787)	
Roommate HS GPA			0.111
			(0.0771)
Roommate Male	0.179	0.0924	-0.330
	(1.490)	(0.0537)	(0.0723)
Constant	10.23	0.112	3.153
	(1.317)	(0.0381)	(0.277)
Observations	179	179	179
R-squared	0.006	0.017	0.157

Notes: Robust standard errors in parentheses.

Table 3: Regressions of own GPA and own study time on own and roommate characteristics

	Own GPA		Own study
	(1)	(2)	(3)
Male	-0.123	-0.132	-0.175
	(0.112)	(0.111)	(0.224)
Black	-0.296	-0.409	0.202
	(0.124)	(0.134)	(0.279)
HS GPA	0.608	0.575	0.224
	(0.108)	(0.106)	(0.221)
Roommate black	0.147	0.0617	0.451
	(0.124)	(0.115)	(0.305)
Roommate HS GPA	0.0413	0.031	0.369
	(0.102)	(0.104)	(0.232)
Own HS study (hours/week)		0.00968	0.0554
		(0.00406)	(0.0111)
Roommate HS study (hours/week)		0.0108	0.0225
		(0.00457)	(0.00995)
Constant	0.748	0.705	0.508
	(0.497)	(0.490)	(1.078)
Observations	348	348	326
R-squared	0.199	0.226	0.193

Notes: Robust standard errors are in parentheses.

Table 4: Regressions of own GPA and own study time on own and average of friend characteristics

	Own GPA		Own study	Diff. Own study
	(1)	(2)	(3)	(4)
Male	-0.164	-0.161	-0.324	
	(0.104)	(0.103)	(0.216)	
Black	-0.231	-0.256	0.195	
	(0.111)	(0.113)	(0.277)	
HS GPA	0.549	0.541	0.330	
	(0.0845)	(0.0831)	(0.175)	
Friend male	0.0402	0.0441	-0.0652	0.672
	(0.125)	(0.125)	(0.267)	(0.357)
Friend black	-0.0976	-0.131	0.0263	0.176
	(0.147)	(0.146)	(0.295)	(0.563)
Friend HS GPA	0.143	0.140	0.315	0.444
	(0.119)	(0.117)	(0.260)	(0.330)
Own HS study (hours/week)		0.00115	0.0379	
		(0.00375)	(0.00800)	
Friend HS study (hours/week)		0.00865	0.0407	0.0411
		(0.00437)	(0.0105)	(0.0143)
Constant	0.674	0.612	0.518	0.0395
	(0.480)	(0.477)	(1.020)	(0.0948)
Observations	608	608	574	272
R-squared	0.202	0.210	0.172	0.048

Notes: The specification in column (4) is computed using first-differences of eq. (2). Robust standard errors are in parentheses.

Figure 1: 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)