How Competition Shapes Peer Effects: Evidence from a University in China

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Abstract

Competition is widely used to increase effort and performance. However, in many domains, performance not only depends on individual effort but also on cooperation between agents. In such cases, competition may decrease individual performance because it may weaken the cooperation between agents as the chance of winning a competition decreases with the success of peers. Education is a natural setting in which help from others can enhance individual performance. Using administrative data from a university in China, this paper examines how competition changes peer effects and peer interactions. Exploiting randomly assigned roommates, we first show that high-ability roommates have slightly detrimental effects on the academic performance of high-ability students. More importantly, we provide novel evidence that negative peer effects significantly increase along various dimensions of competition intensity within dorm rooms. We conducted a survey to investigate potential mechanisms. The survey results reveal that competition discourages help and induces unfriendly behaviours among roommates, which may explain our findings. Our study suggests that we cannot take peer effects as fixed, but rather as being shaped by the competitive nature of the environment.

Keywords: Competition, Peer effects, Higher education

JEL classification: I21; I23; M50

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1. Introduction

Competition is widely used to motivate effort but can also lead to undesired damage to social capital. It is well established in theory that competition may decrease the incentive to help others (Drago and Garvey, 1998) or even induce sabotage among competitors (Lazear, 1989). Such competition-induced changes in peer interactions can be especially costly in contexts where cooperating with and learning from peers is important. Higher education is a natural setting where both competition and peer effects are ubiquitous. College students compete with each other for a higher grade point average (GPA), for a higher ranking, for scholarships, and for important positions in student organizations. Despite the widespread competition in higher education and a rich literature on peer effects, there is no formal examination of how competition shapes peer effects and peer interactions among students. In this paper, we provide the first investigation into this question by estimating and comparing peer effects in academic performance under various levels of competition intensity.

We address this question by exploiting administrative data from a middle-ranked university in China. This setting provides us with a rare opportunity to identify how competition influences peer effects for three reasons. First, the university randomly assigns roommates, which allows us to address the endogeneity of peer group formation. Second, the presence of College Entrance Exam (CEE) score data allows us to measure students' ex-ante academic ability, overcome the reflection problem, and causally estimate the contextual peer effects.[1] Given these two features, we are able to provide a causal interpretation of the estimated peer effects under various levels of competition intensity.[2]

Third, unlike most U.S. institutions in existing studies but similar to many other universities in China and the developing world, this university encourages a competitive environment among students. Specifically, it creates high-stakes benefits to the winners of strongly-emphasized annual scholarship competitions among students.[3] Moreover, to provide trans-

[1]The reflection problem refers to the difficulty in disentangling the impact of individual performance on peer-group performance from the impact of peer group performance on individual performance if both performances are determined simultaneously (Manski, 1993). To overcome reflection problem, We only estimate peer effects that are driven by individuals' ex-ante information, also known as the contextual peer effects following Manski's terminology.

[2]In Sections 2.3 and 4.3, we also address other concerns in peer effects estimation raised by Angrist (2014), such as weak variations in peer composition, measurement errors in ability, and mechanical forces in peer effects estimations.

[3]Immediately after students' initial enrollment, teachers at this university emphasize the importance of winning scholarships. Every year, students in the *same major-cohort* compete with each other for GPA-determined scholarships. For each major-cohortthe quota for scholarships ranges from the top 10% to the top 15%. In addition to honors, scholarships also provide students with decent monetary rewards. Moreover, scholarship winners are more likely to be recommended for internships by the university to desired local connected companies.

parency in the scholarship evaluation process, the university publicly announces each student's ranking along with detailed GPA information within each major-cohort at the end of each academic year, making the competition even more significant.[4] Such an emphasis on competition enables us to study how competition influences peer effects in an environment where competition is salient.

To benchmark our study against the classical peer effects literature, we first use a linear-in-means model to investigate the impact of high-ability roommates, whose scores in CEE rank in the top tercile within the major-cohorts.[5] As the dorm size varies from four to eight at this university, we measure peer quality for each student in a dorm room by using the proportion of high-ability roommates in that dorm room. We find that having more high-ability roommates slightly decreases a student's own academic performance. As we will subsequently discuss, such negative peer effects from good peers are probably the result of the competitive environment in this university.

Our focus, however, is not on the average peer effects, but instead on how peer effects vary with competition intensity. Measuring competition across students is inherently challenging. We use five different dimensions of competition intensity that allow us to paint a comprehensive picture of how competition influences peer effects. Along each dimension, we examine how peer effects change in a more competitive environment. The five dimensions of competition intensity and the corresponding results are as follows:

1. *High-ability competitors:* The effects of competition should be concentrated among high-ability students, who have higher chances of winning a scholarship (or a top-ranking) competition. For students with a relatively low likelihood of winning, we do not expect strong competition effects. Therefore, we examine the impact of high-ability roommates on students with various ability levels. Consistent with the prediction, we find significant negative effects of high-ability roommates only if the focal students are also of high ability. Moreover, by exploring different cutoffs for defining high-ability students, we find that a student with higher ability experiences a more negative peer effect from his or her high-ability roommates.
2. *Size of the competition pool:* In this university, competition for scholarships and top rankings occurs at the major-cohort level, whereas we can only causally estimate peer effects within the dorm rooms. Competition within a dorm room should be less important if there are more competitors outside the dorm room, since the expected benefit of surpassing roommates is lower. Thus, students in a larger major-cohort should be less likely than

[4]This practice may raise an external validity concern, which we discuss in Section 4.6.
[5]Our results are robust to various cutoffs for defining high-ability roommates. The details are in Section 3.2.

students in a smaller major-cohort to treat their roommates as potential competitors. Consistent with this prediction, we find that a larger major-cohort size significantly attenuates the negative peer effects among high-ability students within dorm rooms. Moreover, this heterogeneity in major-cohort size can be observed only among high-ability students, that is, the more-likely winners of scholarship (or top-ranking) competitions but not among middle- or low-ability students.

3. *Same major-cohort:* Because students are ranked within each major-cohort and each major-cohort has a certain quota for scholarships, students should mainly compete with peers from the same major-cohort. In line with this fact, we find significantly negative peer effects of high-ability roommates on high-ability students only if they are from the same major-cohorts. In contrast, we find imprecisely estimated positive peer effects of high-ability roommates if they are from different major-cohorts, which is qualitatively in line with some of the previous papers based on U.S. institutions.

4. *Similarity in cultural backgrounds:* Social comparison theory in the psychology literature emphasizes that competitors' background similarity (such as gender, race, and place of origin) intensifies competition because people tend to compare themselves with others sharing similar attributes (see Wood (1989) and Garcia, Tor and Schiff (2013) for comprehensive reviews). Consistent with this theory, we find that negative peer effects are more salient if a high-ability student and his or her high-ability roommates are from the same cultural zone than if they are from different cultural zones.[6]

5. *Similarity in academic ability:* Students may be more likely to perceive each other as competitors if they are closer to one another in ability. Following this hypothesis, we calculate the gap in the standardized CEE scores between the best and the second-best students in each dorm room.[7] Hypothetically, a smaller gap in academic ability represents stronger competition intensity between the top two students in the dorm rooms. Correspondingly, we find that a one standard deviation increase in competition intensity (measured by the reversion of gap) decreases the best students' overall GPA by 6.5% of a standard deviation.

Overall, the five tests exploiting different dimensions of competition intensity are remarkably consistent with each other, each showing that peer effects become more negative in a more competitive environment. They are also robust to other academic performance measurements, such as the standardized GPA for required modules only, relative ranking of GPA within the

[6] Cultural zones are defined by local language zones. People in different cultural zones have different dialects and are from different parts of China. We provide more details on this topic in Section 3.2.

[7] The best and second-best students in the dorm rooms are ranked by their CEE scores.

major-cohorts, and an indicator of GPA in the top tercile within the major-cohorts, as the dependent variables. One may have concerns over or alternative explanations for the interpretation of each piece of evidence separately. But taken together, the weight of our evidence supports the idea that competition shapes peer effects among students.[8]

To investigate the underlying mechanisms through which competition shapes peer effects, we conducted a follow-up survey among currently enrolled students at this university and asked them about the details of daily interactions with their roommates. We find that in a more competitive environment, the roommates with the best academic performance in each dorm room are *less* likely to help the respondents and *more* likely to exhibit unfriendly behaviors toward the respondents. They also have fewer daily interactions with one another, such as studying, dining out, exercising, or shopping together, in a more competitive environment. In summary, the survey results suggest that competition intensity directly changes how students interact with each other, which may drive adverse peer effects under competition. Based on the survey data, we also test other potential mechanisms, such as changes in psychological feelings and effort reallocation. The results do not support those channels being significant.

Our study contributes to the peer effects literature in three ways. First and foremost, we are the first to show that both the direction and the magnitude of peer effects on academic performance vary with the competition intensity among students, which shapes how students interact with each other. Most existing papers focus on human capital and behavioral spillovers without considering the role of competition among students.[9] Our study suggests that we cannot take peer effects as fixed, but rather as something shaped by the competitive nature of the environment. From a policy perspective, institutions could set incentives that determine the magnitude and even the direction of peer effects. Therefore, it is important to consider the policy impact on peer effects in the university policy-making process.

Second, the peer effects literature has begun to reach a consensus that peer effects are context-specific (see Sacerdote (2011) and Sacerdote (2014) for comprehensive reviews). Peer effects in academic achievements are salient in some studies but absent in others.[10] However,

[8]Section 4 discusses and rules out alternative explanations that may lead to negative peer effects we document, such as grading on a curve, mean reversion, and changes in self-esteem.

[9]See Sacerdote (2001); Zimmerman (2003); Stinebrickner and Stinebrickner (2006); Lyle (2007); Carrell, Fullerton and West (2009); Imberman, Kugler and Sacerdote (2012); Abdulkadiroğlu, Angrist and Pathak (2014); Booij, Leuven and Oosterbeek (2017); Feld and Zölitz (2017); Zarate (2020) as examples of human capital spillovers. See Figlio (2007); Kling, Liebman and Katz (2007); Carrell, Malmstrom and West (2008); Gould, Lavy and Daniele Paserman (2009); Carrell and Hoekstra (2010); Lavy and Schlosser (2011); Carrell, Hoekstra and Kuka (2018) as examples of poor behavior spillovers.

[10]The evidence on peer effects in higher education is mixed. For perspective, Sacerdote (2001), Carrell, Fullerton and West (2009), Booij, Leuven and Oosterbeek (2017), and Feld and Zölitz (2017) find modest positive average peer effects in academic performance. Stinebrickner and Stinebrickner (2006) and Brady, Insler and Rahman (2017) find mixed evidence of peer effects for different subgroups or different peer group definitions. Foster

little is known about the underlying pattern of why peer effects vary across settings and the specific factors driving the heterogeneity.[11] Our paper sheds light on this question by showing that competition, a specific but ubiquitous context, may drive peer effects in a negative direction.

Third, most existing studies on peer effects in higher education use data from prestigious institutions in developed countries.[12] Given the uniqueness of those institutions, more research is needed to understand peer effects in more general settings. Our paper differs from these studies by presenting evidence derived from a university admitting students around the median of the CEE scores, which is arguably more generalizable to students in China and other developing countries.

In addition to the peer effects literature, our paper also contributes to a growing body of literature on the costs of competition and tournaments. Existing papers show that competition may result in undesirable consequences from various perspectives: discouraging effort for low-ability participants (Brown, 2011; Fang, Noe and Strack, 2020), increasing dishonesty and corrupted business practices (Cai and Liu, 2009; Schwieren and Weichselbaumer, 2010; Snyder, 2010; Bennett et al., 2013), and creating psychological pressures on participants (Smith, 2013; Hickman and Metz, 2018; Berry, Kim and Son, 2019). We complement these studies by emphasizing an additional cost of competition—decreasing the social capital among competitors. Our results demonstrate that competition shapes peer interactions by making collaboration more costly or even inducing unfriendly behaviours and leads to negative peer effects among students. Although how tournaments affect peer interactions is well established in theory, most empirical work concentrates on lab experiments or sports settings (see Chowdhury and Gürtler (2015) for a review).[13] To our knowledge, we are the first to directly examine the relationship between competition and peer interactions in education, a non-laboratory and a non-sports context.

(2006) and Lyle (2007) find no evidence of peer effects among college students.

[11] In one related paper, Tincani (2017) theoretically predicts that rank concerns can generate heterogeneous peer effects even without peer interactions. Consistent with her model prediction, she empirically finds that increasing the dispersion of peer ability has heterogeneous effects on students' achievement.

[12] The peer effects in higher education literature includes studies focusing on prestigious institutions such as Dartmouth (Sacerdote, 2001), Williams (Zimmerman, 2003), Maryland (Foster, 2006), West Point (Lyle, 2007; Jones and Kofoed, 2020), the Air Force Academy (Carrell, Malmstrom and West, 2008; Carrell, Fullerton and West, 2009; Carrell, Sacerdote and West, 2013) and Berea College (Stinebrickner and Stinebrickner, 2006).

[13] Dye (1984) and Lazear (1989) are the first economists to theoretically investigate sabotage behaviors in contests. The theory is further developed by other scholars, such as Drago and Garvey (1998); Chen (2003); Gürtler and Münster (2010); Gürtler, Münster and Nieken (2013). Due to a shortage of detailed peer interaction data, lab experiments are natural ways to empirically test the theory (see Harbring and Irlenbusch (2011), Harbring and Irlenbusch (2008), and Carpenter, Matthews and Schirm (2010) as examples of lab experiments). Beyond the lab, some existing field studies about peer interactions in competition are restricted to sports partly due to the clear contest environment and better data availability for sports competitions (such as tennis (Brown and Minor, 2014), Judo (Balafoutas, Lindner and Sutter, 2012), horse racing (Brown and Chowdhury, 2017), and soccer (Deutscher et al., 2013)).

The paper most closely related to ours in this strand of the literature is Chan, Li and Pierce (2014). Based on 61 saleswomen working at 11 cosmetic counters over a long period, they find a positive peer effect when a team-based commission is offered and a negative peer effect when an individual-based commission is offered. In addition to a different context, our paper differs from theirs in that we directly focus on the impact of competition on peer effects. Since individual-based commissions without tournaments or other ranking-based bonuses do not necessarily introduce direct competition within teams, their results are only suggestive of the effect of competition on peer interactions.

The remainder of the paper is organized as follows. Section 2 introduces the institutional background and data. Section 3 lists our main results, especially the five different tests exploiting the different dimensions of competition intensity. Section 4 discusses potential mechanisms and other concerns. Section 5 concludes the paper.

2. Institutional Background and Data

2.1. Institutional Background

The university we study is a medium-sized, middle-ranked, comprehensive institution in southern China. It awards Bachelor's degrees after four years of study and offers a total of 125 undergraduate majors.[14] Each year, the university enrolls approximately 3,000 new full-time undergraduates.[15] Taking 2011 as an example, the majority of the admitted students' CEE scores ranked from the 40^{th} to the 80^{th} percentile in the population of local test takers who were admitted by any university in China in that year.

Several features of this university fit our research purpose. First, the university strongly encourages competition among students. Students are motivated to study hard and compete for top rankings and various scholarships, which are awarded annually within the major-cohorts and evaluated predominantly based on students' yearly GPA.[16] For perspective, immediately after the first enrollment, the students are instructed by teachers on the importance of winning a scholarship: "Winning scholarships is an important signal to distinguish yourself from your

[14] Most Bachelor's degree programs are four years, except for Architecture and Sculpture (five years) and Clinical Medicine (six years). The undergraduate majors cover 10 discipline categories, namely, science, engineering, literature, history, philosophy, law, medicine, art, economics, and management.

[15] Students can be admitted if they satisfy the following two criteria: 1) they apply for the university through the official university reporting system and 2) their CEE scores pass the university's admission lines for the corresponding tracks to which they belong.

[16] At the end of each academic year, students (including prior scholarship winners) meeting the performance requirements are awarded scholarships. In general, each year for each major-cohort, the top 10%-15% of students win scholarships. Usually, each student can be awarded at most one scholarship in each academic year and students with higher GPA rankings achieve more prestigious scholarships.

peers, especially at a nonprestigious university like ours." Second, the generosity of the monetary rewards also attracts students to compete for them. The scholarships at this university range from 2,000 to 10,000 CNY (312 to 1,560 USD, at the exchange rate of 6.41 CNY to 1 USD), amounting to 0.5 to 2 years of tuition or 2 to 10 months of average student living expenses. Last, the university gives priority to scholarship winners in recommending them for internships at local connected companies.[17]

To ensure a transparent scholarship evaluation process, the university announces individual GPAs and rankings within the major-cohorts at the end of each academic year. This announcement, a common practice among schools in China, may intensify the competition among students in two ways. First, the precise ranking information reveals the identities of each students' close competitors. Second, the public announcement itself may make the competition more salient as being considered smart may be directly important for individual utility (Bursztyn, Egorov and Jensen, 2019).[18]

Second, the roommate assignment process is made on a random basis at this university. The university first divides the freshmen in each major into one to five groups. Each group is an administrative unit and contains approximately 20 to 50 students.[19] Conditional on the group, the university randomly places freshmen in available single-gender dorm rooms by using the University Hostel Management System (UHMS) software. In other words, the assignment process is conditional on the group level and is made without reference to students' CEE scores, family background, and behaviors such as smoking or keeping late hours.[20]

We highlight that approximately 12.8% of dorm rooms in our sample have a mix of students from different major-cohorts. This is because the UHMS randomly matches these left-overs with roommates first from the pool of other groups within the same major-cohorts, and second from other majors when the number of remaining students from one group is insufficient to fill a dorm room (dorm room size varies from four to eight). Therefore, there could be some mixed major-cohorts dorm rooms, although, students in the same dorm rooms in most cases are from the same major-cohorts. In addition, students spent a considerable amount of time in the

[17]The follow-up survey that we conducted further confirms students' strong sense of competition at this university. Among the 2,541 surveyed students, approximately 55% believed that scholarships are important and worth working hard to pursue and over 80% thought that competition plays a key role in achieving success in college.

[18]One may have an external validity concern that our results are solely driven by the practice of this ranking announcement; However, in Section 4.6 we show that negative peer effects exist even before the first time the university publicizes students' GPAs and rankings.

[19]The group is an administrative unit used to organize students and distribute or collect information among students. Students in the same group usually, but not necessarily, take the same courses. They also have many official team-building activities. Therefore, they have a greater chance of interacting with each other.

[20]Given the importance of randomness in this application, Section 2.3 provides supporting evidence that the roommate assignment process is indeed random.

dorm rooms. According to the survey we conducted at this university, approximately 96% of surveyed students reported that they lived in the dormitory more than five days per week during the school time.[21] Moreover, partly as a result of the limited seats in study rooms and libraries, students spent a substantial amount of study time in their dorm rooms. The average study time that surveyed students spent in the dormitories was 2.4 hours per day, or 69% of the average total study time outside of class (3.5 hours per day).

Finally, also important to note is that the dorm room structure in our setting, common among developing countries, substantially differs from that in most developed countries. Each dorm room may accommodate four to eight students, with approximately 50-70 square feet per student. The room is equipped with multiple beds and workstations for students' lives and study activities. In such small shared spaces, the students' activities are largely exposed to their roommates. Such close interactions, on the one hand, may promote connections and communication among roommates, but on the other hand, they may induce interruptions and conflicts.

2.2. Data

Our main analysis uses administrative data provided by the university.[22] It covers students who entered this university as freshmen between 2009 and 2018 and consists of three components. The first component is the transcript data, which includes each student's grade (in a hundred-mark system) in every module taken in every semester. For each student, we calculate the overall GPA with course credits as weights to measure his or her academic performance in college.[23] Considering the potential variance in grading style across majors and cohorts, we further standardize the GPA within major-cohorts.[24] One may be concerned about endogeneity in the overall GPA as a result of students' self-selection into courses. To ease this concern, we

[21] More details about the survey are introduced in Section 4.1.

[22] We also collected additional data through a survey among students enrolled between 2016 and 2019 for mechanism analysis purposes. We describe and report these data in Section 4.1.

[23] For graduated students, we calculate their four-year GPA; for students still enrolled in the university or who had dropped out at the time of the data collection, we calculate their overall GPA based on all of the grades that they obtained until the point of data collection. Note that China has one of the lowest college dropout rates in the world, with sources from the Ministry of Education stating that less than 1% of students failed to complete their degrees (Marioulas, 2017). For the university we study, the average dropout rate is around 3%.

[24] There may be concerns that using standardized GPA may mechanically lead to negative peer effects since more high-performance classmates from the same major-cohort may lower the standardized GPA of the focal observation. This mechanical relationship should not be a concern in our regressions since 1) our identification source is how high-ability students are distributed across different dorm rooms instead of the number of high-ability students in each major-cohort, and 2) we define high-ability students by their relative ranking in CEE within each major-cohort instead using a cutoff based on absolute ability measurement. To further rule out this concern, we replicate our analysis using placebo roommates from the same major-cohorts and do not find the similar pattern as using the actual roommates (see Section 4.3 and Figure A.7 for details).

also calculate the standardized GPA only for required modules.

The second component is the student admission data, including students' College Entrance Exam (CEE) scores, years of enrollment, majors, and rich demographic factors, such as gender, city of origin, rural-urban status, and China Communist Party (CCP) membership before enrollment. To solve the reflection problem, we use students' CEE scores to measure their pre-treatment academic ability.[25] Analogous to the SAT/ACT in the U.S., the CEE is the prerequisite for entrance into higher education institutions in China at the undergraduate level. However, the CEE actually plays an even more important role in China's college admission system than the SAT or ACT does in the U.S. because the CEE is the only admission standard for the majority of students and universities. Given its importance, CEE scores are widely used as a proxy for individuals' pre-college academic ability (e.g., Li et al. (2012), Hoekstra, Mouganie and Wang (2018), and Bai et al. (2020)).

The administration of the CEE is not uniform across China; instead, it is written and graded by provincial education authorities. Therefore, the CEE scores of students from different provinces are not comparable with each other. To ensure the comparability of CEE scores in our analysis, we exclude students from provinces other than the province where the university is located, leaving us with 90%-95% of the sample.[26] Note that to retain as much of the sample as possible, we only remove non-local students in the dorm rooms and retain the local students, thereby calculating the average characteristics of roommates based on the remaining local students in the dorm rooms.[27]

Another source of the in-comparability of CEE scores lies in the division of students into the humanities track and the STEM track. Students must choose one of the two tracks during their first or second year of high school and take the CEE for the corresponding track after their third year.[28] Thus, even within the same province, CEE scores are not comparable for students across different tracks. To address this issue, we further remove students in majors that admit students from both tracks, such as economics and public administration, leaving us with 87 out

[25]In the manuscript, we use the term *ability* as a shorthand for *academic ability*, unless otherwise specified.

[26]To protect the university's identity, we do not provide the exact ratio of non-local students because it is public information in China, which can be tracked online.

[27]The exclusion of non-local roommates would not bias our estimates as long as the process of roommate assignment is orthogonal to the city of origin. In Section 4.5, we conduct a robustness check by dropping dorm rooms containing non-local students, and the results remain quantitatively similar. One may consider including the full sample and using the percentile ranking of CEE scores within the corresponding provinces as an alternative pre-treatment ability measurement. However, given substantial interprovincial inequalities of educational inputs and the ability distribution in China (Yang, Huang and Liu, 2014), this application cannot mitigate the in-comparability issue.

[28]The exam subjects for the STEM-track students include Chinese, English, advanced math, physics, chemistry, and biology, whereas the exam subjects for humanities-track students are Chinese, English, math, history, political science, and geography.

of 125 majors, approximately 66.9% of the sample.[29]

Using the remaining sample, we plot the relationship between students' CEE performance and their academic performance at the university in Figure A.1, with CEE percentile ranking within the major-cohorts on the x-axis, standardized overall GPA on the y-axis of panel (a), and an indicator of overall GPA in the top 10% within the major-cohorts on the y-axis of panel (b).[30] As shown, students with a higher percentile ranking in CEE are more likely to have a higher standardized overall GPA and a better chance that his or her GPA is in the top 10%. These positive correlations between students' CEE scores and their grade outcomes at the university support our use of CEE scores as a pre-treatment academic ability measurement.

The final component is a full history of roommate assignments. In principle, roommates are unchangeable during the four years of university study unless irreconcilable conflicts occur among roommates. In our sample, less than 3% of the students switched dorm rooms, and they were randomly reassigned to other dorm rooms with vacancies.[31] For those who have multiple dorm room records, we use their initial dormitory assignments to define their roommates, as subsequent switches could be endogenous. Although our estimates are in the spirit of intention-to-treat effects, they should be fairly similar to the treatment-on-treated effects since only a few cases of roommate switching exist. Consistent with this claim, our main results are robust to restricting to dorm rooms without any change in dorm room composition. Linking these three data components together results in 16,116 students from 385 major-cohorts in our main sample. Table A.1 reports the summary statistics.[32]

[29] One may consider including mixed-track majors and using the percentile ranking of CEE scores within the corresponding tracks as an alternative ability measurement. However, students from one track may enjoy advantages over students in the other track when studying certain majors. In other words, even students from different tracks who have the same CEE ranking within the corresponding tracks may have different chances of winning scholarships. Taking the finance major as an example, the possibility of STEM-track students having an overall GPA in the top 10% is 15.8%, approximately two times as high as the chance for humanities-track students (7.4%).

[30] We do not know the exact identity of the scholarship winners. Considering that students with a yearly GPA ranking in the top 10%-15% within the major-cohorts are awarded scholarships at this university, we use the indicator of a student's overall GPA being in the top 10% as a proxy for the chance of winning scholarships.

[31] To minimize the occurrence of the unauthorized switching of dormitories or moving out, dorm administrators conduct periodic room inspections. If an unauthorized switch is detected, the student will receive a warning, and a public notice about the incident will be posted. In serious cases, the student's accommodation contract will be cancelled.

[32] For some missing demographic factors, we assign mean values to these items. Specifically, 600 students (3.72%) missed information on the city of origin and we impute the city of origin indicators using the means of each indicator from the corresponding major-cohorts. Information on rural-urban residency was missing for the entire 2018 cohort. Therefore, we impute these missing values with the mean value of the full sample.

2.3. Random Assignment Tests and the Weak Variation Concern

The random assignment of roommates is critical to overcoming the selection problem when estimating peer effects. We first show a traditional balancing test in Table 1 where we regress students' own CEE scores on roommates' background characteristics. Column (1) only includes the mean of roommates' CEE scores. We further add the minimum and the maximum roommates' CEE scores in column (2), roommates' mean demographic characteristics in column (3), and dorm size fixed effects in column (4). As shown in columns (1) to (4), roommates' characteristics are not statistically significantly associated with students' own CEE scores. Considering the potential multi-collinearity of roommates' characteristics, we test the joint significance of roommates' characteristics for each regression. The corresponding p-values are presented in the last row of Table 1. The results also show that roommates' characteristics do not have strong joint predictive power for focal students' own CEE scores.

However, mechanically negative relationships could exist between one's own and peers' pre-determined characteristics even in a random assignment context as individuals cannot be their own peers. Hence, the traditional balancing test shown in Table 1 may be subject to a negative bias. We correct this bias in Table 2 following the solution proposed by Guryan, Kroft and Notowidigdo (2009). Specifically, for each characteristic "Z", such as CEE scores, an indicator of CEE scores in the top 33% within the major-cohorts, percentile ranking in CEE, CCP membership, rural residency, and an indicator of coming from the local city, we include the group level leave-one-out mean of "Z" as a control when examining the relationship between focal students' own "Z" and roommates' average characteristics of "Z".

Table 2 indicates that the relationships between own and roommates' pre-determined characteristics are not statistically significant except for column (6).[33] Although the point coefficient of interest in column (6) is statistically significant at the 10% level, it is economically small. Specifically, a one standard deviation increase in the ratio of local roommates increases the likelihood of focal students coming from the local city by 0.5 percentage points, equivalent to 1.07% of the dependent variable standard deviation (and 1.53% of its mean). In summary, after correcting the bias, Table 2 further supports the random assignment of roommates in our context.

However, when peer effects estimations are based on naturally occurring variations from random assignments, it may suffer from weak variations in peer composition. This weak sup-

[33] As shown by Guryan, Kroft and Notowidigdo (2009), when the variation in group size is small, the coefficient of the bias correction term (leave-one-out group mean of Z) approximately equals $-(\bar{N}-1)$, where $\bar{N}$ is the average group size. As the variation in group size increases, the absolute value of this coefficient declines. The average group size in our data is 32.61 with a standard deviation of 7.62.

port problem can be especially a concern for large peer groups, such as squadrons, classrooms, and dorm buildings. Angrist (2014) relates this concern to the weak-instrument type of bias and argues that, asymptotically on peer group size, the first stage disappears.

We argue that this support problem is less likely a concern in our setting. First, the peer group size in our study is relatively small, with dorm sizes ranging from four to eight. Second, the share of high-ability students varies substantially across dorm rooms. Figure A.2 panel (a) plots the distribution of the ratio of high-ability students in each dorm room based on the full sample. A large dispersion can be clearly observed with a median of 0.33, 10^{th} percentile of 0, and 90^{th} of 0.625.

Notably, part of the variation in panel (a) comes from dorm rooms of different sizes, which may be absorbed by the dorm size fixed effects. To ease the concern, we also depict the distributions of the ratio of high-ability students within a dorm room based on subsamples consisting of dorm rooms accommodating four students (panel (b)) and dorm rooms accommodating eight students (panel (c)), respectively. The dark bars represent the raw distributions and the light bars are the theoretical binomial distributions if the assignment of roommates is truly random. Two points are worth highlighting. First, variations in peer compositions remain after teasing out the factor of different dorm sizes since the dorm sizes are relatively small. Second, the fact that the raw distribution is reasonably close to the theoretical binomial distribution again is consistent with the random assignment of roommates in our context.

3. Empirical Results

To benchmark our study against the peer effects literature, in Section 3.1, we begin our analysis by estimating the average peer effects on students' academic performance. In Section 3.2, we then examine how peer effects vary with the level of competition intensity within the dorm rooms, which is the main focus of our analysis.

3.1. Benchmark Estimates

Following the peer effects literature, we first estimate the average peer effects on students' academic performance using a linear-in-means model in which we regress student's academic performance during college on their own and their roommates' pre-treatment academic ability (based on CEE score) and characteristics. Formally, the regression can be written as:

$$Y_{id} = \beta Z^{d}_{-i} + \theta_1 A_i + \theta_2 X_i + \theta_3 \overline{X}^{d}_{-i} + Group_i \times Gender_i + Size_d + \epsilon_{id} \tag{1}$$

where Y_{id} denotes the academic performance, such as the standardized GPA, of student i in dorm room d. The key independent variable of interest, Z^d_{-i}, represents peer quality in the dorm room d, measured by *either* the mean of the standardized CEE scores of student i's roommates in dorm room d *or* the leave-one-out ratio of high-ability students in dorm room d. High-ability students refers to students whose CEE scores rank in the top tercile within their corresponding major-cohorts.[34] A_i is student i's prior academic ability, measured by the percentile ranking of own CEE score within the major-cohorts. X_i is a vector of student i's demographic characteristics, including his or her rural or urban residency, his or her CCP membership before college enrollment, and a set of dummy variables indicating his or her city of origin. $\overline{X}^d_{-i}$ is a vector of the average pretreatment characteristics of student i' s roommates in dorm room d.

The coefficient of interest is β, which estimates the dorm room peer effects on the focal students' academic performance. To have a causal interpretation of β and flexible control of gender differences across majors, we include a group-gender fixed effect, $Group_i \times Gender_i$, in all of our regressions. We also include a dorm-size fixed effect, $Size_d$, to control for the direct effects of the number of roommates. To address the potential error correlation across students within a major-cohort, we cluster all standard errors at the major-cohort level. It is important to note that β only represents contextual peer effects generated by the background information (CEE score) before those students' enrollment in this university.

Table 3 reports the benchmark estimates based on equation (1). The outcome variables are measurements of students' overall academic performance at college, including their standardized GPA, their standardized GPA only for compulsory courses, their GPA percentile ranking within the major-cohorts, and whether they ranked in the top tercile within the major-cohorts. Panel A shows the results with the mean standardized CEE scores of roommates as the independent variable. We find little evidence that the average quality of roommates matters. The point estimates for all of the outcome variables are close to zero and are not statistically significant at conventional levels.

However, using the roommates' mean CEE scores as the peer quality measurement may average out the effects of roommates of various ability levels. Since competition for scholarships or top rankings may mainly occur among high-ability students, the impact of high-ability roommates is of special interest to us. Thus, we replace the average CEE scores with the share of high-ability roommates as an alternative independent variable in equation (1).

In Table 3 panel B, we find that students' academic performance is negatively correlated

[34]Our results are robust to alternative cutoffs for defining high-ability students. Details can be found in Section 3.2.

with the proportion of high-ability roommates within each dorm room. In other words, students assigned more high-ability peers perform slightly worse. Taking column (1) as an example, the point estimate equals -0.065, which is significant at the 10% level and implies that a one standard deviation increase in the share of high-ability roommates (0.237) decreases the students' overall GPA by 1.5% (=0.065$\times$ 0.237) of a standard deviation. This slightly negative peer effect remains when we switch to other academic performance measurements in columns (2) to (4), although those coefficients are small and not statistically significant. The slightly negative effects of high-ability roommates that we document are not in line with some existing peer effects studies in higher education (see Sacerdote (2014) for a review). One hypothesis is that students in our study face much more intensive competitive environments. To examine this hypothesis and, more importantly, to investigate how competition may change peer effects, in Section 3.2, we study peer effects under various contexts of competition intensity.

3.2. Peer Effects along Various Dimensions of Competition Intensity

In this subsection, we provide novel evidence on how peer effects change with competition intensity, which is the focus of our study. In theory, three main factors may intensify the competition between student i and his or her roommate j: **(1)** the expected benefit of outperforming j in pursuing scholarships or top rankings, such as the probability that i receives a scholarship or a better scholarship if i surpasses j; **(2)** the probability that i scores better than j if j performs slightly worse; and **(3)** the behavioural factors that make i more likely to compare himself with j, such as similar demographic backgrounds.

In an ideal empirical test of the impact of competition on peer effects, we additionally want students to be randomly assigned into subsets of different competition intensities on top of a random assignment of roommates. However, it is difficult to obtain such a natural experiment and to have a unified measurement of competition intensity among students. Therefore, we approximate this by exploring different dimensions of competition intensity with variations in either of the factors listed above. Along each dimension, we examine how peer effects within dorm rooms change in a more competitive environment.

We start our analysis by focusing on high-ability students. Among such students, competition effects are more salient because, first, high-ability students are more likely to be scholarship-marginal, and second, even if they perform slightly worse, middle- or low-ability students to surpass them is less likely. Consistent with the effects of competition, we only find strong negative effects of high-ability roommates on high-ability students but not on middle- and low-ability students.

However, changes in this measure of competitiveness (proxied by ability level) are, by definition, associated with changes in peer quality. Therefore, we then fix peer quality and split high-ability roommates into subgroups that generate different competition intensities due to factor 1). Specifically, high-ability roommates from the same major-cohort and from a smaller major-cohort are more likely to be direct competitors of the focal observations because the return of outranking one another is higher.[35] Consistent with the competition effects, we find stronger negative peer effects when the expected return of outranking roommates is larger.

Next, we explore variations in competition intensity within the dorm rooms due to factor **(2)**. Specifically, we use the gap in CEE scores between two students in a dorm room as an inverse measurement of the competition intensity between them. The closer their academic ability, the more likely they pass or get passed by each other, and a more competitive environment between the two students. In line with the competition-induced negative peer effects, we find that a larger gap in CEE scores is associated with better student performance.

We also explore increases in competition intensity within the dorm rooms resulting from factor **(3)**. As emphasized by social comparison theory in the psychology literature, people are more likely to compare themselves with others sharing a similar background, such as gender, place of origin, and ethnicity. Therefore, similarity among students increases the competition intensity among them. Consistent with social comparison theory and competition effects, we find significantly stronger negative effects if high-ability roommates are from the same cultural zone than if they are from different cultural zones.

We want to highlight that, although we do not have an additional layer of randomization dividing students into groups with and without competition, most of the competition intensity measurements we mentioned above are based on exogenously generated variation in the composition of roommates. To be specific, whether students are matched with roommates from the same major, from the same cultural zone, or with closer CEE scores are also exogenously generated by the randomization of roommates. Bearing in mind the aforementioned sketch and outline of our analysis, the following are the details of our analysis along each dimension of competition intensity:

a. High-ability competitors. The first piece of evidence proxies the level of competition intensity by whether students are academically strong enough to be potential competitors of high-ability roommates in pursuing GPA-based scholarships or top GPA rankings. If competition is the main driving force, we expect the negative effects reported in Section 3.1 to be larger

[35] Scholarships and rankings are evaluated within the major-cohorts at this university; therefore, it is not beneficial for top students to outrank high-ability roommates from different major-cohorts. In addition, outranking a high-ability roommate increases the chance that a student will win a scholarship more when they are from a smaller major-cohort.

among students with higher chances of winning. We thus interact the variable of interest (the share of high-ability roommates) with the tercile of a student's ability. Specifically, we utilize the following specification:

$$
\begin{aligned}
Y_{id} = \beta_1 Top_i \times Z^d_{-i} + \beta_2 Middle_i \times Z^d_{-i} + \beta_3 Bottom_i \times Z^d_{-i} + \gamma_1 Top_i + \gamma_2 Middle_i \\
+ \theta_1 A_i + \theta_2 X_i + \theta_3 \overline{X}^d_{-i} + Group_i \times Gender_i + Size_d + \epsilon_{id}
\end{aligned}
\tag{2}
$$

where Top_i, $Middle_i$, and $Bottom_i$ are indicators of whether student i, based on his or her own CEE scores, belongs to the top, middle, and bottom terciles in the corresponding major-cohort. Similar to equation (1), Z^d_{-i} refers to the leave-one-out ratio of student i's high-ability roommates in the dorm room d. High-ability roommates are defined as students with CEE scores in the top tercile within the major-cohorts. A_i is student i's percentile ranking of own CEE score within the major-cohort, measuring i's prior academic ability.[36] X_i is a vector of student i's demographic characteristics. $\overline{X}^d_{-i}$ is a vector of the average pretreatment characteristics of student i' s roommates in dorm room d. We control for a group-gender fixed effect, $Group_i \times Gender_i$, and a dorm-size fixed effect, $Size_d$. Standard errors are clustered at the major-cohort level. The coefficients β_1, β_2, and β_3 measure the effects of high-ability roommates on top-, middle-, and bottom-ability students' academic performance, respectively. As pointed out in a critical review by Angrist (2014), apart from selection and reflection problems, there are some other concerns in the peer effects estimation such as measurement errors and mechanical forces. In Section 4.3, we provide additional analyses to address those concerns.

Table 4 presents the corresponding results. Two points merit mentioning. First, as reported in column (1), the significant decreases in standardized GPA are mainly driven by the "top-top" pairs, who are more likely to be scholarship winners. The effects of the ratio of high-ability roommates on middle- and low-ability students are small and not statistically significant. One-sided tests in the last two rows reject the null hypothesis, indicating that the negative peer effects for "top-top" pairs are significantly larger than those for "top-middle" pairs and "top-bottom" pairs. Such results are consistent with the lower competition intensity between high-ability students and other lower ranked students. As argued above, even if high-ability student perform slightly worse, it is less likely for middle- or low-ability students to surpass them. In Table A.2 and Table A.3, we also show that middle- and low-ability roommates do not have negative effects on the the focal observation no matter his or her ability levels. These findings are also consistent with the idea that competition shapes peer effects since middle- and low-

[36] Our results are robust to alternative ability measurements, such as CEE scores, CEE ordinal ranking, and an indicator of CEE scores being in the top three within the major-cohorts. Detalis can be found in Section 4.5.

ability roommates are less likely to be scholarship-marginal.

To ensure that our findings are not driven by the self-selection of students into courses, in column (2) of Table 4, we recalculate the GPA by restricting it to compulsory courses. The point estimates are similar. This pattern of results is also robust to using the GPA percentile ranking and the indicator of GPA ranking in the top tercile within the major-cohorts as the dependent variables, as shown in columns (3) and (4).

Second, the coefficients of the "top-top" pairs from columns (1) to (4) are much larger than the corresponding coefficients in Table 3 panel B. Specifically, the point estimates of columns (1) to (4) are -0.160, -0.172, -0.055, and -0.088, which indicate that a one standard deviation increase in the share of high-ability roommates (0.237) decreases the high-ability students' standardized GPA, standardized GPA for required courses, percentile ranking of GPA, and the possibility of GPA ranking in the top tercile by 3.8%, 4.0%, 4.6%, and 4.3% of a standard deviation, approximately 2.5 to 5.5 times as large as that of the average treatment effect shown in Table 3 panel B. As a benchmark, based on the pre-treatment group, Carrell, Sacerdote and West (2013) find that a one standard deviation increase in the ratio of high SAT-V peers increases the GPA of low-ability students by 5.2% (=$\frac{0.464 \times 0.074}{0.661}$) of a standard deviation.

One may argue that, in Table 4, using the top tercile as a threshold to define high-ability students is arbitrary to some degree. Thus, we examine the heterogeneous effects of the top 33% roommates across different cutoffs to define high-ability focal observations. Specifically, we estimate multiple regressions using the following specification:

$$\begin{aligned} Y_{id} = \beta_{1X} TopX_i \times Z^d_{-i} + \beta_{2X} NotTopX_i \times Z^d_{-i} + \gamma_X TopX_i \\ + \theta_1 A_i + \theta_2 X_i + \theta_3 \overline{X}^d_{-i} + Group_i \times Gender_i + Size_d + \epsilon_{id} \end{aligned} \tag{3}$$

where $TopX_i$ is a binary variable indicating whether student i belongs to the top $X\%$ in a major-cohort according to own CEE scores. $NotTopX_i$ represents the complementary set of $TopX_i$. The term Z^d_{-i} still refers to the leave-one-out ratio of student i's high-ability roommates (CEE scores in the top 33% within the major-cohorts) in dorm room d. Other notations mirror those in equation (1). We estimate regressions based on equation (3) for each integer X between 3 and 99. The coefficient of interest, β_{1X}, measures the effects of the ratio of the top 33% roommates on the academic performance of students whose CEE scores ranked in the top $X\%$ within the major-cohorts. For example, the results shown in Table 4 are one specific case where X=33.

Figure 1 plots the estimated β_{1X} for each X and the corresponding 95 percents confidence intervals from the corresponding regressions, with coefficients representing the effect of the top 33% roommates on the y-axis and the indicator of the top $X\%$ students on the x-axis. From panels (a) to (d), the outcome variables in turn are the students' standardized GPA, their standardized GPA for only compulsory courses, the percentile ranking of GPA within the major-cohorts, and an indicator of GPA in the top 33% within the major-cohorts. The vertical lines at X=33 from panels (a) to (d) correspond to the estimates in the first row in Table 4.

As shown in Figure 1, our findings of negative peer effects among high-ability students are not sensitive to various cutoffs (around X=33) for defining "top" (or "high-ability") students. Moreover, the negative effects of high-ability roommates generally increase as the cutoff decreases from 99 to approximately 10. We find similar patterns of coefficients across different dependent variables in Figure 1. The pattern itself is consistent with competition-driven negative peer effects, since a smaller value of X represents students of higher ability (more likely winners of scholarships), and suggests more intensive competition between focal students and their high-ability roommates. In contrast, for X smaller than 10, the point estimates reverse toward zero as X further decreases (except for panel (d)). This pattern should be interpreted with caution, given that those coefficients are imprecisely estimated with relatively large standard errors. If anything, the diminishing effects among the highest-level students support the impact of competition on peer effects, since the competition intensity is expected to decrease in a lopsided competition in which one's ability is far above one's roommates' ability.[37]

In this part, we show that the negative peer effects are concentrated among high-ability students, who are the likeliest winners of scholarships or top rankings (as shown in Figure A.1). However, using ability level as a proxy of competitiveness is, by definition, associated with changes in peer quality. In the next three dimensions of competition intensities, we fix the peer quality and split high-ability roommates into subgroups that generate different competition intensities within the dorm rooms.

b. Size of the major-cohorts. Apart from the students' own ability, the number of competitors outside the dorm rooms may also influence the competition intensity within the dorm rooms. Since competition for scholarships and higher rankings mainly occur within the major-cohorts, a larger major-cohort size indicates a less important competition within the dorm rooms. This is because the expected benefit of surpassing roommates will be lower in a larger com-

[37] As a second check, we further relax the definition of high-ability roommates from those roommates with CEE scores in the top 33% within the major-cohorts to those roommates in the top X%. Following a similar fashion, X takes integer values between 3 and 99. Figure A.3 depicts the effects of the top X% roommates on the y-axis and the indicator denoting the top X% students on the x-axis. In line with the findings of Table 4, the plot indicates larger negative peer effects in the "top-top" pairs, in which competition is more intensive. Again, the results support the argument that competition may lead to negative peer effects.

petition pool. In other words, students from a small major-cohort are more likely to perceive roommates as their potential competitors. If this is the case, we expect stronger competition effects among smaller major-cohorts.

We directly test this hypothesis in Table 5 panel A, in which we focus on high-ability students because competition is more likely to be concentrated among the "top-top" pairs, as suggested by Table 4. We include the interaction between the ratio of the top 33% roommates and the major-cohort size to investigate the heterogeneous effects of high-ability roommates across major-cohorts of different sizes.[38] One concern is that major-cohorts of different sizes may be substantially different from each other in other dimensions.[39] We also include a full set of interactions between major dummies and the ratio of top 33% roommates. Therefore, the source of variation in the major-cohort size in the interaction term is from the variation in sizes of the same major across different cohorts.[40] In this way, we can partial out the characteristics of the majors related to both the size of the major-cohort and the effects of high-ability roommates.[41]

Table 5 shows positive significant coefficients of the interaction term between the ratio of the top 33% roommates and the major-cohort size.[42] This result implies that the negative effects of high-ability roommates decrease with the size of the competition pool. In other words, the larger the major-cohort size (the less intensive the competition within the dorm rooms) is, the smaller the negative peer effects within a dorm room. This relationship is robust to various measurements of the focal students' academic performance, as shown in columns (1) to (4). Taking column (1) as an example, the estimated coefficient suggests that a ten-student increase in the major-cohort size will attenuate the impact of the ratio of high-ability roommates on a high-ability student's standardized GPA by 0.04. This magnitude suggests that the negative peer effects among high-ability students based on the average major-cohort size reported in Table 4 column (1) will be attenuated to zero when the size of the major-cohort increases to

[38]The distribution of major-cohort size is shown in Figure A.4, with a mean of 96.33 and a median of 76. Since the marginal effect of one additional student in the same major-cohort may decrease with the major-cohort size, we also use the log major-cohort size as a robustness check to capture this potential concavity. The results are shown in Table A.4 and indicate a similar pattern.

[39]For perspective, major-cohorts of humanities majors in our sample are, on average, 15% larger than those of STEM majors.

[40]After controlling for the major fixed effect, the remaining variation in the major-cohort size has a standard deviation of 38.4, accounting for approximately 36.05% of the variation in the major-cohort size (based on the R^2).

[41]The university has 15 different schools (e.g., School of Mechanical and Electrical Engineering), and majors within each school may share similar characteristics. To allow for more variations in major-cohort size, we conduct a robustness check instead including a full set of interactions between *school* dummies and the ratio of top 33% roommates. The results are qualitatively similar and available upon request.

[42]Since the full set of interactions between *major dummies* and the *ratio of the top 33% roommates* has absorbed the estimate of the *ratio of the top 33% roommates* itself in the regression, we do not show its coefficients in Table 5 but for a reference we list the main peer effects estimated from Table 4 row 1 at the panel bottom.

136 (=96 + $\frac{0.160}{0.004}$).

If the major-cohort size serves as a reasonable proxy for the competition intensity within the dorm rooms, we expect no significant heterogeneous effects of major-cohort size for "top-middle" or "top-bottom" pairs, as competition is mainly concentrated among the "top-top" pairs. Therefore, as placebo tests, we extend the above analysis among high-ability students to middle- and bottom-ability students in panels B and C of Table 5. As expected, the interaction terms show no significant correlations between the impact of high-ability roommates and the size of major-cohorts on middle- and low-ability students. Moreover, the corresponding coefficients are much smaller in magnitude than those for the high-ability sample shown in panel A.

c. Same major-cohorts. The third piece of corroborating evidence also exploits the rules of scholarship and ranking evaluation at this university. Each year, the university assigns a quota for scholarships to each major-cohort and awards scholarships mainly based on students' yearly GPAs.[43] In parallel, the relative rankings are also calculated and announced within each major-cohort. Since students mainly compete with peers from the same major-cohort, high-ability students should face a more intensive competition if their high-ability roommates are from the same major-cohort. To test this hypothesis, we split high-ability roommates by whether they belong to the same major-cohort as the focal students and investigate how they differentially influence the focal students with high-, middle-, and low-ability. Since living with roommates from the same major-cohort may have its own effect on a student's academic performance irrespective of competition (such as being more likely to discuss lectures and homework), we also include the ratio of roommates from the same major-cohort in the regression and allow it to have different effects on students in different ability categories. As introduced in Section ref-section:background, which students are assigned roommates from different major-cohorts is also done on a random basis. It can be viewed as a second layer of randomization in which students are randomly assigned to dorm rooms of different competition intensities on top of the random assignment of roommates.

Table 6 presents the corresponding results. Notably, negative peer effects exist only when "top-top" pairs share the same major-cohort, in which competition occurs. In contrast, the point estimates turn positive if high-ability roommates are from different major-cohorts, where there is hardly any competition for scholarships or top rankings. Although imprecisely estimated, these positive estimates are qualitatively in line with some previous papers based on U.S. higher education institutions, where most dorm rooms accommodate students from different majors.

[43] Students may earn extra points through extracurricular activities, but their yearly GPA is the dominant factor in the scholarship evaluation process.

This pattern is robust to various outcomes from columns (1) to (4). Taking column (1) as an example, a 10% increase in the ratio of high-ability roommates from the same major-cohort *decreases* the high-ability students' standardized GPA by 2.1% of a standard deviation, 1.32 times as large as the effect of 1.6% in Table 4 column (1). In contrast, a 10% increase in the ratio of high-ability roommates from different major-cohorts *increases* high-ability students' GPAs by 2.0% of a standard deviation (imprecisely estimated). Moreover, consistent with the pattern in Table 4, we do not find significant effects of high-ability roommates from the same major-cohort on middle- or low-ability students, possibly because they are less likely to be potential competitors.

However, these results need to be interpreted with caution. Since only 12.8% of the dorm rooms in our sample contain students from multiple major-cohorts, the standard errors are much larger for coefficients related to different major-cohorts than for those related to the same major-cohort. As a result, it is difficult to statistically distinguish the point estimates from each other. We conduct one-sided tests to check whether the coefficients of "top-top" pairs from the same major-cohort are statistically smaller than those from different major-cohorts. The p-values are provided at the bottom of Table 6. Even in a one-sided test, only column (4) can marginally reject the null hypothesis. Although the positive point estimates for the "Top 33% X Ratio of the Top 33% Roommates with Different major-cohorts" for all outcome variables are reassuring to some extent, we consider these results to be suggestive rather than conclusive evidence on the role of competition.

d. Similarity in cultural background. Behavioural factors could also affect the competition intensity within a dorm room. In the psychology literature, social comparison theory emphasizes that the background similarity of competitors intensifies competition because people tend to compare themselves with others sharing similar attributes, such as gender, ethnicity, and place of origin (see Wood (1989) and Garcia, Tor and Schiff (2013) for comprehensive reviews). Based on this theory, we expect stronger negative peer effects among high-ability students from similar backgrounds if these negative peer effects are mainly driven by competition among high-ability students. Specifically, we consider students from the same cultural zone to have similar backgrounds. This university is located in a province with three different cultural zones. People from different cultural zones have different social customs and dialects with ancestors originating from different parts of China.[44]

[44]We first assign each county in the local province to a specific cultural zone based on the *Language Atlas of China* (2^{nd} ed.), edited by the Chinese Academy of Social Sciences in 2012. Then, we assign each student to a cultural zone based on their county of origin. Each cultural zone represents 64.66%, 23.31%, and 12.02% of our sample. The ratio of roommates from the same cultural zone ranges from 0 to 1, with a mean value of 50.74%.

Following a specification similar to that in Table 6, we split the high-ability roommates by whether they come from the same cultural zone and examine how they differently influence the focal students with high-, middle-, and low-ability. Table 7 reports the corresponding results.[45] We find negative significant peer effects only among "top-top" pairs from the same cultural zone.[46] The corresponding estimates from columns (1) to (4) are -0.356, -0.376, -0.132, and -0.175, about twice as large as our baseline estimates for the"top-top" pairs in Table 4. Taking column (1) as an example, a one standard deviation increase in the ratio of high-ability roommates from the same cultural zone (0.160) decreases the GPA of high-ability students by 5.7% of a standard deviation.

Moreover, the point estimates in row 1 (the same cultural zone) are much larger than those in row 2 (different cultural zones) and the coefficients in row 2 are not statistically significant. For perspective, the impact of high-ability roommates from the same cultural background on high-ability students' standardized GPA is 4.45 times stronger than that of high-ability roommates from different cultural zones. This pattern holds for all four dependent variables, with factors ranging from 3.04 to 6.60. We conduct one-sided tests to check whether the coefficients of "top-top" pairs from the same cultural zone are statistically smaller than those from different cultural zones. The corresponding p-values for the one-sided tests are displayed at the bottom of Table 7. The results show that the differences are statistically significant for all outcome variables in columns (1) to (4).

e. Similarity in academic ability. As argued above, students in the same dorm room are more likely to perceive each other as competitors if (1) their ability levels are closer, and (2) they are likely winners of the competition. This argument has two implications. First, because the best and second-best students in a dorm room are more likely to be high-ability students and the most-likely winners for scholarship competition among all room members, the ability gap between these two students can serve as a proxy for the competition intensity between them.[47] Second, a closer ability gap between the second- and third-best students (or the third- and fourth-best students) in each dorm room, in contrast, may not necessarily represent stronger

[45]The sample size in Table 7 decreases by 3,037 relative to that of the main results in Table 4. This is because we restrict this analysis to dorm rooms in which every room member has information on the county of origin. In Table A.5, this restricted sample is used to replicate our main results and the corresponding results are similar to those in Table 4.

[46]One-sided tests in the last two rows of the table clearly reject the null hypothesis, indicating larger negative peer effects of high-ability roommates on high-ability students than on middle- and low-ability students.

[47]The best student in a dorm room is defined as a student whose CEE scores rank first in his or her dorm room. We followed a similar rule to define the second-, third-, and forth-best students in the dorm room. In our data, according to their CEE scores, 81.10% (56.42%) of the best students (the second-best students) in each dorm room belong to the top 33% of their corresponding major-cohorts.

competition intensity between them, because in most cases they are not high-ability students (potential winners of scholarships).[48] These two implications provide us with another approach to test how competition shapes peer effects in our data.

Following the first implication, we compute the Gap_d as the difference in standardized CEE scores between the best and second-best students (from the same major-cohort) in dorm room d. A smaller gap in the standardized CEE scores represents a more competitive environment between the top two students in a dorm room. If competition leads to negative peer effects, we expect that the top two students with a larger gap in academic ability should have smaller negative peer effects and, thus, better academic performance. Specifically, we employ the following specification to examine this hypothesis:

$$\begin{aligned} Y_{id} = {} & \beta_1 Gap_d \times Best_i^d + \beta_2 Gap_d \times 2ndBest_i^d + \beta_3 Gap_d \times 3rdBest_i^d \\ & + \beta_4 Gap_d \times Others_i^d + Best_i^d + 2ndBest_i^d + 3rdBest_i^d \\ & + \theta_1 A_i + \theta_2 X_i + \theta_3 \overline{X}_{-i}^d + Size_d + Group_i \times Gender_i + \epsilon_{id} \end{aligned} \tag{4}$$

where $Best_i^d$, $2ndBest_i^d$, $3rdBest_i^d$, and $Others_i^d$ indicate whether, based on CEE scores, student i ranks first, second, third, or other among dorm room members from the same major-cohort. Gap_d measures the gap in the standardized CEE scores between the best and second-best students (from the same major-cohort) in dorm room d. Gap_d serves as an ***inverse*** proxy of competition intensity between the top two students in dorm room d.[49] Other notations mirror those in equation (1). Correspondingly, β_1, β_2, β_3, and β_4 represent the impacts of the *inverse* competition intensity between the top two students in the dorm room on the best, second-best, third-best, and other students in the same dorm room, respectively. If competition is the main diving force of the negative peer effects on high-ability students, we expect positive estimates of β_1 and β_2.

Table 8 presents the corresponding results. We find a significant positive relationship between the *inverse* measurement of competition intensity Gap_d and the academic performance of the best students in the dorm rooms. This relationship is consistent across alternative measures of academic performance across columns in the table. Taking column (1) as an example, a one standard deviation increase in Gap_d (0.823) increases the best students' GPA by 6.3% (=0.076×0.823) of a standard deviation. This pattern suggests that the best students in the

[48] In our data, according to their CEE scores, only 26.58% (9.50%) of the third-best (the forth-best) students in each dorm room belong to the top 33% of their corresponding major-cohorts.

[49] Because Gap_d is defined between the top two students from the same major-cohort in the same dorm room, we remove those who are the only students from their major-cohorts in the corresponding dorm rooms, which account for 1.77% of the observations.

corresponding dorm rooms perform better in a less competitive environment, proxied by a larger value of Gap_d. However, one may argue that a larger Gap_d may mechanically lead to a higher GPA of the best student in a dorm room irrespective of competition bacause Gap_d is, by definition, positively related to the best students' ability. To ease this concern, we highlight that all of the regressions have included students' own academic ability A_i to account for the direct relationship between students' ability and their academic performance in college. Therefore, the point estimates of the coefficients of Gap_d should be interpreted as the net effects of the ability gap, holding students' ability fixed.

Although we find significant positive effects of Gap_d on the best students' academic performance, these effects are not symmetric. First, as shown in Table 8, the effects of Gap_d on the performance of the second-best students are not distinguishable from zero and have a much smaller magnitude.[50] The asymmetric results for the best and second-best students in the dorm rooms are consistent with the theory of sabotage in tournaments. The theoretical model in Chen (2003) predicts that the total attack received by a tournament contestant increases in his or her own productive ability. Therefore, the best students in the dorm rooms, *ceteris paribus*, are more likely to be the target of sabotage and are more affected by competition than the second-best students. We also find direct evidence supporting this hypothesis in Section 4.1 using survey data on roommate interactions. Second, we also find small and insignificant effects of Gap_d on the third-best and other lower-ranked students in the dorm rooms.[51] These results can be considered as placebo tests. If Gap_d is a reasonable proxy for competition intensity, it is not expected to affect the third-best and other lower-ranked students, as it only represents the competition intensity between the top two students in the dorm rooms.

In addition, since competition can be more intensive between the best and second-best students in dorm rooms when these students have higher chances of winning scholarships, we should also expect stronger effects among the best students of higher ability. We test this hypothesis by splitting the regression sample into two subsamples based on the CEE rankings (within each major-cohort) of the best students in each dorm room. The top-half (bottom-half) sample includes dorm rooms whose best students rank above (below) the median among all of the best students in each dorm room.[52]

Table A.6 presents the results for the top-half and bottom-half samples in panels A and

[50]One-sided tests at the bottom of Table 8 indicate that the impact on the best students is significantly larger than that on the second-best students.

[51]One-sided tests in the last two rows of Table 8 also indicate that the impact of Gap on the best students is significantly larger than that on the third-best and other lower-ranked students.

[52]The best students in each dorm room in the top-half sample are 23.4% more likely to rank in the top 10% in overall GPA than those in the bottom-half sample.

B, respectively. The academic performance of the best students is positively correlated with Gap_d only in the top-half sample, whereas no significant effects are found if they are in the bottom-half sample. This pattern suggests that the positive correlation we find in Table 8 is mainly driven by the top-half sample. Echoing the results in Table 4, Table A.6 indicates larger peer effects among more likely winners of the competition for scholarships (or top rankings). Moreover, since the point estimates of $Gap \times Best$ for the bottom-half sample in Table A.6 panel B are not distinguishable from zero and, in some cases, negative, such results can also serve as a placebo test showing that the positive effects of Gap_d on the best students' academic outcomes based on the full sample in Table 8 are not mechanical.

In contrast to the gap between the best and the second-best students in a dorm room, a smaller ability gap between the second- and third-best students (or the third- and fourth-best students) may not represent a higher level of competition intensity between them, because, in most cases, they are not high-ability students and may have lower chances of winning the competition. We redefine Gap_d as the difference in the standardized CEE scores between the second- and third-best students (or the third- and fourth-best students) in dorm room d and re-estimate regressions similar to equation (4). The corresponding results are reported in Table A.7 (and Table A.8). Consistent with our expectation, the ability gap does not have significant effects on the second-best and third-best students (or the third-best and fourth-best students) in the dorm room. These results also suggest that the ability gap between two students can be interpreted as a proxy for competition intensity only if the two students are good enough to be likely winners of a scholarship. The insignificant effects of the redefined Gap_d in Table A.7 (and Table A.8) also confirm that the positive effects documented in Table 8 are not mechanical. If the positive effects documented in Table 8 were the results of mechanical reasons, we would also expect positive significant effects of redefined Gap_d on the second-best (or the third-best) students.

Summary. Thus far, we have examined peer effects under various dimensions of competition, and the tests consistently show that negative peer effects become more pronounced in more competitive environments. Taken individually, each piece of empirical evidence may not be sufficient to establish that competition changes peer effects. However, taken together, the weight of the evidence supports that competition induces negative peer effects. This further corroborates our conjecture that the finding of negative peer effects, different from that in most existing studies, may be the result of intensive competition in our setting.

4. Discussion

In this section, we first discuss the potential mechanisms through which competition may lead to negative peer effects. Next, we rule out alternative explanations other than competition, such as grading on a curve, lower self-esteem, and mean reversion. Finally, we discuss the heterogeneity, robustness, and external validity of our main results.

4.1. Potential Mechanisms

In the previous section, we have shown that competition induces negative peer effects among roommates. Here, we propose and examine several non-mutually exclusive mechanisms of why competition may lead to negative peer effects.

To examine potential mechanisms, we designed a survey to measure the following student characteristics: attitudes toward scholarships and competition, time allocated to study and other activities, psychological status, and peer interactions with roommates based on their experience in the 2018-2019 academic year. The survey was distributed and collected by the administrative staff of the university and targeted undergraduate students enrolled between 2016 and 2019.[53] The survey was conducted online in the spring semester in 2020.[54] The average response rate of the survey reached 49.1%.[55] We link the survey data to the students' administrative data including their background characteristics, transcripts, and dorm assignments. Following the same selection procedure applied in the main sample construction, we exclude students from other provinces and from majors that admit both STEM and humanity tracks, and we are left with 2,534 surveyed students with merged administrative data.[56]

Since each dorm room may accommodate four to eight students, it is infeasible to survey how each pair of roommates interacts. As a result, we focus on how a student interacts with his or her roommate with the best academic performance, who is more likely to be a competitor for scholarships (or top rankings). Before asking questions about roommate interactions, we provided the surveyed students with the following instructions: "For the next few questions, please think about the roommate who has the best academic performance excluding yourself."

[53] Although students in the 2019 cohort were targeted by the survey, they are not included in our analysis because we do not have administrative data on them.

[54] The survey was conducted online during the coronavirus pandemic when students were under home quarantine. Therefore, at the beginning of the survey and at the beginning of each related question, we reminded the respondents that their answers should be based on their campus experience in the previous semester.

[55] The response rates for the 2017 and 2018 cohorts were 46.7% and 74.5%, respectively, whereas the response rate for the 2016 cohort was only 26.0%.

[56] In Table A.9, we replicate our main results using this merged survey sample. Compared with the results in Table 4 and Table 8, the estimated coefficients in Table A.9 based on surveyed students are slightly larger in size and are less precisely estimated.

Because of the privacy requirements of the university we study, in the survey, we were not allowed to ask the respondents to directly name the roommate with the best academic performance (referred to as "the best roommates" hereafter). To have a better sense of data quality, we then required all respondents to choose from one of two options: "I am clear about who is the roommate with the best academic performance" or "I have more than one roommate with exceptional academic performance. I will randomly choose one of them as the subject of the following questions."

Approximately 43.4% of the respondents (1,104 out of 2,541) state that they are unsure about who are the best roommates in the dorm rooms.[57] These students are more likely to come from larger dorm rooms and have less competitive attitudes, such as feeling that it is less important to surpass competitors.[58] We expect noisy estimates for the sample of students who are uncertain about the best roommates' identity for two main reasons. First, misidentifying the best roommates can introduce measurement error into the analysis as we aim to understand how students interact with the best roommates. Second, when students are unsure about who are the actual best roommates, they may choose the roommates with whom they are closer as the subject of the questions. Therefore, in the following mechanism analysis, we mainly focus on the students who have clear perceptions about their best roommates, which leaves us with 1,437 observations in the regression sample (*top-known sample*). We also show results based on the sample of students who are unclear about the best roommates in the dorm rooms (*top-unknown sample*).

a. Peer interactions. It is well-established in theory that competition may decrease the incentive to help one another (Drago and Garvey, 1998) and may even induce sabotage among competitors (Lazear, 1989). High-ability students may perceive each other as competitors for scholarships (or top rankings) and, thus, may refuse to help each other or even sabotage each other in their academic pursuits. To test this hypothesis, we exploit a specification that mirrors the one in Table 8 based on equation (4). As before, we use Gap_d, the differences in standardized CEE scores between the best and second-best students in dorm room d, as an *inverse* proxy of competition intensity between the top two students in this dorm room. We then examine the

[57]Their uncertainty about the identity of the best roommates suggests that some of them do not pay attention to the public ranking (GPA) announcements at the end of each academic year. Two factors may even exacerbate this situation. First, the survey was conducted in May and June, nearly a year after the previous public announcement. As a result, the students may not clearly remember their roommates' academic performance. Second, the survey was conducted online during the coronavirus pandemic period, during which students had been isolated at home for nearly five months. Being away from campus life and roommates for long stretches of time may have led to their vague impression about who are their best roommates.

[58]Table A.10 compares the statistics of the surveyed students who are clear about the identity of their best roommates in the dorm rooms with students who are not.

impacts of Gap on how the best, second-best, third-best, and other students in each dorm room interact with their best roommates, respectively.

Table 9 presents the corresponding results for peer interactions. The dependent variables in columns (1)-(3) are three different measurements of positive peer interactions based on the survey responses. In the survey, we provide each respondent with a list of nine different activities in which one may engage with his or her best roommate, such as studying, dining out, shopping, exercising, or participating in extra-curricular activities. We calculate the number of activities they frequently participate in together as a measurement of the closeness between them, denoted by "Interactions" in column (1). We also asked each respondent about the frequency with which he or she discussed studies with his or her best roommate and how helpful the best roommate was. We further convert these two questions into dummy variables "Discuss Study" and "Help" in columns (2) and (3) for easier interpretations.[59] The dependent variables in columns (4)-(6) are unfriendly behaviors from roommates. In the survey, we provided each respondent with a list of ten different types of unfriendly behaviors, such as "refused to answer my questions about study", "affected my daily routine" and "engaged in physical conflict with me". We asked each respondent to choose all of the unfriendly behavior from his or her best roommate against the respondent. We then categorize those ten behaviors into three groups: "Isolate", "Confront", and "Disturb". Each category is coded as a dummy indicator of experiencing any unfriendly behaviors included within the corresponding category.[60]

The results in Table 9 panel A suggest that the relationship between the best student in a dorm room and his or her best roommate significantly improves in a less competitive environment.[61] In such an environment, the best students in dorm rooms have more daily interactions and discuss studies more frequently with their best roommates. They also consider their best roommates to be more helpful. These effects are not only statistically significant at the 5% level but also economically meaningful. Specifically, from columns (1) to (3), a one standard

[59] To be specific, "Discuss Study" equals one if the respondents *always* or *often* discussed academics (e.g., homework and classes) with their best roommates and equals zero if the answer is "occasionally", "rarely", or "never" . "Help" equals one if the respondents consider their best roommate to be *very helpful* or *somewhat helpful* in general. And it equals zero if the answer is "neither helpful nor unhelpful", "somewhat unhelpful ", or "very unhelpful".

[60] To be specific, "Isolate" takes the value of one if the respondent has ever encountered the following problems from his or her best roommates: "refusing to answer my questions about studies", "refusing to share study resources such as learning notes, "being isolated", and "being gossiped about". "Confront" equals one if the respondent have ever encountered the following problems from his or her best roommate: "quarrelling with me or abusing me", "threatening me", and "engaging in physical conflict with me". "Disturb" equals one if respondents has ever encountered problems from his or her best roommates including "interrupting my study" and "affecting my daily routine".

[61] The best student in a dorm room is defined as a student with the highest CEE scores among all of the members living in the dorm. Gap is an inverse measurement of the competitiveness between the top two students in the dorm rooms. The larger the value of Gap is, the lower is the level of competition intensity.

deviation increase in Gap (0.905) increases the dependent variables by 12.5%, 11.3%, and 13.5% of a standard deviation, respectively. In addition, in a less competitive environment, the best roommate is less likely to isolate or to disturb the best student. For example, a one standard deviation increase in Gap (0.905) decreases the probability of being isolated by the best roommates by 2.53 percentage points, representing a 30.63% decrease relative to the average probability of being isolated among the best students in each dorm room in the top-known sample (8.26 percentage points).

We also highlight that the pattern of peer interactions in Table 9 panel A is remarkably consistent with that of academic performance in Table 8. The ability gap between the best and the second-best students in a dorm room affects only the outcome variables of the best student in a dorm room. In summary, the results suggest that competition intensity directly changes how peers interact with each other and peer effects.

In Table 9 panel B, we replicate our analysis for the sample in which the surveyed students are not certain about the identity of their best roommates. As expected, we do not find economically or statistically significant effects of Gap on various aspects of the interactions between the best students and their best roommates.

b. Psychological feelings. Competition also could lead to worse academic performance by influencing students' psychological feelings. For example, students may feel more stressful or have more fragile self-esteem when competition intensifies. Similarly, we use Gap as an inverse proxy for competition intensity between the best and the second-best students within the dorm rooms. The psychological feelings we focus on are the motivation, stress, and lack of confidence brought about by the best roommates. Specifically, we ask the students to evaluate the degree to which the best roommates make them feel motivated, stressed, and lacking in confidence. For each of these feelings, in the regression analysis, we define strong feelings as ones and neutral or below as zeros.[62] Table A.11 provides the corresponding results for both the top-known sample (panel A) and the top-unknown sample (panel B). We find that the students' psychological feelings do not significantly vary with the competition intensity between the top two students in a dorm room in both panels A and B; that is, they are not less motivated, more stressed, or less confident. Such results suggest that negative psychological feelings are unlikely to play an important role in how competition changes peer effects.

[62]For example, the surveyed students are asked, "How motivated or unmotivated did "the roommate with best academic performance in your dorm room" make you feel in the last semester?"; they are allowed to choose one option from "Very motivated", "Somewhat motivated", "Neither motivated nor unmotivated", "Somewhat unmotivated", and "Very unmotivated". We assign a value of one to students who choose "Very motivated" and "Somewhat motivated" and assign a value of zero to those who choose the other options.

c. Effort reallocation. Competition has also been shown to have discouraging effects on effort, especially for those with a lower likelihood of winning (Brown, 2011; Fang, Noe and Strack, 2020). Students living with high-ability roommates may strategically reallocate their effort to other domains, such as student organizations, part-time jobs, and internships, which could also be beneficial to their long-term labor market outcomes. They may even give up the competition and spend less effort on academic pursuits to avoid direct competition with high-ability roommates. If this is a driving force of the negative peer effects, we expect high-ability students to spend more time on tasks other than studies when competition intensifies. To test this hypothesis, we employ a similar specification using the indicator Gap as an inverse proxy for competition intensity among the top two students within the dorm rooms. The outcome variables are the hours the surveyed students spent playing games (daily), studying (daily), participating in student organizations (weekly), and working at a part-time job or internship (weekly). Table A.12 provides the corresponding results for both the top-known (panel A) and top-unknown samples (panel B), We find that focal students spend neither less nor more time on other tasks when Gap decreases in both panels A and B. These results do not support the effort reallocation mechanism.

4.2. Alternative Explanations Other than Competition

The results in Section 3 are consistent with competition-driven negative peer effects. In this subsection, we consider and rule out some other potential explanations that could be consistent with some of our main results.

a. Grading on a curve. Grading on a curve is prevalent in institutions. This relative evaluation practice may mechanically lower the GPA of some students with similar academic performance. We argue that, for several reasons, grading on a curve is very unlikely to be the driving force of the negative peer effects that we document.

First, this university has no policy requiring grading on a curve of any kind. It neither has any preset quota for the ratio of students receiving a specific grade nor limits the percentage of students above or below specific cutoffs. However, the absence of a related policy cannot guarantee the absence of faculty members actually practicing it on their own. Indeed, the university vice-principal believes that it is common for faculty members to adjust the grades of students on the margin of failing the course. Because the negative peer effects that we discovered are mainly concentrated on the top students, the grade adjustment at the bottom should not be a driving force of our results. The university vice-principal also believes that, at this university, it is not common for faculty members themselves to preset any limits on the ratio of students with good grades.

Even if some faculty members grade on a curve, it should have a much larger effect in the categorical grading system (such as letter grading) than in the continuous grading system (from 0 to 100) applied in this university.[63] This is because adjustments in categorical grades have a much larger influence on students' GPA than those in continuous grades. For example, the difference between an A and an A- is reflected in the GPA as a gap of 0.3 out of 4, which represents 7.5% ($\frac{0.3}{4}$) of the full scale. However, it has a minimal effect on continuous grades since it most likely introduces a gap of only one or two out of one hundred points.

Although the university applies a continuous grading system, grading on a curve remains a concern if grades are concentrated at some specific grade points, making the continuous grading system essentially categorical. Figure A.5 displays the distribution of students' grades in each module. It shows a reasonably smooth distribution for grades above 60, which largely eases this concern. The apparent discontinuity at grade 60 is also consistent with the vice-principal's statement about the adjustment for students on the margin of failing the course.

b. Lower self-esteem In the main results, we show that living with more high-ability roommates decreases the academic performance of high-ability students. One may argue that the negative peer effects may be driven by students' lower self-esteem rather than by competition. The existence of roommates of superior ability might lower students' self-esteem and, consequently, reduce their academic performance.

Our results are inconsistent with this mechanism. Table 8 demonstrates that only the best students' academic performance are influenced by the ability gap between the top two students in the dorm rooms while the second-best students are unaffected. The finding that only the best students respond to the ability gap directly refutes the alternative explanation that the second-best students' lower self-esteem for facing superior roommates (the best students) leads to the negative peer effects we document. However, it is also possible that the best students' worse performance is the result of their potential fragile self-esteem. Namely, the existence of roommates of similar ability living in the same room may engender the best students' negative emotions, such as stress, anxiety, and lack of self-confidence, reducing their academic performance. This hypothesis is not consistent with the results in Table A.11, which shows that the best students' psychological feelings such as motivation, pressure, and confidence are not significantly related to the ability gap between the top two students.

[63] This university applies the continuous grading system from 0 to 100. When calculating the ranking and the total GPA, they use the original continuous grading system without converting it to a categorical grading system.

c. Potential competitors or just similarity In Section 3.2, we find that negative peer effects are mainly concentrated among high-ability students. We interpret this phenomenon as a higher level of competition intensity resulting from high-ability students' better chances of ranking at the top or winning scholarships. However, this phenomenon is also consistent with another explanation that a higher level of competition intensity is simply due to their similarity in ability, but not necessarily a result of their ranking as top students who are potential competitors of scholarships or top rankings.

If the results are solely driven by similarity independent of students' superiority, we should also expect significant peer effects of low- (middle-) ability roommates on low- (middle-) ability students. However, the results in Tables A.2 and A.3 conflict with this hypothesis. The coefficients of interest displayed in the second and third rows are close to zero and not statistically significantly different from zero at conventional levels. The findings suggest that similarity in ability is not sufficient to generate negative peer effects. Such effects exist only if students are similar to roommates in the sense that they are all of high ability.

This evidence further rules out the mechanism of grading on a curve as a driver of our results. If faculty members squeezing or decompressing the grade distribution was the main driving force, we would also observe negative peer effects among "middle-middle" and "bottom-bottom" pairs, who have similar but relatively lower academic ability.

d. Mean reversion One may also argue that mean reversion could explain the decrease in high-ability students' academic performance. These students might outperform their baselines in the CEE and then return to their normal performance level in college. However, mean reversion is highly unlikely to be the driving force of the negative peer effects among high-ability students. First, the positive relationship between percentile ranking in CEE and standardized GPA (as shown in Figure A.1) does not support the mean reversion hypothesis. Second, even if mean reversion occurred, it would not drive our estimates as long as focal students' overperformance in the CEE is orthogonal to the ratio of high-ability roommates in the dorm rooms. Although we cannot directly test this orthogonality because of the unobservability of overperformance in the CEE, the random assignment of roommates at this university should largely ease this concern.

4.3. Other Concerns of Peer Effects Estimations

Angrist (2014) shows, building on earlier work by Acemoglu and Angrist (2000), that measurement error in pre-treatment ability can lead to overestimation or underestimation of peer effects because the measurement error in pre-treatment ability enters the equation in both own ability and peer ability measurements. Feld and Zölitz (2017) further show that measurement error only leads to attenuation bias if the peer group assignment is random and can lead to substantial overestimation of peer effects in settings in which peer group assignment is systematic. While CEE score is a noisy measurement of academic ability, the measurement error should lead to attenuation bias in our context, since the assignment of students to dorm rooms is random. Therefore, the true effects may be even more negative than what we estimate.

To directly show that the measurement error should lead to attenuation bias in our context, following the spirit of Carrell, Hoekstra and Kuka (2018), Feld and Zölitz (2017), and Merlino, Steinhardt and Wren-Lewis (2019), we re-estimate the model by introducing varying amounts of measurement errors into student CEE scores. Specifically, we add noise that is distributed $N \sim (0, X\%)$ to the raw standardized CEE score, where X=10, 30, 50, ..., 150. The larger value of X, the more measurement errors we artificially introduce in the academic ability measurement. In other words, the artificial errors range from 10% to 150% of the standard deviation of the authentic standardized CEE scores. For each X, we recalculate students' relative rankings based on these noisy CEE scores and re-estimate equation (2). We conduct this exercise 1,000 times for each X and plot the average coefficient (and 5th and 95th percentiles) of β_1 generated in this process for each X in Figure A.6. As a reference, the estimated β_1 of column (1) Table 4 is indicated at X=0, where the authentic CEE scores are used. As Figure A.6 shows, the average point estimates decreases with X as we introduce more measurement errors. This finding is consistent with dorm room assignment being random and shows that measurement errors bias our results toward zero. Hence, our estimates can be viewed as lower-bond estimations of the effects of high-ability students.

To further address the mechanical bias in peer effect estimation arising from measurement error in both peer and own ability measurements, we follow the simulation-based falsification test in Bietenbeck (2020) and randomly group students from the same major-cohort into dorm rooms such that students are assigned to a group of "placebo" roommates with whom they may not interact as roommates in the real world. We then re-estimate the impacts of "placebo" roommates on students' overall GPA based on equation (2), with standardized GPA as the dependent variable. Any effects of the high-ability placebo roommates on high-ability students (β_1) should reflect bias from mechanical forces. We replicate this exercise 10,000 times and show the distribution of the estimated β_1 in Figure A.7. The vertical line in the figure indicates the estimated β_1 of column (1) Table 4 based on the authentic assignment of roommates. The true coefficient is clearly an outlier, as it is smaller than 99.8% of the placebo coefficients. This finding suggests that the negative effects of high-ability roommates are not the result of mechanical forces.

4.4. Heterogeneity

In this subsection, to study potential heterogeneous peer effects, we re-estimate equation (2) with different subsamples. Specifically, we focus on heterogeneity with respect to gender and major (STEM versus humanity). Figure 2 summarizes the corresponding results, with the coefficients representing the effects of high-ability roommates on the y-axis and the indicators for different subsamples on the x-axis. Panels (a) to (d) correspond to different outcome variables, including the standardized GPA, standardized GPA only for required courses, percentile ranking of GPA within the major-cohorts, and the possibility of ranking in the top tercile within the major-cohorts, respectively. Each bar in each panel represents the coefficient β_1 in equation (2) on the corresponding dependent variable and subsample.

We first examine the heterogeneous effects by gender. Extensive literature investigates gender differences in competitiveness attitudes, and mixed results across different cultures have been found. Even within Chinese culture, the gender gap in willingness to compete varies significantly across ethnic groups and locations. Based on data from Yunnan Province, Zhang (2019) finds that males are more competitively inclined than females in some minority groups in China (Yi and Mosuo). In contrast, she also documents negligible gender differences in competitiveness attitudes among Han Chinese people from the same location. Booth et al. (2019) find that females in Beijing are more competitively inclined than their male counterparts but find no statistically significant gender difference for Taipei. Because the dominant majority of students at the university we study are Han Chinese and this university is geographically and culturally closer to Taipei than Beijing, based on the results of Zhang (2019) and Booth et al. (2019), we expect a small gender difference in competitiveness attitudes among students at this university. Consistent with the expectation, we find that the negative effects of high-ability roommates are similar for male and female high-ability students across the four outcome variables. Although the point estimates are slightly higher for male students, the differences are not statistically significant from one another.

Turning to the heterogeneity across majors, we find consistently larger effects for students from STEM majors. Even for the standardized GPA (panel (a)), for which the difference between the estimates for STEM students and those for humanity students is the smallest among the four dependent variables, the estimated effects for humanities students are approximately half of those for STEM students. The point estimates for humanities students are quite close to zero when the outcome variable is the standardized GPA only for required courses (panel (b)) and become positive when the outcome is an indicator of the GPA ranking in the top 33% (panel (d)). Such heterogeneity may be driven by STEM students caring more about scholarships (or GPA and top rankings) than humanities students. This argument is supported by the survey evidence. We find that STEM respondents are 24.5% more likely to agree that students should compete for scholarships than are humanities respondents.[64]

We propose two potential reasons that explain these differences in competition attitudes. First, students from STEM majors might be more likely to apply for jobs emphasizing analytical skills, which can be easily reflected in students' GPA. In contrast, students from humanities majors may be more likely to apply for jobs emphasizing social skills, which are barely reflected in GPA. As a result, STEM students may care more about their GPA and ranking than humanities students. Second, grading may be more objective for STEM students. Therefore, GPA could be a better reflection of the academic ability of STEM students than that of humanities students.

4.5. Robustness

In this subsection, we show that our main results are robust to a number of sample selection procedures, alternative specifications, and alternative standard error estimation assumptions.

First, in Table A.13, we re-estimate equation (2) under different sample selection procedures, with standardized GPA as the dependent variable. As a reference point, column (1) replicates the main sample results in column (1) of Table 4. The sample used in column (1) includes both students who had graduated and students who had not finished college at the time of the data collection. Therefore, our performance measurements, such as standardized GPA and GPA ranking within the major-cohorts, consist of the four-year academic performance of graduated students as well as the one- to three-year performance of then-enrolled students at the time of the data collection. This may raise an issue of comparability. As a robustness check, in column (2), we restrict the sample to graduated students only. The estimate is similar to that in column (1).

Since the CEE scores are not comparable across different provinces, we restrict our main sample to students from the local province. We calculate the dorm room characteristics and roommate compositions without considering students from other provinces (approximately 5%

[64] In comparison, in the survey sample, male respondents are only 11.9% more likely than female respondents to agree that students should compete for scholarships, suggesting that male and female students have limited differences in attitudes toward scholarships, which is consistent with the insignificant heterogeneous effects by gender we find above.

- 10% of students at the university are from other provinces). This practice could induce measurement error, although the randomness of dorm assignments may ease this concern to some degree. In column (3), we restrict the sample to dorm rooms without any students from other provinces, and the results are robust.

Less than 3% of students in our data have ever switched dorm rooms. To address the endogenous switching of dorm rooms, in the previous analysis, we define each student's roommates according to his or her initial dorm room assignment. However, this practice makes our estimations a *de facto* "intention-to-treat effect" and may be subject to attenuation bias. Although less than 3% of students changed dorm rooms, those students may affect the roommate compositions of other students in the original dorm rooms as well as newly assigned dorm rooms. This is of particular concern given that each dorm room has four to eight students. As a robustness check, in column (4), we drop all dorm rooms containing students who had ever switched roommates. The estimate should measure the "treatment-on-treated effects" on this subsample, and the results are similar to those in column (1).

Next, in Table A.14, we conduct robustness checks of our main findings by altering the specifications. For ease of comparison, column (1) replicates the results from the baseline specification in column (1) Table 4. In columns (2), (3), and (4), we remove the demographic controls, dorm-size fixed effects, and both, respectively. Given the randomness of the dorm assignment, our estimates should not be sensitive to those exclusions. As expected, the results are robust to those in column (1), supporting the validity of our identification strategy. In addition, we re-estimate the regression using alternative controls of focal students' prior academic ability. We replace the percentile ranking of own CEE scores within the major-cohorts by own CEE scores in column (5) and the ordinal ranking of own CEE scores within the major-cohorts in column (6). The new estimates are similar in both size and statistical significance. Considering that "being top" itself may have lasting impacts on school achievement independent of underlying ability (Murphy and Weinhardt, 2020), in column (7) we additionally include an indicator of CEE scores being the top three within the major-cohorts, and the result is robust.

Finally, we present standard errors for the main results under various clusters. Throughout the analysis, we cluster the standard error at the major-cohort level at which competition among students occurs. In TableA.15, we present standard errors for the main results under various clusters, such as major, group, and dorm room in columns (2), (3), and (4), respectively. The precision and statistical significance of the estimates remain similar.

4.6. *How Significant is the Role of the Public Announcement of Rankings?*

As introduced in Section 2.1, one feature of the university is the public announcement of students' GPA and rankings at the end of each academic year. Since this practice is uncommon in developed countries, it raises an external validity concern that our results may be driven mainly by precise information on close competitors' performance and identities. We directly test this possibility by examining the dynamic effects over college years. Since the first publication of one's GPA and ranking occurs at the end of one's freshman year, we should not expect strong negative effects of high-ability roommates on high-ability students' first-year performance if the precise information in the public announcement drives our results.

Figure A.8 reports how peer effects vary by college year based on equation (2), in which the dependent variable is replaced with performance during each college year.[65] The dependent variables are the standardized GPA for the corresponding academic years. The effects of high-ability roommates on high-ability students' first-year GPA are significantly negative with a magnitude of 0.148, similar to the corresponding estimate in Table 4. Moreover, the negative peer effects of high-ability roommates are persistent during college, despite some fluctuations in point estimates. This finding implies that negative peer effects among top students exist even before the first GPA and ranking announcement, suggesting that the negative peer effects are not driven mainly by the precise information of close competitors. Students may already have a sense of their roommates' academic ability based on everyday interactions. Although we rule out the effects of precise information, it is still possible that the public announcement of performance plays an important role in generating negative peer effects by making competition more salient to all students. In particular, senior students may inform freshmen students of the coming public announcement of their performance.

Furthermore, we highlight that this publication practice is quite common in schools in China, which has the world's largest education system. According to a survey conducted by the social survey center of China Youth Daily and involving 2,001 respondents in 2018, 74.4% of respondents stated that their local schools publicly announced students' grades or rankings.[66] The publication of performance is also widespread in workplace competition worldwide, although this practice is not common in developed countries' education systems.

[65] Panel (a) reports the dynamic pattern for the full sample. Since enrolled students have only one to three years of academic performance during college, we also show the results of the balanced sample in panel (b) by restricting the analysis to students with data on all fours years of academic performance.

[66] Source: http://www.chinanews.com/gn/2018/03-06/8460560.shtml.

5. Conclusion

Despite a rich body of literature on peer effects, evidence on how competition changes peer interactions and peer effects remains scarce. We rely on administrative data from a university in China to study peer effects under competition on students' academic performance. To the best of our knowledge, we are the first to show that the direction and magnitude of peer effects are functions of competition intensity among students and shape how students interact with each other.

By exploiting the random assignment of roommates within major-cohort groups, we first document that the presence of high-ability peers in a dorm room has significant negative effects on the academic performance of students living in the same dorm room. More importantly, such negative effects vary with the degree of competitiveness, which is measured in five different dimensions: (a) high-ability competitors; (b) size of the competition pool; (c) same major-cohorts; (d) similarity in cultural background; and (e) similarity in academic ability levels. The results from these different measures consistently show that a more competitive environment results in more negative peer effects in dorm rooms. To further lend support to the competition hypothesis, we rule out other possible channels, such as grade on a curve, lower self-esteem, mean reversion, measurement errors, and mechanical forces.

To shed light on how competition may influence outcomes, we conduct a follow-up survey among currently enrolled students at the university and ask them about their peer interactions with roommates. We find that competitive environments reduce helping and increase unfriendly behaviors among roommates. We provide evidence that competitive environments may directly change how peers interact with each other and, thus, shape peer effects.

Our findings show that peer effects are endogenous to the environment of the peer group. From a policy perspective, institutions could set incentives that determine the magnitude and even the direction of peer effects. Therefore, it is important to consider the policy impact on peer effects in universities' future policy making. In fact, this study has important policy implications for not only China but also other countries, especially developing countries that have also experienced massive competition for limited education resources. Attention should be given to addressing possible adverse peer effects on the academic performance of high-ability students facing fierce competition. Some of our results also suggest a low-cost way to ease the competition intensity within a dorm room and potentially improve student performance in China. For example, having more mixed-major dorm rooms may avoid direct competition among roommates. However, as Carrell, Sacerdote and West (2013) shows, designing the optimal dorm room assignment policy should be done cautiously.

One limit of our analysis is that we cannot distinguish whether the negative peer effects are driven by competing for the scholarship or for top rankings in GPA. Understanding the source of competition can be of particular interest and important for the relevant university policies, such as setting up scholarships and publicly announcing GPA rankings. Another limitation is that we only consider college students' academic performance as outcome variables. Investigating how competition influences peer effects on other outcomes such as students' job market results and subjective well-being may be important topics for future research.

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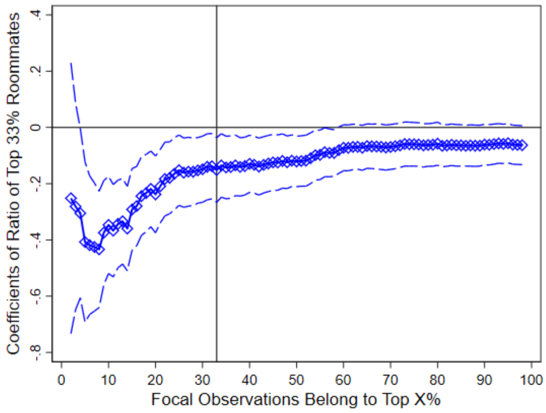
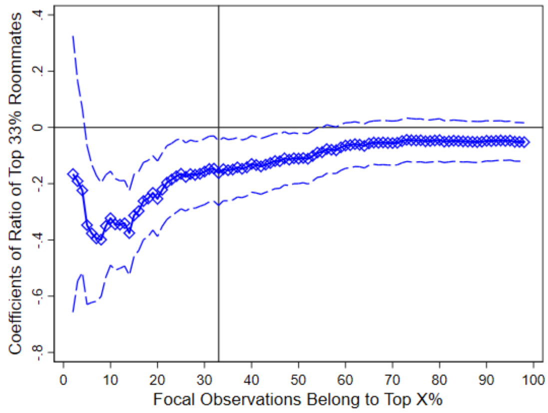
Figure 1: The Effects of High-Ability Roommates on Students in the Top X%

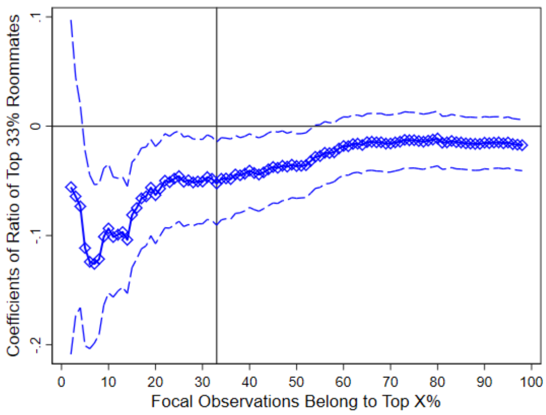
(a) Standardized GPA



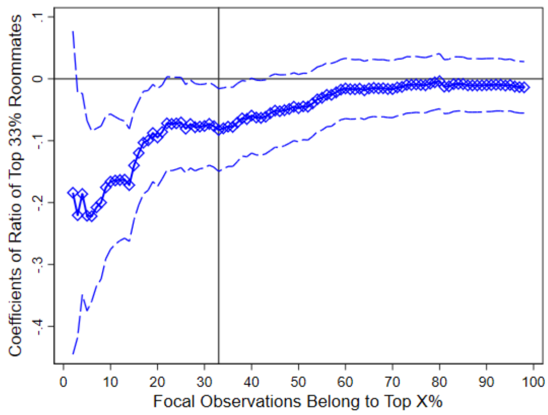
(b) Standardized GPA (Required Courses)



(c) GPA Percentile Ranking

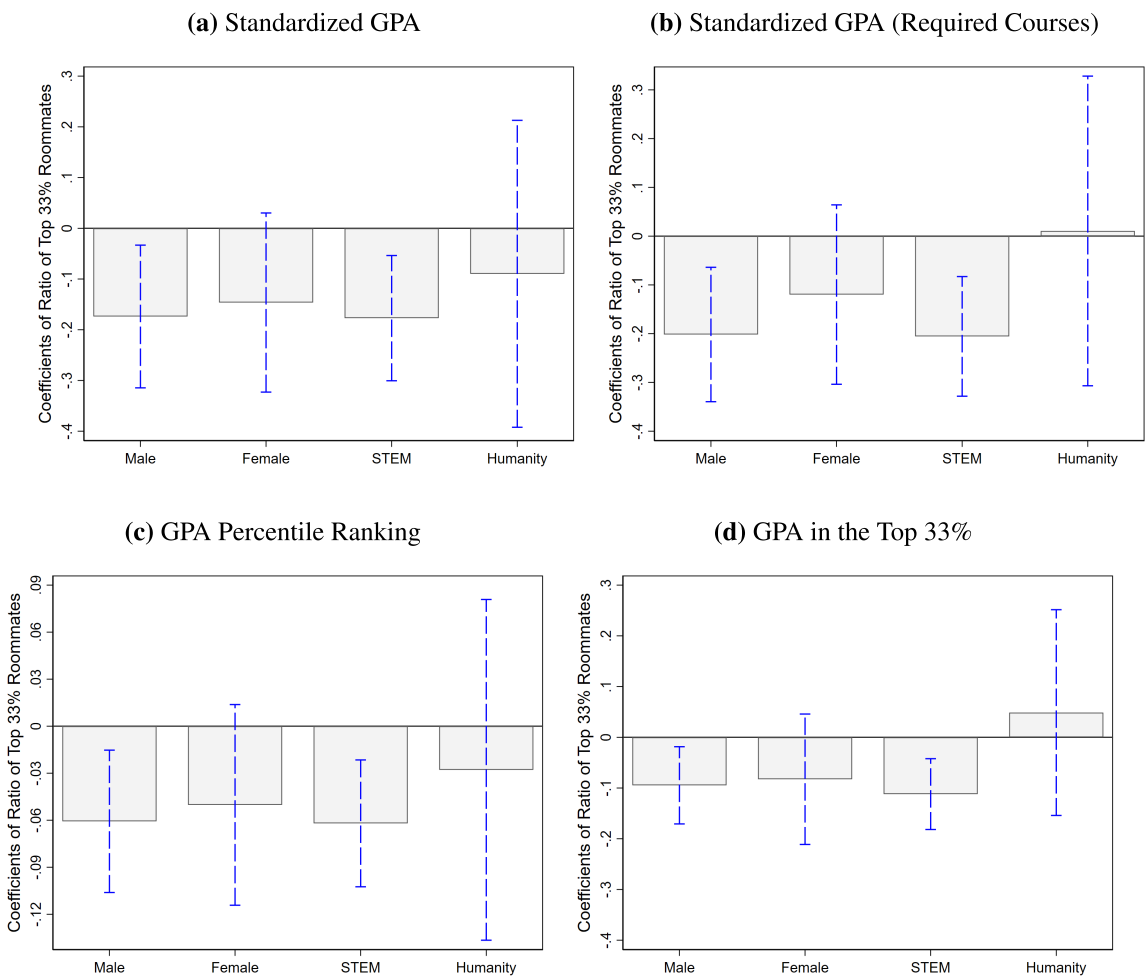


(d) GPA in the Top 33%



Notes: This figure plots the estimates of the coefficients on the proportion of high-ability roommates (CEE scores in the top 33% of the major-cohort) for students with various levels of academic ability (CEE scores ranking in the Top X% of the major-cohort, and integer X ranging from 3 to 99) and their 95% confidence intervals. The vertical lines denote X=33, the cutoff we use to define "high-ability students" in the main analysis. The horizontal lines denote the impact of zero. The outcome variables from panel (a) to panel (d) are the focal students' standardized GPA, standardized GPA only for required courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. The specifications replicate those in Table 3. Robust standard errors are clustered at the major-cohort level.

Figure 2: Heterogeneity by Gender and by Major



Notes: This figure plots the estimates of the coefficients on the proportion of high-ability roommates (CEE scores in the top 33% of the major-cohort) across genders and across majors. The dashed lines denote the 95% confidence intervals. The horizontal solid lines denote the impact of zero. The outcome variables from panel (a) to panel (d) are focal students' standardized GPA, standardized GPA only for required courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator of the overall GPA being the top 33% of the major-cohort. The specifications replicate those in Table 3. Robust standard errors clustered at the major-cohort level.

Table 1: Balancing Test - Basic

	(1)	(2)	(3)	(4)
Dependent Variable:	CEE	CEE	CEE	CEE
Roommates' CEE Scores (Mean)	-0.034	-0.049	-0.051	-0.053
	(0.048)	(0.116)	(0.117)	(0.118)
Roommates' CEE Scores (Min)		-0.003	-0.004	-0.004
		(0.055)	(0.055)	(0.055)
Roommates' CEE Scores (Max)		0.018	0.019	0.020
		(0.051)	(0.052)	(0.053)
Ratio of Local Roommates			-0.076	-0.070
			(0.485)	(0.485)
Ratio of Rural Roommates			0.334	0.343
			(0.317)	(0.320)
Ratio of CCP Roommates			0.212	0.245
			(0.630)	(0.629)
Group FE	Yes	Yes	Yes	Yes
Drom Size FE	No	No	No	Yes
Observations	16,116	16,116	1,6116	16,116
R-Squared	0.959	0.959	0.959	0.959
Joint Test (p-value)	0.477	0.843	0.904	0.896

Notes: Columns (1)-(4) each present results from a separate OLS regression. The outcome variables are focal students' academic ability, measured by their CEE scores. The independent variables of interest, indicated in the row entries, include roommates' academic ability (CEE scores in mean, maximumand minimum values) and roommate demographic factors (the ratio of *local*, *rural*, and *CCP* roommates in the dorm rooms). *Local* is an indicator of a student from the local city. *Rural* is an indicator of a student from a rural area. *CCP* is an indicator of being a member or youth member of the China Communist Party at enrollment. All regressions control for the group fixed effects. Column (4) additionally controls for the dorm size fixed effects. Robust standard errors clustered at the major-cohort level are shown in parentheses. The p-values for joint tests are shown in the last row entries. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table 2: Balancing Test - Including Leave-one-out Group Mean

Dependent Variable Z:	(1) CEE	(2) CEE in the Top 33%	(3) Percentile Ranking in CEE	(4) CCP	(5) Rural	(6) Local
Roommates' mean of **Z**	0.006	-0.003	0.013	-0.010	0.011	0.018*
	(0.014)	(0.013)	(0.012)	(0.014)	(0.010)	(0.010)
Group mean of **Z** (leave-one-out)	-20.399***	-25.160***	-24.947***	-25.361***	-24.685***	-25.113***
	(1.319)	(1.046)	(1.034)	(1.209)	(1.102)	(1.020)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Dorm Size FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,116	16,116	16,116	16,116	16,116	16,116
R-Squared	0.994	0.888	0.881	0.892	0.874	0.901

Notes: Columns (1)-(6) each present results from a separate OLS regression. The outcome variables in each column, denoted by "**Z**", are the focal students' academic ability (CEE scores, an indicator of CEE scores in the top 33% of the major-cohort, and the percentile ranking of CEE scores within the major-cohorts) and their demographic factors (*CCP*, *Local*, and *Rural*). The independent variables of interest for each column are roommates' average characteristics of the corresponding "**Z**" and the leave-one-out group mean of "**Z**" (partialing out the focal student). All regressions control for the group fixed effects. Robust standard errors clustered at the major-cohort level are shown in parentheses. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

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Table 3: Benchmark: Average Peer Effects Estimation

	(1)	(2)	(3)	(4)
Dependent Variable:	Std GPA	Std GPA (Required)	GPA Percentile Ranking	GPA in the Top 33%
Panel A				
Roommates' Std CEE Scores (Mean)	-0.004	-0.004	0.000	0.009
	(0.019)	(0.019)	(0.007)	(0.011)
Observations	16,116	16,116	16,116	16,116
R-Squared	0.221	0.215	0.230	0.183
Panel B				
Ratio of Top 33% Roommates	-0.065*	-0.054	-0.018	-0.016
	(0.035)	(0.035)	(0.012)	(0.021)
Observations	16,116	16,116	16,116	16,116
R-Squared	0.221	0.215	0.230	0.183
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Columns (1)-(4) each present results from a separate OLS regression. The independent variables of interest are the average standardized CEE score across roommates in the dorm rooms in panel A and the proportion of high-ability roommates in the dorm rooms (CEE scores in the top 33% of the major-cohort) in panel B. The outcome variables are focal students' academic performance, including standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. Demographic control variables include focal students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), their demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table 4: Main: Peer Effects on Students of Various Ability Levels

Dependent Variable:	(1) Std GPA	(2) Std GPA (Required)	(3) GPA Percentile Ranking	(4) GPA in the Top 33%
Top 33% X Ratio of Top 33% Roommates	-0.160***	-0.172***	-0.055***	-0.088**
	(0.058)	(0.058)	(0.019)	(0.034)
Middle 33% X Ratio of Top 33% Roommates	0.012	0.048	0.021	0.051*
	(0.054)	(0.053)	(0.017)	(0.029)
Bottom 33% X Ratio of Top 33% Roommates	-0.057	-0.050	-0.025	-0.015
	(0.057)	(0.057)	(0.019)	(0.034)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Observations	16,116	16,116	16,116	16,116
R-Squared	0.222	0.216	0.231	0.184
One-sided Test (p-values)				
Top-Top $\geqslant$ Middle-Top	0.013	0.002	0.001	0.001
Top-Top $\geqslant$ Bottom-Top	0.096	0.057	0.122	0.058

Notes: Columns (1)-(4) each present results from a separate OLS regression. The independent variables of interest are the proportion of high-ability roommates interacted with student ability indicators (CEE scores in the top, middle, and bottom terciles within the major-cohorts). The outcome variables are focal students' academic performance, including standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include focal students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), their demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. The p-values for one-sided tests are shown in the last two row entries. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table 5: Heterogeneity by Major-Cohort Size

	(1)	(2)	(3)	(4)
Dependent Variable:	Std GPA	Std GPA (Required)	GPA Percentile Ranking	GPA in the Top 33%
Panel A: High-ability Sample				
Ratio of Top 33% Roommates X Major-Cohort Size	0.004***	0.004***	0.001***	0.002**
	(0.001)	(0.001)	(0.000)	(0.001)
Observations	5,842	5,842	5,842	5,842
R-Squared	0.34	0.34	0.34	0.30
Baseline Effects in Table 4	-0.160***	-0.172***	-0.055***	-0.088**
Panel B: Middle-ability Sample				
Ratio of Top 33% Roommates X Major-Cohort Size	-0.001	-0.000	-0.000	0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Observations	5,808	5,808	5,808	5,808
R-Squared	0.321	0.312	0.324	0.292
Panel C: Low-ability Sample				
Roommates' Ratio of Top 33% X Major-Cohort Size	0.000	0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Observations	4,466	4,466	4,466	4,466
R-Squared	0.384	0.369	0.379	0.337
Ratio of Top 33% Roommates X Major Dummies	Yes	Yes	Yes	Yes
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Columns (1)-(4) each present results from a separate OLS regression. Panels A-C are subsamples consisting of high-, middle-, and low-ability students. For each panel, the independent variable of interest is the proportion of high-ability roommates interacted with the major-cohort size; the outcome variables are focal students' academic performance, including standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. Baseline effects represent coefficients of Table 4 row 1 estimating the main peer effects among "top-top" pairs. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include focal students' ability measurement, their demographic characteristics, and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

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Table 6: Same vs. Different Major-Cohorts

Dependent Variable:	(1) Std GPA	(2) Std GPA (Required)	(3) GPA Percentile Ranking	(4) GPA in the Top 33%
Top 33% X Ratio of Top 33% Roommates from Same Major-Cohort	-0.211***	-0.223***	-0.070***	-0.117***
	(0.077)	(0.076)	(0.025)	(0.045)
Top 33% X Ratio of Top 33% Roommates from Different Major-Cohorts	0.204	0.094	0.011	0.136
	(0.299)	(0.293)	(0.100)	(0.172)
Middle 33% X Ratio of Top 33% Roommates from Same Major-Cohort	0.000	0.045	0.022	0.056
	(0.069)	(0.067)	(0.022)	(0.039)
Middle 33% X Ratio of Top 33% Roommates from Different Major-Cohorts	0.042	0.120	0.019	0.110
	(0.343)	(0.349)	(0.101)	(0.161)
Bottom 33% X Ratio of Top 33% Roommates from Same Major-Cohort	-0.111	-0.114	-0.046*	-0.022
	(0.073)	(0.073)	(0.025)	(0.044)
Bottom 33% X Ratio of Top 33% Roommates from Different Major-Cohorts	0.303	0.541*	0.113	-0.080
	(0.306)	(0.305)	(0.088)	(0.139)
Top 33% X Roommates' Ratio of Same Major-Cohort	0.091	0.078	0.018	0.049
	(0.118)	(0.118)	(0.037)	(0.063)
Middle 33% X Roommates' Ratio of Same Major-Cohort	0.124	0.090	0.036	0.046
	(0.116)	(0.120)	(0.036)	(0.057)
Bottom 33% X Roommates' Ratio of Same Major-Cohort	0.286**	0.326***	0.090**	0.006
	(0.113)	(0.116)	(0.035)	(0.054)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Observations	16,116	16,116	16,116	16,116
R-Squared	0.223	0.216	0.231	0.184
One-sided Test (p-values)				
Top-Top (same major-cohort) $\geqslant$ Top-Top (diff major-cohorts)	0.093	0.153	0.228	0.089
Top-Top (same major-cohort) $\geqslant$ Middle-Top (same major-cohort)	0.018	0.003	0.003	0.001
Top-Top (same major-cohort) $\geqslant$ Bottom-Top (same major-cohort)	0.167	0.143	0.241	0.061

Notes: Columns (1)-(4) each present results from a separate OLS regression. The independent variables of interest are the proportion of high-ability roommates from the same (different) major-cohorts interacted with student ability indicators (top, middle, and bottom). The outcome variables are focal students' academic performance, including standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. All regressions control for the group-gender fixed effects, the dorm-size fixed effects, and demographic controls. Robust standard errors clustered at the major-cohort level are shown in parentheses. The p-values for one-sided tests are shown in the last three row entries. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table 7: Same vs. Different Cultural Zones

	(1)	(2)	(3)	(4)
Dependent Variable:	Std GPA	Std GPA (Required)	GPA Percentile Ranking	GPA in the Top 33%
Top 33% X Ratio of Top 33% Roommates from the Same Cultural Zone	-0.356***	-0.371***	-0.132***	-0.175***
	(0.106)	(0.107)	(0.036)	(0.066)
Top 33% X Ratio of Top 33% Roommates from Different Cultural Zones	-0.080	-0.122	-0.020	-0.050
	(0.097)	(0.099)	(0.033)	(0.061)
Middle 33% X Ratio of Top 33% Roommates from the Same Cultural Zone	0.106	0.141	0.049	0.067
	(0.106)	(0.104)	(0.033)	(0.056)
Middle 33% X Ratio of Top 33% Roommates from Different Cultural Zones	-0.044	0.041	0.027	0.045
	(0.093)	(0.094)	(0.031)	(0.059)
Bottom 33% X Ratio of Top 33% Roommates from the Same Cultural Zone	-0.134	-0.130	-0.054	-0.060
	(0.108)	(0.108)	(0.036)	(0.059)
Bottom 33% X Ratio of Top 33% Roommates from Different Cultural Zones	-0.022	-0.003	-0.018	-0.028
	(0.114)	(0.119)	(0.038)	(0.066)
Top 33% X Ratio of Roommates from the Same Cultural Zone	0.038	0.033	0.027	0.037
	(0.065)	(0.064)	(0.021)	(0.036)
Middle 33% X Ratio of Roommates from the Same Cultural Zone	-0.053	-0.019	-0.015	-0.013
	(0.059)	(0.061)	(0.020)	(0.035)
Bottom 33% X Ratio of Roommates from the Same Cultural Zone	-0.028	-0.019	-0.004	-0.003
	(0.077)	(0.079)	(0.025)	(0.043)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Observations	13,136	13,136	13,136	13,136
One-sided Test (p-values)				
Top-Top (same cultural zone) $\geqslant$ Top-Top (diff cultural zones)	0.022	0.035	0.008	0.066
Top-Top (same cultural zone) $\geqslant$ Middle-Top (same cultural zone)	0.001	0.000	0.000	0.001
Top-Top (same cultural zone) $\geqslant$ Bottom-Top (same cultural zone)	0.063	0.048	0.051	0.077

Notes: Columns (1)-(4) each present results from a separate OLS regression. The independent variables of interest are the proportion of high-ability roommates from the same (different) cultural zones interacted with student ability indicators (top, middle, and bottom). Each student is assigned to a cultural zone based on their county of origin. The outcome variables are focal students' academic performance, including standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. All regressions control for the group-gender fixed effects, the dorm-size fixed effects, and demographic controls. Robust standard errors clustered at the major-cohort level are shown in parentheses. The p-values for one-sided tests are shown in the last three row entries. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

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Table 8: Ability Gap between 1^{st} and 2^{nd} Best and Academic Performance

	(1)	(2)	(3)	(4)
Dependent Variable:	Std GPA	Std GPA (Required)	GPA Percentile Ranking	GPA in the Top 33%
Gap X Best	0.076***	0.082***	0.024***	0.040***
	(0.021)	(0.021)	(0.007)	(0.011)
Gap X Second-Best	0.018	0.011	0.003	0.009
	(0.021)	(0.021)	(0.007)	(0.012)
Gap X Third-Best	0.029	0.024	0.009	0.007
	(0.021)	(0.022)	(0.007)	(0.012)
Gap X Others	0.014	0.008	0.004	-0.000
	(0.015)	(0.015)	(0.006)	(0.009)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Observations	15,848	15,848	15,848	15,848
R-Squared	0.223	0.217	0.231	0.184
One-sided Test (p-values)				
Best $\leqslant$ Second-Best	0.012	0.004	0.007	0.021
Best $\leqslant$ Third-Best	0.026	0.012	0.033	0.011
Best $\leqslant$ Others	0.002	0.001	0.004	0.000

Notes: Columns (1)-(4) each present results from a separate OLS regression. The independent variables of interest are *Gap* interacted with student ability indicators (CEE scores ranked the best, second, third, and the other of the dorm room). *Gap* is defined as the difference in the standardized CEE scores between the best and second-best students of the dorm room. The outcome variables are focal students' academic performance, including standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include focal students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), their demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. The p-values for one-sided tests are shown in the last three row entries. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table 9: Mechanism: Peer Interactions

Dependent Variable:	(1) Interactions	(2) Discuss Study	(3) Help	(4) Isolate	(5) Confront	(6) Disturb
Panel A: Top-Known Sample:						
Gap X Best	0.289**	0.112**	0.133**	-0.028**	-0.009	-0.034**
	(0.140)	(0.054)	(0.054)	(0.013)	(0.008)	(0.014)
Gap X Second Best	0.135	-0.008	-0.036	-0.018	-0.015	-0.007
	(0.172)	(0.071)	(0.067)	(0.019)	(0.010)	(0.017)
Gap X Third Best	0.078	0.030	0.084	0.039	-0.010	0.010
	(0.187)	(0.077)	(0.080)	(0.027)	(0.011)	(0.017)
Gap X Others	0.009	-0.006	0.025	-0.020	-0.008	0.010
	(0.100)	(0.061)	(0.061)	(0.015)	(0.007)	(0.013)
Observations	1,437	1,437	1,437	1,437	1,437	1,437
R-Squared	0.312	0.298	0.316	0.278	0.244	0.241
Dependent S.D.	2.091	0.894	0.889	0.298	0.138	0.241
Panel B: Top-Unknown Sample:						
Gap X Best	-0.118	0.003	-0.058	0.006	0.010	0.048
	(0.204)	(0.066)	(0.071)	(0.016)	(0.006)	(0.030)
Gap X Second Best	-0.052	-0.100	-0.043	0.023	-0.004	0.007
	(0.174)	(0.063)	(0.065)	(0.021)	(0.015)	(0.019)
Gap X Third Best	0.027	-0.057	-0.069	0.002	-0.006	-0.004
	(0.190)	(0.071)	(0.084)	(0.014)	(0.007)	(0.013)
Gap X Others	0.348**	0.055	0.096	0.007	-0.011	-0.002
	(0.170)	(0.053)	(0.060)	(0.017)	(0.015)	(0.020)
Observations	1,104	1,104	1,104	1,104	1,104	1,104
R-Squared	0.333	0.379	0.368	0.309	0.345	0.355
Dependent S.D.	2.042	0.862	0.846	0.267	0.149	0.236
Group-Gender FE	Yes	Yes	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns (1)-(6) each present results from a separate OLS regression. Panel A ("top-known sample") includes the surveyed students who are *clear* about the best roommates in the dorm rooms; panel B ("top-unknown sample") includes the surveyed students who are *unclear* about the best roommates in the dorm rooms. The independent variables of interest are Gap interacted with student ability indicators (CEE scores ranked the best, second, third, and the other in the dorm rooms). Gap is defined as the difference in the standardized CEE scores between the best and second-best students in the dorm room. The outcome variables measure the frequency with which the focal students interact with their best roommates. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), their demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

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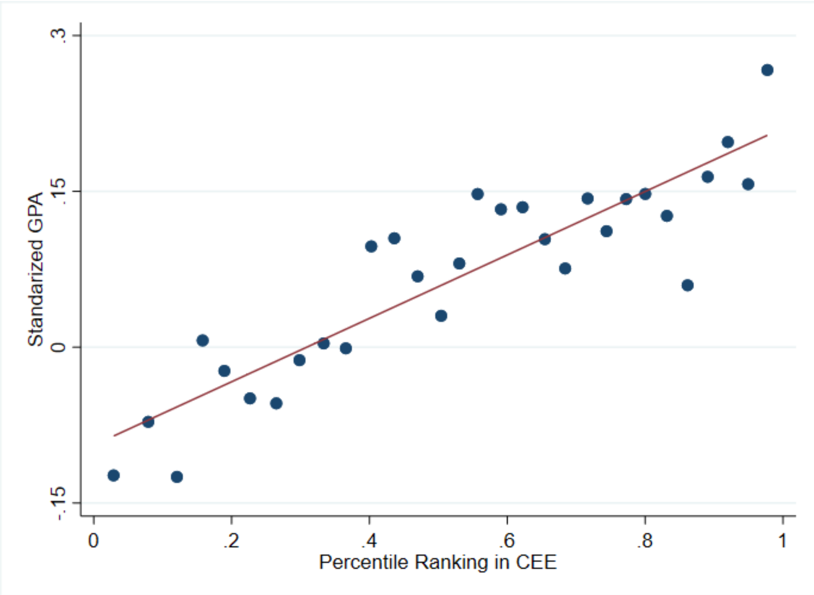
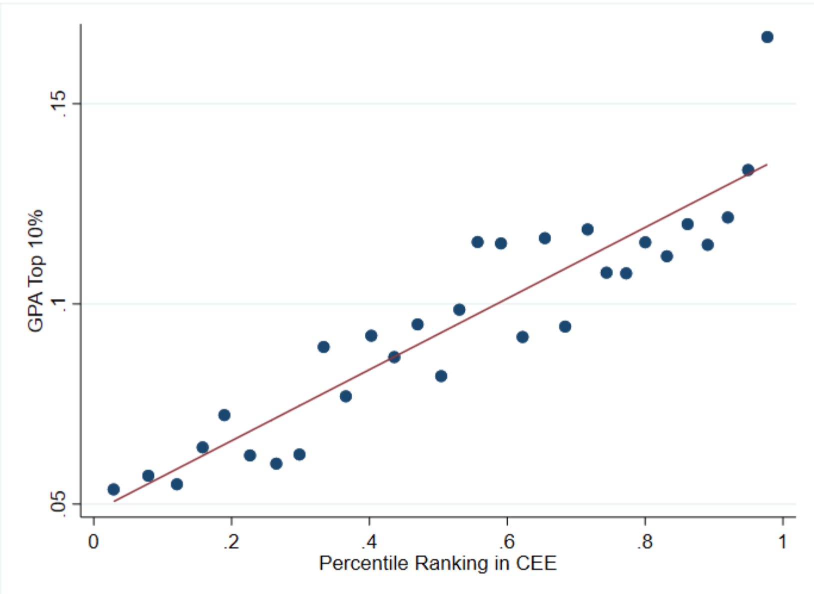
A. Appendix

Figure A.1: The Relationship between CEE Performance and Academic Performance

(a) Standardized GPA



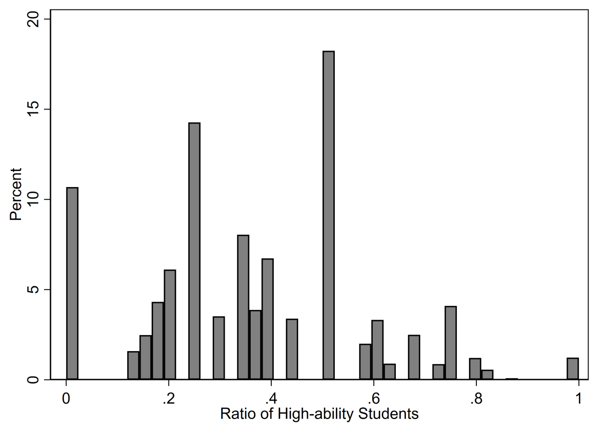
(b) GPA in the Top 10%



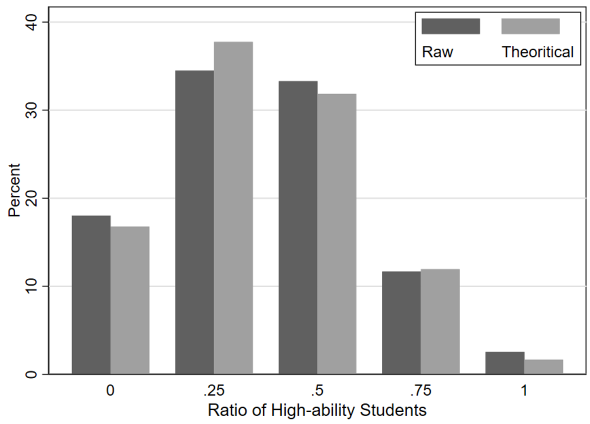
Notes: This figure plots the relationship between the students' CEE performance before college and their academic performance in college. The x-axis is the students' CEE percentile ranking within the major-cohorts. The y-axis in panel (a) is the students' standardized overall GPA and the y-axis in panel (b) is an indicator of whether the students' overall GPA ranks in the top 10% within the major-cohorts.

Figure A.2: Distribution of Ratio of High-ability Students

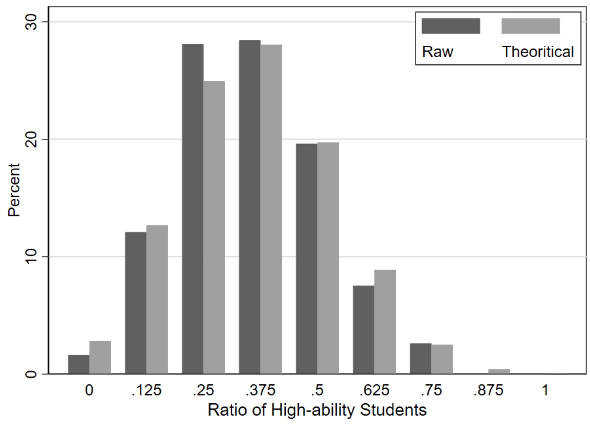
(a) Full Sample



(b) Four-People Dorms



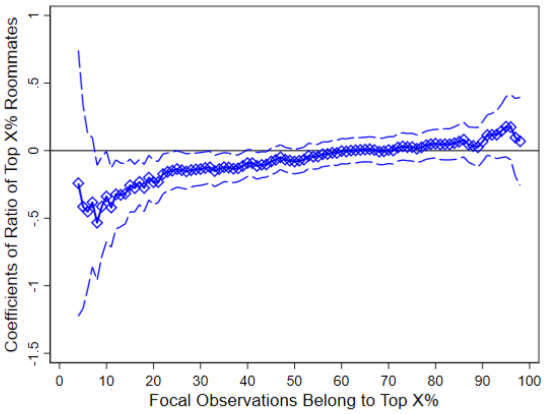
(c) Eight-People Dorms



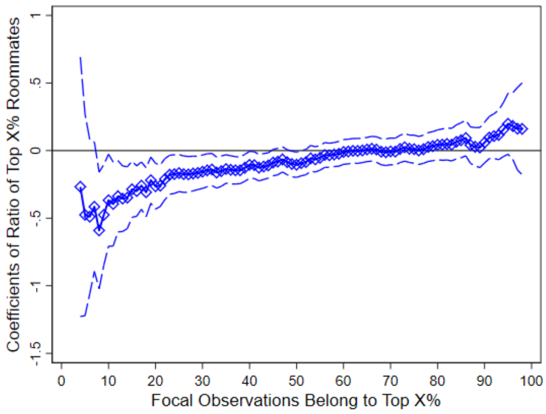
Notes: This figure plots the distributions of high-ability students in each dorm room based on the full sample consisting of dorm rooms with different sizes (panel (a)), a subsample consisting of four-people dorm rooms (panel (b)), and a subsample consisting of eight-people dorm rooms (panel (c)). The dark bars in panels (b) and (c) represent the distributions based on the raw data and the light bars are theoretical binomial distributions if the assignment of dorm rooms is truly random.

Figure A.3: The Effects of the Top X% Roommates on Students in the Top X%

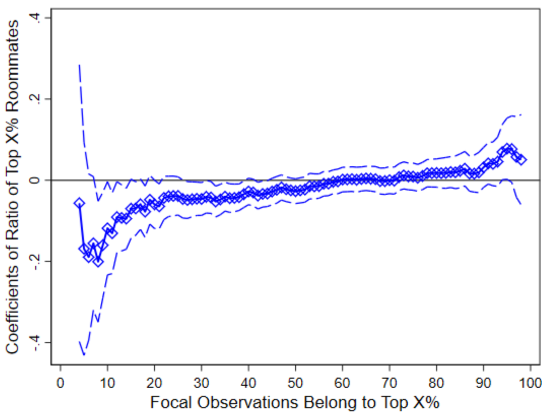
(a) Standardized GPA



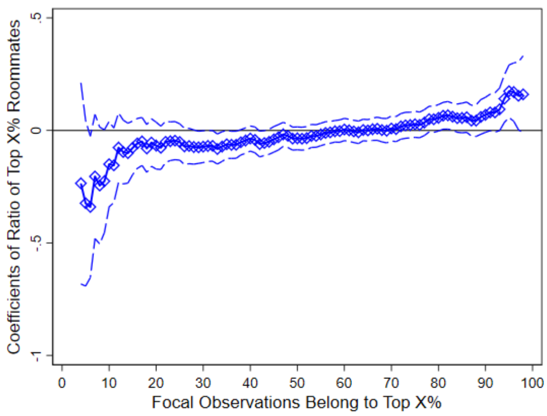
(b) Standardized GPA (Required Courses)



(c) GPA Percentile Ranking

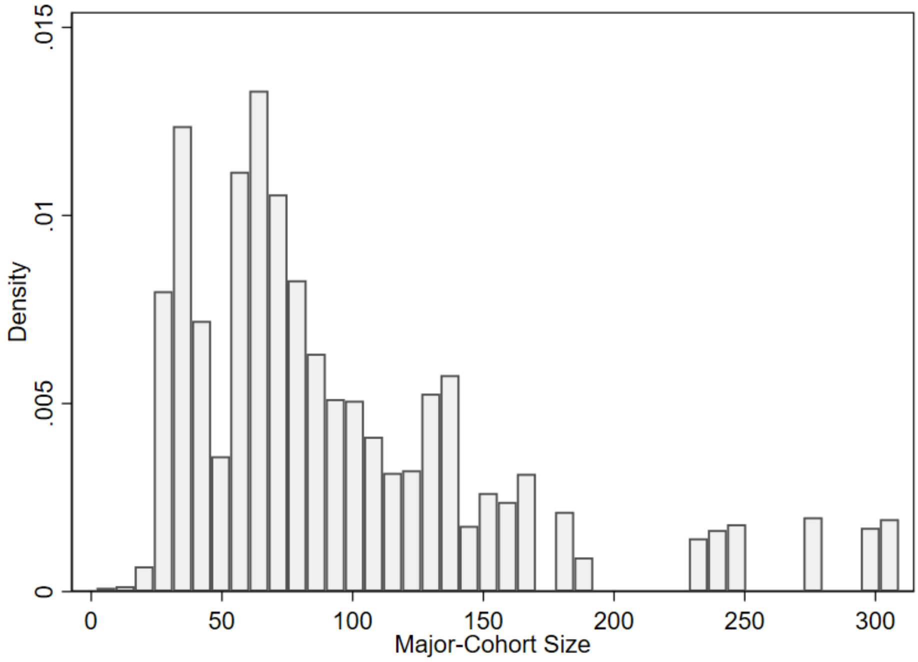


(d) GPA in the Top 33%



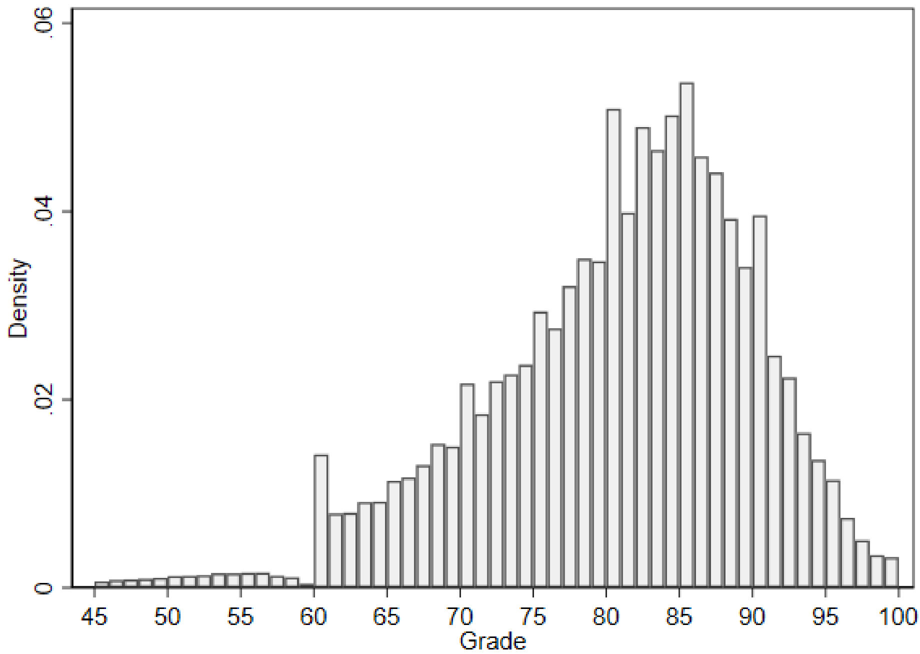
Notes: This figure plots the estimates of the coefficients on the proportion of the top X% roommates for students with various levels of academic ability (CEE scores ranking in the Top X% of the major-cohort, and integer X ranging from 3 to 99) and their 95% confidence intervals. The horizontal lines denote the impact of zero. The outcome variables from panel (a) to panel (d) are focal students' standardized GPA, standardized GPA only for required courses, percentile ranking of their overall GPA within the major-cohorts, and the indicator of the overall GPA being the top 33% of the major-cohort. The specifications replicate those in Table 3. Robust standard errors clustered at the major-cohort level.

Figure A.4: Distribution of Major-Cohort Size



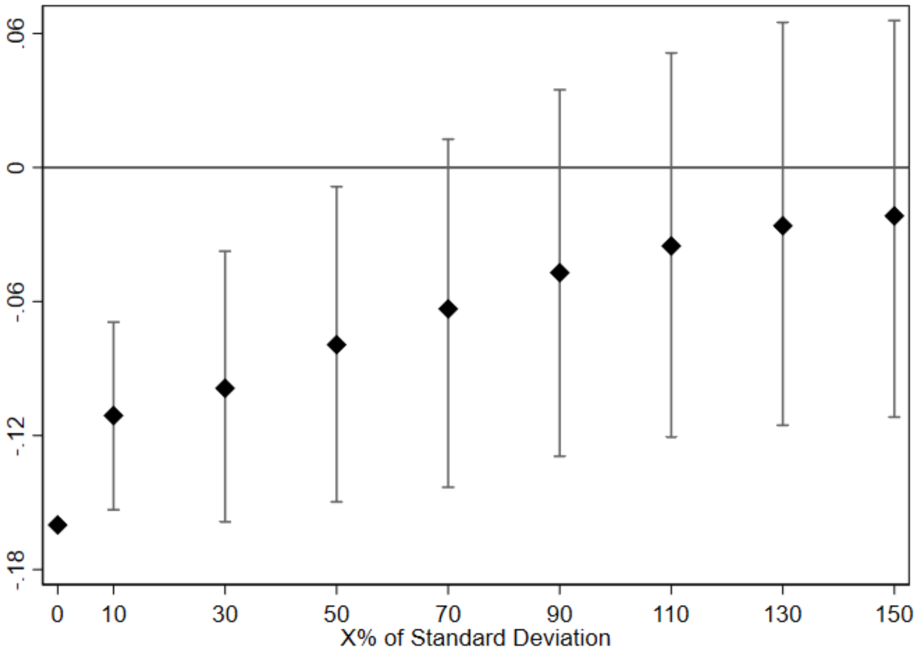
Notes: This figure plots the distribution of major-cohort size for the main sample (385 major-cohorts in total), with a mean value of 96.33 and a standard deviation of 63.99.

Figure A.5: Distribution of Grades



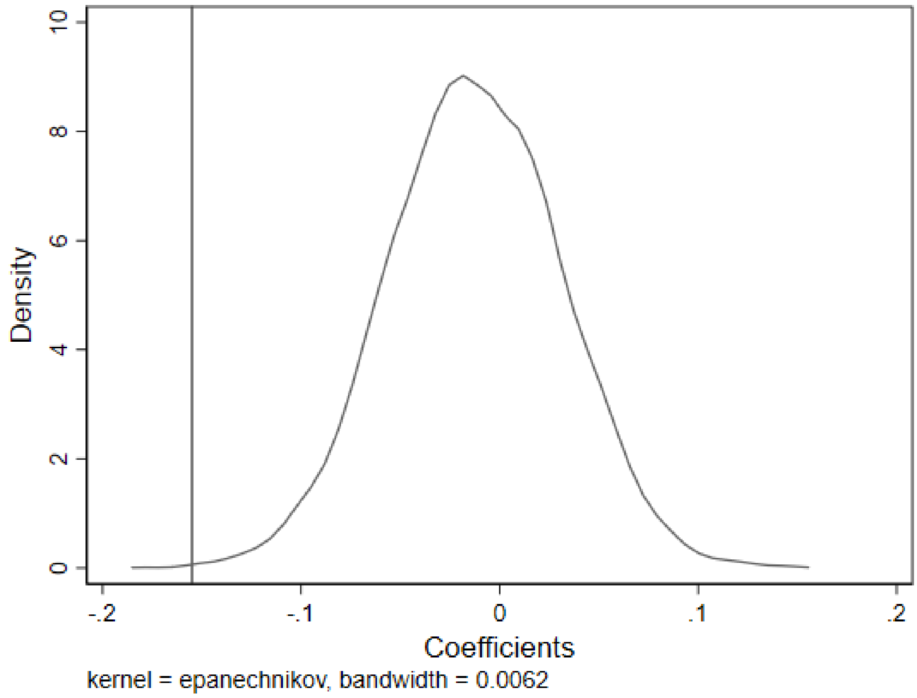
Notes: This figure plots the distribution of the students' original grades of each module during the college, with mean values of 79.53 points and a standard deviation of 11.45 points.

Figure A.6: Sensitivity of Main Results to Measurement Error



Notes: We construct a "placebo" student ability measurement by artificially introducing errors into student CEE scores. Errors follows $N \sim (0, X\%)$ with X=10, 30, 50, ..., 150, that is, errors range from 10% to 150% of the authentic CEE scores' standard deviation. Based on the "placebo" CEE scores, we re-estimate equation (2) for 1000 times for each X. The dots represent the average estimated coefficients, and the bars indicates the 5^{th} and 95^{th} percentiles of the estimated coefficients. The dot at X(error)=0 indicates the point estimate of our main result in Table 4 column (1) for a reference.

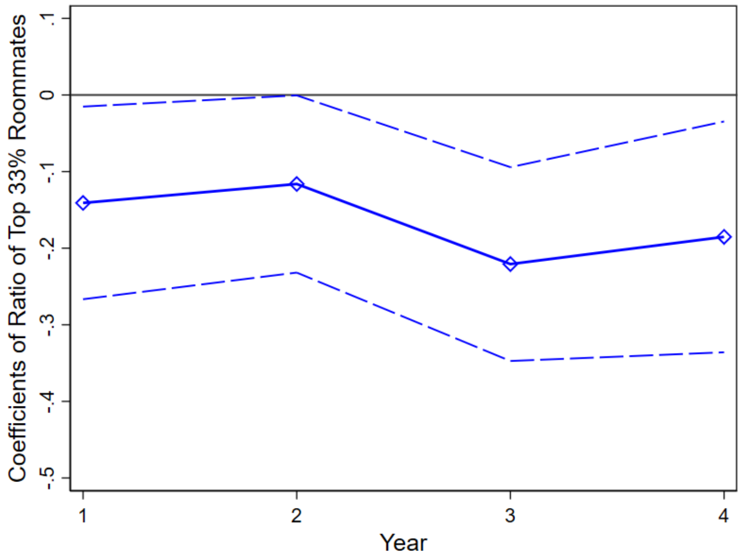
Figure A.7: Distribution of Coefficients Based on Placebo Roommates



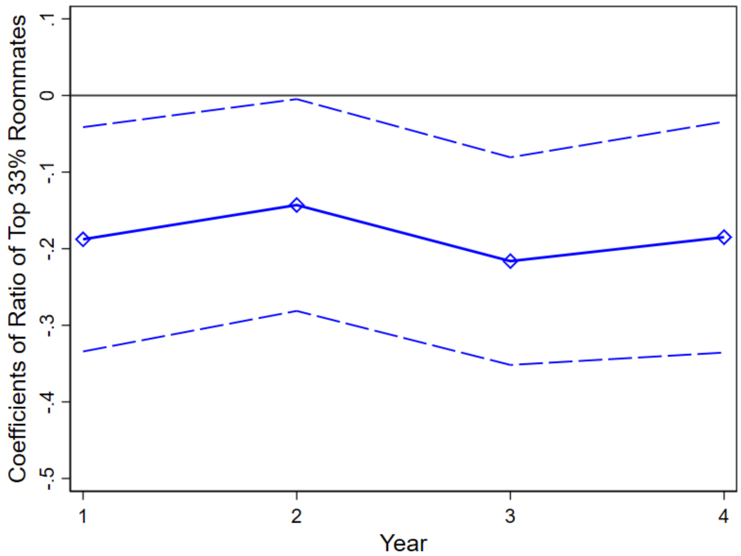
Notes: We randomly assign students to "placebo" dorm rooms such that each student is randomly assigned to "placebo" roommates with whom they may not interact in the real world. We then re-estimate equation (2) based on the "placebo" dorm assignment. We replicate this exercise 10,000 times and present the distribution of the estimated coefficient β_1 in this figure. The solid vertical line indicates the point estimate of our main result in Table 4 column (1) as a reference.

Figure A.8: The Dynamic Peer Effects on Standardized GPA

(a) Full Sample



(b) Balanced Sample



Notes: Each dot presents a separate OLS estimate of the coefficient on the proportion of high-ability students for the full sample (panel (a)) and the balanced sample (panel (b)). The dashed lines denote the 95% confidence intervals. The outcome variables are students' standardized GPA in Year 1, Year 2, Year 3, and Year 4 at college. The specifications replicate those in Table 3. Robust standard errors clustered at the major-cohort level are shown in parentheses. ***significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table A.1: Summary Statistics

Variable	Mean	Std. Dev.
Male	0.655	0.475
STEM	0.833	0.373
CCP (Youth) Member	0.942	0.233
Rural	0.475	0.469
From the Local City	0.325	0.468
Dorm Size	5.577	1.423
CEE Score	522.473	38.221
Percentile Ranking in CEE	0.533	0.277
Ratio of Top 33% Roommates	0.361	0.237
GPA Percentile Ranking	0.515	0.281
GPA in the Top 33%	0.362	0.481
Observations	16,116	

Notes: This table reports the means and standard errors for our main regression sample at the individual level. *Male* is an indicator of being male. *STEM* is an indicator of a student from the STEM track. *CCP* is an indicator of being a member or youth member of the China Communist Party at enrollment. *Rural* is an indicator of a student from a rural area. *From the Local City* is an indicator of a student from the local city. *Dorm Size* is the number of students living in a dorm room. *CCE scores* are the scores on the National College Entrance Examination. *Percentile Ranking in CEE* is the percentile ranking of CEE scores within the major-cohorts. *Ratio of Top 33% Roommates* is the number of roommates with CEE scores in the top 30% of the major-cohort over the total number of students in the same dorm rooms. *Std GPA* is the GPA standardized within the major-cohorts. *Std GPA (required)* is the standardized GAP for required courses. *GPA Percentile Ranking* is the percentile ranking of an overall GPA within the major-cohorts. *GPA in the Top 33%* is an indicator for an overall GPA being in the top 33% of the major-cohort.

Table A.2: The Effects of Middle-Ability Roommates on Students of Various Ability Levels

Dependent Variable:	(1) Std GPA	(2) Std GPA (Required)	(3) GPA Percentile Ranking	(4) GPA in the Top 33%
Top 33% X Ratio of **Middle 33%** Roommates	0.151**	0.167***	0.049**	0.082**
	(0.061)	(0.062)	(0.020)	(0.034)
Middle 33% X Ratio of **Middle 33%** Roommates	-0.000	-0.036	-0.011	-0.034
	(0.061)	(0.062)	(0.020)	(0.034)
Bottom 33% X Ratio of **Middle 33%** Roommates	0.079	0.075	0.036*	0.049
	(0.058)	(0.060)	(0.020)	(0.032)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Observations	16,116	16,116	16,116	16,116
R-Squared	0.222	0.216	0.231	0.184

Notes: Columns (1)-(4) each present results from a separate OLS regression. The independent variables of interest are the proportion of **middle 33%** roommates interacted with the student ability indicators (CEE scores in the top 33%, middle 33%, and bottom 33% of the major-cohort). The outcome variables are focal students' academic performance, including standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. Specifications mirror those in Table 4. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include focal students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. The p-values for one-sided tests are shown in the last two row entries. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table A.3: The Effects of Low-Ability Roommates on Students of Various Ability Levels

Dependent Variable:	(1) Std GPA	(2) Std GPA (Required)	(3) GPA Percentile Ranking	(4) GPA in the Top 33%
Top 33% X Ratio of **Bottom 33%** Roommates	0.003	-0.004	0.004	-0.000
	(0.064)	(0.064)	(0.021)	(0.035)
Middle 33% X Ratio of **Bottom 33%** Roommates	-0.010	-0.009	-0.010	-0.017
	(0.060)	(0.060)	(0.020)	(0.033)
Bottom 33% X Ratio of **Bottom 33%** Roommates	-0.014	-0.016	-0.009	-0.031
	(0.063)	(0.065)	(0.022)	(0.037)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Observations	16,116	16,116	16,116	16,116
R-Squared	0.221	0.215	0.230	0.183

Notes: Columns (1)-(4) each present results from a separate OLS regression. The independent variables of interest are the proportion of the **Bottom 33%** roommates interacted with the student ability indicators (CEE scores in the top 33%, middle 33%, and bottom 33% of the major-cohort). The outcome variables are focal students' academic performance, including standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. Specifications mirror those in Table 4. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include focal students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. The p-values for one-sided tests are shown in the last two row entries. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table A.4: Heterogeneity by Major-Cohort Size (Log)

	(1)	(2)	(3)	(4)
Dependent Variable:	Std GPA	Std GPA (Required)	GPA Percentile Ranking	GPA in the Top 33%
Panel A: High-ability Sample				
Ratio of Top 33% Roommates X ln(Major-Cohort Size)	0.618***	0.673***	0.214***	0.279**
	(0.211)	(0.208)	(0.073)	(0.123)
Observations	5,842	5,842	5,842	5,842
R-Squared	0.338	0.337	0.339	0.305
Panel B: Middle-ability Sample				
Ratio of Top 33% Roommates X ln(Major-Cohort Size)	-0.014	0.011	-0.013	0.109
	(0.202)	(0.194)	(0.071)	(0.124)
Observations	5,808	5,808	5,808	5,808
R-Squared	0.321	0.312	0.324	0.293
Panel C: Low-ability Sample				
Ratio of Top 33% Roommates X ln(Major-Cohort Size)	0.023	0.077	-0.009	-0.129
	(0.164)	(0.159)	(0.053)	(0.093)
Observations	4,466	4,466	4,466	4,466
R-Squared	0.384	0.369	0.379	0.337
Ratio of Top 33% Roommates X Major Dummies	Yes	Yes	Yes	Yes
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Columns (1)-(4) each present results from a separate OLS regression. Panels A-C are subsmples consisting of high-, middle-, and low-ability focal students. For each panel, the independent variable of interest is the proportion of high-ability roommates interacted with the **log major-cohort size**; the outcome variables are focal students' academic performance, including standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include focal students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), their demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

A.12

Table A.5: Peer Effects on Students of Various Ability Levels (County of Origin Non-missing Sample)

	(1)	(2)	(3)	(4)
Dependent Variable:	Std GPA	Std GPA (required)	Percentile Rank	GPA Top 33%
Top 33% X Ratio of Top 33% Roommates	-0.176***	-0.201***	-0.062***	-0.092**
	(0.060)	(0.062)	(0.021)	(0.038)
Middle 33% X Ratio of Top 33% Roommates	0.032	0.081	0.034*	0.050
	(0.059)	(0.058)	(0.019)	(0.033)
Bottom 33% X Ratio of Top 33% Roommates	-0.058	-0.052	-0.027	-0.032
	(0.061)	(0.064)	(0.020)	(0.036)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Observations	13,136	13,136	13,136	13,136
R-Squared	0.243	0.237	0.251	0.202
P(Top $<$ Middle Students)	0.005	0.000	0.000	0.001
P(Top $<$ Bottom Students)	0.071	0.034	0.093	0.108

Columns (1)-(4) each present results from a separate OLS regression. The sample is restricted to dorm rooms where no students' county of origin is missing in the data. The independent variables of interest are the proportion of high-ability roommates interacted with student ability indicators (CEE scores in the top, middle, and bottom terciles within the major-cohorts). The outcome variables are focal students' academic performance, including standardized GPA, standardized GPA for compulsory courses only, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include focal students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), demographic characteristics (rural-urban status, CCP membership, and the city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. p-values for one-sided tests are shown in the last two row entries. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

A.13

Table A.6: Ability Gap and Academic Performance by Subsample

Dependent Variable:	(1) Std GPA	(2) Std GPA (Required)	(3) GPA Percentile Ranking	(4) GPA in the Top 33%
Panel A: Top-Half Sample				
Gap X Best	0.100***	0.104***	0.033***	0.053***
	(0.028)	(0.027)	(0.010)	(0.016)
Gap X Second Best	0.013	0.012	0.002	0.004
	(0.028)	(0.029)	(0.010)	(0.017)
Gap X Third Best	0.017	0.010	0.008	0.002
	(0.026)	(0.029)	(0.009)	(0.016)
Gap X Others	0.022	0.011	0.010	0.003
	(0.019)	(0.021)	(0.008)	(0.012)
Observations	7,762	7,762	7,762	7,762
R-Squared	0.286	0.275	0.289	0.239
Panel B: Bottom-Half Sample				
Gap X Best	-0.058	-0.047	-0.010	0.016
	(0.068)	(0.070)	(0.022)	(0.038)
Gap X Second Best	0.032	0.005	0.001	0.029
	(0.061)	(0.060)	(0.020)	(0.033)
Gap X Third Best	0.072	0.085	0.013	0.023
	(0.064)	(0.068)	(0.022)	(0.034)
Gap X Others	-0.018	0.005	-0.012	0.000
	(0.062)	(0.064)	(0.020)	(0.033)
Observations	8,086	8,086	8,086	8,086
R-Squared	0.269	0.268	0.281	0.235
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Columns (1)-(4) each present results from a separate OLS regression. The independent variables of interest are Gap interacted with student ability indicators (CEE scores ranked the best, second, third, and the other in the dorm rooms). Panel A is restricted to the top-half sample including dorm rooms whose best students, based on their CEE scores, are higher than the median among all of the best students in each dorm room, while panel B is restricted to the bottom-half sample including dorm rooms whose best students are equal to or are less than the median. Gap is defined as the difference in the standardized CEE scores between the best and second-best students of the dorm room. The outcome variables are the focal students' standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), their demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table A.7: Ability Gap between 2^{nd} and 3^{rd} Best and Academic Performance

	(1)	(2)	(3)	(4)
Dependent Variable:	Std GPA	Std GPA (Required)	GPA Percentile Ranking	GPA in the Top 33%
Gap X Best	-0.043	-0.034	-0.013	-0.005
	(0.033)	(0.035)	(0.011)	(0.019)
Gap X Second-Best	-0.007	0.006	-0.001	-0.004
	(0.033)	(0.034)	(0.011)	(0.019)
Gap X Third-Best	-0.001	0.011	0.000	-0.010
	(0.030)	(0.031)	(0.010)	(0.017)
Gap X Others	-0.007	-0.013	-0.001	0.016
	(0.025)	(0.025)	(0.009)	(0.014)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Observations	15,525	15,525	15,525	15,525
R-Squared	0.220	0.214	0.228	0.182

Notes: Columns (1)-(4) each present results from a separate OLS regression. The independent variables of interest are Gap interacted with student ability indicators (CEE scores ranked the best, second, third, and other in the dorm rooms). Gap is defined as the difference in the standardized CEE scores between the **second** and the **third** best students in the same dorm rooms. The outcome variables are focal students' academic performance, including standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include focal students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table A.8: Ability Gap between 3^{rd} and 4^{th} Best and Academic Performance

	(1)	(2)	(3)	(4)
Dependent Variable:	Std GPA	Std GPA (Required)	GPA Percentile Ranking	GPA in the Top 33%
Gap X Best	-0.046	-0.041	-0.014	-0.023
	(0.034)	(0.033)	(0.012)	(0.020)
Gap X Second Best	0.011	0.020	0.006	0.002
	(0.037)	(0.039)	(0.012)	(0.021)
Gap X Third Best	0.022	0.019	0.009	0.020
	(0.038)	(0.041)	(0.013)	(0.022)
Gap X Others	-0.009	0.006	-0.004	0.003
	(0.027)	(0.029)	(0.010)	(0.017)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Observations	15,038	15,038	15,038	15,038
R-Squared	0.219	0.213	0.228	0.182

Notes: Columns (1)-(4) each present results from a separate OLS regression. The independent variables of interest are Gap interacted with student ability indicators (CEE scores ranked the best, second, third, and other in the dorm rooms). Gap is defined as the difference in the standardized CEE scores between the **third** and the **forth** best students in the same dorm rooms. The outcome variables are focal students' academic performance, including standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include focal students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table A.9: Replication of the Main Results Using the Survey Sample

Dependent Variable:	(1) Std GPA	(2) Std GPA (Required)	(3) GPA Percentile Ranking	(4) GPA in the Top 33%
Panel A				
Top 33% X Ratio of Top 33% Roommates	-0.232*	-0.204*	-0.079*	-0.104
	(0.128)	(0.109)	(0.042)	(0.071)
Middle 33% X Ratio of Top 33% Roommates	0.002	0.077	0.013	0.080
	(0.091)	(0.098)	(0.033)	(0.060)
Bottom 33% X Ratio of Top 33% Roommates	-0.005	0.032	-0.003	0.063
	(0.126)	(0.136)	(0.043)	(0.079)
Observations	2,541	2,541	2,541	2,541
R-Squared	0.276	0.261	0.259	0.215
Panel B				
Gap X Best	0.101**	0.098**	0.038***	0.063**
	(0.043)	(0.044)	(0.014)	(0.024)
Gap X Second Best	0.065*	0.036	0.033**	0.068***
	(0.035)	(0.035)	(0.013)	(0.022)
Gap X Third Best	0.120***	0.075	0.043***	0.064**
	(0.040)	(0.045)	(0.016)	(0.026)
Gap X Others	0.019	0.026	0.010	0.000
	(0.031)	(0.042)	(0.015)	(0.022)
Observations	2,541	2,541	2,541	2,541
R-Squared	0.279	0.263	0.265	0.220
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes

Notes: This table replicates the main results using the survey sample. Columns (1)-(4) each present results from a separate OLS regression. Panel A corresponds to the results in Table 4, and panel B corresponds to the results in Table 8. The outcome variables are focal students' academic performance, including standardized GPA, standardized GPA only for compulsory courses, percentile ranking of their overall GPA within the major-cohorts, and an indicator for the overall GPA being in the top 33% of the major-cohort. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include focal students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table A.10: Summary Statistics for the Survey Sample

	Top-Known Sample		Top-Unknown Sample		
	Mean	S.D.	Mean	S.D.	Difference
Pre-determined Characteristics					
Male	0.67	0.47	0.64	0.48	-0.03
STEM	0.84	0.36	0.84	0.36	-0.00
CCP (Youth) Member	0.93	0.26	0.91	0.29	0.02
From the Local City	0.21	0.41	0.21	0.40	-0.00
Ratio of Top 33% Roommates	0.35	0.28	0.36	0.28	-0.00
Percentile Ranking in CEE	0.46	0.27	0.45	0.27	-0.01
Dorm Size	5.05	1.95	5.30	2.04	0.25**
Attitude Toward Competition					
Competition Is Important for Success in College	0.84	0.37	0.80	0.40	-0.04*
Surpassing Competitors Is Important in College	0.57	0.50	0.52	0.50	-0.05*
Approve of Competitive Behaviors in College	0.66	0.47	0.62	0.49	-0.05*
Observations	1,437		1,104		2,541

Notes: This table reports the means and standard errors for the survey samples. Columns (1) and (2) are the surveyed students who are **clear** about their best roommates in the dorm rooms. Columns (3) and (4) are the surveyed students who are **unclear** about their best roommates in the dorm rooms. The variable definitions of the pre-determined characteristics mirror those in Table A.1. Survey questions about competition attitude equal one if the respondents agree with the statements and zero if they disagree with. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

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Table A.11: Mechanism: Psychological Feelings

	(1)	(2)	(3)
Dependent Variable:	Motivated	Pressure	Low Confidence
Panel A: Top-Known Sample			
Gap X Best	0.090	-0.010	-0.027
	(0.055)	(0.057)	(0.056)
Gap X Second Best	-0.022	-0.120	-0.091
	(0.080)	(0.081)	(0.085)
Gap X Third Best	-0.004	-0.004	-0.022
	(0.080)	(0.083)	(0.077)
Gap X Others	-0.014	0.054	0.084
	(0.064)	(0.086)	(0.062)
Observations	1,437	1,437	1,437
R-Squared	0.310	0.287	0.286
Dependent S.D.	0.966	1.061	1.087
Panel B: Top-Unknown Sample			
Gap X Best	0.016	0.050	0.142*
	(0.082)	(0.079)	(0.078)
Gap X Second Best	-0.077	-0.134*	0.011
	(0.075)	(0.071)	(0.071)
Gap X Third Best	0.031	0.015	0.098
	(0.089)	(0.082)	(0.079)
Gap X Others	0.089	0.116*	-0.012
	(0.054)	(0.065)	(0.082)
Observations	1,104	1,104	1,104
R-Squared	0.373	0.337	0.311
Dependent S.D.	0.925	0.995	1.036
Group-Gender FE	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes

Notes: Columns (1)-(3) each present results from a separate OLS regression. Panel A ("top-known sample") includes the surveyed students who are *clear* about the best roommates in the dorm rooms; panel B ("top-unknown sample") includes the surveyed students who are *unclear* about the best roommates in the dorm rooms. The independent variables of interest are *Gap* interacted with student ability indicators (CEE scores ranked the best, second, third, and the other in the dorm rooms). *Gap* is defined as the difference in the standardized CEE scores between the best and second-best students in the dorm room. The outcome variables are the degree to which the best roommates make focal students feel motivated, stressed, and unconfident, with one denoting strong feelings and zero denoting neutral or below. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. Demographic control variables include students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), their demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table A.12: Mechanism: Effort Allocation

	(1)	(2)	(3)	(4)
Dependent Variable:	Game	Study	Organization	Part-time Work
Panel A: Top-Known Sample				
Gap X Best	-0.079	0.063	0.069	0.257
	(0.153)	(0.149)	(0.205)	(0.205)
Gap X Second Best	0.083	-0.126	-0.143	-0.049
	(0.127)	(0.092)	(0.174)	(0.217)
Gap X Third Best	-0.192	0.046	0.442*	0.331
	(0.155)	(0.191)	(0.231)	(0.279)
Gap X Others	-0.210	0.121	-0.090	-0.132
	(0.130)	(0.128)	(0.120)	(0.164)
Observations	1,437	1,437	1,437	1,437
R-Squared	0.293	0.360	0.348	0.392
Dependent S.D.	2.001	2.122	2.380	3.085
Panel B: Top-Unknown Sample				
Gap X Best	0.209	0.187	-0.069	0.364
	(0.154)	(0.154)	(0.173)	(0.250)
Gap X Second Best	-0.355**	0.131	0.073	-0.160
	(0.157)	(0.140)	(0.204)	(0.220)
Gap X Third Best	0.172	0.020	-0.156	-0.069
	(0.195)	(0.163)	(0.162)	(0.215)
Gap X Others	-0.102	-0.058	0.173	0.779***
	(0.162)	(0.133)	(0.179)	(0.209)
Observations	1,104	1,104	1,104	1,104
R-Squared	0.304	0.383	0.347	0.447
Dependent S.D.	1.995	2.061	2.252	3.141
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Columns (1)-(4) each present results from a separate OLS regression. Panel A (”top-known sample”) includes the surveyed students who are *clear* about the best roommates in the dorm rooms; panel B (”top-unknown sample”) includes the surveyed students who are *unclear* about the best roommates in the dorm rooms. The independent variables of interest are *Gap* interacted with student ability indicators (CEE scores ranked the best, second, third, and the other in the dorm rooms). *Gap* is defined as the difference in the standardized CEE scores between the best and second-best students in the dorm room. The outcome variables are hours per day in playing games, hours per day in studying, hours per week in club activities or student organizations, and hours per week in part-time jobs or internships. All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include students' ability measurement (percentile ranking of their CEE scores within the major-cohorts), their demographic characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of their roommates in the same dorm rooms. Robust standard errors clustered at the major-cohort level are shown in parentheses. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table A.13: Robustness - Various Sample Selection Procedures

Dependent Variable: Std GPA	(1)	(2)	(3)	(4)
Top 33% X Ratio of Top 33% Roommates	-0.160***	-0.177**	-0.172**	-0.183***
	(0.058)	(0.071)	(0.069)	(0.061)
Middle 33% X Ratio of Top 33% Roommates	0.012	0.027	-0.006	0.029
	(0.054)	(0.063)	(0.064)	(0.058)
Bottom 33% X Ratio of Top 33% Roommates	-0.057	-0.079	-0.069	-0.026
	(0.057)	(0.070)	(0.066)	(0.057)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Observations	16,116	9830	11,886	13,605
R-Squared	0.222	0.246	0.229	0.230
Sample	**Main**	**Graduated**	**Local Dorms**	**No-change Dorms**

Notes: This table reports the main results estimated using alternative samples. The independent variable of interest is the proportion of high-ability roommates. The outcome variable is focal students' standardized GPA. Column (1) replicates Table 4 column (1) as reference. Column (2) restricts the sample to graduated students only, column (3) restricts the sample to dorm rooms without students from outside provinces, and column (4) restricts the sample to dorm rooms without roommate switches. The specification mirrors that in Table 4 column (1). All regressions control for the group-gender fixed effects and the dorm-size fixed effects. The demographic control variables include the students' ability measurement (standardized CEE scores and percentile ranking of CEE scores within the major-cohorts), individual characteristics (rural-urban status, CCP membership, and city of origin), and the average characteristics of the roommates in the same dorm room. Robust standard errors clustered at the major-cohort level are shown in parentheses. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

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Table A.14: Robustness - Various Specifications

Dependent Variable: Std GPA	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top 33% X Ratio of Top 33% Roommates	-0.160***	-0.135**	-0.157***	-0.120**	-0.148**	-0.162***	-0.156***
	(0.058)	(0.060)	(0.058)	(0.057)	(0.059)	(0.059)	(0.058)
Middle 33% X Ratio of Top 33% Roommates	0.012	0.020	0.015	0.049	0.007	0.014	0.012
	(0.054)	(0.053)	(0.054)	(0.053)	(0.054)	(0.054)	(0.054)
Bottom 33% X Ratio of Top 33% Roommates	-0.057	-0.062	-0.057	-0.017	-0.060	-0.055	-0.057
	(0.057)	(0.056)	(0.056)	(0.052)	(0.057)	(0.057)	(0.057)
Group-Gender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	No	No	Yes	Yes	Yes
Demographic Controls	Yes	No	Yes	No	Yes	Yes	Yes
Ability Control	Percentile Ranking	Percentile Ranking	Percentile Ranking	Percentile Ranking	CEE Scores	Ordinal Ranking	Plus Top 3 Indicator
Observations	16,116	16,116	16,116	16,116	16,116	16,116	16,116
R-Squared	0.222	0.198	0.222	0.176	0.223	0.221	0.223

Notes: This table reports the main results estimated using alternative specifications. The independent variable of interest is the proportion of high-ability roommates. The outcome variable is focal students' standardized GPA. The result in column (1) replicates the one in Table 4 column (1) as reference. From columns (2) to (4), we in turn remove the demographic controls, dorm-size fixed effects, and both. In columns (5) and (6), we replace the original ability control for focal students with their CEE scores in column (5) and the ordinal ranking of their CEE scores in column (6). In column (7) we additionally include an indicator of CEE scores being the top three within the major-cohorts. Standard errors are clustered at the major-cohort level. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

Table A.15: Robustness - Various Inference Methods

Dependent Variable: Std GPA	(1)	(2)	(3)	(4)
Top 33% X Ratio of Top 33% Roommates	-0.160***	-0.160***	-0.160***	-0.160***
	(0.058)	(0.057)	(0.055)	(0.051)
Middle 33% X Ratio of Top 33% Roommates	0.012	0.012	0.012	0.012
	(0.054)	(0.052)	(0.053)	(0.051)
Bottom 33% X Ratio of Top 33% Roommates	-0.057	-0.057	-0.057	-0.057
	(0.057)	(0.057)	(0.057)	(0.054)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Observations	16,116	16,116	16,116	16,116
R-Squared	0.222	0.222	0.222	0.222
Clustered S.E.	**Major-cohort**	**Major**	**Group**	**Dorm**

Notes: This table reports the main results estimated under various inference methods. The independent variable of interest is the proportion of high-ability roommates. The outcome variable is focal students' standardized GPA. The result in column (1) replicates the one in Table 4 column (1) as reference. From columns (2) to (4), standard errors are clustered at the major, group, and dorm room levels, respectively. *** significant at the 1 percent level; ** significant at the percent level; * significant at the 10 percent level.

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