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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 where students are randomly assigned to teaching sections and find that students with a higher rank in their section achieve higher grades, become 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.

JEL: I21, J16, J31
Keywords: rank, social comparisons, higher education, peer effects

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I. Introduction

In their career decisions, students face considerable uncertainty. Decisions such as whether to go to college or what major to choose need careful assessment of the expected costs and benefits. This assessment is challenging because students have limited information about their own ability and, therefore, 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 college, which is a formative period for many people. Career decisions made in college have profound consequences for people's lives. But students 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) of all previous college course grades. 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 the 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. This effect appears to be driven by gender-specific responses in effort. While men increase their study hours in response to a higher rank, we observe no such reaction from 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 10percentile 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.

We explore two channels that may explain why rank in the first year affects career choices: 1) altered self-perceptions and 2) changes in first-year performance. To test for the first channel, we use data from student course evaluations. We show that highly ranked students perceive their peers as less helpful for studying and understanding the material. We view this as suggestive evidence that rank affects a student's self-perception which, in turn, may influence major choices. We further show that half of the effect of rank on major choices is explained by the effect on first-year performance. This suggests that the ordinal rank has an indirect effect on major choices through its effect on first-year performance. One potential explanation for this effect is that students use their first-year performance as an additional signal of their ability. In this case, the indirect effect would amplify the effect of a high initial rank on major choice.

Taken together, our results show that students base their career decisions on noisy information. After we condition on 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 choices 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 extend the recent literature in economics on the role of rank in education. This literature focuses on class rank in primary and secondary school. Based on data from different countries and school types, this literature finds strong causal effects of rank on test scores (Murphy and Weinhardt 2014), 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). We contribute to this literature in three ways. First, this paper is the first to establish the effect of a student's ordinal rank in a field setting with clean random assignment. Identification in previous studies relies on nonexperimental variation in cohort composition within schools. While this strategy rules out many sources on selection bias, it is impossible to rule out all confounding factors. By showing that we obtain similar results with random assignment, our findings lend credibility to identification in nonexperimental contexts. 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 short period. This distinguishes our work from the previous literature, which has focused on settings in which students have the same peers for several years. In our setting, the same students interact for merely a few weeks. Nevertheless, this short-term exposure appears to be sufficient to influence career decisions.

II. Theoretical Considerations

In this section we provide a simple theoretical framework that outlines the mechanisms through which a student's ordinal rank in a peer group can affect outcomes. Our model explains how a students' rank based on predetermined achievement shapes the perception about one's own ability, which in turn affects effort provision and subsequent performance. Moreover, the model explains how ordinal rank can affect major choices through two channels. Rank may affect outcomes: 1) directly, by changing the perceived costs and benefits of a major, and 2) indirectly, through grades in first-year courses, which can act as an additional signal of a student's ability. Below, we formalize this intuition behind the possible mechanisms. Appendix A-II provides the microfoundations of the model.

Rank, effort, and grades. In a given term, the student takes two courses $j \in \{A, B\}$ —for example, *Microeconomics* and *Macroeconomics.* She maximizes the expected net payoff from studying for the exams in both subjects by choosing optimal effort levels. We assume that grades $y_j(e_j)$ are strictly increasing in effort e_j. Effort provision is costly, and the total amount of effort is fixed. The effort cost $c(e_j, a_j)$ depends on a student's perceived ability a_j: the higher the perceived ability, the easier it appears for a student to prepare for the exam and the lower the expected cost of effort, $\frac{\partial c(e_j)}{\partial a_j} < 0$ is. Consequently, a student with a higher perceived ability in a given subject chooses to exert more effort in that subject and less effort in the other.

The ordinal rank affects grades by shaping a student's perceptions about their ability. The mechanism works as follows. A student with a higher rank in Microeconomics than in Macroeconomics perceives herself as more able in Microeconomics, exerts more effort in this subject, and attains a higher grade. Consequently, the marginal effect of rank r_j on the grade in subject j can be summarized as

$$\frac{dy_j}{dr_j} = \frac{\partial y_j}{\partial e_j}\frac{\partial e_j}{\partial a_j}\frac{\partial a_j}{\partial r_j}. \tag{1}$$

The first factor on the right-hand side, $\partial y_j/\partial e_j$, represents the extent to which an increase in effort translates into a higher grade. The second factor, $\partial e_j/\partial a_j$, describes the aforementioned mechanism that a higher perceived ability induces students to choose more effort. The third factor, $\partial a_j/\partial r_j$, describes the extent to which the ordinal rank affects perceived ability.

Theory, along with the empirical evidence, suggests that all three derivatives are positive. First, it appears intuitive that students who exert more effort have on average higher test scores, a fact for which Stinebrickner and Stinebrickner (2008) provide causal evidence. Second, individuals with higher perceived ability tend to exert more effort, either because they have a lower perceived effort cost or because they are overconfident about their ability (Bénabou and Tirole, 2002; Pikulina et al., 2018; Chen and Schildberg-Hörisch, 2018). Finally, there is vast evidence in psychology that a person's ordinal rank in a group has a positive effect on perceived ability (Marsh, 1987). In light of these findings, we derive the following hypothesis:

Hypothesis 1: *A higher rank within a peer group induces students to exert more effort, through which they attain a higher grade.*

Rank and major choice. When choosing a major, a student has to weigh the expected benefits against the costs of taking each subject. As before, we assume the costs depend on a student's perceived ability, which may be influenced by a student's rank in the corresponding first-year course. For example, students who are highly ranked may perceive themselves as more able in a given subject and might become more interested in the course topic. Let p_j be the probability that a student chooses major j, let r_j be the rank in this subject in the first year, and let a student's perceived ability $a_j(r_j)$ be an increasing function in the ordinal rank. We allow the choice probability to depend directly on the perceived relative ability in subject j as well as the grade in subject j in the first year: $p_j = f\big(a_j(r_j),\, y_j(r_j)\big)$. Total differentiation of this function yields:

$$\frac{dp_j}{dr_j} = \frac{\partial f}{\partial a_j}\frac{\partial a_j}{\partial r_j} + \frac{\partial f}{\partial y_j}\frac{\partial y_j}{\partial e_j}\frac{\partial e_j}{\partial a_j}\frac{\partial a_j}{\partial r_j}. \tag{2}$$

This equation includes two effects that have been documented in the existing literature. The direct effect $\frac{\partial f}{\partial a_j}\frac{\partial a_j}{\partial r_j}$ summarizes channels through which rank affects a student's perceptions about the costs and benefits of choosing a given major. To a student with a high rank in Microeconomics, the expected net benefit from taking a Microeconomics major may be higher than the expected net benefit from taking Macroeconomics, thus inducing her to choose Microeconomics. Therefore, the direct effect is most likely positive. Empirical evidence for this channel is provided by Murphy and

Weinhardt (2014), who identify the effect of ordinal achievement rank on the subject choices of secondary students.

The second term in the above equation describes an indirect effect through the student's first-year grade. As described in the model of effort choice, a higher rank can induce a student to choose more effort and attain a higher grade. This channel amplifies the direct effect of rank on the probability of choosing a major if students use their grade as an additional signal about their ability in subject j. While a higher rank shapes initial beliefs about ability, a higher first-year grade may reinforce these beliefs. In the existing literature, Arcidiacono (2004) provides empirical evidence for this mechanism. Based on these findings, we derive the following hypothesis from Equation (2):

Hypothesis 2: *A higher ordinal rank in a first-year subject increases the probability that a student chooses this subject as a major or elective course.*

III. Institutional Setting and Data

A. Organization of Teaching at the Business School

We use data from a Dutch business school that offers bachelors, masters, 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. As of the second year, students choose from a number of elective courses and select one major.

Teaching at the business school is organized into four regular teaching periods per academic year, with each teaching period lasting about two months. 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 around group work. While students attend lectures once or twice per week, sections 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, or graduate 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 in teaching periods 2–4 of the first year for two reasons. First, in the first year of the program, students are exclusively assessed in 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, it is necessary to restrict the sample to courses from teaching period 2 onward 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 of 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 among all previous 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 are 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 study 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, 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 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. 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 bachelors 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 would have 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 rank represents the percentile of a student in the group's GPA distribution. All grades making up the GPA were determined *before* a student's random assignment 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

$$r = \frac{absolute\ rank - 1}{N - 1}. \qquad (3)$$

While the percentile rank, is not explicitly made known to the student, we argue that students discern 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.

Variation in the ordinal rank and information content. For a given GPA, the assignment of students to teaching sections induces considerable variation in the 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 ranks 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 ranks in their teaching sections. Students know their own GPA, but they do not know where they stand in the GPA distribution of all the other students. 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 GPA distribution. Likewise, a student ranked last could be anywhere between the bottom and the center of the 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. 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:

$$y_{itsc} = \beta\, r_{itsc} + f(gpa_{it}) + \boldsymbol{X_i}'\gamma + \boldsymbol{\delta_{tsc}} + \varepsilon_{itsc}. \qquad (4)$$

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 predetermined GPA, we flexibly control for GPA. In our preferred specification, we include a third-order polynomial, although we obtain similar estimates in models with higher-order polynomials as well as dummies for deciles of the overall GPA distribution.[1] The vector $\boldsymbol{X_{it}}$ controls for predetermined individual characteristics, namely age, gender, and indicators for nationality (Dutch, German, or other nationality). In addition, we follow Murphy and Weinhardt (2014) 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.[2]

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 the rank is individually assigned *within* sections. By conditioning on section fixed effects, we perform a within-transformation that subtracts from each variable the section mean. 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

[1] Results are available from the authors upon request.
[2] 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.

ordinal ranking is preserved and β is identified from differences across sections in the variance, 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:

$$cov(\varepsilon_{itsc}, r_{itsc} | f(gpa_{it}), \boldsymbol{X_{it}}, \delta_{tsc}) = 0 \tag{5}$$

In our setting, the validity of this assumption is plausible for two reasons. First, by conditioning on section fixed effects, we eliminate all potential confounders at the peer group level. One such confounder is the average GPA of a peer group. The average GPA in a section is mechanically related to a person's rank—better peers result in a lower rank. In addition, most of the peer effects literature shows that average GPA has a direct impact on student outcomes using data from the same setting (Feld and Zölitz, 2017). The inclusion of section fixed effects breaks this mechanical correlation and eliminates mean GPA as a confounder. It also absorbs 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 assigned quasi-randomly, 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 the 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 10percentile increase in the ordinal rank, which is equivalent to moving up one rank position in a group of 11 students.[3]

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 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 10percentile increase in the ordinal rank increases the probability of passing by about 0.8 percentage points—a 1percent increase relative to the baseline. Column (3) shows that, conditional on passing the course, a 10percentile increase in the 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.

While the results discussed so far focus on the rank among all students in a section, it is not obvious that this is 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 10percentile 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 baseline probability of 7 percentage points. It also increases the probability of passing the course by 1.6 percentage point (column 2). With respect to grades, a 10percentile increase in the ordinal rank among same-gender peers leads to an increase of 3 percent of a standard deviation (column 3).

[3] 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).

Furthermore, we find substantial effects of the same-gender rank on grades in follow-up courses. A 10percentile 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 10percentile increase in the 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.

[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, 2014), 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 (4) 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]

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 outlined in Section II, the impact of rank on specialization choices may be driven by two effects: a direct effect through a student's perceived comparative advantage, and an indirect effect through actual higher performance in a respective first-year course. Put differently, students who are highly ranked in a specific introductory class might become more interested in the course topic through a perceived comparative advantage in that course, even if they do not perform well in absolute terms. Such a mechanism of self-selection has been theoretically described and empirically tested by Cicala et al., (2018). In addition, Section VI.A shows that students with a higher rank have better grades. These grades may, in turn, serve as a signal of ability in that subject and amplify the direct effect of rank on major choice.

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.[4]

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 a larger number of follow-up courses and are more likely to choose more demanding math-intensive elective courses. Most important, 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 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.

To provide an estimate for how much of the reduced-form estimate of rank on choice is mediated through the effect of rank on first-year performance we estimate a *horserace model* whereby we include the grades of the respective first-year courses in the regression in Panel B of Table 4. The importance of grades as a mediator is then computed as the product of the coefficient of rank on first-year performance in Table 3 and the coefficient of grades in the regression in Panel B of Table 4. Our

[4] Math intensity, in contrast to the other outcomes, varies at the studentlevel, 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.

results indicate that about 50 percent of the total effect of rank on major choices is mediated by the effect on earlier performance, while the remaining 50 percent are explained by other channels.[5]

[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 the graduation probability, students' satisfaction with their 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 – the survey was only conducted among students who actually graduated. Given that the rank increases the graduation probability, it is an important finding that students at the margin—who perhaps only graduated because of their higher rank—do not have worse earnings when they enter the labor market.

[5] The interpretation of this quantity as the fraction of the total effect mediated by the effect on actual first-year performance relies on the additional—and, admittedly, fairly strong—assumption of unobservable mediators being independent of the actual performance conditional on predetermined observable individual characteristics (Heckman and Pinto, 2015).

[Table 5 here]

E. 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 five 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, 3) students' perception of the quality of their section instructor, 4) students' perception of the quality of the teaching material, and 5) students' overall perception of the quality of the course. Except for the category of study hours, which is measured based on one survey question, all 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 proxy. Another channel is students' beliefs about their own ability. In the absence of survey information on students' beliefs, the perceived quality of peers provides us with 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 the interaction with their peers as worse compared to students with the same GPA but a low rank. This points to students' being aware of the ranking 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 quality—which in turn suggests that they perceive themselves as more able than their peers. The effect of rank on self-concept is consistent with earlier experimental research in psychology (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. Likewise, we find little evidence that rank affects students' perceptions of the teaching material or their overall evaluation of the course (columns 4 and 5).

[Table 6 here]

F. 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 relative rank positions to be less important to women than to men. If this were the case, rank should also trigger behavioural responses that differ between men and women. While lab evidence does not point to gender differences in e 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, 2014).

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 not significant 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. Given that we also find stronger effects of rank on performance among male students, these results are consistent with the predictions of the model outlined in Section II. 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 their 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 men to be substantially more sensitive to their rank than women and to 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 this 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 are unsure about their relative ability and preparedness for different study specializations—place considerable weight on comparisons to other students. Their position relative to peers that 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 information. 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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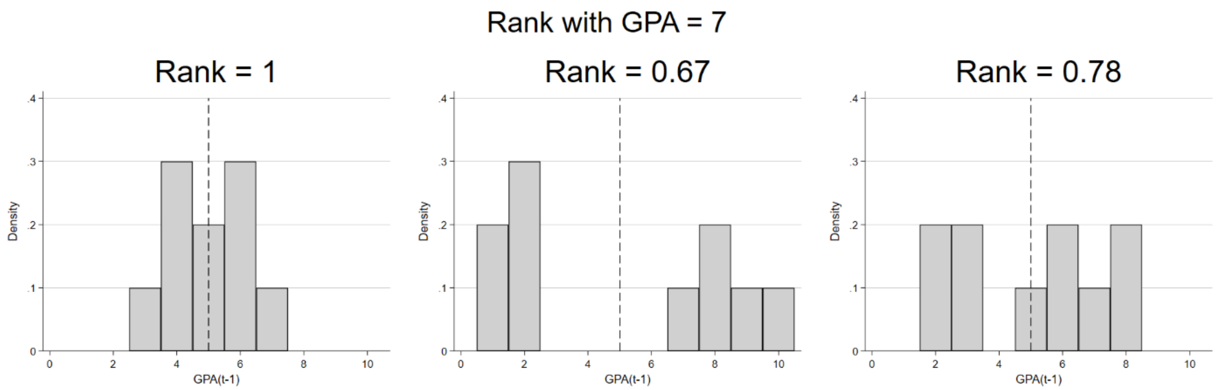
TABLES AND FIGURES

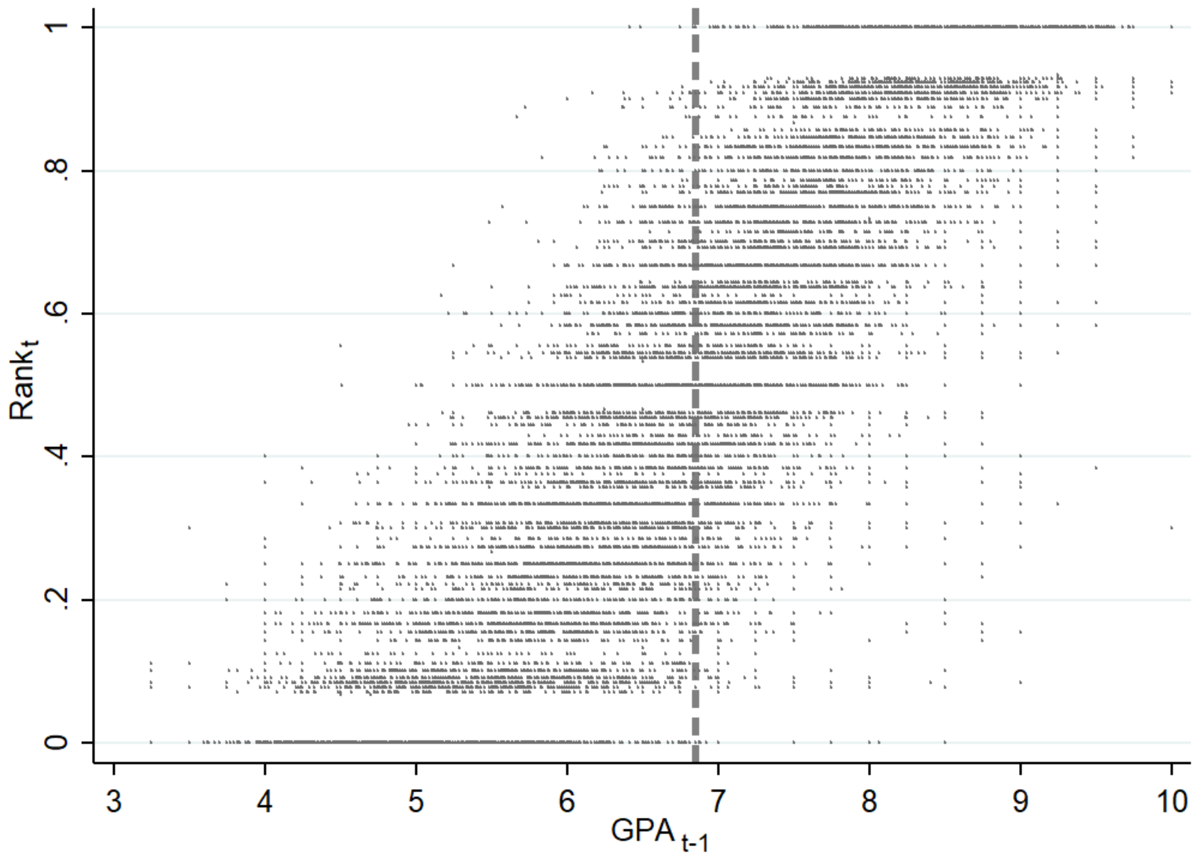
FIGURES

Figure 1: Absolute GPA and Ordinal Rank within Sections



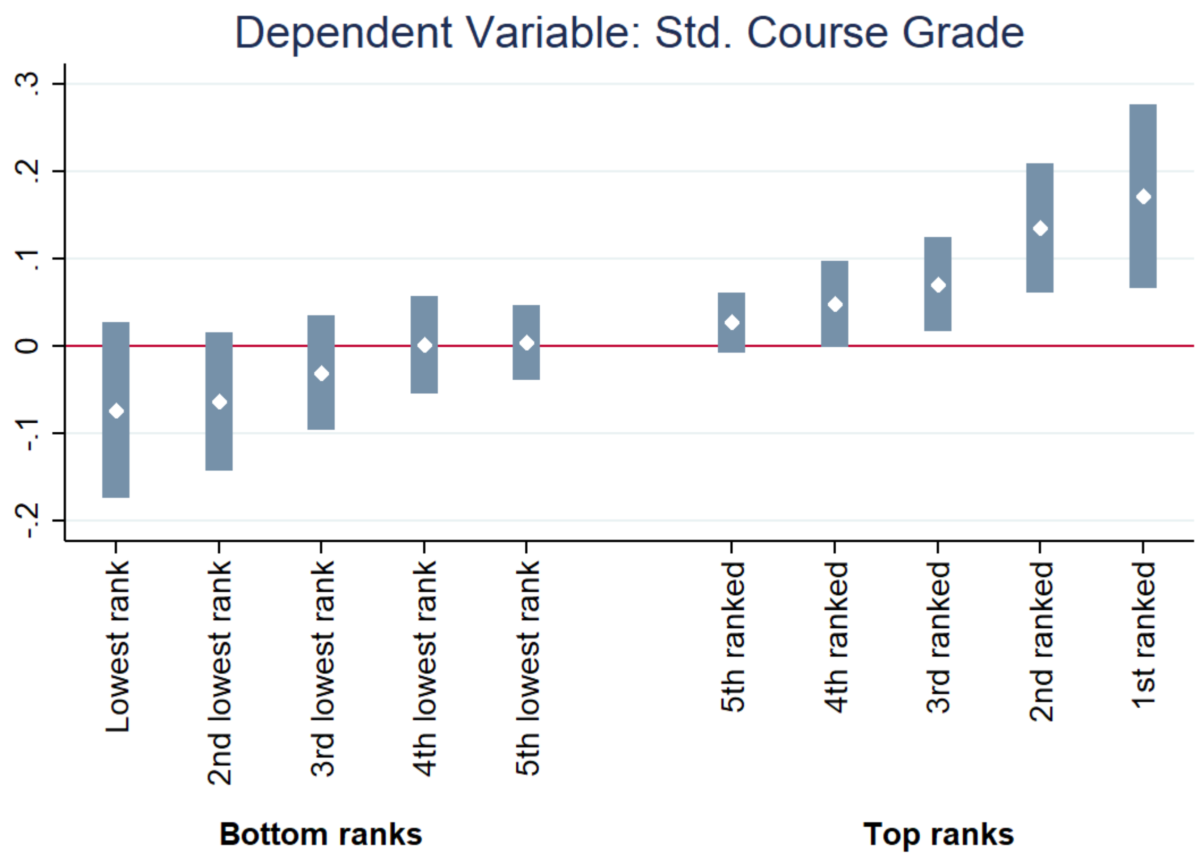
NOTE— This figure illustrates the variation in the ordinal rank across three different exemplary sections holding constant the own GPA level and the section average GPA. Each panel displays the GPA distribution in a section with 10 students. The vertical dashed line denotes the mean section GPA, which 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 percentconfidence 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	0.00100	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

Panel A: Baseline results	(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

Panel B: Controlling for performance	(1)	(2)	(3)	(4)
Rank	-0.0010	-0.0387	-0.0263	0.0400
	(0.029)	(0.045)	(0.038)	(0.037)
Rank same gender	0.0207	0.0216	0.0676***	0.0528***
	(0.017)	(0.027)	(0.016)	(0.019)
Rank same nationality	0.0120	0.0276	0.0673***	0.0462***
	(0.013)	(0.023)	(0.017)	(0.014)
Mean dependent variable	.2528	.3805	0.5197	.4989
Observations(Rank)	21,845	21,845	21,845	21,845
Observations(Rank same gender)	21,744	21,744	21,744	21,744
Observations(Rank same nationality)	21,166	21,166	21,166	21,166
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. In the regressions in Panel B, we additionally control for the grade in the respective first-year course. 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	80.736	10.2346
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, e.g. 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	(4) Teaching Material Evaluation Index	(5) Overall Course Evaluation Index
Rank	-0.2182**	0.5091	-0.0049	0.0273	0.0337
	(0.102)	(0.928)	(0.096)	(0.106)	(0.102)
Rank same gender	-0.1215*	0.0050	0.0305	-0.0008	0.0359
	(0.073)	(0.639)	(0.066)	(0.070)	(0.065)
Rank same nationality	0.0119	-0.3856	0.0497	0.1163*	0.1181*
	(0.062)	(0.572)	(0.052)	(0.067)	(0.070)
Mean dependent variable	-.0182	13.2969	-.033	-.0237	-.0004
Course-year FE	YES	YES	YES	YES	YES
Parallel course FE	YES	YES	YES	YES	YES
Section × peer group FE	YES	YES	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)–(5) are constructed based on the course evaluation questions shown in Appendix Table A4. To obtain the index, we first standardized the answers to each question, then added across 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 the 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 the 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: Split Sample Regressions by Mean Section GPA and Section Standard Deviation GPA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Course Dropout				Passed Course				Std Grade			
Subgroup:	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low Mean GPA Section	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low mean GPA Section	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low Mean GPA Section
Rank	-0.0108	-0.0436**	0.0006	0.0127	0.1283**	0.1062**	0.0504	0.1568***	0.3643***	0.2837***	0.2118**	0.2985***
	(0.027)	(0.020)	(0.021)	(0.026)	(0.049)	(0.048)	(0.044)	(0.058)	(0.113)	(0.096)	(0.091)	(0.101)
Rank same gender	-0.0644***	-0.0504***	-0.0441***	-0.0508***	0.1584***	0.1151***	0.1023***	0.1624***	0.2813***	0.2516***	0.1842***	0.3232***
	(0.011)	(0.010)	(0.009)	(0.011)	(0.025)	(0.023)	(0.020)	(0.027)	(0.046)	(0.044)	(0.045)	(0.045)
Rank same nationality	-0.0434***	-0.0331***	-0.0255***	-0.0370***	0.0695***	0.0852***	0.0542***	0.0987***	0.1528***	0.1699***	0.1203***	0.1836***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.022)	(0.018)	(0.018)	(0.018)	(0.039)	(0.034)	(0.035)	(0.034)

	(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			
Subgroup:	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low Mean GPA Section	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low mean GPA Section	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low Mean GPA Section
Rank	0.1788	0.0694	0.0627	0.1945	-0.0143	-0.0158	-0.0570*	-0.0156	0.0128	-0.0060	-0.0878*	0.0050
	(0.168)	(0.122)	(0.150)	(0.118)	(0.038)	(0.029)	(0.032)	(0.029)	(0.059)	(0.052)	(0.048)	(0.050)
Rank same gender	0.1573**	0.1297	0.2260***	0.0675	0.0062	0.0144	-0.0047	0.0158	0.0190	0.0308	0.0025	0.0300
	(0.067)	(0.080)	(0.053)	(0.060)	(0.016)	(0.012)	(0.012)	(0.014)	(0.027)	(0.019)	(0.017)	(0.025)
Rank same nationality	-0.0088	0.1617***	0.0925	0.0842	0.0060	0.0100	-0.0148	0.0208**	0.0419*	0.0215	-0.0043	0.0484***
	(0.086)	(0.061)	(0.067)	(0.051)	(0.012)	(0.010)	(0.010)	(0.009)	(0.022)	(0.014)	(0.015)	(0.015)

Table A3 (continued)

	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
Dependent variable:	Taking Math Electives				Graduating in Related Subject Major				On Time Graduation			
Subgroup:	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low Mean GPA Section	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low mean GPA Section	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low Mean GPA Section
Rank	0.0042	-0.0149	-0.0545	-0.0637	0.0464	0.0262	-0.0915**	0.0493	0.1636***	0.0842**	-0.1058***	0.2079***
	(0.054)	(0.042)	(0.044)	(0.050)	(0.044)	(0.034)	(0.040)	(0.040)	(0.053)	(0.040)	(0.040)	(0.052)
Rank same gender	0.0393	0.0194	-0.0159	0.0469*	0.0687***	0.0831***	0.0087	0.1130***	0.1343***	0.1282***	0.0584***	0.1697***
	(0.024)	(0.022)	(0.020)	(0.024)	(0.016)	(0.017)	(0.016)	(0.015)	(0.023)	(0.022)	(0.020)	(0.024)
Rank same nationality	0.0063	0.0259*	-0.0130	0.0334**	0.0515***	0.0716***	0.0330**	0.0744***	0.0705***	0.1136***	0.0671***	0.1019***
	(0.017)	(0.015)	(0.014)	(0.015)	(0.016)	(0.014)	(0.014)	(0.015)	(0.019)	(0.018)	(0.017)	(0.018)

	(37)	(38)	(39)	(40)	(41)	(42)	(43)	(44)	(45)	(46)	(47)	(48)
Dependent variable:	Graduation				Study Satisfaction				Log Earnings			
Subgroup:	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low Mean GPA Section	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low mean GPA Section	High SD GPA Section	Low SD GPA Section	High Mean GPA Section	Low Mean GPA Section
Rank	0.1496***	0.0531	-0.1127***	0.1769***	0.3061	-0.0251	0.1095	0.0585	0.1141	0.1043	0.2893	0.0855
	(0.050)	(0.039)	(0.040)	(0.048)	(0.206)	(0.170)	(0.155)	(0.200)	(0.250)	(0.201)	(0.209)	(0.194)
Rank same gender	0.1224***	0.1243***	0.0488**	0.1653***	0.1231	0.0185	0.0362	0.0705	0.2185**	-0.1414	0.0358	0.0190
	(0.023)	(0.023)	(0.020)	(0.026)	(0.081)	(0.090)	(0.080)	(0.090)	(0.108)	(0.100)	(0.092)	(0.097)
Rank same nationality	0.0533***	0.1020***	0.0485***	0.0922***	0.0563	0.1386*	0.0912	0.0840	0.0246	-0.0333	0.1145	-0.1025
	(0.017)	(0.018)	(0.016)	(0.018)	(0.061)	(0.078)	(0.068)	(0.066)	(0.078)	(0.102)	(0.096)	(0.090)

NOTE— Each cell reports the point estimate from separate OLS regressions. All regressions control for gender, age, a third-order polynomial in GPA, 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

Table A4: List of Course Evaluation Question

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
The learning materials stimulated me to start and keep on studying.	Teaching material evaluation index
The learning materials stimulated discussion with my fellow students.	Teaching material evaluation index
The learning materials were related to real life situations.	Teaching material evaluation index
The textbook, the reader and/or electronic resources helped me studying the subject matters of this course.	Teaching material evaluation index
In this course, the online learning platform has helped me in my learning.	Teaching material evaluation index
Please give an overall grade for the quality of this course	Overall course evaluation index
The course fits well in the educational program.	Overall course evaluation index
The course objectives made me clear what and how I had to study.	Overall course evaluation index

A-II. Microfoundations of the Conceptual Framework

In Section II, we provide descriptions of the most important channels through which the ordinal rank affects grades and major choices. Here we present a simple theoretical model that provides the microfoundation for these channels.

Rank, Optimal Effort Allocation, and Grades

We first outline a simple model of effort allocation, which illustrates how the ordinal ranks in different subjects affect a student's optimal effort allocation and affect her grades.

In the same term, a student takes two courses $j \in \{A, B\}$. In each course, she is randomly assigned to a section. At the end of the term, she has to sit an exam in each course. The student has one unit of effort that she can split between both courses, $e_A + e_A = 1$. We assume that the final grade in a course is equal to the effort level, $y_j = e_j$. The student does not know her ability in each course, but she receives two signals at the start of the term, namely her GPA from previous courses ($gpa \in [0,1]$), as well as her percentile rank $r_j \in [0,1]$ in the GPA distribution of the tutorial group. Her perceived ability is a linear combination of both signals,

$$a_j = \alpha \; gpa + (1 - \alpha) r_j, \;\; with \;\; 0 < \alpha < 1. \tag{A1}$$

The student's utility from a course is the difference between the grade and the perceived effort cost $u_j = y_j - c(e_j)$. To ensure a closed-form solution, we assume that the perceived cost function is convex in effort, $c(e_j) = e_j^2 / a_j$, whereby a student with a higher perceived ability has a lower perceived cost of effort. The student's maximization problem is

$$\max_{e_A, e_B} \quad y_A + y_B - c(e_A) - c(e_B)$$

$$= \max_{e_A} \quad e_A + (1 - e_A) - \frac{e_A^2}{a_A} - \frac{(1-e_A)^2}{a_B}. \tag{A2}$$

The optimal effort levels are given by

$$e_A^* = \frac{a_A}{a_A + a_B}, \quad e_B^* = \frac{a_B}{a_A + a_B}. \tag{A3}$$

Equation (A3) yields the following prediction about the impact of the ordinal ranks on effort provision and ultimately on grades.

Prediction 1: If the ranks differ between both courses, a student will exert more effort and achieve a higher grade in the course in which she has a higher rank.

To see this, consider first a case in which both ranks are equal, $r_A = r_B$, in which the perceived ability in both courses is the same, $a_A = a_B$, and the level of effort as well as the grade equals 0.5 in either subject. If the ranks differ, for example $r_A > r_B$, the student perceives herself as more able in course 1, $a_A > a_B$, resulting in greater effort and a higher grade in this course, $y_A = e_A^* > e_B^* = y_B$.

Rank and Major Choice

The effect of rank on major choice can be illustrated based on a discrete choice model. After receiving their grades y_A and y_B, students choose one of the two subjects as a major. A student maximizes her lifetime utility over the choice of a major,

$$U = \max\{u_A, u_B\}, \tag{A4}$$

Each major provides students with a utility

$$u_j = w - \frac{c}{a'_j}, \tag{A5}$$

which is the difference between lifetime earnings w and the perceived cost of pursuing a major, c/a'_j. The costs consist of a constant parameter c and a student's perceived ability a'_j. Each major pays the same lifetime earnings w. For a student with a higher perceived ability in subject j, choosing this subject as a major appears less costly. Each major pays the same lifetime earnings w. When choosing the major, the student has three signals available, namely the initial GPA, the subject-specific rank in the section, and the end-of-term grade. The student's perceived ability in a subject is a linear combination of all three signals,

$$a'_j = \beta_1 \; gpa + \beta_2 r_j + \beta_3 y_j, \tag{A6}$$

with $\beta_1 + \beta_2 + \beta_3 = 1$. As described in the previous section, the grade y_j also depends on the rank and the GPA.

A student chooses whichever major provides her with a higher utility. The prediction from

Equation (A6) is straightforward.

Prediction 2: If the ranks differ between both subjects, a student chooses as a major the subject in which she has a higher rank.

If $r_A > r_B$, then a student has a higher perceived ability in subject A and, consequently, choosing major A is utility-maximizing. It is important to note that this prediction does not depend on the weight of the absolute grade y_j. Even if $\beta_3 = 0$, this prediction holds. The term $\beta_3 y_j$ is included in Equation (A6) to illustrate two distinct channels through which the ordinal rank can affect major choice. The term $\beta_2 r_j$ represents a direct channel, namely a student's perceived comparative advantage in subject 1 relative to subject 2. The term $\beta_3 y_j$ represents the indirect channel through grades. As shown in Section VI.A, the ordinal rank affects grades, which in turn serves as a signal for a student's ability.