Achievement Rank Affects Performance and Major Choices in College*

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Abstract

This paper studies how a student's ordinal achievement rank affects performance and specialization choices in university. We exploit data from a setting in which students are randomly assigned to teaching sections and find that students with a higher rank in their section achieve higher grades, are more likely to graduate, and are more likely to choose related follow-up courses and majors. These effects are stronger for men who, in contrast to women, respond to a higher rank with an increase in their study effort. Our results highlight that social comparisons with peers can have lasting effects on students' careers.

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I. Introduction

Students face considerable uncertainty in their career decisions. They must carefully assess the expected costs of benefits of decisions such as whether to go to college or what major to choose. Given that students have limited information about their own ability, this assessment is challenging and they need to form beliefs. Ability beliefs have been shown to be malleable and often depend on external cues from a student's environment (Wiswall and Zafar 2015; Stinebrickner and Stinebrickner 2012, 2014; Zafar 2011; Bobba and Frisancho 2016). Social comparison is an important factor that may shape ability beliefs. Research in psychology has shown that a person's ordinal rank in a peer group—whether a person is ranked first, second, or last—is an important determinant of self-perception. A person with a higher rank, all else being equal, tends to perceive herself as more capable (Marsh 1987).

Motivated by these findings, this paper investigates whether a person's ordinal rank affects important career choices. We focus on decisions made during the college years, which is a formative period for many people. Career decisions made in college have profound consequences for people's lives. Students, however, typically make these decisions at a stage when they have had limited opportunities to learn about their ability. In this setting, students may view their ordinal rank as a signal about their ability.

To estimate the causal impact of rank on student outcomes, we exploit a quasi-experimental setting at a Dutch business school. Within each course, students are randomly assigned to teaching sections—small tutorial groups—of up to 16 students. We compute students' ordinal ranks within their section based on their grade point average (GPA) in all previous college courses. These rankings are not made public, but students have ample opportunity to infer their rank through frequent interactions. The random assignment of students provides us with exogenous variation in the ordinal rank for a given GPA level. Our analysis compares students with the same GPA who, by chance, had different ranks in their section.

We find that the ordinal rank in a peer group is an important determinant of educational outcomes in college. The analysis yields four main findings. First, we provide evidence that rank affects contemporaneous performance. An increase in rank by 10 percentiles—one position in a group of 11 students—increases performance by 2 percent of a standard deviation. It also increases the probability of passing the course by 1 percent. Second, we show that same-gender peers appear to be the most relevant comparison group. The effect of the ordinal rank among same-gender peers is considerably larger than the effect of the rank among all section peers. Third, we document large gender differences in the rank effects. Among men, the effect of rank is about 2.5 times greater than the effect among women. Fourth, we show that ordinal rank in first-year sections has persistent effects on career choices. Students who rank highly among their section peers choose more math-intensive elective courses. Students with a high rank in a particular section are also more likely to choose follow-up courses and majors related to that section: a 10 percentile increase in rank in a compulsory subject increases the probability of choosing that subject as a major by 1 percentage point. Finally, we present evidence on longer-run effects, showing that a high rank at the beginning of a student's studies positively affects the probability of graduating.

Using data from student course evaluations, we explore several channels that may explain why a student's rank affects his or her career choice. We find that students with a higher rank give a lower rating to the interaction with their section peers. This is indicative of rank affecting a student's self-perception vis-à-vis her peers, which in turn may affect her choices. We also find a positive effect of rank on self-reported study hours for men, which could explain why men respond more strongly to rank than women.

Taken together, our results suggest that students base their career decisions on noisy information. After we control flexibly for GPA, the entire variation in the ordinal rank is due to the random assignment of students to groups and contains little information on a student's actual ability. The fact that we observe a strong effect of rank on career choice suggests that students use their rank as a heuristic to infer their true ability. Because the inference is based on a large degree of noise, it may lead to suboptimal decisions. It appears that highly ranked students benefit from their rank through better performance. Low-ranked students, in contrast, make less ambitious choices than they otherwise would.

With this paper, we contribute to the literature on rank effects in education, which has mainly focused on class rank in primary and secondary school. Studies find strong effects of rank on test scores in secondary school (Murphy and Weinhardt 2018), engagement in risky behaviors (Elsner and Isphording 2017b; Cicala et al. 2018), college enrollment (Elsner and Isphording 2017a), as well as long-run effects on earnings (Denning et al. 2018). Our contribution to this literature is threefold. First, our paper is the first to estimate rank effects in a setting with clean random assignment. Identification in previous studies relies on nonexperimental variation in cohort composition within schools. While this strategy helps to minimize selection bias, it is impossible to rule out all confounding factors. By obtaining similar results with in a setting with random assignment, our findings lend credibility to identification in nonexperimental settings. Second, this paper provides the first causal evidence of rank effects in college. The rank effects we find for people in their early twenties turn out to be similar to those found by other studies in secondary schools, suggesting that rankings influence student outcomes throughout the educational career. Third, we show that rank effects emerge even if peer groups interact for a limited time. In our case, students meet their peers for about four hours a week for a period of two months. This short-term exposure appears to be sufficient for students to allow their rank to influence their decisions. Our setting differs from that in previous studies in which students have the same peers for several years (Murphy and Weinhardt 2018, Elsner and Isphording 2017).[1] In this regard, we complement recent evidence on the short-term influence of peers (Thiemann 2017) and role models (Breda et al. 2018), which shows that exposure to peers for just a few days or even hours affects students' choices.

More broadly, this paper contributes to the literature on peer effects in education. Our results highlight that a person's ordinal rank in a peer group is an important channel through which the composition of one's peers affects individual outcomes. In our identification strategy, we isolate the rank effect from other commonly estimated peer effects.[2] Therefore, our results show that the rank effect is a peer effect in its own right and not a mere reflection of other types of peer effects.

II. Theoretical Considerations

There are several plausible mechanisms through which a student's ordinal rank can affect performance and career choices. A mechanism frequently documented in psychology is the effect of rank on a student's self-concept, often labeled as the "big-fish-in-a-little-pond effect" (Marsh 1987). Numerous experiments show that students who rank highly in their peer group perceive themselves as more capable than otherwise-identical students with a lower rank. A higher perceived ability, in turn, may translate into higher returns to effort and lead to higher performance and more ambitious career

[1] Our work also complements the research on relative performance feedback, which estimates the impact of knowing one's rank on individual outcomes. This research identifies the impact of the salience in one's rank by comparing people with the *same* rank but a different level of knowledge about it (e.g. Bursztyn and Jensen 2015; Azmat et al, forthcoming). Our study, along with others mentioned in the main text, estimates the effect of having a higher rank through comparing otherwise identical people with *different* ranks.

[2] See Sacerdote (2011) for a review and a comprehensive list of definitions of what constitutes a peer effect.

choices. A similar chain of causality can be present if the ordinal rank affects a student's motivation or self-confidence.

A second mechanism operates through a student's perceived comparative advantage. Cicala et al (2018) provide a theoretical model that shows how a student's rank may shape her perceived comparative advantage relative to her peers. This, in turn, may affect effort provision and choices. In their model, there are two types of students, namely, "nerds," whose social status is determined by their achievements, and "troublemakers," who derive their status from engaging in disruptive behavior. A student with a high rank has a perceived comparative advantage in being a "nerd," whereas the same student with a lower rank would have a perceived comparative advantage in being a "troublemaker." Translated into the college context, a student who has a high rank in a subject may perceive that she has a comparative advantage in that subject relative to her peers. This perception may induce her to exert more effort, leading to higher performance and increasing the likelihood of choosing that subject as her major.

These mechanisms explain why it is plausible to find a reduced-form effect of a student's ordinal rank on performance and specialization choices. In the analysis that follows, we mainly focus on the causal identification of this reduced-form effect for different types of peer groups. At a later stage, we use survey data to distinguish between the mechanisms.

III. Institutional Setting and Data

A. Organization of Teaching at the Business School

We use data from a Dutch business school that offers bachelor, master, and PhD programs in the field of Economics and Business. In this section, we describe the setting and provide descriptive statistics.

A similar description of the institutional details is provided in Zölitz and Feld (2018) as well as Feld and Zölitz (2017).

Our analysis focuses on the two largest study programs in which all first-year bachelor students follow the same general course structure and the same set of compulsory courses. Beginning in the second year, students choose from a number of elective courses and select one major. Within an academic year, there are four regular teaching periods, each lasting about seven weeks. Students sit written exams at the end of the period. Grades range from 1 to 10, with 10 being the highest score. The lowest passing grade is 5.5. Students can retake failed exams up to two times.

The business school's teaching and learning concept is centered on group work. While students attend lectures once or twice per week, section meetings are the main focus of their studies. These two-hour-long meetings typically take place twice a week. In this learning concept, students work on the study material at home and then come together to discuss the material with their peers. The instructor, who can be a professor, lecturer, graduate student, or undergraduate student, guides the discussion. This style of teaching and learning ensures that the level of student-to-student interaction is generally high.

B. Sample Description

Our estimation sample consists of five adjacent cohorts who entered the business school between 2009 and 2013. We restrict our sample to courses taught after the first period in the first year. We do this for two reasons. First, in the first year of the program, students are assessed exclusively by written exams at the end of each teaching period. This, together with the fact that exams are centrally graded, minimizes concerns that section teachers may have a direct impact on grades. If section teachers had a direct impact on grades, we would be concerned that the rank effect may mechanically result from grading on a curve. Second, we must restrict the sample to courses beginning with teaching period 2 because we measure rank based on a student's GPA at the start of the period, and period 2 is the first period for which a GPA is available. These restrictions leave us with an estimation sample of 3,920 students and 23,573 student-course observations. When we analyze graduation probabilities, we avoid censoring the data by further restricting our sample to students who, given their enrollment year, could have graduated by the end of our observation period. Table 1 displays the descriptive statistics for our estimation sample. Panel A shows student-level characteristics. In total, 37 percent of students are female. Most students are German (52 percent), followed by Dutch (30 percent). The average age of first-year students is 19 years. Panels B and C display our main outcomes of interest. We report the summary statistics for these outcomes at the student-course level, giving more weight to students observed more often—as is the case in our empirical analysis. Panel B lists indicators of student performance at the level of student-course combinations. On average, we observe each student in six first-year courses. The average student enters a course with a GPA—the average grade of past courses—of 6.9. Around 7 percent of students who registered for a course drop out during the term. The average passing rate for first-year courses is 71 percent and the average grade is 6.4. In addition to students' contemporaneous performance, we also look at students' follow-up grades in the same subject. We define a follow-up grade as the next grade a student obtains in the same course-subject cluster. Course clusters refer to groups of courses that focus on similar subjects. Examples of course clusters are microeconomics, finance, or accounting. For example, the follow-up grade of Microeconomics I is the grade in Microeconomics II.

Panel C shows indicators for students' specialization choices as well as longer-run outcomes. After students have completed their compulsory first-year courses, they can choose between several follow-up courses. Depending on the respective first-year course, students can take up to seven noncompulsory follow-up courses. Table A2 in the Appendix provides an overview of the linkage between first-year and follow-up courses. For any given subject, around 24 percent of students choose at least one follow-up course. Similar to the linkage between first-year and follow-up courses, we link first-year courses to majors. Many first-year courses are linked to multiple follow-up majors. For example, the first-year course *Organization and Marketing* is linked to two majors—*Marketing* and *Organization*. This results in 49 percent of students choosing a follow-up major for the respective first-year course. Students can only choose one major; they typically make this decision at the end of the second year. We also create an indicator variable for whether students take any math-intensive elective courses. We classify an elective course as mathematical if its description contains one of the following terms: math, mathematics, mathematical, statistics, statistical, or theory-focused. In 47 percent of cases, students take at least one mathematical elective.

Panel C further shows that about 69 percent of the observed students finish their studies with a degree. To elicit information on study satisfaction and earnings, we conducted an online survey in 2016. The survey had a response rate of 37 percent. Reassuringly, we find no evidence that rank is related to the response probability. On average, students have annual entry wages of about €42.500 and retrospectively rate their satisfaction with their overall studies at eight out of ten points.

Panel D shows that the average number of students per section is 12.6, although it varies between 9 and 16 students. Panel D also provides an overview of the rank variables that we construct at the section level. The rank is constructed as a student's percentile in the GPA distribution of the respective peer group; it is bound between 0 and 1 and uniformly distributed with mean of 0.5. We discuss the construction of the rank in greater detail in Section IV.

[Table 1 here]

C. Random Assignment of Students to Teaching Sections

A key feature of the business school is that, within courses, students are assigned to sections through a conditional random assignment procedure. In a first step, after receiving a list of registered students and available instructors, the scheduler creates time slots and assigns rooms and teachers to these slots. In a second step, students are randomly allocated to the available sections, stratified by nationality. Teachers and students do not interfere in this process. The policy to balance student nationality across sections was implemented in 2011 to avoid having all-German or all-Dutch sections. Some bachelor courses are also stratified by exchange-student status to avoid that, by chance, too many exchange students are allocated to one section. In about 5 percent of sections, schedulers must manually adjust the allocation to solve scheduling conflicts that arise if, by chance, a student is scheduled to attend sections in two parallel courses at the same time. To account for this conditioning of the random assignment, we include parallel course fixed effects throughout the paper. In practice, however, these fixed effects have no impact on our results.

The assignment of students to sections is binding. Switching from the assigned section to another is allowed only for medical reasons or when the student is a top athlete and must attend sports practice. Students are required to attend their designated section. To be admitted to the exam, they must not miss more than three meetings. Instructors keep a record of attendance. The attendance data are not centrally stored and thus are not available to us.

IV. The Ordinal Achievement Rank

Our regressor of interest is a student's ordinal rank among her section peers. We compute this rank based on the predetermined GPA of all students in a section, such that the rank represents the percentile of a student in the group's GPA distribution. All grades making up the GPA were determined *before* the student was randomly assigned to a section. To construct the percentile rank in a section with N students, we first rank students in absolute terms, assigning rank N to the student with the highest GPA and rank 1 to the student with the lowest GPA in the section. Because teaching sections differ in size, we convert the absolute rank to a percentile rank that is bounded between 0 (lowest GPA in section) and 1 (highest GPA in section), which ensures that our results are not driven by variation in section size. We compute the percentile rank based on the formula

$$r = \frac{absolute\ rank - 1}{N - 1}. \qquad (1)$$

While the percentile rank is not explicitly communicated to the student, it is likely that students infer their rank through the intensive student-to-student interaction in the sections. In particular, students may become aware of their rank after the grades from the previous term are released, which often triggers intense discussions among students. For the causal interpretation of our estimates, it is not necessary that students have perfect knowledge of their rank. Students having imperfect knowledge of their rank is equivalent to measurement error in the rank variable, which may attenuate our estimates and work against our finding an effect.

Variation in the ordinal rank and information content. For a given GPA, the assignment of students to teaching sections induces considerable variation in their rank. Figure 1 illustrates this variation based on three exemplary teaching sections. A student with a GPA of 7 would have the highest rank (r = 1) in section 1, a rank of 0.67 in section 2, and a rank of 0.78 in section 3. The figure also illustrates that rank is a function of many characteristics of the ability distribution within a section. In all three examples, the mean peer ability is the same. And yet, a given GPA leads to significant variation in rank because the distributions differ in their variance, skewness, kurtosis, and, more broadly, the overall shape.

[Figure 1 here]

Figure 2 illustrates why the ordinal rank is a noisy indicator of a student's ability. The figure displays the relationship between students' GPA and their local rank in their teaching section. Students know their own GPA, but they do not know where they stand in the GPA distribution of the entire student population. They may infer this information from their within-section rank. The relationship between GPA and rank is positive, indicating that the within-section rank contains *some* information about a student's position in the global GPA distribution. However, for any given rank position, there is considerable variation in GPA. A student ranked first in her section ($r = 1$) could be anywhere between the center and the top of the global GPA distribution. Likewise, a student ranked last could be anywhere between the bottom and the center of the global GPA distribution.

[Figure 2 here]

V. Empirical Strategy

A. Empirical Model

Our empirical strategy exploits the random assignment of students into sections within the same course, which induces idiosyncratic variation in the ordinal rank for a given GPA level. The same student may have a high rank in one section but a low rank in another, which is purely due to the random assignment of students to sections. Murphy and Weinhardt (2014) developed this identification strategy, which has since become standard in the literature. We contributed to the literature by leveraging random assignment, which lends credibility to the identifying assumption. In the following, we first describe the components of the empirical model before discussing the identification assumption and the identifying variation.

We estimate the effect of a student's ordinal rank on several outcomes based on the following equation:

$$y_{itsc} = \beta\, r_{itsc} + f(gpa_{it}) + \boldsymbol{X_i}'\gamma + \boldsymbol{\delta_{tsc}} + \varepsilon_{itsc}. \tag{2}$$

The dependent variable y_{itsc} is the outcome of student i in teaching period t, who attends course c and, within this course, has been randomly assigned to section s. Therefore, each section is nested in a unique cohort-period-course combination. We regress this outcome on the percentile rank within a section, $r_{itsc} \in [0,1]$.

To compare students with the same absolute level of predetermined GPA, we flexibly control for GPA. For the identification of the causal effect of the ordinal rank, β, it is crucial to eliminate all cardinal differences in GPA by choosing the correct functional form. Because the functional form is unknown, we control for GPA using different parametric and nonparametric specifications.[3] In our

[3] See Table A3 and Table A4 in the Appendix for robustness checks in which we control for fourth-order polynomials as well as dummies for deciles of the global GPA distribution.

preferred specification, we include a third-order polynomial, although we obtain similar estimates when we control for decile dummies of the overall GPA distribution. The vector $\boldsymbol{X_{it}}$ controls for predetermined individual characteristics, namely age, gender, and indicators for nationality (Dutch, German, or other). In addition, we follow Murphy and Weinhardt (2018) and Elsner and Isphording (2017a) by conditioning on section fixed effects $\boldsymbol{\delta_{tsc}}$, which absorb any average differences in observable and unobservable characteristics between sections.

The error term ε_{itsc} captures all determinants of the outcome that are not captured by other regressors. Given the random assignment of students within courses, we follow Abadie et al. (2017) and cluster the standard errors at the course level.[4]

B. Identification

Identifying variation. Our coefficient of interest, β, measures the marginal impact of an increase in the ordinal rank on the outcome, holding constant the GPA level and controlling for section fixed effects. While it is intuitive that random assignment of students induces idiosyncratic variation in the ordinal rank, critical readers may wonder where the identifying variation comes from when we condition on section fixed effects. The coefficient β can be identified on top of section fixed effects because rank is individually assigned *within* sections. By conditioning on section fixed effects, we perform a within-transformation that subtracts the section mean from each variable. While this transformation centers the (residual) ability distribution of each section at the same mean, it does not change the *shape* of the ability distribution. Therefore, despite controlling for section fixed effects, the ordinal ranking is preserved and β is identified from differences across sections in the variance,

[4] When referring to the course level, we imply unique cohort-term-course combinations; for example, the grades in Microeconomics in the second term of the starting cohort in 2008.

skewness, kurtosis, and higher moments of the ability distribution. Intuitively, we identify β by comparing students with the same GPA across *all* sections in the sample, that is, across sections within the same course as well as across sections in different courses, but after controlling for mean differences across sections. Table A1 quantifies the identifying variation in the most important variables. Even after controlling for individual GPA and section fixed effects, a considerable degree of variation remains. Table A1 shows that using more narrowly defined peer groups by gender and nationality reduces the group size and therefore increases the residual variation of rank.

Identifying assumption. For β to be causally identified, the rank has to be as good as randomly assigned, such that the following assumption of strict exogeneity holds:

$$cov(\varepsilon_{itsc}, r_{itsc} | f(gpa_{it}), \boldsymbol{X_{it}}, \delta_{tsc}) = 0 \qquad (3)$$

In our setting, the validity of this assumption is plausible for two reasons. First, by conditioning on section fixed effects δ_{tsc}, we eliminate all potential confounders at the peer group level. This is important because our aim is to identify the rank effect net of all other mechanisms through which peers affect individual outcomes. For example, the section fixed effects absorb variation in mean GPA across sections, in variance in GPA, in the share of high-ability peers (however high ability is defined), and in the share of female students, share of immigrants, etc. All these variables arguably have a direct effect on the outcome, but our regression framework eliminates the direct effects. Furthermore, the section fixed effects absorb any shock that is common to all students within a section.

Second, the random assignment of students to sections ensures that a student's rank, conditional on GPA, is uncorrelated with the student's observable and unobservable characteristics. In particular, the random assignment prevents students from strategically choosing sections to achieve a high rank.

Quasi-random assignment of the ordinal rank. To confirm that our measure of the ordinal rank is as good as randomly assigned, we perform balancing tests in which we regress exogenous student characteristics on the ordinal rank, a third-order polynomial in GPA, as well as various sets of fixed effects. Table 2 shows estimates from 15 separate regressions. Out of the 15 coefficients, only one is significant at the 10 percent level. These results are consistent with random assignment of students to sections and support the assumption of strict exogeneity of rank conditional on GPA and section fixed effects.

[Table 2 here]

VI. Results

A. Ordinal Rank and Student Performance

We first estimate the effect of rank on student performance in the first year. Table 3 displays the estimated effects of the ordinal rank on three measures of performance. This and the following tables report coefficients from separate regressions of the dependent variables shown in the columns on the ordinal rank based on the definitions described in the rows. Each coefficient represents the marginal effect of an increase in a student's ordinal rank, holding constant individual achievement and mean peer achievement. To interpret our findings relative to a meaningful benchmark, it is useful to divide the coefficients by 10 and consider the effect of a 10 percentile increase in the ordinal rank, which is equivalent to moving up one rank position in a group of 11 students.[5]

The first row of Table 3 shows the estimated effect of the ordinal rank among all students in a section on the probabilities that a student drops out of the course or passes the course, as well as on standardized grades in the current and follow-up course. Column (1) shows that rank has no significant effect on the probability of dropping out of the course. Column (2) shows the estimate of rank on the probability of passing the course. We find that a 10 percentile increase in ordinal rank increases the probability of passing by about 0.8 percentage points—a 1 percent increase relative to the baseline. Column (3) shows that a 10 percentile increase in rank raises course grades by 2 percent of a standard deviation. We also find a positive effect of rank on grades in follow-up courses, although this effect is statistically insignificant.

Although the results discussed so far focus on the rank among all students in a section, this may not be the most relevant reference group. Rather than comparing themselves with all peers in their section, students may be more likely to compare themselves with similar peers, for example, students of the same gender or nationality. We test this idea by computing a students' rank within peer groups stratified by gender and nationality. Estimates based on these more narrowly defined groups point to stronger effects. A 10 percentile increase in the ordinal rank among same-gender peers leads to a 1 percentage point lower probability of dropping out (Column 1)—a strong effect given the

[5] For reasons of clarity, we do not express changes in the ordinal rank in standard deviations because the standard deviation of rank net of section fixed effects depends on the comparison group. As shown in Table A1, column (3), the conditional standard deviation is lower for the rank among all peers (sd = 0.09) than for the rank among same-gender (sd = 0.18) or same-nationality peers (sd = 0.23).

baseline probability of 7 percentage points.[6] It also increases the probability of passing the course by 1.6 percentage points (Column 2). With respect to grades, a 10 percentile increase in the ordinal rank among same-gender peers leads to an increase of 3 percent of a standard deviation (Column 3). Furthermore, we find large effects of the same-gender rank on grades in follow-up courses. A 10 percentile increase in rank among same-gender peers increases performance in follow-up courses on average by 1.8 percent of a standard deviation (Column 4). In general, the estimated effects of rank among same-gender peers are about 1.5 to 2 times larger than the effects estimated for the rank among all peers and are statistically significant for all four outcomes.

Effects based on same-nationality peers fall between those of the rank among same-gender peers and those of the rank within the entire section. A 10 percentile increase in rank among same-nationality peers leads to a 0.8-percentage-points-lower dropout probability, a 1.2 percentage points higher probability of passing, and an increase in grades by 2.1 percent of a standard deviation. From these results, we conclude that same-gender peers appear to be the most relevant peer group when students compare themselves to others.

Our results show that the importance of a student's ordinal rank is economically significant. This becomes evident when we compare our effect size in Column (2) to other effects found in similar settings. The impact of a 10 percentile increase in rank is similar to the impact of having an instructor with one-standard-deviation-higher teacher value-added (Feld et al. forthcoming) and slightly larger than the impact of a one-standard-deviation increase in average peer achievement (Feld and Zölitz 2017).[7] Moreover, the size of the effect we find is similar to Murphy and Weinhardt (2018) who find

[6] The finding that same-gender rank reduces the dropout risk is important for the interpretation of same-gender rank effect on grades, which are only observed for students who do not drop out. Results in Column (1) imply that we will identify a lower bound of the impact of rank on performance. Due to their higher same-gender rank some academically weak students decide to remain in the course and obtain an exam grade. This imposes a downward bias on the impact of rank on grades and implies that we identify a lower bound of the true effect size.

[7] Feld and Zölitz (2017) find that a one standard deviation increase in peer GPA raises grades by 1.26 percent of a standard deviation. Feld et al. (forthcoming) examine the costs and benefits of using instructors with different academic ranks and estimate teacher

that a one standard deviation increase in rank raises test scores by about .08 standard deviations—compared to .07 standard deviations in our setting.

[Table 3 here]

B. Nonlinear Effects

While the results in Section VI.A show that a student's ordinal rank affects student performance on average, this effect may mask nonlinear effects along the rank distribution. Although previous research in secondary schools finds a linear effect (Murphy and Weinhardt 2018), experimental evidence suggests that being ranked first or last induces the highest effort because people presumably have a desire to be ranked first or a distaste for being ranked last (Gill et al. 2018; Kuziemko et al. 2014).

To analyze heterogeneous effects along the rank distribution, we run a semiparametric regression whereby we replace the ordinal rank in Equation (2) with sets of dummy variables for the bottom and top five absolute rank positions. The omitted reference group in this estimation is students between the top and bottom five ranks. Figure 3 illustrates the estimation results. The effects appear linear and roughly symmetric for the left and right tail of the ability distribution. These results do not provide evidence against a linear effect of rank on performance and support the linear specification used throughout the remaining estimations.

[Figure 3 here]

value-added for instructors in the same environment.

C. Effect of Rank on Specialization Choices

We now examine to what extent a higher rank also affects subsequent specialization choices. These may have far-reaching consequences for a student's educational career and later labor market success. The choice of a major is closely related to the subsequent choice of an occupation and therefore can translate into significant earnings differences (Arcidiacono 2004). As such, field and major choices can be seen as important investments into job-specific human capital (Wiswall and Zafar 2015).

As outcomes, we use four indicators for student choices: 1) a binary indicator for whether a student chooses any follow-up course to the relevant first-year course, 2) the number of relevant follow-up courses chosen by a student, 3) a binary indicator for whether a student chooses a related major, and 4) an indicator for whether a student chooses any elective with a high math intensity.[8]

Panel A of Table 4 shows the results for the impact of rank on specialization choices. With the exception of a positive effect of rank on choosing mathematical electives, the estimates of the rank effect are not statistically significant for the rank among all section peers. For more narrowly defined peer groups, especially for same-gender peers, we observe large and highly significant effects. Students with a 10 percentile higher rank among same-gender peers have a 0.5 percentage point higher probability of choosing a related follow-up course, relative to a baseline probability of 24 percent. Likewise, they take more follow-up courses and are more likely to choose more demanding math-intensive elective courses. Most importantly, the rank in a first-year course affects the choice of a major field about one year later. Being ranked 10 percentiles higher in a first-year course increases the

[8] Math intensity, in contrast to the other outcomes, varies at the student level, while rank varies at the course-by-student level. The estimates are in this case to be interpreted as the effect of having a higher rank in one subject during the compulsory stage. In our estimation sample, we observe each student about six times. The fact that each student enters the regression multiple times may suggest that standard errors should be clustered at the student level. However, the Moulton problem only leads to biased standard errors if the regressors are correlated. In our case, the random assignment ensures that the regressors are uncorrelated within student.

likelihood of choosing a related major by about 1 percentage point. As with the results on student performance, our findings suggest that same-gender peers are the relevant reference group for social comparisons.

[Table 4 here]

D. Effects on Longer-Term Outcomes

In this section, we analyze whether one's rank in the first year affects longer-term study outcomes besides educational choices—namely, graduation probability, students' satisfaction with their college studies, and earnings.

The results are shown in Table 5. Consistent with previous findings, the estimates are strongest for the rank among same-gender peers. Moving up the rank distribution by 10 percentiles increases the probability of graduating by 2.4 percentage points relative to a baseline of about 70 percent. In contrast, we observe inconclusive and imprecisely estimated effects on study satisfaction. Likewise, the effects on log earnings after graduation are small and statistically insignificant. This may indicate either that the major choices induced by the ordinal rank have no effect on earnings, or they may only be visible later in students' careers. For the interpretation of the effect on earnings, it is important to note that we only observe earnings for students who actually completed their Bachelor of Science degree, as the survey was only conducted among students who actually graduated. Given that rank increases the graduation probability, it is an important finding that students at the margin—those who perhaps only graduated because of their higher rank—do not have worse earnings when they enter the labor market.

[Table 5 here]

E. Robustness Checks

To ensure that the effect of rank is not confounded by picking up direct effects of absolute achievement on performance and choices, it is vital to correctly specify the effect of absolute achievement. Although we already condition our main results on a third-order polynomial, in Appendix Tables A3 and A4, we assess the robustness of our results to an even more flexible nonparametric specification for absolute GPA. In both tables, we include dummies for deciles of the global GPA distribution. Both tables show that our results are robust to this more demanding and flexible specification.

F. Mechanisms

In this section, we use data from student course evaluations to shed light on potential mechanisms behind the observed effects. These evaluations are short online surveys completed by the students at the end of each teaching period. Based on several survey items of the course evaluation survey, we construct three dependent variables, namely: 1) the self-reported number of hours per week spent studying for the course, 2) students' perception of the quality of their section peers, and 3) students' perception of the quality of their section instructor. Except for the category of study hours, which is measured based on one survey question, the other outcomes are standardized indices based on several questions. To compute these indices, we standardize the answers to each underlying question to a mean of zero and a standard deviation of one, add the standardized scores across questions, and again standardize this sum to a mean of zero and a standard deviation of one.

Estimating the effect of rank on these variables is informative about potential underlying mechanisms that may explain why ordinal rank affects performance and choices. One such channel is effort, for which self-study hours are a proxy. Another channel is students' beliefs about their own ability. In the absence of direct survey information on students' beliefs, the perceived quality of peers provides us with indirect information on how students evaluate their peers in relation to their own perceived ability. Finally, perceived quality of teachers and teaching material are informative about potential effects running through teachers' being responsive to a student's rank. For example, students with a higher rank may receive more attention from the instructor or perform better if instructors teach to the top of the class.

Table 6 shows the estimation results. In Column (1), we find that students with a high rank perceive interaction with their peers as worse compared to students with the same GPA but a low rank. This points to students' being aware of rankings based on the intense interaction in the teaching sections. It also points to students' changing their perceptions of their peers' quality—conditional on their actual own and average peer ability—which in turn suggests that they perceive themselves as more able than their peers. This effect is consistent with work in psychology showing that the ordinal rank affects a person's self-concept (Marsh 1987).

In Column (2), we find no significant effect of the ordinal rank on self-reported study hours—our proxy for effort. This result may appear surprising, as it would be difficult to achieve a higher grade without exerting more effort. However, study hours only measure the *extensive* margin of effort, whereas students may adjust effort along the *intensive* margin by studying more efficiently. In addition, we will see in the next section that the insignificant and small average estimate masks important heterogeneity by gender, with male students strongly adjusting their effort in response to a higher rank. In Column (3), we find no evidence that student rank affects teacher evaluations. This finding does not support the hypothesis of teachers' changing their behavior in response to a student's rank.

[Table 6 here]

G. Gender Differences in Rank Effects

Evidence from observational and experimental data documents a significant gender gap in the willingness to compete (Andersen et al. 2013, Sutter and Glätzle-Rützler 2014, Niederle and Vesterlund 2007). If women indeed dislike competing or simply care less about competing with their peers, one may expect ordinal rank positions to be less important to women than to men. If this were the case, rank should also trigger behavioral responses that differ between men and women. While lab evidence does not point to gender differences in the response to a given rank (Gill et al. 2018), previous evidence from the field shows that women and men react differently to their rank, with male students being more responsive than female students (Murphy and Weinhardt 2018).

To test for gender differences, we re-estimate our main effect on performance, choices, and longer-run outcomes in subsamples split by gender. The results are summarized in Table 7. When rank is based on same-gender peers, the results indeed confirm a stronger effect of rank for male students. The estimated coefficient of rank among same-gender peers on performance is 2.5 times larger for male than for female students. The effect of rank on the probability of passing the course is three times larger among men than among women and the effect of rank on the probability of dropping out is two times larger among men than among women (columns 1–9).

Moreover, the results in Table 6, columns (10)–(12) reveal that the zero average effect of rank on effort masks a considerable difference between men and women. While the effect is insignificant for women, it is positive and statistically significant for men. Moving up the rank distribution by 10 percentiles increases the self-reported number of study hours by 5 percent, or 0.23 hours. For men, a higher rank induces more effort and in turn leads to higher grades.

Our results on longer-term outcomes and choices consistently reproduce the pattern of stronger effects for male students. The effect of rank on the probability of choosing a related major is almost three times as high for male as for female students. Effects on log earnings are less precisely estimated and remain insignificant for both men and women. Taken together, these results show that men are systematically more sensitive to the ranking among their peers than women.

[Table 7 here]

VII. Conclusion

In this paper, we present empirical evidence showing that a student's rank in a small peer group affects educational choices and performance in college. Exploiting random assignment of students to sections, we show that rank is an important driver of student performance and students' specialization choice in university. Our results show that students who rank highly in their section achieve higher grades in centrally graded exams. These effects appear to be driven by comparisons among same-gender peers. Moreover, we find that men are substantially more sensitive to their rank than women and that they systemically adjust their study effort in response to a higher rank. Students with a high rank in a compulsory subject also become more likely to attend follow-up courses in that subject and to choose that subject as a major. With respect to longer-run outcomes, we observe significant effects on follow-up grades and the probability of graduating, which suggests that rank effects do not fade out quickly.

These findings provide important insights into the decision-making of students. Our results suggest that students—who may be unsure about their relative ability and preparedness for different study specializations—place considerable weight on comparisons to other students. Their position relative to peers who they currently observe seems to serve as a signal about where they stand in terms of the global ability distribution. Because in our case peers are randomly assigned, this signal carries substantially more noise than signal. Nevertheless, when making important career decisions, students appear to rely on their rank as a heuristic, thereby placing considerable weight on noisy information.

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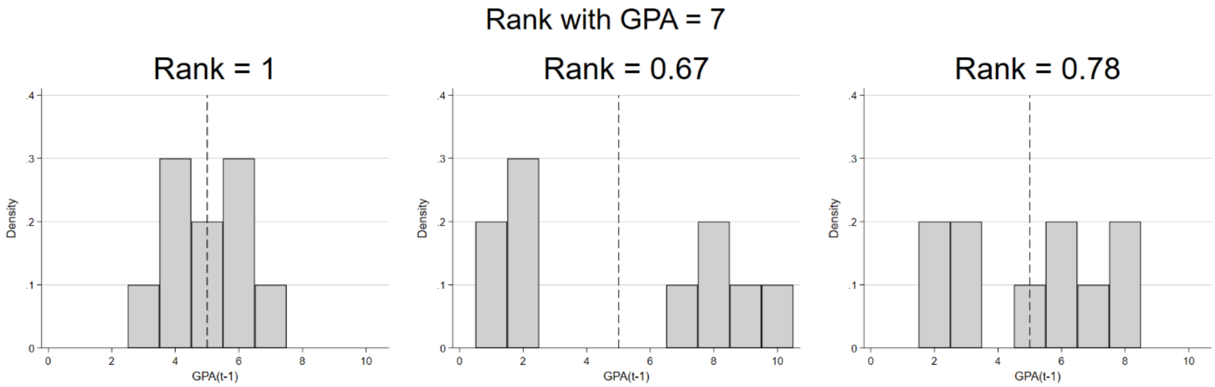
TABLES AND FIGURES

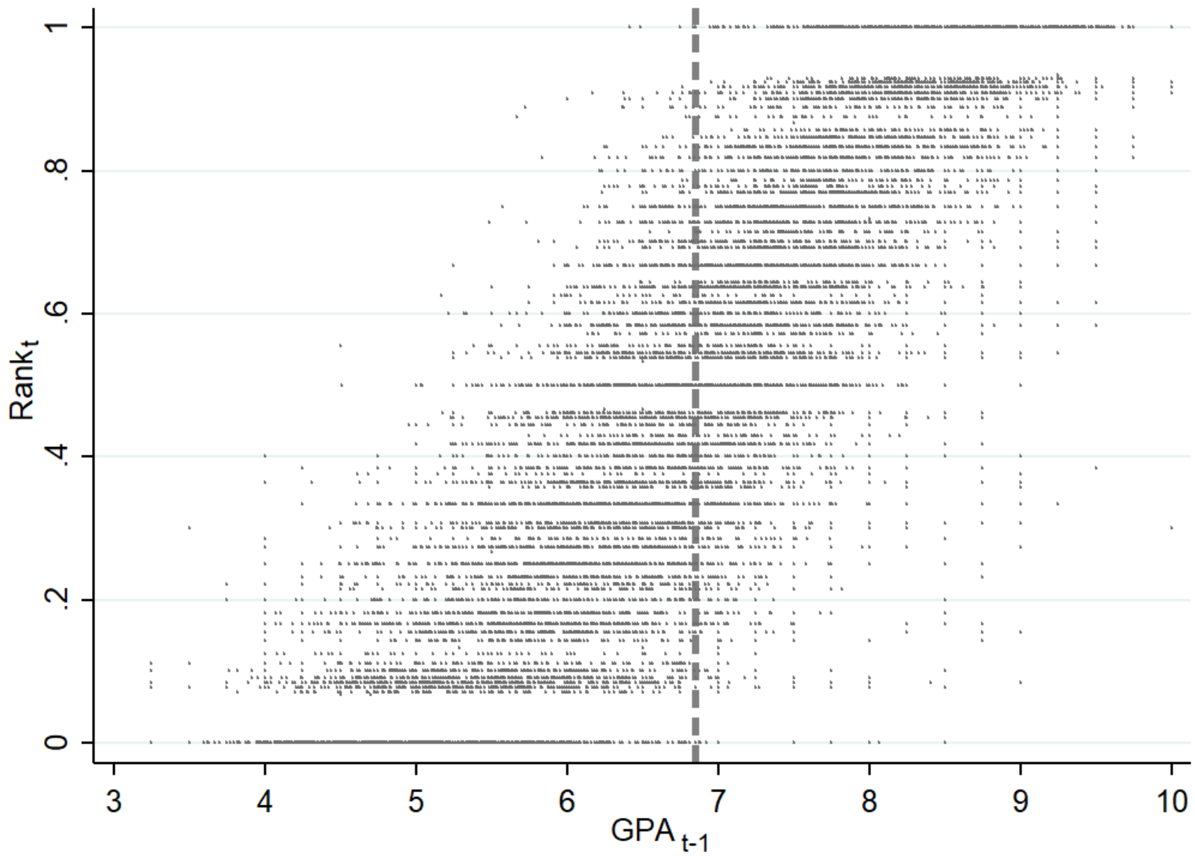
FIGURES

Figure 1: Absolute GPA and Ordinal Rank within Sections



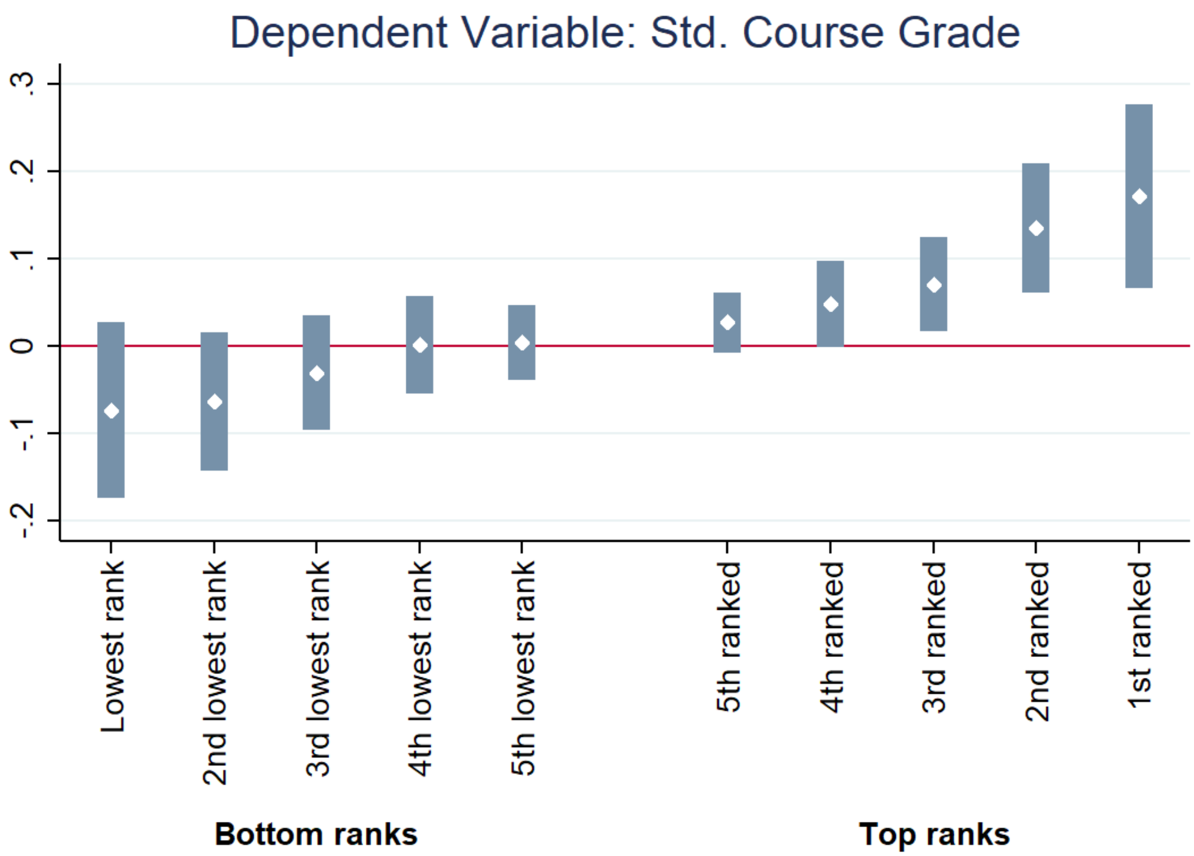
NOTE—This figure illustrates the variation in the ordinal rank across three different exemplary sections holding constant the own-GPA level and the section average GPA. Each panel displays the GPA distribution in a section with 10 students. The vertical dashed line denotes the mean section GPA, which is identical at 5 in all three sections. The figure shows that with differences in distributions, a GPA of 7 can lead to percentile ranks of 0.67, 0.78, and 1.

Figure 2: Variation in Rank within Sections for a Given GPA



NOTE— This figure illustrates the variation in ordinal ranks in our data set in period t for a given GPA measured in t-1. The vertical dashed line refers to the median grade point average (GPA) of the estimation sample. The variation in ranks is largest in the center of the distribution, while grades determine rank almost perfectly in the tails of the GPA distribution.

Figure 3: Nonlinear Effect of Rank on Student Performance



NOTE— This figure displays the coefficients of a semiparametric regression of standardized grades on binary indicators for absolute rank positions (top 5 positions and bottom 5 positions, compared to the remaining rank positions in between). Controls and fixed effects are identical to those in Table 2. Bars indicate 95 percent confidence intervals.

TABLES

Table 1: Descriptive statistics

Panel A: Student Background Characteristics	(1) N	(2) Mean	(3) Sd	(4) Min	(5) Max
Female	3,920	0.374	0.484	0	1
Dutch	3,920	0.301	0.459	0	1
German	3,920	0.519	0.5	0	1
Exchange student	3,920	0.004	0.066	0	1
Age	3,920	19.08	1.471	16.19	32.98
Panel B: Student Performance					
GPAt-1 (based on past courses)	23,526	6.900	1.310	2.250	10
Course dropout	23,526	0.0714	0.258	0	1
Passed course	23,526	0.705	0.456	0	1
Course grade	21,846	6.393	1.686	1	10
Same subject follow-up course grade	9,393	6.625	1.767	1	10
Panel C: Student choices and longer-run outcomes					
Taking a follow-up course	23,526	0.240	0.427	0	1
Number of follow-up courses	23,526	0.362	0.760	0	7
Graduating in related subject major	23,526	0.490	0.500	0	1
Taking math electives	23,526	0.473	0.499	0	1
Graduation	13,629	0.690	0.463	0	1
Earnings	6,283	42.56	37.85	0.001	650
Retrospective study satisfaction	8,159	8.072	1.142	1	10
Panel D: Rank variables constructed at the section level					
Rank	23,526	0.491	0.312	0	1
Rank in same-gender group	23,456	0.490	0.341	0	1
Rank in same-nationality group	22,941	0.490	0.365	0	1
Section size	23,526	12.59	1.460	9	16

NOTE— Descriptive statistics of estimation sample. “Sd” refers to the standard deviation of the respective variable. Earnings are in 1,000 EUR. Panels B and C report outcomes at the student-course level. The number of observations for “graduation” is lower because we set this variable as missing for all students who could not have graduated over the observed sample period. The number of observations is lower for “Earnings” and “Retrospective study satisfaction” as these are only observable for students who took part in the graduate survey we conducted.

Table 2: Randomization check—Dependent Variable: Individual Level Characteristics

	(1)	(2)	(3)
Female	-0.0138	-0.0162	0.0095
	(0.026)	(0.026)	(0.033)
Dutch	0.0088	0.0103	0.0350
	(0.018)	(0.018)	(0.025)
German	0.0245	0.0224	-0.0627*
	(0.022)	(0.022)	(0.036)
Exchange student	-0.0002	0.0011	0.0010
	(0.002)	(0.001)	(0.002)
Age	0.1118	0.1097	0.1689
	(0.069)	(0.069)	(0.105)
Observations	23,526	23,526	23,526
Course-year FE	YES	YES	YES
Parallel course FE	NO	YES	YES
Section FE	NO	NO	YES

NOTE—Each cell in the table represents the coefficient from a separate regression of the respective student characteristics displayed on the left on rank and the fixed effects displayed at the bottom. All regressions include a third-order polynomial in GPA. Robust standard errors, clustered at the course level, are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: The Impact of Rank on Performance

	(1) Course Dropout	(2) Passed Course	(3) Std. Grade	(4) Std. Follow-up Grade
Rank	-0.0315	0.0765**	0.2270***	0.0941
	(0.022)	(0.033)	(0.071)	(0.099)
Rank same gender	-0.0994***	0.1636***	0.3040***	0.1814***
	(0.013)	(0.020)	(0.040)	(0.048)
Rank same nationality	-0.0813***	0.1157***	0.2141***	0.0344
	(0.012)	(0.016)	(0.030)	(0.079)
Mean dependent variable	.0714	0.7051	-.0001	-.0065
Observations(Rank)	23,526	23,526	21,845	8,141
Observations(Rank same gender)	23,456	23,456	21,744	7,655
Observations(Rank same nationality)	22,941	22,941	21,166	7,222
Course-year FE	YES	YES	YES	YES
Parallel course FE	YES	YES	YES	YES
Section × peer group FE	YES	YES	YES	YES

NOTE— Each cell reports the point estimate from a separate OLS regression of the performance measure listed at the top on the rank definition listed on the left. All regressions control for gender, age, nationality as well as third-order polynomial in GPA. The (section × peer group) fixed effects refer to the respective peer group the rank is based on, for example, section peers with the same gender. Robust standard errors, clustered at the course level, are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: The Impact of Rank on Specialization Choice

	(1) Taking Follow-up Course	(2) Number of Follow-up Courses	(3) Taking Math Electives	(4) Graduating in Related Subject Major
Rank	0.0091	-0.0040	0.0802**	0.0016
	(0.033)	(0.055)	(0.037)	(0.041)
Rank same gender	0.0490***	0.0722**	0.1184***	0.1125***
	(0.018)	(0.032)	(0.023)	(0.019)
Rank same nationality	0.0317**	0.0658**	0.0984***	0.0995***
	(0.014)	(0.026)	(0.016)	(0.018)
Mean dependent variable	.2395	.3615	.4727	0.4900
Observations(Rank)	23,526	23,526	23,526	23,526
Observations(Rank same gender)	23,456	23,456	23,456	23,456
Observations(Rank same nationality)	22,941	22,941	22,941	22,941
Course-year FE	YES	YES	YES	YES
Parallel course FE	YES	YES	YES	YES
Section × peer group FE	YES	YES	YES	YES

NOTE— Each cell reports the point estimate from separate OLS regressions of the choice outcome listed at the top on the rank definition listed on the left. All regressions control for gender, age, nationality as well as a third-order polynomial in GPA. The (section × peer group) fixed effects refer to the respective peer group the rank is based on, for example, section peers with the same gender. Robust standard errors, clustered at the course level, are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: The Impact of Rank on Longer-Run Outcomes

	(1) Graduation	(2) Study Satisfaction	(3) Log Earnings
Rank	0.0288	-0.2710	-0.0634
	(0.038)	(0.166)	(0.187)
Rank same gender	0.2351***	0.0356	-0.0853
	(0.022)	(0.085)	(0.122)
Rank same nationality	0.1815***	-0.0490	-0.0889
	(0.018)	(0.103)	(0.129)
Mean dependent variable	.6957	80.74	10.23
Observations(Rank)	13,512	8,123	6,183
Observations(Rank same gender)	13,461	7,586	5,459
Observations(Rank same nationality)	13,043	6,865	4,936
Course-year FE	YES	YES	YES
Parallel course FE	YES	YES	YES
Section × peer group FE	YES	YES	YES

NOTE— Each cell reports the point estimate from a separate OLS regressions of the outcomes listed at the top on the rank definition listed on the left. All regressions control for gender, age, nationality as well as a third-order polynomial in GPA. The (section × peer group) fixed effects refer to the respective peer group the rank is based on, for example section peers with the same gender. Robust standard errors, clustered at the course level, are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Mechanisms – Evidence from Student Course Evaluations

	(1) Peer Interaction Index	(2) Study Hours	(3) Teacher Evaluation Index
Rank	-0.2182**	0.5091	-0.0049
	(0.102)	(0.928)	(0.096)
Rank same gender	-0.1215*	0.0050	0.0305
	(0.073)	(0.639)	(0.066)
Rank same nationality	0.0119	-0.3856	0.0497
	(0.062)	(0.572)	(0.052)
Mean dependent variable	-.0182	13.2969	-.033
Course-year FE	YES	YES	YES
Parallel course FE	YES	YES	YES
Section × peer group FE	YES	YES	YES

NOTE— Each cell reports the point estimate from a separate OLS regressions of the outcomes listed at the top on the rank definition listed on the left. Indices in columns (1) and (3) are constructed based on the course evaluation questions shown in Appendix Table A6. To obtain the index, we first standardized the answers to each question, then summed up all questions that enter the index and standardized this sum to a mean of zero and unit variance. All regressions control for gender, age, nationality as well as a third-order polynomial in GPA. The (section × peer group) fixed effects refer to the respective peer group the rank is based on, for example, section peers with the same gender. Robust standard errors, clustered at the course level, are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Gender Differences in the Impact of Rank

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable:	Course Dropout			Passed Course			Std. Grade			Study Hours		
Subgroup:	All students	Female	Male	All students	Female	Male	All students	Female	Male	All students	Female	Male
Rank	-0.0241	-0.0721**	-0.0002	0.0864**	0.1213**	0.0745*	0.2448***	0.1672*	0.2928***	0.2386	0.4691	0.4902
	(0.022)	(0.030)	(0.027)	(0.034)	(0.048)	(0.040)	(0.075)	(0.096)	(0.089)	(1.093)	(2.008)	(1.314)
Rank same gender	-0.0994***	-0.0618***	-0.1471***	0.1636***	0.0874***	0.2420***	0.3040***	0.1880***	0.4435***	0.0050	-1.4544	2.2927**
	(0.013)	(0.016)	(0.019)	(0.020)	(0.023)	(0.028)	(0.040)	(0.044)	(0.060)	(0.639)	(0.884)	(0.885)
Rank same nationality	-0.0595***	-0.0619***	-0.0579***	0.0876***	0.0938***	0.0867***	0.1624***	0.1817***	0.1546***	-0.2147	-1.2478*	0.6188
	(0.009)	(0.012)	(0.010)	(0.014)	(0.022)	(0.017)	(0.024)	(0.039)	(0.034)	(0.463)	(0.726)	(0.508)
Mean dependent variable	.0715	.0514	.0831	.7050	.7326	.6888	-.0001	.0455	-.0276	11.9013	12.8351	11.25

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Dependent Variable:	Std. Follow-up Grade			Taking Follow-up Course			Number of Follow-up Courses			Taking Math Electives		
Subgroup:	All students	Female	Male	All students	Female	Male	All students	Female	Male	All students	Female	Male
Rank	0.1538	0.3707**	0.0704	0.0086	0.0168	0.0071	-0.0069	-0.0062	-0.0005	0.0968**	0.1242**	0.0798*
	(0.095)	(0.166)	(0.132)	(0.033)	(0.045)	(0.042)	(0.051)	(0.066)	(0.064)	(0.038)	(0.054)	(0.044)
Rank same gender	0.2007***	0.1169	0.3199***	0.0490***	0.0363*	0.0731***	0.0722**	0.0423	0.1251***	0.1184***	0.0436	0.2119***
	(0.047)	(0.082)	(0.087)	(0.018)	(0.021)	(0.026)	(0.032)	(0.034)	(0.046)	(0.023)	(0.027)	(0.029)
Rank same nationality	0.0652	0.0723	0.0591	0.0212*	0.0149	0.0250	0.0578***	0.0542	0.0609**	0.0569***	0.0675***	0.0513***
	(0.051)	(0.073)	(0.056)	(0.012)	(0.023)	(0.016)	(0.020)	(0.035)	(0.025)	(0.013)	(0.022)	(0.016)
Mean dependent variable	-.0214	.0095	-.0369	.239	.2204	.2499	.3607	.3137	.3881	.4722	.4069	.51

	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)
Dependent Variable:	Graduating in Related Subject Major			Graduation			Log Earnings		
Subgroup:	All students	Female	Male	All students	Female	Male	All students	Female	Male
Rank	0.0119	-0.0712	0.0592	0.0379	-0.0194	0.0703	-0.0324	-0.2004	0.0709
	(0.042)	(0.061)	(0.048)	(0.042)	(0.066)	(0.048)	(0.209)	(0.444)	(0.250)
Rank same gender	0.1125***	0.0672**	0.1792***	0.2351***	0.1092***	0.3794***	-0.0853	0.0269	-0.2137
	(0.019)	(0.026)	(0.035)	(0.022)	(0.025)	(0.030)	(0.122)	(0.199)	(0.187)
Rank same nationality	0.0691***	0.0552**	0.0781***	0.1238***	0.1258***	0.1247***	-0.1009	-0.4308**	0.0497
	(0.015)	(0.024)	(0.020)	(0.013)	(0.023)	(0.016)	(0.081)	(0.191)	(0.122)
Mean dependent variable	.4901	.5419	.4605	.6958	.7611	.6599	10.2667	10.118	10.3422

NOTE— Each cell reports the point estimate from separate OLS regressions. All regressions control for gender, age, nationality, a third-order polynomial in GPA, Section × peer group FE as well as the same fixed effects as in the previous regression tables. Robust standard errors clustered at the course level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX

A-I. Identifying Variation

Table A1 displays the variation in the ordinal rank conditional on GPA and different sets of fixed effects. The results indicate that even in the most demanding specifications, our identification can rely on a significant degree of variation in the treatment variable.

Column (1) shows the raw standard deviation of the ordinal rank with various definitions of peer groups (rows 1–3) and the standard deviation in rank after controlling for a third-order polynomial in GPA (rows 4–6). With narrower peer group definitions, the group size gets smaller and, consequently, the variation in the ordinal rank increases. Controlling for GPA reduces the variation in the ordinal rank, although a considerable amount of variation remains. In column (2), we condition on course fixed effects, which reduces the amount of variation in rank, although not by a substantial margin.

The standard deviations in column (3) represent the amount of identifying variation in our estimation. Compared to column (2), the variation is reduced by only a small amount if we condition on section fixed effects (column 3). When rank is computed among all peers in a section, the variation in rank conditional on ability is *sd = 0.09*, which is roughly equivalent to one rank position in a group of 15. The amount of variation more than doubles if we consider more narrowly defined peer groups. These results highlight that our empirical strategy rests on a significant amount of identifying variation in the underlying data.

Table A1: Variation in Rank Conditional on Ability and Fixed Effects

	(1) Std. Dev.	(2) Std. Dev. Net of Course FE	(3) Std. Dev. Net of Section FE
Rank	0.3123	0.3121	0.3119
Rank same gender	0.3406	0.3404	0.3402
Rank same nationality	0.3648	0.3647	0.3644
Rank conditional on ability	0.1392	0.1212	0.0901
Rank same gender conditional on ability	0.2113	0.2003	0.1841
Rank same nationality conditional on ability	0.2508	0.2417	0.2284

Note— Column (3) includes fixed effects for sections as well as the respective characteristic that defines the peer group in which we calculate the rank, for example section-times-gender fixed effects in row 2. When conditioning on ability, we include a third-order polynomial of GPA. Robust standard errors, clustered at the course level, are displayed in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A2: Mapping of Courses into Follow-Up Courses and Majors

(1) First Year Course	(2) Follow-Up Courses	(3) Related Major Subject
Accounting	Finance and Accounting, Management Accounting, Auditing, Internal Control and AIS, International Financial Accounting	Accounting
Economics and Business	Behavioral Economics, Economic Psychology, Game Theory and Economics, Globalization Debate, Information, Markets and Organizations, Thinking Strategically, Job Performance and the Employment Relationship,	
Finance	Finance and Accounting, Investment Analysis and Portfolio Management, Financial Management and Policy, International Financial Management, Options and Futures, Auctions and Electronic Markets, Banking, Financial Markets, Financial Economics,	Finance
Fundamentals of Supply Chain Management	Operations Management, Global Supply Chain Mgmt, Global Transportation Management, Digital Supply Networks	Supply Chain Management
International Economic Relations	Globalization Debate, Innovation in Business and Economic Growth, International Economics,	Economics
Macroeconomics	Macroeconomics and Economic Policy, Productivity, Development Economics, History of Economic Thought, Job Performance and the Employment Relationship	Economics
Management of Organizations and Marketing	Management of Organizations, Marketing Management, Corporate Governance, Management Information Systems, Management of Operations and Product Development, Entrepreneurship and Small Business Management, Brand Management, Strategic Marketing, Consumer Behavior, Services Marketing, Comparative ss Strategy, Management, Organizational Behavior, Human Resources Management, Birthing New Ventures, Business and Politics in Europe, Comparative Income and Business Taxation (TAX3009) Comparative Management, Crisis Management in Organizations, Ethics, Organizations and Society, International Business Law, Mobilizing Resources for Entrepreneurial Start-up and Growth, Public Management Reform and Public Entrepreneurship, Social & Environmental Entrepreneurship, Managerial Economics, Marketing and SCM, International Business	Organization / Marketing
Microeconomics	Understanding Society, Industrial Organization, Behavioral Economics, Public Economics, International Competition Policy, Institutions, Behavior and Welfare, Design of Tax Systems, Economic Psychology, Economics and Sociology, Game Theory and Economics, Information, Markets and Organizations, Institutions, Behavior and Welfare, International Competition Policy, Public Finance, Public Management Reform and Public Entrepreneurship, Thinking Strategically	Economics
Quantitative Methods	Quantitative Methods III, Dynamic Modelling and Dynamic Optimization, Empirical Econometrics, Forecasting for Economics and Business, Game Theory and Economics, Quantitative Business, Quantitative Methods III (IES), Thinking Strategically, Time Series Modelling, Quantitative Business, Systems Analysis and Design	-
Strategy	Global Business, Business and Politics in Europe, International Business History, Project and Process Mgmt, Strategic Management of Technology and Innovation	Strategy

Table A3: Main Performance Results with Additional Controls for GPA Decile

	(1) Course dropout	(2) Passed course	(3) Std. Grade	(4) Std. Follow-up Grade
Rank	-0.0315	0.0710**	0.2105***	0.1574*
	(0.023)	(0.034)	(0.069)	(0.093)
Rank same gender	-0.0240*	0.0635***	0.1142***	0.1827***
	(0.013)	(0.021)	(0.043)	(0.056)
Rank same nationality	-0.0260**	0.0392**	0.0725**	-0.0365
	(0.012)	(0.016)	(0.028)	(0.079)
Mean dependent variable	.0714	0.7051	-.0001	-.0051
Observations(Rank)	23,526	23,526	21,845	9,228
Observations(Rank same gender)	23,456	23,456	21,744	8,697
Observations(Rank same nationality)	22,941	22,941	21,166	8,233
Course-year FE	YES	YES	YES	YES
Parallel course FE	YES	YES	YES	YES
Section-rank-base FE	YES	YES	YES	YES

NOTE— Each cell reports the point estimate from a separate OLS regression of the performance measure listed at the top on the rank definition listed on the left. All regressions control for gender, age, nationality, a third-order polynomial in GPA as well as dummies for deciles of the overall GPA distribution. The (section × peer group) fixed effects refer to the respective peer group the rank is based on, for example, section peers with the same gender. Robust standard errors, clustered at the course level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Main Choice Results with Additional Controls for GPA Decile

	(1) Taking Follow-up Course	(2) Number of Follow-up Courses	(3) Taking Math Electives	(4) Graduating in Related Subject Major
Rank	0.0117	0.0024	0.0845**	0.0003
	(0.033)	(0.055)	(0.040)	(0.041)
Rank same gender	0.0091	0.0006	0.0266	0.0447**
	(0.022)	(0.033)	(0.024)	(0.022)
Rank same nationality	0.0024	0.0178	0.0296*	0.0537***
	(0.016)	(0.025)	(0.015)	(0.019)
Mean dependent variable	.2395	.3615	.49	.4727
Observations(Rank)	23,526	23,526	23,526	23,526
Observations(Rank same gender)	23,456	23,456	23,456	23,456
Observations(Rank same nationality)	22,941	22,941	22,941	22,941
Course-year FE	YES	YES	YES	YES
Parallel course FE	YES	YES	YES	YES
Section-rank-base FE	YES	YES	YES	YES

NOTE— Each cell reports the point estimate from separate OLS regressions of the choice outcome listed at the top on the rank definition listed on the left. All regressions control for gender, age, nationality, third-order polynomial in GPA as well as dummies for deciles of the overall GPA distribution. The (section × peer group) fixed effects refer to the respective peer group the rank is based on, for example, section peers with the same gender. Robust standard errors, clustered at the course level, are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A5: List of Course Evaluation Questions

Question	Index
How many hours per week on the average did you spend on self-study?	Study hours
My tutorial group has functioned well.	Peer interaction index
Working in tutorial groups with my fellow-students helped me to better understand the subject matters of this course.	Peer interaction index
The tutor encouraged all students to participate in the (tutorial) group discussions.	Teacher evaluation index
The tutor initiated evaluation of the group functioning.	Teacher evaluation index
The tutor stimulated the transfer of what I learned in this course to other contexts.	Teacher evaluation index
Evaluate the overall functioning of your tutor in this course with a grade	Teacher evaluation index
The tutor sufficiently mastered the course content.	Teacher evaluation index
The tutor was enthusiastic in guiding our group.	Teacher evaluation index