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

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Abstract

Competition is widely used to enhance effort and performance. However, in many domains, like education, competition could backfire, as performance is not solely reliant on individual efforts but also on collaboration endeavors among peers. Utilizing university administrative data, we examine how competition changes peer effects and peer interactions. Exploiting randomly assigned roommates, we first demonstrate that high-ability roommates have detrimental effects on the academic performance of high-ability students. More importantly, such negative peer effects significantly increase along various dimensions of competition intensity within dorm rooms. Follow-up survey findings reveal that competition hinders mutual assistance and fosters unfriendly behaviors among roommates.

Keywords: Competition, Peer effects, Higher education

JEL classification: I21; I23; M50

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1. Introduction

Competition, a strong motivator for effort, can also yield negative effects on social capital. Considering the potential for competitors to exert externalities on one another, theoretical research has established that competition could reduce the inclination to assist others (Drago and Garvey, 1998) and may even foster acts of sabotage among rivals (Lazear, 1989). These competition-induced changes in peer interactions can be particularly detrimental in collaborative settings. Higher education exemplifies one such setting where students commonly collaborate while competing for top grade point averages (GPA), scholarships, and leadership roles. Despite the omnipresence of competition in higher education and rich literature on peer effects, how competition shapes peer effects and student interactions remains heavily understudied. We examine this question by estimating and comparing peer effects on students' academic performance under varying levels of competition intensity.

We leverage administrative data from a mid-tier Chinese university, which suits our research goal for several reasons. First, the university cultivates a competitive atmosphere among students through high-stakes annual scholarship competitions. Second, it randomly assigns roommates, allowing us to address the endogeneity of peer group formation. Third, it has information on the College Entrance Exam (CEE) scores. CEE scores allow us to measure students' ex-ante academic ability, and further casually estimate the *exogenous* (contextual) peer effects.[1] In sum, these features enable us to provide a causal interpretation of the estimated peer effects across various levels of competition intensity.

Measuring competition intensity among students is inherently challenging. Therefore, we utilize four different dimensions of competition intensity that enable us to paint a comprehensive picture of how competition influences peer effects. Along each dimension, we study how

[1]Contextual peer effects refer to peer effects driven by individual pre-determined characteristics (Manski, 1993).

peer effects change in a more competitive environment, as outlined below:

1. High-ability competitors. The impact of competition should be more pronounced among high-ability students, given their higher chances of winning scholarships. Thus, we investigate how high-ability roommates affect students of different ability levels. As predicted, our findings reveal that high-ability roommates have a negative impact exclusively on high-ability students.

2. Same major-cohort. At this university, students compete with peers within their own major-cohort for GPA rankings and scholarships. Consistent with this, our analysis reveals significant negative peer effects of high-ability roommates only when two high-ability students share the same major-cohort. Conversely, when high-ability roommates belong to different major-cohorts, we observe noisily estimated positive peer effects.

3. Size of major-cohorts. Scholarships at this university are competed for within the major-cohorts, whereas our peer effects estimations are confined to dorm rooms. The incentive to compete within the dorm room should decrease with the growing size of the major-cohort, which reduces the expected benefit of surpassing roommates. Consistent with this, our findings indicate that the major-cohort size significantly mitigates the negative peer effects we observed. Notably, this heterogeneous effect is exclusively observed among high-ability students.

4. Similarity in academic ability. Students are more likely to perceive each other as competitors when their academic abilities are closely matched. Following this, we calculate the gap in CEE scores between the best and the second-best students within each dorm room. We find that the academic performance of the best students decreases with a smaller gap, representing an enhanced competition intensity between them.

Overall, the four tests, each examining different dimensions of competition intensity, consistently show that peer effects become more negative in more competitive environments. One might have concerns over or alternative explanations for the interpretation of individual pieces of evidence. However, taken together, the weight of our evidence supports the idea that competition shapes peer effects among students. Furthermore, to reinforce our findings, we investigate the interactions between these dimensions and find mutual enhancement of various dimensions of competition intensity. For example, the major-cohort size only matters when two students are from the same major-cohort and possess high ability.

We conducted a follow-up survey among then-enrolled undergraduates at this university to gain insight into the underlying mechanisms through which competition shapes peer effects. The survey inquired about their daily interactions with roommates. Our findings reveal that, in more competitive dorm rooms, the academically top-performing roommates are less likely to assist the respondents and more inclined to show unfriendly behaviors, such as disturbances and conflicts. They also engage less in daily interactions, such as collaborative studying, exercises, dining out, or shopping together. These results suggest that competition directly influences the interactions among students, resulting in adverse peer effects in competitive settings. Additional examinations find no evidence supporting other potential mechanisms or explanations, such as psychological feelings, effort reallocation, grades on a curve, and learning-by-teaching.

Our study contributes to the peer effects literature in three ways. First, we are pioneers in showing that the direction and magnitude of peer effects on academic performance are contingent on the level of competition intensity among students, which shapes peer interactions. Most existing papers focus on human capital and behavioral spillovers without considering the role of competition among students.[2] Our findings also highlight the malleability of peer effects, suggesting that we cannot regard peer effects as fixed but rather as something shaped by the

[2]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.

competitive nature of the environment. This holds important policy implications, as institutions can influence the magnitude and even the direction of peer effects through strategic incentives. Therefore, it is crucial to weigh the policy's impact on peer effects and peer interactions in the decision-making processes of universities.

Second, the literature has begun to reach a consensus that peer effects are context-specific (see Sacerdote (2011) and Sacerdote (2014) for reviews). Peer effects on academic achievements in higher education are salient in some studies but absent in others.[3] However, little is known about the underlying pattern of why peer effects vary across settings and the specific factors driving the heterogeneity.[4] Our study illuminates this question by demonstrating that competition, a specific but ubiquitous context, may drive peer effects in a negative direction.

Third, most studies on peer effects in higher education use data from prestigious institutions in developed countries.[5] Our study deviates from these studies by focusing on a non-prestigious university that admits students around the median range of CEE scores, arguably more generalizable to students in China and other developing countries.

Our study further contributes to growing research on the costs associated with competition. Previous studies have shed light on various undesirable consequences related to competition, including demotivating participants with lower abilities (Brown, 2011; Fang, Noe and Strack, 2020), encouraging unethical behaviors (Cai and Liu, 2009; Schwieren and Weichselbaumer, 2010; Snyder, 2010; Bennett et al., 2013), and causing psychological stress (Smith, 2013; Hick-

[3] For example, Sacerdote (2001), Carrell, Fullerton and West (2009), Booij, Leuven and Oosterbeek (2017), and Feld and Zölitz (2017) find modest positive average peer effects on academic performance. Stinebrickner and Stinebrickner (2006) and Brady, Insler and Rahman (2017) find mixed effects for different subgroups or peer definitions. Foster (2006) and Lyle (2007) find no evidence of peer effects.

[4] Tincani (2017) theoretically predicts that the concerns about ranking can yield heterogeneous peer effects even without direct peer interactions.

[5] 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), and the Air Force Academy (Carrell, Malmstrom and West, 2008; Carrell, Fullerton and West, 2009; Carrell, Sacerdote and West, 2013), with the exception of the dataset used by Stinebrickner and Stinebrickner (2006). Notably, Han and Li (2009) and Ha (2016) examine academic peer effects within elite colleges in China. Both studies do not find robust peer effects on students' academic performance, yet Han and Li (2009) reveals a significant gender heterogeneity.

man and Metz, 2018; Berry, Kim and Son, 2019). We complement these studies by underscoring its additional cost – the erosion of social capital among competitors. Despite rich theoretical discussion about how tournaments affect peer interactions, most empirical work concentrates on lab experiments or sports settings (see Chowdhury and Gürtler (2015) for a review).[6] We directly examine the relationship between competition and peer interactions in an educational setting.

Section 2 introduces the background and the dataset. Section 3 delves into the main findings, and Section 4 analyzes mechanisms. Section 5 concludes. The online appendix discusses random assignment tests, data construction details, concerns about peer effect estimations, alternative mechanisms, and other potential explanations beyond competition.

2. Institutional Background and Data

2.1. Institutional Background

The university we study is a middle-ranked, comprehensive institution in southern China, notably promoting various competitive GPA-based scholarships among students. Scholarships are awarded annually within the major-cohorts, with the top 10%-15% in GPA from each major-cohorts being designated as winners. Financially, these scholarships typically cover 2-10 months of living expenses. Additionally, the university prioritizes scholarship recipients for internship recommendations at local connected companies. The signaling value of these scholarships in the job market is also highly emphasized, as highlighted by a head teacher during the new student enrollment session: "Winning scholarships is an important signal to distinguish yourself from your peers, especially at a non-prestigious university like ours."

[6] Dye (1984) and Lazear (1989) are the first economists to theoretically investigate sabotage behaviors in contests. The theory has been further developed by Drago and Garvey (1998); Chen (2003); Gürtler and Münster (2010); Gürtler, Münster and Nieken (2013).

The vast majority of students in this university reside in dorms. According to the survey, 96% of students live in dorms at least five days a week, spending on average 2.4 hours daily studying there, representing 69% of their total study time outside of classes.[7] Each dorm room accommodates four to eight students, as is typical in Chinese universities. A dorm room features multiple beds and workstations. In such a small shared space (approximately 50-70 square feet per student), roommates inevitably influence each other in their daily lives.

The university assigns roommates randomly. Specifically, incoming freshmen within each major are sorted into one to five administrative units (termed **"groups"** hereafter), comprising 20 to 50 students each.[8] Within each group, the university uses software to randomly place freshmen in available single-gender dorm rooms. Due to leftovers after the same-major assignment process, around 12.8% of the dorm rooms accommodate students from different major-cohorts. Evidence shown in Appendix A.1 confirms the randomness of the roommate assignment process.

2.2. Data

The university provided us with administrative data covering students from ten entering cohorts from 2009 to 2018. The dataset comprises three components. The first component is student transcript data, detailing each student's scores (out of 100) for each module taken in each semester. To mitigate the issue of course self-selection, we calculate the overall GPA solely based on required modules and standardize it within each major-cohorts.

The second component is student admission data, containing their CEE scores, high-school tracks (humanities or STEM), enrollment year, major, gender, city of origin, rural-urban origins, and China Communist Party membership before enrollment. We use students' CEE scores

[7]For more details on the survey, refer to Section 4.

[8]These groups are structured to facilitate student management. While students in the same group may not always share the same courses, they often participate in official team-building activities for each group.

to measure their pretreatment academic ability.[9] However, comparing CEE scores across different provinces or high-school tracks can be challenging due to the fact that students undergo province-track-specific training in high schools and subsequently take province-track-specific tests in CEE. To ensure the comparability of CEE scores, we exclude students from provinces other than the hometown province of the university (comprising less than 10% of the sample) and further remove students in majors that admit students from both tracks, such as economics and public administration, leaving us with 87 out of 125 majors, 66.9% of the sample.[10]

In Figure A.1, we illustrate the relationship between students' CEE performance and their academic performance in college. As depicted, students with higher percentile rankings in CEE are correlated with higher standardized GPAs and a greater likelihood of achieving a GPA in the top 10%.[11] These positive correlations between CEE scores and college GPAs provide support for our utilization of CEE scores as a measure of academic ability.

The final component comprises the full history of roommate assignments. Students cannot change roommates throughout their college years, except when irreconcilable conflicts occur. Students involved in the conflict are randomly reassigned to other rooms with vacancies. In our sample, fewer than 3% of the students switched dorm rooms; thus, we define roommates based on their initial assignments.[12] Linking three data components together provides us with 16,116 students from 385 major-cohorts. Table A.1 columns (1)-(2) reports the summary statistics.

[9]CEE, essential for undergraduate admission in China, is a comprehensive set of tests on students' skills in math, Chinese, English, and track-specific subjects such as physics or history. 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).

[10]Alternatively, we utilize track-specific CEE scores, along with other observable variables, to generate predicted GPAs for each student, as a unified academic ability measure across tracks. The results obtained using predicted GPAs and a sample that retains mixed-track major-cohorts consistently reveal a similar pattern to our main result in Table 1 column (1). This underscores the robustness of our main findings even when considering these mixed-track majors. However, it's important to acknowledge the limitations of this approach. Competition and peer effects could influence the CEE-GPA relationships, introducing endogeneity in the predicted ability measure. This could distort the ranking prediction of students from different tracks, especially when there is heterogeneity in the impacts of competition. Detailed results are available upon request.

[11]"GPA being in the top 10%" is a proxy of students' scholarship eligibility.

[12]The robustness test, which confines the analysis to dorm rooms where students never changed roommates, is presented in Table A.4 column (4).

3. Peer Effects along Various Dimensions of Competition Intensity

An ideal empirical test of the impact of competition on peer effects would involve further random assignments of students into distinct subsets with various degrees of competition intensity on top of the random assignment of roommates. However, a natural experiment of this kind and a consistent competition intensity measure are hard to obtain. Therefore, we approximate this by exploring diverse dimensions of competition intensity. Along each dimension, we examine how peer effects change in a more competitive environment.

a. High-ability competitors. The first piece of evidence proxies the degrees of competition intensity by whether students are academically strong enough to be potential competitors for high-ability roommates in pursuing GPA-based scholarships. We expect that the competition effects will be concentrated among students with higher chances of winning scholarships. Therefore, we interact the "the ratio of high-ability roommates" with students' ability indicators in the following specification:

$$\begin{aligned} Y_{id} = \beta_1 Top_i \times Z^d_{-i} + \beta_2 Middle_i \times Z^d_{-i} + \beta_3 Bottom_i \times Z^d_{-i} + \gamma_1 Top_i + \gamma_2 Middle_i \\ + \theta_1 A_i + \theta_2 X_i + \theta_3 \overline{X}^d_{-i} + Group_i \times Gender_i + Size_d + \epsilon_{id} \end{aligned} \tag{1}$$

where Y_{id} represents outcome variables such as the standardized GPA for required courses of student i during his college years. The indicators Top_i, $Middle_i$, and $Bottom_i$ classify student i's CEE score, into the top, middle, or bottom tercile within the respective major-cohort. Z^d_{-i} is the leave-one-out ratio of student i's high-ability roommates (top tercile in CEE scores within the major-cohort) in dorm room d. A_i represents the percentile ranking of i's CEE scores within the major-cohort, measuring i's prior academic ability. X_i represents individual demographic characteristics, including rural or urban residency, CCP membership before college enrollment, and city of origin dummies. $\overline{X}^{d}_{-i}$ denotes a vector of the average pretreatment characteristics of student i' s roommates in dorm room d. To have a causal interpretation, we control for group-gender fixed effects, $Group_i \times Gender_i$, the level at which roommates are randomly assigned. We also include dorm-size fixed effects, $Size_d$, to control for the direct effects of the number of roommates. Standard errors are clustered at the major-cohort level. The coefficients β_1, β_2, and β_3 measure the contextual peer effects, i.e., the impact of high-ability roommates (determined by CEE scores) on the academic performance of top-, middle-, and bottom-ability students, respectively.[13]

In Table 1, column (1) showcases the corresponding results. We observe significant negative effects of high-ability roommates, specifically among high-ability focal observations, who have a higher likelihood of winning scholarships, whereas the impacts on middle- and low-ability students are minor and lack statistical significance.[14] One-sided tests 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. These findings align with the lower level of competition intensity between high-ability students and their lower-ranked roommates. Our findings remain consistent across diverse academic performance measures, including overall GPA, GPA for elective courses, percentile rankings, and an indicator for the GPA being in the top 33% of the major-cohort, as shown in columns (2) to (5) of Table 1. Regarding the magnitude, taking the column (1) as an example, the point estimate of -0.172 implies that a one-standard-deviation increase in the proportion of high-ability roommates (0.237) decreases the standardized GPA of high-ability students by 4.0% of a-standard-deviation. As a benchmark,

[13] Appendix A.3 addresses other peer effects estimation concerns raised by Angrist (2014).

[14] There is mixed evidence in the existing literature on the impacts of high-ability peers on low-ability students. The absence of benefits for low-ability students from having high-ability peers in our context aligns with findings from some existing studies, such as Carrell, Sacerdote and West (2013), Feld and Zölitz (2017), and Zárate (2023). Factors such as diminished confidence and limited interactions with high-ability roommates may play a role.

Carrell, Sacerdote and West (2013) find that, based on the pretreatment group, a one-standard-deviation increase in the proportion of high SAT-V peers enhances the GPA of low-ability students by 5.2% of a-standard-deviation (calculated as $\frac{0.464\times0.074}{0.661}$).[15]

Acknowledging that using the top-tercile as a threshold to classify high-ability students is somewhat arbitrary, we investigate the heterogeneous effects of top-tercile roommates across different cutoffs to define high-ability focal observations. Our approach involves multiple regressions with the following model:

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

$TopX_i$ indicates whether student i ranks within the top $X\%$ in the major-cohort by CEE score and $NotTopX_i$ is its complement. Z^d_{-i} is the leave-one-out ratio of i's top-tercile roommates in dorm room d. Other notations mirror those in equation (1). We estimate equation (2) for every integer X from 3 to 99. The key coefficient, β_{1X}, measures the impact of the top 33% roommates on students in the top $X\%$ of their major-cohorts by CEE scores. For example, X equals 33 in Table 1 column (1).

Figure 1 depicts the estimated β_{1X} for each X and their respective 95% confidence intervals. The y-axis displays the effect of the top 33% roommates, while the x-axis shows the top $X\%$ students. Around X=33, the negative peer effects remain robust to various cutoffs for defining "high-ability" students. Moreover, the negative impact of high-ability roommates intensifies as X decreases from 99 to about 10. This pattern is consistent with competition-driven negative peer effects since a lower value of X represents higher-ability students and suggests stronger

[15]We also examine the impacts of middle- and low-ability roommates on students of various abilities, and they do not show adverse effects on focal students. These findings further support the idea that competition shapes peer effects, as lower-ranked roommates are less likely to be perceived as competitors. Detailed results can be provided upon request.

competition between focal students and their high-ability roommates. Conversely, as X decreases further (below 10), the estimates trend toward zero. This pattern should be interpreted with caution due to large standard errors. If anything, this reverse trend is also consistent with the competition-driven peer effects, as competition lessens in a lopsided competition where one's ability far exceeds that of roommates.

b. Same major-cohorts. As scholarships are assessed within the major-cohorts, we expect that high-ability students will only compete with high-ability roommates from the same major-cohort. Hence, we classify high-ability roommates based on whether they belong to the same major-cohort as the focal students. We then explore how these roommates affect high-, middle-, and low-ability focal students differently.

Table 2 demonstrates that negative peer effects are evident only when ”top-top” pairs share the same major-cohorts, where competition occurs. In contrast, the point estimates turn positive when high-ability roommates belong to different major-cohorts, where competition is minimal. Although imprecisely estimated, these positive estimates align qualitatively with U.S. studies where dorms normally mix students from various majors. However, these findings should be interpreted cautiously. Only 12.8% of the dorm rooms in our sample involve mixed major-cohorts, leading to larger standard errors for coefficients related to different major-cohorts than the same major-cohort. Therefore, we view these results as suggestive rather than conclusive evidence regarding the role of competition.[16]

c. Size of major-cohorts. Since scholarship competition takes place within the major-cohorts, a larger major-cohort size implies that the competition within dorm rooms is less intense. This is because the benefit of outperforming roommates decreases when there is a larger pool of competitors outside the dorm room. Essentially, students from smaller major-cohorts

[16]Consistent with Table 1 columns (1), we do not observe significant effects of high-ability roommates from the same major-cohort on middle- and low-ability students.

are more likely to perceive their roommates as potential competitors.

We test this hypothesis among high-ability students in Panel A of Table 3 by introducing an interaction term between the ratio of top 33% roommates and major-cohort size. Since majors of varying sizes may differ in other aspects, we incorporate saturated interactions between major dummies and the ratio of top 33% roommates.[17] Therefore, the variation in major-cohort size within the interaction term stems from different cohorts within the same major. The positive and significant coefficient of the interaction term in column (1) suggests that the detrimental effects of high-ability roommates diminish as the competition pool expands. In terms of magnitude, a coefficient of 0.004 implies that the negative peer effects among high-ability students would vanish when major-cohort size increases by 43 (calculated as $\frac{0.172}{0.004}$), close to half of the average major-cohort size in our analysis sample.

Since the competition predominantly centers within "top-top" pairs, we anticipate no noteworthy heterogeneous impacts of high-ability roommates across varying major-cohort sizes, especially among middle- and low-ability students. As placebo tests, we perform additional analyses among students with lower abilities in columns (2)-(3) of Table 3 Panel A. As anticipated, the coefficients of the interaction terms lack statistical significance, displaying considerably smaller magnitudes than those observed for high-ability students in column (1).

To provide additional support, we integrate the aforementioned dimension of competition into the analysis, i.e., the same versus different major-cohorts. If the size of major-cohort serves as an effective inverse proxy for competition intensity, then it can only alleviate the negative peer effects when high-ability roommates come from the same major-cohort. As shown in Panel B, major-cohort size diminishes the negative effects of high-ability roommates exclusively when these roommates belong to the same major-cohort and the focal students are also high-ability. Conversely, when high-ability roommates are from different major-cohorts, indi-

[17] For example, the average size of humanities majors is about 15% larger than that of STEM majors in our sample.

cating no direct competition with focal students, major-cohort size exerts no influence, even among the high-ability students. As placebo tests, columns (2) and (3) show that major-cohort size has no effect on students in the middle or bottom terciles, regardless of whether their high-ability roommates are from the same or a different major-cohort.

d. Similarity in academic ability. High-ability students should be more likely to perceive each other as potential scholarship competitors when possessing similar abilities. Therefore, the ability gap between the best and the second-best students (determined by their CEE scores) in a dorm room can serve as a reverse proxy for the competition intensity between them, given their high-ability status.[18]

To test it, we calculate Gap_d, 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_d represents a more competitive environment between the top two students in the dorm room. If competition results in negative peer effects, we anticipate that the top two students with a larger Gap_d will experience less pronounced negative peer effects and, thus, better academic performance. To examine this, we employ the following specification:

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

where $Best_i^d$, $2ndBest_i^d$, $3rdBest_i^d$, and $Others_i^d$ denote the rank of student i (first, second, third, or lower) among the same major-cohort members in dorm room d based on CEE scores. Other notations mirror those in equation (1). The coefficients β_1 to β_4 quantify the impacts of the *inverse* competition intensity between the top two students on the students of varying ranks

[18] In each dorm room, 81.10% of the best students and 56.42% of the second-best students fall within the top 33% of their major-cohorts.

within the dorm rooms. If competition primarily drives the negative peer effects on high-ability students, we expect positive estimates for β_1 and β_2.

Table 4 column (1) validates a significant positive correlation between the *inverse* competition intensity (Gap_d) and the academic performance of the best students in dorm rooms.[19] A one-standard-deviation increase in Gap_d (0.823) leads to a 7.8% standard deviation increase in the best students' GPA, suggesting better performance among the best students in less competitive environments. Conversely, the impact of Gap_d on second-best students is noticeably smaller. The observed asymmetry in patterns for the best and second-best students align with Chen (2003)'s theoretical model, showing that higher-ability competitors are more likely to be sabotaged and more affected by competition than their lower-ability counterparts. The survey data in Section 4 further corroborates this asymmetry in being sabotaged. Additionally, the minimal effects of Gap_d on third-best and lower-ranked students affirm Gap_d as a measure of competition intensity solely between the top two students in the dorm rooms.

A potential concern could arise that a larger Gap_d might mechanically result in a higher GPA of the best student in a dorm room, irrespective of competition, due to the inherent positive relationship between Gap_d and the best students' ability. We mitigate this concern by including the students' own academic ability A_i in all our regressions to account for the direct relationship between students' ability and their academic performance in college. Therefore, the coefficients of Gap_d should be interpreted as the net effects of the ability gap, holding students' ability fixed.

As competition is expected to heighten between students with higher chances of winning scholarships, we expect stronger effects of Gap_d between the top two students in a dorm room only when both have a good chance of winning scholarships. To examine this, we divide the regression sample into two groups based on the second-best students' CEE rankings within the

[19]The Gap_d is defined for dorm room d only when the top-two students in dorm room d belong to the same major-cohort, resulting in the exclusion of 268 observations.

major-cohorts. The top-half (bottom-half) sample comprises dorm rooms where the second-best students rank above (below) the median among all the second-best students in each dorm room.[20] Our findings, presented in Table A.2, reveal a positive correlation between the academic performance of the best students and Gap_d exclusively in the top-half sample (column 1), not in the bottom-half sample (column 2). This suggests a stronger influence of peer effects among students with higher likelihoods of winning in the competition and also implies that the observed positive effect of Gap_d on the best students in the full sample is not driven by mechanical factors.

In contrast to the top two students in dorm rooms, a narrower ability gap between other lower-ranked students in a dorm room may not imply a higher level of competition between them, as they are less likely to emerge as scholarship winners. Therefore, in Table A.2 columns (3)-(4), we redefine Gap_d as the standardized CEE score difference between the lower-ranked students in the dorm rooms, and the redefined Gap_ds do not yield significant effects on the lower-ranked students. These findings confirm that the ability gap between two students can be considered a reliable proxy for competition intensity only if the two students are academically proficient enough to be potential scholarship winners.

Summary. Thus far, we have demonstrated stronger negative peer effects in more competitive environments by examining four distinct dimensions of competition intensity. In the online appendix Section A.4, we develop a unified measurement to characterize the degree of competition intensity within dorm rooms and reach a similar conclusion.[21]

[20] The top-half sample features dorm rooms where the second-best student is within the top 26.46% of their major-cohorts. This indicates that both the best and second-best students in these dorm rooms are of high ability, implying substantial chances of winning scholarships for both.

[21] Given the potential association between academic performance and labor market outcomes, in the online appendix Section A.8, we explore the peer effects on students' job market outcomes. Drawing from the post-graduation data of the 2018 cohort only, we find no statistically significant impacts of high-ability roommates on their likelihood of attending graduate schools or being employed but observe a significantly negative impact on students' monthly wages among employed students.

4. Potential Mechanisms

In this section, we delve into the mechanism underlying how competition generates negative peer effects through a survey conducted with students from the entering cohorts of 2016 to 2018. The survey elicits information on students' interactions with their best academic performance roommates (termed "the best roommates" hereafter), their attitudes toward competition, time allocation for study and other activities, and their psychological well-being. Administered and collected by university administrative staff during the spring semester of 2020, the survey garnered a response rate of 49.1%. Applying the same sample selection standard as the main sample, we have 2,534 surveyed students merged with the administrative data.[22]

We initiate the survey about roommate interactions with the following guidance: "For the upcoming questions, consider the roommate who exhibits the best academic performance excluding yourself." Due to privacy constraints mandated by the university, we are unable to request respondents to explicitly identify their best roommates. To assess data quality, we required all respondents to choose one of two options: "I am aware of who the roommate with the best academic performance is" or "I have multiple roommates with exceptional academic performance. I will randomly choose one of them as the subject of the following questions."

1,094 out of 2,534 (43.2%) respondents expressed uncertainty about the identity of their best roommates (*top unkonwn sample*). As shown in Table A.1 column (3)-(7), these students tend to reside in larger dorm rooms and exhibit less competitive attitudes, such as considering it less important to outperform their peers. Estimates from the top unknown sample are expected to be noisy due to measurement errors. Additionally, their uncertainty may lead them to select roommates they are closer to for survey questions. Therefore, we mainly focus on the 1,430

[22]We replicate our main results using this merged survey sample, and the coefficients are slightly larger but less precisely estimated. The results are available upon request.

students with clear perceptions about their best roommates (*top-known sample*).[23]

Some theory papers predict that competition can reduce the incentive for mutual assistance (Drago and Garvey, 1998) and may even provoke sabotage among competitors (Lazear, 1989). To test this hypothesis, we employ a specification that mirrors the one in Table 4 based on equation (3). As previously, Gap_d serves as an *inverse* indicator of competition intensity between the top two students in a dorm room. We investigate the effects of Gap_d on the interactions of students of varying ranks in each dorm room with their best roommates.

Table 4 columns (2)-(7) present results regarding the frequency of interaction between focal students and their best roommates. Results for positive interactions are outlined in columns (2)-(4), while results for unfriendly behaviors are in columns (5)-(7).[24] The findings suggest that, in less competitive environments, the best students in dorm rooms engage in more daily interactions with their best roommates, discuss studies more frequently with their best roommates, and receive more assistance from their best roommates. These effects are statistically significant at the 5% level and economically meaningful. Specifically, a one-standard-deviation increase in Gap_d (0.905) increases the dependent variables by 14.8%, 11.2%, and 11.5% of a standard-deviation, respectively. Moreover, in less competitive environments, the best students are less likely to have conflicts with or to be disturbed by their best roommates. For instance, a one-standard-deviation increase in Gap_d decreases the probability of being disturbed by the best roommates by 2.81 percentage points, a 45.47% decrease from the sample mean (6.18 percentage points). The pattern of peer interactions is remarkably consistent with that of academic performance in column (1). The ability gap between the best and the second-best students in the dorm rooms only affects the best students. Overall, these results support that competition

[23]As expected, no significant patterns are observed based on the top unknown sample. Results are available upon request.

[24]Dependent variable construction is detailed in Section A.5.

intensity directly changes peer interactions and peer effects.[25] We also explore other potential mechanisms, including psychological stress and shifting efforts to non-academic activities. We do not find support in alternative channels as detailed in the appendix Section A.5.

5. Conclusion

Our study is pioneering in showing that competition shapes peer effects through peer interactions. Leveraging four dimensions of competition intensity, we show that heightened competition leads to negative peer effects in dormitory settings. The follow-up survey further indicates less collaborative behavior and more unfriendly behaviors among roommates in more competitive environments.

Our findings carry significant policy implications not only for China but also for countries with a pronounced competitive education system. Educational institutions can strategically use incentives to shape peer effects and should consider the impact of policies on peer effects during policy formulation. Our findings offer insights into cost-effective strategies to enhance student performance, such as mixed-major dorm arrangements to minimize direct competition. However, as demonstrated by Carrell, Sacerdote and West (2013), designing the optimal group assignment policy should be done cautiously.

[25] We also introduce an interaction term between Gap_d and the size of major-cohort to lend further support. A larger major-cohort size suggests less intense competition within dorm rooms. Hence, we anticipate negative coefficients for the interaction terms regarding friendly interactions and positive coefficients for unfriendly behaviors from the best roommates. The results are consistent with our expectations, although some estimates lack statistical significance. The results are available upon request.

References

Abdulkadiroğlu, Atila, Joshua Angrist, and Parag Pathak. 2014. "The elite illusion: Achievement effects at Boston and New York exam schools." *Econometrica*, 82(1): 137–196.

Angrist, Joshua D. 2014. "The perils of peer effects." *Labour Economics*, 30: 98–108.

Bai, Chong-en, Ruixue Jia, Hongbin Li, and Wang Xin. 2020. "Entrepreneurial Reluctance: Academic Talent and Firm Creation in China."

Bennett, Victor Manuel, Lamar Pierce, Jason A Snyder, and Michael W Toffel. 2013. "Customer-driven misconduct: How competition corrupts business practices." *Management Science*, 59(8): 1725–1742.

Berry, James, Hyuncheol Bryant Kim, and Hyuk Son. 2019. "When Student Incentives Don't Work: Evidence from a Field Experiment in Malawi."

Booij, Adam S, Edwin Leuven, and Hessel Oosterbeek. 2017. "Ability peer effects in university: Evidence from a randomized experiment." *The Review of Economic Studies*, 84(2): 547–578.

Brady, Ryan R, Michael A Insler, and Ahmed S Rahman. 2017. "Bad company: Understanding negative peer effects in college achievement." *European Economic Review*, 98: 144–168.

Brown, Jennifer. 2011. "Quitters never win: The (adverse) incentive effects of competing with superstars." *Journal of Political Economy*, 119(5): 982–1013.

Cai, Hongbin, and Qiao Liu. 2009. "Competition and corporate tax avoidance: Evidence from Chinese industrial firms." *The Economic Journal*, 119(537): 764–795.

Carrell, Scott E, and Mark L Hoekstra. 2010. "Externalities in the classroom: How children exposed to domestic violence affect everyone's kids." *American Economic Journal: Applied Economics*, 2(1): 211–28.

Carrell, Scott E, Bruce I Sacerdote, and James E West. 2013. "From natural variation to optimal policy? The importance of endogenous peer group formation." *Econometrica*, 81(3): 855–882.

Carrell, Scott E, Frederick V Malmstrom, and James E West. 2008. "Peer effects in academic cheating." *Journal of Human Resources*, 43(1): 173–207.

Carrell, Scott E, Mark Hoekstra, and Elira Kuka. 2018. "The long-run effects of disruptive peers." *American Economic Review*, 108(11): 3377–3415.

Carrell, Scott E, Richard L Fullerton, and James E West. 2009. "Does your cohort matter? Measuring peer effects in college achievement." *Journal of Labor Economics*, 27(3): 439–464.

Chen, Kong-Pin. 2003. "Sabotage in promotion tournaments." *Journal of Law, Economics, and Organization*, 19(1): 119–140.

Chowdhury, Subhasish M, and Oliver Gürtler. 2015. "Sabotage in contests: a survey." *Public Choice*, 164(1-2): 135–155.

Drago, Robert, and Gerald T Garvey. 1998. "Incentives for helping on the job: Theory and evidence." *Journal of labor Economics*, 16(1): 1–25.

Dye, Ronald A. 1984. "The trouble with tournaments." *Economic Inquiry*, 22(1): 147–149.

Fang, Dawei, Thomas Noe, and Philipp Strack. 2020. “Turning up the heat: The discouraging effect of competition in contests.” *Journal of Political Economy*, 128(5): 1940–1975.

Feld, Jan, and Ulf Zölitz. 2017. “Understanding peer effects: On the nature, estimation, and channels of peer effects.” *Journal of Labor Economics*, 35(2): 387–428.

Figlio, David N. 2007. “Boys named Sue: Disruptive children and their peers.” *Education finance and policy*, 2(4): 376–394.

Foster, Gigi. 2006. “It’s not your peers, and it’s not your friends: Some progress toward understanding the educational peer effect mechanism.” *Journal of public Economics*, 90(8-9): 1455–1475.

Gould, Eric D, Victor Lavy, and M Daniele Paserman. 2009. “Does immigration affect the long-term educational outcomes of natives? Quasi-experimental evidence.” *The Economic Journal*, 119(540): 1243–1269.

Gürtler, Oliver, and Johannes Münster. 2010. “Sabotage in dynamic tournaments.” *Journal of Mathematical Economics*, 46(2): 179–190.

Gürtler, Oliver, Johannes Münster, and Petra Nieken. 2013. “Information policy in tournaments with sabotage.” *The Scandinavian Journal of Economics*, 115(3): 932–966.

Guryan, Jonathan, Kory Kroft, and Matthew J Notowidigdo. 2009. “Peer effects in the workplace: Evidence from random groupings in professional golf tournaments.” *American Economic Journal: Applied Economics*, 1(4): 34–68.

Han, Li, and Tao Li. 2009. “The gender difference of peer influence in higher education.” *Economics of Education Review*, 28(1): 129–134.

Ha, Wei. 2016. “Quasi-experimental evidence of academic peer effects at an Elite University in People’s Republic of China.” *Asia Pacific Education Review*, 17(4): 703–718.

Hickman, Daniel C, and Neil E Metz. 2018. “Peer effects in a competitive environment: Evidence from the PGA Tour.” *Economic Inquiry*, 56(1): 208–225.

Hoekstra, Mark, Pierre Mouganie, and Yaojing Wang. 2018. “Peer quality and the academic benefits to attending better schools.” *Journal of Labor Economics*, 36(4): 841–884.

Imberman, Scott A, Adriana D Kugler, and Bruce I Sacerdote. 2012. “Katrina’s children: Evidence on the structure of peer effects from hurricane evacuees.” *American Economic Review*, 102(5): 2048–82.

Jones, Todd R, and Michael S Kofoed. 2020. “Do peers influence occupational preferences? Evidence from randomly-assigned peer groups at West Point.” *Journal of Public Economics*, 184: 104154.

Kling, Jeffrey R, Jeffrey B Liebman, and Lawrence F Katz. 2007. “Experimental analysis of neighborhood effects.” *Econometrica*, 75(1): 83–119.

Lavy, Victor, and Analia Schlosser. 2011. “Mechanisms and impacts of gender peer effects at school.” *American Economic Journal: Applied Economics*, 3(2): 1–33.

Lazear, Edward P. 1989. “Pay equality and industrial politics.” *Journal of Political Economy*, 97(3): 561–580.

Li, Hongbin, Lingsheng Meng, Xinzheng Shi, and Binzhen Wu. 2012. “Does having a cadre parent pay? Evidence from the first job offers of Chinese college graduates.” *Journal of Development Economics*, 99(2): 513–520.

Lyle, David S. 2007. "Estimating and interpreting peer and role model effects from randomly assigned social groups at West Point." *The Review of Economics and Statistics*, 89(2): 289–299.

Manski, Charles F. 1993. "Identification of endogenous social effects: The reflection problem." *The review of economic studies*, 60(3): 531–542.

Marioulas, Julian. 2017. "China: A world leader in graduation rates." *International Higher Education*, , (90): 28–29.

Merlino, Luca Paolo, Max Friedrich Steinhardt, and Liam Wren-Lewis. 2019. "More than just friends? School peers and adult interracial relationships." *Journal of Labor Economics*, 37(3): 663–713.

Sacerdote, Bruce. 2001. "Peer effects with random assignment: Results for Dartmouth roommates." *The Quarterly Journal of Economics*, 116(2): 681–704.

Sacerdote, Bruce. 2011. "Peer effects in education: How might they work, how big are they and how much do we know thus far?" In *Handbook of the Economics of Education*. Vol. 3, 249–277. Elsevier.

Sacerdote, Bruce. 2014. "Experimental and quasi-experimental analysis of peer effects: two steps forward?" *Annual Review of Economics*, 6(1): 253–272.

Schwieren, Christiane, and Doris Weichselbaumer. 2010. "Does competition enhance performance or cheating? A laboratory experiment." *Journal of Economic Psychology*, 31(3): 241–253.

Smith, Jonathan. 2013. "Peers, pressure, and performance at the national spelling bee." *Journal of Human resources*, 48(2): 265–285.

Snyder, Jason. 2010. "Gaming the liver transplant market." *The Journal of Law, Economics, & Organization*, 26(3): 546–568.

Song, Yang, George Loewenstein, and Yaojiang Shi. 2018. "Heterogeneous effects of peer tutoring: Evidence from rural Chinese middle schools." *Research in Economics*, 72(1): 33–48.

Stinebrickner, Ralph, and Todd R Stinebrickner. 2006. "What can be learned about peer effects using college roommates? Evidence from new survey data and students from disadvantaged backgrounds." *Journal of Public Economics*, 90(8-9): 1435–1454.

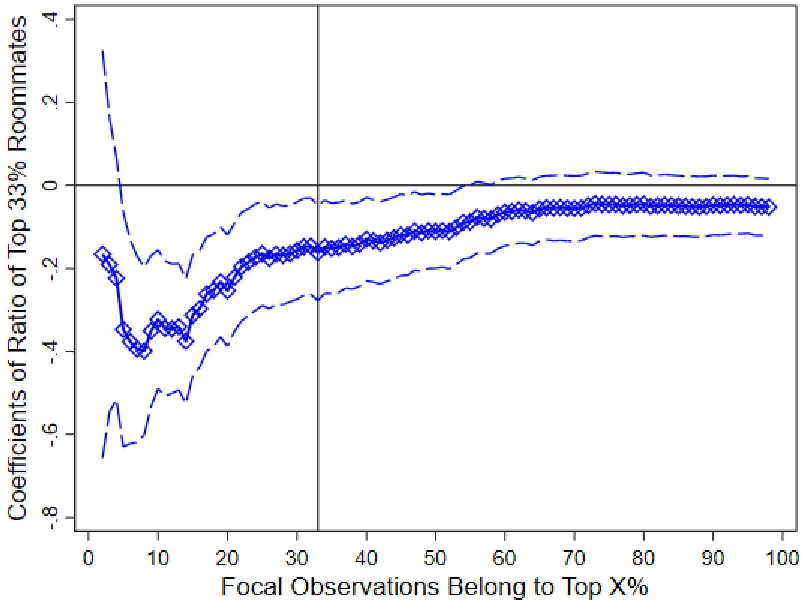
Tincani, Michela. 2017. "Heterogeneous peer effects and rank concerns: Theory and evidence."

Zarate, Roman Andres. 2020. "An Experimental Approach to Peer Effects: Evidence on Social and Academic Skills."

Zárate, Román Andrés. 2023. "Uncovering peer effects in social and academic skills." *American Economic Journal: Applied Economics*, 15(3): 35–79.

Zimmerman, David J. 2003. "Peer effects in academic outcomes: Evidence from a natural experiment." *Review of Economics and Statistics*, 85(1): 9–23.

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



Notes: This figure plots the estimates of the coefficients on the ratio 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 the integer X ranging from 3 to 99) based on equation (2) 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. Robust standard errors are clustered at the major-cohort level.

Table 1: Peer Effects on Students of Various Ability

Dependent Variable:	(1) Std GPA (Required)	(2) Std GPA	(3) Std GPA (Elective)	(4) GPA Percentile Ranking	(5) GPA in the Top 33%
Top 33% X Ratio of Top 33% Roommates	-0.172***	-0.160***	-0.136**	-0.055***	-0.088**
	(0.058)	(0.058)	(0.054)	(0.019)	(0.034)
Middle 33% X Ratio of Top 33% Roommates	0.048	0.012	-0.019	0.021	0.051*
	(0.053)	(0.054)	(0.058)	(0.017)	(0.029)
Bottom 33% X Ratio of Top 33% Roommates	-0.050	-0.057	-0.065	-0.025	-0.015
	(0.057)	(0.057)	(0.062)	(0.019)	(0.034)
Group-Gender FE	Yes	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Observations	16,116	16,116	16,109	16,116	16,116
R-Squared	0.216	0.222	0.209	0.231	0.184
One-sided Test (p-values)					
Top-Top $\geqslant$ Middle-Top	0.002	0.013	0.001	0.001	0.063
Top-Top $\geqslant$ Bottom-Top	0.057	0.096	0.122	0.058	0.188

Notes: Columns (1)-(5) each present results from a separate OLS regression. The independent variables of interest are the ratio 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 for required courses, standardized GPA, standardized GPA for elective 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. It is noted that there are 7 observations fewer in column (3) due to students dropping out before taking any elective courses. All regressions control for group-gender fixed effects and 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 5 percent level; * significant at the 10 percent level.

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Table 2: Same vs. Different Major-Cohorts

Dependent Variable:	(1) Std GPA (Required)
Top 33% X Ratio of Top 33% Roommates from Same Major-Cohort	-0.223***
	(0.076)
Top 33% X Ratio of Top 33% Roommates from Different Major-Cohorts	0.094
	(0.293)
Middle 33% X Ratio of Top 33% Roommates from Same Major-Cohort	0.045
	(0.067)
Middle 33% X Ratio of Top 33% Roommates from Different Major-Cohorts	0.120
	(0.349)
Bottom 33% X Ratio of Top 33% Roommates from Same Major-Cohort	-0.114
	(0.073)
Bottom 33% X Ratio of Top 33% Roommates from Different Major-Cohorts	0.541*
	(0.305)
Top 33% X Roommates' Ratio of Same Major-Cohort	0.078
	(0.118)
Middle 33% X Roommates' Ratio of Same Major-Cohort	0.090
	(0.120)
Bottom 33% X Roommates' Ratio of Same Major-Cohort	0.326***
	(0.116)
Group-Gender FE	Yes
Dorm-Size FE	Yes
Demographic Controls	Yes
Observations	16,116
R-Squared	0.216
One-sided Test (p-values)	
Top-Top (same major-cohort) $\geqslant$ Top-Top (diff major-cohorts)	0.153
Top-Top (same major-cohort) $\geqslant$ Middle-Top (same major-cohort)	0.003
Top-Top (same major-cohort) $\geqslant$ Bottom-Top (same major-cohort)	0.143

Notes: The independent variables of interest are the ratio of high-ability roommates from the same (different) major-cohorts interacted with student ability indicators (top, middle, and bottom). The outcome variable is focal students' standardized GPA for required courses. All regressions control for group-gender fixed effects, 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 5 percent level; * significant at the 10 percent level.

Table 3: Interactions with Other Competition Measurements

Dependent Variable:	(1) Std GPA (required)	(2) Std GPA (required)	(3) Std GPA (required)
Panel A: Heterogeneity by Major-Cohort Size			
Ratio of Top 33% Roommates X Major-Cohort Size	0.004***	-0.000	0.001
	(0.001)	(0.001)	(0.001)
Ratio of Top 33% Roommates X Major Dummies	Yes	Yes	Yes
R-Squared	0.340	0.321	0.369
Panel B: Interactions of High-Ability Roommates with Others			
Ratio of Top 33% Roommates from Same Major-Cohort X Major-cohort Size	0.0050**	-0.0011	0.0002
	(0.0020)	(0.0020)	(0.0016)
Ratio of Top 33% Roommates from Different Major-Cohort X Major-cohort Size	-0.0045	-0.0090	0.0039
	(0.0053)	(0.0091)	(0.0044)
Roommates' Ratio of Same Major-Cohort	-0.0805	0.1684	0.0555
	(0.1409)	(0.1570)	(0.1403)
Roommates' Ratio of Top 33% X Major Dummies	Yes	Yes	Yes
R-Squared	0.343	0.334	0.400
P(Same MC X MC Size > Different MC X MC Size)	0.030	0.181	0.773
FEs and Controls	Yes	Yes	Yes
Observations	5,842	5,808	4,466
Sample	Top Tercile	Middle Tercile	Bottom Tercile

Notes: Columns (1)-(3) are subsamples consisting of high-, middle-, and low-ability students. Each column presents results from a separate OLS regression. For Panel A, the independent variable of interest is the ratio of high-ability roommates interacted with the major-cohort size. For Panel B, the independent variables of interest are the ratio of high-ability roommates from same (different) major-cohort interacted with the major-cohort size. The outcome variable is focal students' standardized GPA for required courses. All regressions control for group-gender fixed effects, 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 Panel B last row entry. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

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Table 4: Ability Gap and Academic Performance/Peer Interactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Main	Mechanisms: Peer Interactions					
Dependent Variable:	Std GPA (Required)	Interactions	Discuss Study	Help	Isolate	Confront	Disturb
Gap X Best	0.082***	0.343***	0.112**	0.115**	-0.020	-0.016***	-0.031**
	(0.021)	(0.122)	(0.054)	(0.054)	(0.013)	(0.006)	(0.014)
Gap X Second Best	0.011	0.125	0.028	0.010	-0.020	-0.012	-0.008
	(0.021)	(0.174)	(0.073)	(0.073)	(0.021)	(0.009)	(0.018)
Gap X Third Best	0.024	0.028	-0.015	-0.066	0.016	0.001	-0.010
	(0.022)	(0.171)	(0.067)	(0.074)	(0.024)	(0.008)	(0.014)
Gap X Others	0.008	-0.000	-0.009	0.061	-0.010	-0.010	0.016
	(0.015)	(0.095)	(0.056)	(0.058)	(0.017)	(0.006)	(0.014)
Group-Gender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,848	1,440	1,440	1,440	1,440	1,440	1,440
R-Squared	0.217	0.305	0.288	0.300	0.273	0.238	0.234
Dependent S.D.	0.861	2.096	0.902	0.890	0.294	0.136	0.241

Notes: Columns (1)-(7) each present results from a separate OLS regression. Column (1) employs the full regression sample, while columns (2)-(7) focus on the surveyed students who are *clear* about their 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 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 Gap_d is defined for dorm room d only when the top-two students in dorm room d belong to the same major-cohort, resulting in the exclusion of 268 observations. The outcome variables are focal students' standardized GPA for required courses for column (1); the frequency of interactions between focal students and their best roommates for columns (2)-(7). All regressions control for group-gender fixed effects, dorm-size fixed effects, and demographic controls. 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.

A. Appendix

A.1. Random Assignment Tests

Our analysis hinges on the assumption that roommates are randomly matched, as should be the case given the university's assignment procedure. To test the validity of this assumption, we employ the approach proposed by Guryan, Kroft and Notowidigdo (2009), as detailed in Table A.3.[26] Specifically, we introduce the group level leave-one-out mean of "Z" as a control when regressing students' own characteristics "Z" against their roommates' characteristics.[27] As shown, neither roommates' pre-determined characteristics (in Panel A) nor their performance in CEE (in Panels B and C) holds predictive significance for focal students' characteristics, supporting the random assignment assumption.[28]

A.2. Data Construction

a. GPA calculation For graduated students, we calculate their four-year GPA; for students still enrolled in the university 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. Worrying about the compatibility between graduated students and then-enrolled students, in Table A.4 column (2), we show that the results are robust to restrictions to graduated students. For students who dropped out, we calculate their GPA from completed courses. Notably, 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 approximately 3%.

b. Non-local Sample Selection As introduced in Section 2.2, we remove students from other provinces to ensure the comparability of CEE scores. 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 stu-

[26] This approach can address the mechanical negative bias in traditional balancing tests. The results of employing traditional balancing tests also support the hypothesis of random assignment. Detailed results of traditional balancing tests are available upon request.

[27] Group level leave-one-out mean is the average characteristics across group members excluding the focal student. The definition of the "group" is introduced in footnote 8.

[28] Although the point coefficient of interest in Panel A column (6) is significant at the 10% level, it is economically small. To be specific, a one-standard-deviation increase in the ratio of local roommates increases the likelihood of focal students 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). It is noted that some of the coefficient estimates in Panel B are rounded to 0.000 when keeping three decimals. The p-values for estimates from columns (1) and (6) of Panel B are 0.690, 0.386, 0.259, 0.516, 0.563, and 0.836, respectively.

dents in the dorm rooms. The exclusion of non-local roommates would not bias our estimates as long as the roommate assignment process is orthogonal to the city of origin. We conduct a robustness check by dropping dorm rooms containing non-local students, and the results remain quantitatively similar, as shown in Table A.4 column (3).

c. Peer Interactions Variables Construction The dependent variables in Table 4 columns (2)-(4) are three distinct measures of positive peer interactions, as reported in the survey responses. In the survey, respondents were provided with a list of nine various daily activities they could engage in with their best roommate, such as studying, dining out, shopping, exercising, or participating in extracurricular activities. To measure their closeness, we calculated the total number of activities they frequently participated in together, denoted as "Interactions" in column (2). Additionally, we inquired about the frequency with which respondents discussed their studies with their best roommates and asked students to evaluate how helpful their best roommates were. To facilitate interpretation, we transformed these two questions into binary variables, "Discuss Study" and "Help" in columns (3) and (4).[29] In columns (5)-(7), the dependent variables represent unfriendly behaviors exhibited by roommates. In the survey, respondents were presented with a list of ten different types of unfriendly behaviors, such as "refused to answer my questions about the study", "affected my daily routine", and "engaged in physical conflict with me". Respondents were asked to select all the unfriendly behaviors they experienced from their best roommates. We then categorized these ten behaviors into three groups: "Isolate", "Confront", and "Disturb". Each category is coded as a binary indicator representing the presence of any unfriendly behaviors within that respective category.[30]

A.3. Measurement Errors in Peer Effects Estimations

As highlighted by Angrist (2014), measurement error in pre-treatment ability can lead to either overestimation or underestimation of peer effects.[31] In our study, this concern is partic-

[29]To elaborate, "Discuss Study" takes a value of one if respondents *always* or *often* discussed academics (e.g., homework and classes) with their best roommates and zero if the answer is "occasionally", "rarely", or "never". "Help" equals one if respondents considered their best roommates to be *very helpful* or *somewhat helpful* in general. It takes zero if the answer is "neither helpful nor unhelpful", "somewhat unhelpful", or "very unhelpful".

[30]To clarify, "Isolate" takes a value of one if the respondent has ever encountered the following issues with their 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 has ever faced the following issues with their best roommate: "quarreling with me or abusing me", "threatening me", and "engaging in physical conflict with me". "Disturb" equals one if the respondent has ever encountered issues with their best roommates, including "interrupting my study" and "affecting my daily routine."

[31]This is because the measurement error in pre-treatment ability affects both own ability and peer ability measurements in the equation.

ularly relevant due to potential errors in using the CEE score as an ability proxy. [32] Feld and Zölitz (2017) further show that, when peer group assignment is random, measurement error still leads to attenuation bias. Therefore, the random assignment of roommates in our context implies that the true effects might be even more negative than our estimates.

Following the spirit of Carrell, Hoekstra and Kuka (2018), Feld and Zölitz (2017), and Merlino, Steinhardt and Wren-Lewis (2019), we empirically show that measurement error should attenuate our peer effects estimates by artificially introducing varying amounts of measurement errors into student CEE scores and re-estimating the model.[33] As depicted in Figure A.2, the average point estimates are closer to zero as more measurement errors are introduced. This observation aligns with the assumption of random dorm room assignments and demonstrates that measurement errors bias our results towards zero. Therefore, our estimates can be considered lower-bound estimations of the impacts of high-ability roommates.

A.4. Single Measurement of Competition Intensity

In the main draft, we utilize four distinct dimensions of competition intensity and show that peer effects become more negative in more competitive environments along each dimension. In this section, we aim to establish a single measurement to characterize the degree of competition intensity within the dorm rooms. To this end, we develop two distinct approaches for constructing the single measures. The first approach combines attributes of students, dormitories, and major-cohorts extracted from the administrative dataset to create an objective unified measurement of competition intensity. The second one utilizes individual measurements of competition attitude from our survey data to create a subjective unified measurement of competition intensity.

Single Measurement Based on Administrative Data

The intensity of competition should be more pronounced among students in the top tercile,

[32] For example, we would like to use subject-specific CEE scores for different academic tracks (e.g., mathematics scores for the STEM track and Chinese scores for the humanities track) as a more precise ability measurement, but our dataset lacks this level of detail.

[33] Specifically, we introduce noise distributed as $N \sim (0, X\%)$ to the raw standardized CEE score, where X takes values of 10, 30, 50, ..., 150. A higher X implies a greater amount of artificially introduced measurement errors in the academic ability measurement. In other words, the artificial errors span from 10% to 150% of the standard deviation of the authentic standardized CEE scores. For each X, we recompute students' relative rankings based on these noisy CEE scores and re-estimate equation (1). We repeat this procedure 1,000 times for each X and plot the average coefficient (along with the 5th and 95th percentiles) of β_1 resulting from this process for each X in Figure A.2. For reference, the estimated β_1 from column (1) in Table 1, where authentic CEE scores are used, is marked at X=0.

from smaller major-cohorts, and having more roommates from the same major-cohort. Thus, we construct a competition intensity measurement in the following way:

$$Competition = \frac{\text{Ratio of Roommates from the Same Major-cohort} \times I(\text{Top } 33\%)}{\text{Major-cohort Size}}$$

where $I(\text{Top } 33\%)$ is an indicator of whether the observation belongs to the top 33% in the major-cohort based on own CEE scores. For ease of interpretation, we standardized the competition measure with a *minimum* of 0 and a standard deviation of 1.

Table A.5 presents the results illustrating how the impacts of high-ability roommates vary with the standardized competition intensity. In column (1), we intentionally exclude "Ratio of Top 33% Roommates X Major Dummies" to allow the inclusion of "Ratio of Top 33% Roommates" as a benchmark of the impact of high-ability roommates under the minimal competition intensity. Similar to Table 3, we include "Ratio of Top 33% Roommates X Major Dummies" in column (2) so that the variations in major-cohort size are considered within the same major but across different cohorts.

The estimate for "Ratio of Top 33% Roommates" is precisely zero, as evident in the second row of column (1), with a point estimate of -0.0063 and a t-value of 0.16. This suggests that high-ability roommates have no influence on their roommates when facing minimal competition intensity. Furthermore, the first row indicates a negative and significant interaction term, indicating that peer effects become increasingly negative as competition intensity rises. To be specific, a one-standard-deviation increase in competition intensity amplifies the negative impact of high-ability roommates by 0.0839. This magnitude suggests that the average impact of high-ability roommates on high-ability students (-0.172, Table 1 column (1)) represents an environment around two-standard-deviations above the minimal level of competition intensity.

One feature of our current construction of the competition intensity measurement is its incorporation of an indicator variable, $I(\text{Top } 33\%)$, which assigns a competition intensity of zero for two-thirds of the observation. This feature raises the concern that the findings in columns (1)-(2) could be driven solely by changes at the extensive margin (zero or non-zero), essentially making this measurement an indicator of top-tercile students. To address this concern, we replicate the analysis and limit the sample to the top-tercile students, focusing on the impact of the intensive margin for this measurement. The results are summarized in Table A.5 columns (3)-(4). As shown, the interaction terms remain negatively significant with comparable magnitude when focusing on the intensive margin.

Single Measurement Based on Survey Data

Even among students with similar abilities, there is significant variability in their competitive attitudes. Some students may place a higher emphasis on surpassing competitors or winning scholarships than others. Consequently, we should anticipate stronger impacts of competition among students who exhibit a stronger competition attitude. In the survey data, we assess students' competition attitudes through three distinct questions: "Competition is important for success in college", "Surpassing competitors is important in college", and "Winning scholarship is important in college". Responses to each of these questions range from 0 to 4, with 0 indicating "not important at all" and 4 signifying "very important."

Table A.6 displays the heterogeneous impacts of high-ability roommates across focal students with varying levels of competition attitudes. Columns (1)-(3) each adopts distinct questions to define levels of competition attitudes. The first row of the table indicates that a stronger competition attitude tends to drive peer effects in a negative direction. In columns (2) and (3), such effects are not only statistically significant at the 5% level but also economically meaningful. For example, column (2) shows that a one-standard-deviation increase in competition attitude (1.01) enhances the negative impact of high-ability roommates by 0.2577. This increase suggests that the negative impact of high-ability roommates on high-ability students (-0.172, as shown in Table 1 column (1)) would vanish for focal observations whose competition attitude is 0.67 standard deviations below the mean.

Although the first row in column (1) lacks statistical significance, the magnitude of the interaction term coefficient is comparable to those found under the other two definitions of competitive attitude, albeit with a notably larger standard error. This larger standard error in column (1) could stem from the limited variation in responses to the first question. Specifically, 82% of students reported that competing for success in college is important or very important, compared to only 53% who considered surpassing competitors as important or very important.

Moreover, we do not observe a similar pattern in Panel (B) and Panel (C) for middle- and low-ability students, which could be interpreted as placebo tests. Even if they possess a stronger competitive attitude, the reduced likelihood of winning scholarships renders these students less threatening to high-ability roommates. This absence of a pattern further supports the specificity of our findings regarding competition attitudes among high-ability students.

These results should be interpreted cautiously. Students responded to the survey question after being exposed to the dorm room environment, rendering the measured competition attitude endogenous. Therefore, we interpret these findings as suggestive rather than conclusive evidence regarding the role of competition.

A.5. *Other Mechanisms*

a. Psychological feelings. Competition may also lead to worse academic performance by influencing students' psychological feelings. For instance, heightened competition could enhance stress levels or diminish the sense of self-esteem among students. To test this hypothesis, we follow a similar fashion and use Gap as an inverse proxy for the intensity of competition between the best and the second-best students in dorm rooms. We specifically examine students' psychological feelings, including motivation, stress, and self-confidence, stemming from interactions with their best roommates in dorm rooms. In our regression analysis, we categorize strong feelings as ones and neutral or weaker feelings as zeros.[34] Table A.7 reports the corresponding results. Our findings show that students' psychological feelings do not significantly change with the competition intensity between the top two students in dorm rooms. Namely, they do not report being less motivated, more stressed, or less confident due to competition. These results suggest that worse psychological feelings are unlikely to play a vital role in how competition affects peer effects.

b. Effort reallocation. Competition can sometimes deter effort, especially among those who perceive a lower likelihood of success (Brown, 2011; Fang, Noe and Strack, 2020). Students living with high-ability roommates may strategically reallocate their efforts to other domains, such as student organizations, part-time jobs, and internships, which could also benefit their long-term labor market outcomes. In some cases, they might relinquish direct academic competition with their high-ability roommates and invest less effort in their studies. If this phenomenon is a significant driver behind negative peer effects, we would expect high-ability students to allocate more time to activities other than studying as competition intensifies. To test this hypothesis, we employ a similar technique as Table A.7 columns (4)-(7) demonstrated. The outcome variables are the number of hours that surveyed students spend on activities such as playing games (daily), studying (daily), participating in student organizations (weekly), and

[34]For example, students were asked questions like, "To what extent did the roommate with the best academic performance in your dorm room make you feel motivated or unmotivated in the last semester?" We assigned a value of one to students who chose "Very motivated" and "Somewhat motivated" and assigned a value of zero to those who chose "Neither motivated nor unmotivated", "Somewhat unmotivated", and "Very unmotivated."

working part-time jobs or internships (weekly). As shown, focal students do not allocate significantly less or more time to other activities when the Gap decreases. These results do not support the effort reallocation mechanism.

A.6. Alternative Explanations Other than Competition

a. Learning-by-teaching. As emphasized by Song, Loewenstein and Shi (2018), peer tutoring could substantially enhance a tutor's performance. In a dorm room with more high-ability roommates, high-ability students may perform worse due to missed opportunities to teach middle- or low-ability peers. However, the analysis below suggests that learning-by-teaching is less likely to be the predominant factor driving our results.

Our following analysis builds upon the premise that the efficacy of tutoring relies on students sharing classes. The opportunity for learning-by-teaching diminishes if students in the same dorm room have fewer shared courses. Yet a competition-driven hostile environment could have negative impacts even in the absence of shared courses, since the impact of not helping in daily activities or disrupting sleep or study routines are not confined to the same courses. Consequently, the impact of a competition-driven hostile environment should be less sensitive to the number of shared courses among students in a dorm room.

Building on the aforementioned rationale, the ideal approach to test the learning-by-teaching hypothesis is to examine how the impacts of high-ability roommates change with the exogenous variation in course overlap for each dorm room. However, the course overlap directly observed in that data is inherently endogenous, as students with closer relationships may choose similar courses. To address this, we construct a proxy for course overlap based on the degree of course selection freedom at this university. Students in the same major-cohort are expected to be more (or less) likely to enroll in courses together in any given year when there is a higher number of required (or elective) courses in their respective major-cohort-year. Specifically, we calculate the ratio of required courses per major-cohort-year and analyze its interaction with the presence of high-ability roommates. If learning-by-teaching is the main driving force of our findings, we would anticipate a negative significant coefficient for the interaction term, since an increased overlap in course sets would enhance the effects of missed teaching opportunities due to having fewer middle- and low-ability roommates.

Table A.8 summarizes results for high-ability students, the likely beneficiary of learning-by-teaching. The dependent variable is each student's standardized GPA for required courses in each academic year. Column (1) shows a negative and significant effect of the ratio of high-ability roommates (row 3), consistent with our main findings in Table 1 column (1). Notably, the interaction terms, across columns (1)-(4) with various specifications, are consistently positive and not statistically significant, suggesting that the negative peer effects do not significantly vary with the degree of course selection freedom.

Besides, as highlighted in section 3, competition intensity within dorm rooms tends to diminish as the major-cohort size increases, while there is no apparent reason to expect a similar decrease in the negative impacts of missed teaching opportunities to be correlated with major-cohort size. As shown in Table 3 column (1), the negative peer effects decrease with the major-cohort size. This finding aligns more closely with the competition hypothesis rather than the learning-by-teaching one.

In summary, while the learning-by-teaching hypothesis does align with some of our main findings, such as the same versus different major-cohorts and ability gap, additional analyses – particularly the heterogeneous results relating to degrees of course overlap and major-cohort sizes – lend stronger support to the competition over the learning-by-teaching explanation.

b. Grading on a curve. Grading on a curve is a common practice in educational institutions. This relative evaluation practice may mechanically lower the GPA of some students with similar academic performance. However, we argue that grading on a curve is unlikely to be the driving force of the negative peer effects we have identified for several reasons. First, the university does not officially mandate or enforce any grading curve policy.[35] Although the university principal mentioned that some faculty might adjust grades for students on the verge of failing a course, the negative peer effects we documented primarily affect top-performing students. Therefore, grade adjustments at the lower end of the performance spectrum are unlikely to significantly contribute to our findings. Moreover, 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 and GPA system (from 0 to 100) applied in this university. This is because adjustments in categorical grades have a much larger influence on students' GPAs than those in continuous grades.

[35] There are no predetermined quotas for grade distributions, nor are there restrictions on the percentage of students who can receive grades above or below particular thresholds at this university.

A.7. The Dynamic Pattern of Peer Effects

One interesting aspect of our context is that, in principle, students do not change roommates throughout their college years. This enables us to estimate how peer effects evolve over the four-year college period. Figure A.3 illustrates the corresponding results, based on equation (1), where the dependent variable is replaced with standardized GPAs for required courses for each academic year. Our finding reveals that the effect of high-ability roommates on high-ability students' first-year academic performance is significantly negative, with a magnitude of 0.158, similar to the corresponding estimate in Table 1 column (1). Moreover, this negative peer effect persists throughout college, despite some fluctuations in point estimates.

This pattern suggests persistent negative peer effects starting from the first year in college. Since the university will announce everyone's ranking at the end of each academic year, Figure A.3 indicates salient negative peer effects among top students before the first public announcement. Thus, our negative peer effects are not primarily driven by access to precise information about close competitors. Instead, students may already have a sense of their roommates' ability based on their everyday interactions. While we rule out the influence of precise information, it remains possible that the public announcement plays an important role in generating negative peer effects by making competition more salient to all students. In particular, senior students may inform freshmen about the coming public announcement of their performance.

A.8. Peer effects on Long-Term Outcomes

In this section, using the graduation data for the 2018 entering cohort, we explore the impacts on students' long-term outcomes based on equation (1).[36] Table A.9 summarizes the corresponding results. Column (1) examines whether students gain admission to graduate programs at any university. Column (2) analyzes the employment status immediately after graduation for students not pursuing further education. Columns (3) and (4) examine the initial job salary per month and its log transformation among students who found jobs.

First, we do not observe statistically significant impacts of high-ability roommates on the likelihood of attending graduate schools or being employed right after graduation. However, it's important to note that the noisy zero estimate issue may arise, making the results inconclusive due to the limited sample size. For instance, in column (1), a one-standard-deviation increase in the ratio of high-ability roommates (0.24) decreases the probability of attending graduate

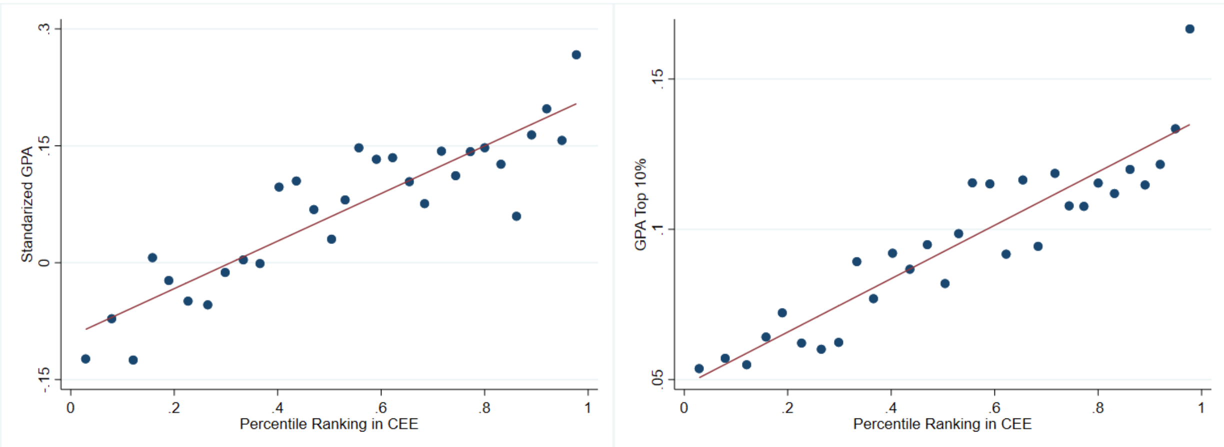
[36]Unfortunately, post-graduation data for earlier cohorts is not accessible.

school by 1.5 percentage points, representing 11.1% of the mean.

Second, we do identify significant negative impacts on students' salaries, as demonstrated in columns (3)-(4). More importantly, these negative effects of high-ability roommates are particularly pronounced among high-ability focal observations, aligning with our findings on academic performance. Specifically, a one-standard-deviation increase in the ratio of high-ability roommates (0.24) results in a 263 CNY reduction in high-ability students' salaries, equivalent to 4.7% of the mean and 12% of the standard deviation. However, it's crucial to exercise caution when interpreting these findings, considering that the students graduated in 2022 amidst the challenging circumstances of the COVID-19 pandemic, which significantly disrupted the job market for young individuals in China. Therefore, the results obtained from this specific cohort may not be readily applicable to other cohorts.

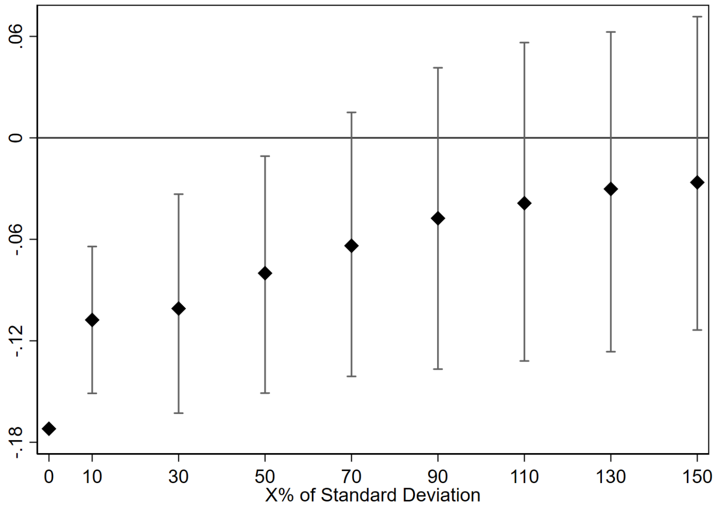
Figure A.1: The Relationship between CEE Performance and Academic Performance

(a) Standardized GPA **(b)** GPA in the Top 10%



Notes: These bin-scatter plots demonstrate the relationships 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 standardized overall GPA and the y-axis in panel (b) is an indicator of the overall GPA ranking in the top 10% within the major-cohorts. Note that the mean of standardized overall GPA is below zero. This is because we standardize the GPA based on the full sample and the drop of observations from non-local provinces when drawing this graph. On average, compared to local students, students from other provinces has a lower GPA by 0.22 of a standard deviation.

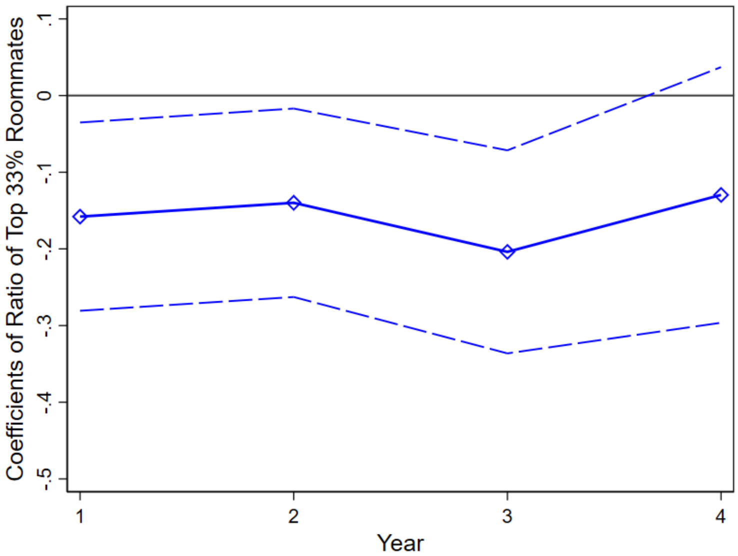
Figure A.2: Sensitivity of Main Results to Measurement Error



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 (1) 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 1 column (1) for a reference.

Figure A.3: The Dynamic Peer Effects on Standardized GPA

(a)



Notes: Each dot presents a separate OLS estimate of the coefficients on the proportion of high-ability roommates. The dashed lines denote the 95% confidence intervals. The outcome variables are students' standardized GPAs for required courses in Year 1, Year 2, Year 3, and Year 4 at college. The specifications replicate those in Table 1 column (1). 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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full Sample		**Survey Sample**				
			Top-Known Sample		Top-Unknown Sample		
Variable:	Mean	S.D.	Mean	S.D.	Mean	S.D.	Difference
Male	0.655	0.475	0.67	0.47	0.64	0.48	-0.03
STEM	0.833	0.373	0.84	0.36	0.84	0.36	-0.00
CCP (Youth) Member	0.942	0.233	0.93	0.26	0.91	0.29	0.02
Rural	0.475	0.469	0.48	0.38	0.47	0.38	0.01
From the Local City	0.325	0.468	0.21	0.41	0.21	0.40	-0.00
Dorm Size	5.577	1.423	5.05	1.95	5.30	2.04	0.25**
CEE Score	522.473	38.221	491.93	17.34	490.63	17.30	-1.30
Percentile Ranking in CEE	0.533	0.277	0.46	0.27	0.45	0.27	-0.01
Ratio of Top 33% Roommates	0.361	0.237	0.35	0.28	0.36	0.28	-0.00
GPA Percentile Ranking	0.515	0.281	0.47	0.29	0.48	0.28	0.01
GPA in the Top 33%	0.362	0.481	0.37	0.48	0.35	0.48	-0.02
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*
Winning Scholarships Is Important in College	-	-	0.53	0.50	0.48	0.50	-0.08*
Observations	16,116		1,440		1,094		2,534

Notes: This table reports the means and standard errors for our main regression sample (columns (1)-(2))) and survey sample (columns (3)-(7)) at the individual level. Columns (3) and (4) are the surveyed students who are **clear** about their best roommates in the dorm rooms. Columns (5) and (6) are the surveyed students who are **unclear** about their best roommates in the dorm rooms. *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. Survey questions about competition attitude equal one if the respondents agree with the statements and zero if they disagree with.

Table A.2: **Ability Gap and Academic Performance by Subsample and Redefined Gap**

	(1) Second-Best Top Half	(2) Second-Best Bottom Half	(3) Gap 2^{nd}- 3^{rd}	(4) Gap 3^{rd}- 4^{th}
Dependent Variable:	Std GPA (Required)	Std GPA(Required)	Std GPA(Required)	Std GPA(Required)
Gap X Best	0.0996***	0.0439	-0.034	-0.041
	(0.0382)	(0.0387)	(0.035)	(0.033)
Gap X Second Best	0.0245	-0.0033	0.006	0.020
	(0.0320)	(0.0289)	(0.034)	(0.039)
Gap X Third Best	0.0024	0.0320	0.011	0.019
	(0.0396)	(0.0298)	(0.031)	(0.041)
Gap X Others	0.0270	-0.0120	-0.013	0.006
	(0.0219)	(0.0290)	(0.025)	(0.029)
Observations	7,983	7,865	15,525	15,038
R-Squared	0.269	0.273	0.214	0.213
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Each column represents 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). Column (1) is restricted to the top-half sample including dorm rooms whose second-best students, based on their CEE scores, are higher than the median among all of the second-best students in each dorm room, while column (2) is restricted to the bottom-half sample including dorm rooms whose second-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 in columns (1)- (2), while it is redefined as the difference between the **second** (**third**) and the **third** (**fourth**) best students in the same dorm rooms in column (3) (column (4)). The outcome variables are the focal students' standardized GPAs for required courses. Specifications mirror the one in Table 4. 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.

A.13

Table A.3: 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
Panel A						
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)
R-Squared	0.994	0.888	0.881	0.892	0.874	0.901
Panel B						
Roommates'CEE Scores (Mean)	0.006	0.000	-0.000	0.000	0.000	0.000
	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Group mean of **Z** (leave-one-out)	-20.399***	-25.164***	-24.941***	-25.370***	-24.676***	-25.114***
	(1.319)	(1.041)	(1.030)	(1.202)	(1.099)	(1.020)
R-Squared	0.994	0.888	0.881	0.892	0.873	0.901
Panel C						
Ratio of Top 33% Roommates	-0.216	-0.003	0.001	-0.002	0.009	-0.002
	(0.175)	(0.013)	(0.007)	(0.002)	(0.008)	(0.006)
Group mean of **Z** (leave-one-out)	-20.393***	-25.160***	-24.939***	-25.370***	-24.676***	-25.114***
	(1.319)	(1.046)	(1.033)	(1.202)	(1.099)	(1.020)
R-Squared	0.994	0.888	0.881	0.892	0.873	0.901
Observations	16,116	16,116	16,116	16,116	16,116	16,116
Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Dorm Size FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns (1)-(6) of panel A-C 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 in panel A-C are roommates' average characteristics of the corresponding "**Z**", the ratio of top 33% roommates, and roommates' average CEE scores, respectively. The leave-one-out group mean of "**Z**" (partialing out the focal student) is included in each regression to alleviate the underlying mechanical relationship. Note that some of the coefficient estimates in panel B are rounded to 0.000 when keeping three decimals. The p-values for estimates from columns (1) and (6) of panel B are 0.690, 0.386, 0.259, 0.516, 0.563, and 0.836, respectively.

A.14

Table A.4: Robustness - Various Sample Selection Procedures

Dependent Variable: Std GPA	(1)	(2)	(3)	(4)
Top 33% X Ratio of Top 33% Roommates	-0.172***	-0.163**	-0.184***	-0.196***
	(0.058)	(0.072)	(0.068)	(0.061)
Middle 33% X Ratio of Top 33% Roommates	0.048	0.033	0.041	0.064
	(0.053)	(0.063)	(0.064)	(0.057)
Bottom 33% X Ratio of Top 33% Roommates	-0.050	-0.071	-0.061	-0.016
	(0.057)	(0.071)	(0.065)	(0.058)
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	0.216	0.243	0.224	0.223
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 ratio of high-ability roommates. The outcome variable is focal students' standardized GPA for required courses. Column (1) replicates Table 1 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 1 column (1). 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.5: Single Measurement of Competition Intensity

	(1)	(2)	(3)	(4)
Dependent Variable:	Std GPA (Required)	Std GPA (Required)	Std GPA (Required)	Std GPA (Required)
Standardized Competition Intensity X Ratio of Top 33% Roommates	-0.0839**	-0.0896***	-0.1157*	-0.2235*
	(0.0328)	(0.0345)	(0.0663)	(0.1155)
Ratio of Top 33% Roommates	-0.0063		0.0565	
	(0.0393)		(0.1231)	
Standardized Competition Intensity	0.0212	0.0262	-0.0027	0.0365
	(0.0161)	(0.0170)	(0.0407)	(0.0539)
Ratio of Top 33% Roommates X Major Dummies	No	Yes	No	Yes
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	5,842	5,842
R-Squared	0.217	0.222	0.326	0.338
Sample	Full	Full	Top-Tercile	Top-Tercile

Notes: Each column presents results from a separate OLS regression. Columns (1)-(2) are based on full sample, and columns (3)-(4) are restricted to the top tercile students only. The independent variable of interest is the competition intensity index interacted with the ratio of top 33% roommates. The outcome variables are students' standardized GPAs for required courses. Specifications mirror the one in Table 4. All regressions control for group-gender fixed effects and 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. The p-values for one-sided tests are shown in the last two row entries. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

A.16

Table A.6: Single Measurement of Competition Intensity

Dependent Variable:Std GPA (required)	(1)	(2)	(3)
Panel A: High-Ability			
Competition Attitude X Ratio of Top 33% Roommates	-0.2631	-0.2577*	-0.3048**
	(0.2315)	(0.1304)	(0.1181)
Ratio of Top 33% Roommates	0.8534	0.7671**	0.8839**
	(0.7270)	(0.3757)	(0.3569)
Competition Attitude	0.1228	0.2024***	0.2204***
	(0.1003)	(0.0610)	(0.0621)
Observations	743	743	743
R-Squared	0.443	0.453	0.453
Panel B: Middle-Ability			
Competition Attitude X Ratio of Top 33% Roommates	-0.0625	0.0960	0.0191
	(0.1980)	(0.1830)	(0.1446)
Ratio of Top 33% Roommates	0.3117	-0.1335	0.0511
	(0.6278)	(0.5293)	(0.4219)
Competition Attitude	0.0318	-0.0775	0.1034*
	(0.0857)	(0.0675)	(0.0611)
Observations	809	809	809
R-Squared	0.405	0.407	0.414
Panel C: Low-Ability			
Competition Attitude X Ratio of Top 33% Roommates	-0.0737	0.1214	0.1620
	(0.3346)	(0.2131)	(0.1864)
Ratio of Top 33% Roommates	0.4350	-0.1697	-0.2229
	(0.9801)	(0.6082)	(0.5060)
Competition Attitude	0.2102	0.0893	0.1474**
	(0.1397)	(0.0894)	(0.0621)
Observations	535	535	535
R-Squared	0.487	0.488	0.505
Attitude Definition	Important to Compete	Important to Surpass Competitor	Important to Win Scholarship
Group-Gender FE	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes

Notes: Each column presents results from a separate OLS regression and denotes a distinct definition of levels of competition attitudes. Panels A-C focus on high-, middle-, and low-ability students, respectively. The independent variable of interest is the ratio of high-ability roommates interacted with student competition attitude. The outcome variable is focal students' standardized GPA for required courses. All regressions control for group-gender fixed effects, dorm-size fixed effects, and demographic controls. 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.

A.17

Table A.7: Other Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Psycological Feelings			Effort Allocation			
Dependent Variable:	Motivated	Pressure	Low Confidence	Game	Study	Organization	Part-time
Gap X Best	0.087	-0.008	-0.030	-0.087	0.115	0.060	0.206
	(0.057)	(0.052)	(0.057)	(0.149)	(0.142)	(0.199)	(0.194)
Gap X Second Best	-0.018	-0.118	-0.097	0.016	-0.138	-0.019	0.086
	(0.083)	(0.092)	(0.090)	(0.130)	(0.098)	(0.161)	(0.221)
Gap X Third Best	-0.026	-0.053	0.033	-0.127	-0.029	0.108	0.168
	(0.072)	(0.080)	(0.072)	(0.125)	(0.161)	(0.194)	(0.299)
Gap X Others	-0.017	0.055	0.056	-0.180	0.125	-0.016	-0.095
	(0.063)	(0.083)	(0.061)	(0.131)	(0.124)	(0.126)	(0.162)
Observations	1,440	1,440	1,440	1440	1440	1440	1440
R-Squared	0.297	0.279	0.274	0.287	0.352	0.336	0.377
Dependent S.D.	0.966	1.061	1.089	1.998	2.127	2.389	3.078
Group-Gender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column presents results from a separate OLS regression focusing on the surveyed students who are *clear* about their best roommates in the dorm rooms. The outcome variables in columns (1)-(3) 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. The outcome variables in columns (4)-(7) 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. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table A.8: Heterogeneity by Course Overlap

	(1)	(2)	(3)	(4)
Dependent Variable:	Std GPA (required)	Std GPA (required)	Std GPA (required)	Std GPA (required)
Ratio of Required Courses X Ratio of Top 33% Roommates	0.109	0.029	0.095	0.012
	(0.116)	(0.122)	(0.116)	(0.121)
Ratio of Required Courses	0.024	0.053	-0.035	-0.004
	(0.045)	(0.047)	(0.059)	(0.061)
Ratio of Top 33% Roommates	-0.130**			
	(0.062)			
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Roommates' Ratio of Top 33% X Major Dummies	No	Yes	No	Yes
Roommates' Ratio of Top 33% X Year Dummies	No	No	Yes	Yes
Observations	18,770	18,770	18,770	18,770
R-Squared	0.251	0.259	0.255	0.263
Sample	Top Tercile	Top Tercile	Top Tercile	Top Tercile

Notes: Columns (1)-(4) each present results from a separate OLS regression based on a sample of top tercile students. Each observation in the table represents a student in a specific academic year. The independent variable of interest is the ratio of top 33% roommates interacted with the ratio of required courses per major-cohort-year. The outcome variable is focal students' yearly standardized GPA for required courses. All regressions control for group-gender fixed effects, dorm-size fixed effects, and demographic controls. 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.9: The Effects of High-Ability Roommates on Students' Long-Term Outcomes

	(1)	(2)	(3)	(4)
Dependent Variable:	Grad School	Employment	Wage	Ln(wage)
Top 33% X Ratio of Top 33% Roommates	-0.061	0.111	-1,096.437***	-0.173**
	(0.068)	(0.079)	(381.689)	(0.068)
Middle 33% X Ratio of Top 33% Roommates	-0.011	0.026	-224.824	0.005
	(0.058)	(0.058)	(434.083)	(0.070)
Bottom 33% X Ratio of Top 33% Roommates	0.010	-0.140	836.614*	0.158*
	(0.068)	(0.090)	(474.432)	(0.092)
Group-Gender FE	Yes	Yes	Yes	Yes
Dorm-Size FE	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Observations	2,084	1,802	1,463	1,463
R-Squared	0.219	0.236	0.263	0.272
P(Top < Middle Students)	0.287	0.820	0.062	0.034
P(Top < Bottom Students)	0.248	0.972	0.001	0.001
Dependent Mean	0.135	0.830	5,617.561	8.561

Notes: Columns (1)-(4) each present results from a separate OLS regression using the sample of the 2018 cohort. The independent variables of interest are the ratio of high-ability roommates interacted with student ability indicators (CEE scores in the top, middle, and bottom terciles within the major-cohorts). The dependent variables are focal students' labor market outcomes, including dummies indicating whether they were admitted to any graduate program, whether they were employed if they were not admitted to graduate schools, wage levels, and log wages among students who searched for jobs (with unemployment coded as missing). Specifications mirror the one in Table 1. 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.