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Working Paper

Achievement rank affects performance and major choices in college

UCD Centre for Economic Research Working Paper Series, No. WP21/10

Provided in Cooperation with:

UCD School of Economics, University College Dublin (UCD)

Suggested Citation: Elsner, Benjamin; Ispording, Ingo Eduard; Zölitz, Ulf (2021) : Achievement rank affects performance and major choices in college, UCD Centre for Economic Research Working Paper Series, No. WP21/10, University College Dublin, UCD Centre for Economic Research, Dublin

This Version is available at:

<https://hdl.handle.net/10419/237588>

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UCD CENTRE FOR ECONOMIC RESEARCH

WORKING PAPER SERIES

2021

**Achievement Rank Affects Performance
and Major Choices in College**

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WP21/10

April 2021

**UCD SCHOOL OF ECONOMICS
UNIVERSITY COLLEGE DUBLIN
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Achievement Rank Affects Performance and Major Choices in College*

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December 2020

Accepted for Publication in the Economic Journal

Abstract:

This paper studies how a student's ordinal rank in a peer group affects performance and specialisation choices in university. By exploiting data with repeated random assignment of students to teaching sections, we find that a higher rank increases performance and the probability of choosing related follow-up courses and majors. We document two types of dynamic effects. First, earlier ranks are less important than later ranks. Second, responses to rank changes are asymmetric: improvements in rank raise performance, while decreases in rank have no effect. Rank effects partially operate through students' expectations about future grades.

JEL: I21, J16, J31

Keywords: rank, social comparisons, higher education, peer effects

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We thank two anonymous referees, Alexandra de Gendre, Jan Feld, and David Huffman as well as seminar participants at Collegio Carlo Alberto, Maastricht University, Lund University, Università Cattolica, EALE, ESPE, and IWAE for helpful comments and suggestions. We are particularly grateful to Arjan Non for sharing survey data with us. Maximilian Mähr provided outstanding research assistance.

1. Introduction

When making educational choices, students face considerable uncertainty. Decisions such as which college to attend or which major to choose require students to carefully assess the expected costs and benefits of each choice. Expected returns to educational choices are subjective and can be influenced by cues from a student's environment (Zafar, 2011; Stinebrickner and Stinebrickner, 2012, 2014; Wiswall and Zafar, 2015; Bobba and Frisancho, 2016). An important factor that may affect expected returns is a student's relative ability in a peer group (Marsh, 1987). Between two otherwise identical people, the person with the higher relative ability tends to be more confident and believes that she is more capable than others.¹ Through this mechanism, a student's relative ability early in her career may influence her expected returns and thus affect her effort, performance, and later career choices.

In this paper, we document the importance of a student's relative ability for performance and specialisation choices in university. We use data from a business school in the Netherlands in which students are repeatedly and randomly assigned to teaching sections. We measure a student's relative ability through her ordinal rank in the distribution of predetermined achievement within a given section. To identify the causal effect of the ordinal rank, we follow Murphy and Weinhardt (2020) and Elsner and Isphording (2017) in comparing students with the same predetermined achievement who, by chance, have different ranks in their section. The rank effect is identified through flexible controls for predetermined achievement as well as fixed effects at the level of the peer group, through which we hold own and peer ability constant.

We document five sets of results. First, we find strong effects of a student's rank on contemporaneous performance. A one standard deviation increase in rank reduces the risk of

¹ For a review of the psychological literature, see Dai and Rinn, 2008.

dropping out of the course by 2.3 percentage points while increasing the chance of passing the course by 3.2 percentage points. It also increases the grade in the respective course by 6.7% of a standard deviation and the grade in a related follow-up course by 4% of a standard deviation. We rule out that these results are driven by grading on a curve and show that the effects are robust to controlling for different functional forms of ability as well as adjustments for multiplicative measurement error.

Second, we document dynamic effects by exploiting the repeated random assignment of students to sections. We first show that the importance of a student's rank increases over time: earlier ranks have a smaller effect on performance than later ranks. We also show that students respond asymmetrically to positive versus negative changes in their rank. Whereas increases in the rank relative to the previous period significantly improve performance, we find no equivalent effect for decreases in rank. These results are consistent with findings on asymmetric belief updating, sometimes termed the *good-news-bad-news effect*, whereby people respond to positive but tend to ignore negative signals (Eil and Rao, 2011; Zimmermann, 2020). Finally, we document effects of accumulated positive and negative rank signals. Performance increases with every additional positive signal and, to a lesser degree, decreases with every additional negative signal.

Third, we show that the effect of the ordinal rank affects specialisation choices in university. A higher rank in a first-year course significantly increases the likelihood of taking a follow-up course in the same subject as well as the likelihood of graduating in a related major. Moreover, students with a higher rank are more likely to choose math-intensive elective courses. We also find a positive effect of a student's ordinal rank on the probability of graduating.

Fourth, we document gender differences in the rank effects. We find that male students react stronger to ranks than female students. This difference is particularly pronounced for

specialisation choices, for which rank effects are twice as large for men compared to women. This gender difference is in line with documented gender gaps in the willingness to compete (Niederle and Vesterlund, 2007) and lower reliance of female students on within-classroom comparisons in shaping their ability beliefs (Chevalier *et al.*, 2009).

Fifth, regarding the underlying mechanisms, we present two pieces of evidence suggesting that ordinal rank shapes student beliefs. We find that a higher rank reduces students' satisfaction with their peer-to-peer interactions. Moreover, we provide direct evidence that a higher rank increases students' expectations about their future grades. Both results suggest that a higher rank induces students to think they are more capable than their peers, shaping their beliefs about their own ability and resulting in a lower rating of peer interactions and higher expected grades.

The existing literature has established the importance of rank for a variety of outcomes. The most influential paper in this literature is Murphy and Weinhardt (2020), who show that a student's rank in British secondary school substantially affects test scores and specialisation choices. Further studies, also based on secondary school data, document effects of ordinal rank on outcomes such as the decision to go to college and college success, risky behaviours, non-cognitive skills, mental health, the choice of STEM subjects, and earnings (Elsner and Isphording, 2017, 2018; Cicala *et al.*, 2018; Denning *et al.*, 2018; Delaney and Devereux, 2019; Pagani *et al.*, forthcoming, Kiessling and Norris, 2020). Recent evidence also points to the existence of rank effects in third-level education, based on administrative data in Brazil (Ribas *et al.*, 2020) and experimental data in the Netherlands (Bertoni and Nisticò, 2019).

With this paper, we expand on this literature along four dimensions.² First, in our setting, the

² More broadly, this paper contributes to the literature on ability peer effects, see Sacerdote (2011) and Epple and Romano (2011) for reviews of the literature. The studies closest to ours are those exploiting random assignment

interaction among peers is intense but short; peer groups only form for seven weeks. Unlike in most previous studies – where the same peers interact for many years – we show that even brief social interactions are sufficient to produce substantial rank effects. Given the different nature of social interactions in university, the rank effects may strongly differ from those in secondary school. Second, in our setting, students are randomly assigned to teaching sections, which allows us to rule out that students self-select into peer groups according to their expected rank.³ Third, our setting offers the unique feature of repeated random assignment to sections. We observe the same student in different peer groups and thus can exploit changes in a student’s rank from period to period. This unique setting allows us to analyse dynamic effects, for example, whether students respond to changes in their rank from one teaching period to another or whether they respond differently to increases versus decreases in their rank. Finally, based on survey data, we can provide direct evidence that expectations are an important channel through which the ordinal rank affects performance and choices.⁴

2. Theoretical Considerations

of groups at tertiary-level institutions to estimate different types of peer effects. Examples are the experimental study by Booij *et al.* (2017) at the University of Amsterdam and observational studies based on data from Bocconi University (De Giorgi *et al.*, 2010; De Giorgi and Pellizzari, 2014), Harvard Business School (Shue, 2013), the same Dutch business school as in the present paper (Feld and Zölitz, 2017) as well as military academies (Lyle, 2007, 2009; Carrell *et al.*, 2009, 2013).

³ To the best of our knowledge, the only other study on rank effects that exploits random assignment – and the only other study looking at rank effects in university – is by Bertoni and Nisticò (2019), based on data of an experiment at the University of Amsterdam by Booij *et al.* (2017). Their paper’s focus differs from ours by showing that rank concerns may bias traditional peer effects estimates, which in turn affects optimal class assignment policies.

⁴ Similar evidence is provided for secondary education by Murphy and Weinhardt (2020), who use survey data to show that a higher rank improves students’ confidence.

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 relative ability on a student's self-concept, often termed *big-fish-in-a-little-pond effect*. 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 (Marsh, 1987). A higher perceived ability, in turn, may translate into higher returns to effort and lead to higher performance and more ambitious career choices. A similar chain of causality can be present if the ordinal rank affects a student's motivation or self-confidence.

Another mechanism operates through a student's perceived comparative advantage. Cicala *et al.* (2018) theoretically show how a student's rank may shape her perceived comparative advantage relative to her peers, which in turn may affect her effort 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 behaviour. 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 context of specialisation choice in college, 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.

Furthermore, the ordinal rank may affect the amount of support a student receives from teachers or peers. For example, teachers may challenge highly ranked students more, which may lead to greater motivation and increased effort. Likewise, weaker students may seek help from highly ranked students, through which highly ranked students gain deeper insight into the material.

These and other mechanisms explain why it is plausible to find a reduced-form effect of a student's ordinal rank on performance and specialisation 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 shed light on some of the mechanisms.

3. Institutional Setting and Data

3.1. Organisation of Teaching at the Business School

We use data from a Dutch business school that offers bachelor, master, and PhD programmes 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 (forthcoming) as well as Feld and Zölitz (2017).

Our analysis focuses on the two largest study programmes. In both programmes, 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 typically take two courses within each teaching period and 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 centred 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 per course. A central feature of the learning concept is that 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.

3.2. Sample Description

Our estimation sample consists of five adjacent cohorts who entered the business school between 2009 and 2013. We restrict our sample in two ways. First, we focus only on the first year of the programme, which is when students are assessed exclusively by written exams at the end of each teaching period. This, together with the fact that exams are centrally graded, minimises concerns that section teachers may have a direct impact on grades and alleviates the concern that the rank effect may mechanically result from grading on a curve. Second, we restrict the sample to courses beginning with teaching period 2, dropping the very first teaching period of the first year. We do this because later, we base our rank measure on a student's predetermined GPA at the start of the period. This predetermined GPA is only available from period 2 onward, when grades from period 1 are observed. These restrictions leave us with an estimation sample of 3,920 students and 23,526 student-course observations. A further restriction applies when we analyse graduation probabilities. Here, we avoid censoring the data by further restricting our sample to students who, given their enrolment 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% of students are female. More than half of the students are German (52%), followed by Dutch (30%). 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. 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 all past courses—of 6.9. Around 7% of students who registered for a course drop out during the term. The average passing rate for first-year courses is 71% and the average end-of-course 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, such as *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' specialisation 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 non-compulsory follow-up courses. Table A1 in the Appendix provides an overview of the linkage between first-year and follow-up courses. For any given subject, around 24% 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, whereby it is possible that the same first-year course is 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% of students choosing a follow-up major for their 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 math-intensive if its description contains one of the following terms: math, mathematics, mathematical, statistics, statistical, or theory-focused. In 47% of cases, students take at least one mathematical elective.

Panel C further shows that about 69% 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%. Reassuringly, we find no evidence that rank is related to the response probability.⁵ On average, students have annual entry wages of about EUR 42,500 and retrospectively rate their satisfaction with their overall studies at eight out of ten points.

[Table 1 here]

3.3. 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 with 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% 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 virtually no impact on our results.

⁵ Appendix Table A2 displays results from regressions of a survey response indicator on rank, absolute GPA, and individual characteristics, resembling our main specification in Equation (2). The estimated coefficient of rank is close to zero and insignificant, which means that our results are not driven by selective survey responses.

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. To be admitted to the exam, they must not have missed more than three meetings. Instructors keep a record of attendance. The attendance data are not centrally stored and thus are not available to us.

3.4. External Validity

We recognise that our data come from only one institution and that students at this business school may not be representative of the higher education population in other countries. However, in contrast to other settings studied in the related literature, e.g. the US Air Force Academy (Carrell *et al.*, 2013), Dartmouth College (Sacerdote, 2001), or Bocconi University (De Giorgi *et al.*, 2010), the school we study is a non-selective institution with substantial diversity in terms of nationalities and socio-economic backgrounds (Feld and Zölitz, 2017). To assess the external validity, it is also noteworthy that the small-group teaching approach used at the institution is quite common in many other environments. Feld *et al.* (2020) conduct a survey and show that 63% of OECD institutions use small-group teaching with class sizes similar to those in our sample. We are therefore not particularly concerned that the rank effects we document in this paper are idiosyncratic to the setting we study.

4. 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 achievement as measured by her GPA of all grades. The GPA is determined *before* the student is randomly assigned to a section. The rank represents the percentile of a student in the GPA distribution among all students in 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, and rank 1 to the student with the lowest GPA in the section. If two or more students have the same GPA, they are assigned the same rank. 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

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

For easier interpretability, we standardise the ordinal rank variable to mean zero and a standard deviation of one.⁶ While the percentile rank is not explicitly communicated, students can 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

⁶ For the standardisation, we use the standard deviation of the residuals of the rank after conditioning on section fixed effects, which reflects the variation underlying the quasi-experiment.

rank is equivalent to measurement error in the rank variable, which may attenuate our estimates and work against finding an effect.

Panel D of Table 1 describes the rank variable. On average, a rank is constructed based on sections with 12.6 students. The percentile rank is bound between 0 and 1 and uniformly distributed with a mean of 0.49.

Variation in the ordinal rank. For a given GPA, the assignment of students to teaching sections induces considerable variation in their rank, which is illustrated in Figure 1. Panel A illustrates the identifying variation similar to Murphy and Weinhardt (2020) and Elsner and Isphording (2017). Panel A shows two sections that have the same average achievement but differ in their spread of the achievement distribution. The difference in the variance of achievement results in different percentile ranks for students A and B depending on the section to which they are assigned. Panel B shows three exemplary sections in our data. While the sections have a similar average peer achievement, a student with median achievement in the population would be assigned to substantially different ranks. In this example, the rank varies between the 30th and 70th percentile. Thus, Panels A and B highlight how ranks can differ while own and average peer achievement are held constant. A given GPA leads to significant variation in rank because the distributions differ in their variance, skewness, kurtosis, and, more broadly, the overall shape. This fact will later enable us to identify the effect of rank conditional on section fixed effects.

[Figure 1 here]

Figure 2 displays variation in ranks conditional on achievement, both in the cross-section and over time. Panel A displays the overall variation in rank in period t for a given GPA measured in $t - 1$, after conditioning on section fixed effects. The variation in ranks is largest in the centre of the distribution and lowest in the tails. A student with a median GPA in the overall population may end up with any rank between first and last in a given section. In the tails of the distribution, GPA determines rank almost perfectly because the highest GPA in the overall population always leads to the highest section rank, and likewise, the lowest GPA always results in the lowest section rank.

Panel B displays changes in a student's rank in t compared to her average rank in $t - 1$. The colours indicate strong positive (green), strong negative (red) as well as little to no changes in rank (orange).⁷ Panel B points to substantial dynamics in students' ranks; due to the repeated random assignment, the same student can experience strong decreases as well as increases in her rank. Panel C shows how the upward and downward changes in ranks mechanically lead to a convergence between average ranks in the first and last periods. Due to the repeated random assignment, students who are initially assigned a low rank are more likely to experience upward changes and vice versa. Panel D highlights the importance of conditioning on absolute GPA, which breaks the mechanical correlation between earlier and later ranks shown in Panel C.

[Figure 2 here]

5. Empirical Strategy

⁷ Underlying this classification is the change in rank between two periods, measured by the difference between a student's current rank in a given section and her average rank in the previous section, $\Delta r_{isct} = r_{isct} - \bar{r}_{isc,t-1}$. We classify changes in the top quartile of the distribution of Δr_{isct} as strong increases and changes in the bottom quartile as strong decreases. The third category – denoting little or no change – includes all rank changes in the second and third quartile.

5.1. Empirical Model

Our empirical strategy exploits the random assignment of students into sections within courses, 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. Aside from the random assignment – which is unique to our setting – this strategy follows the analysis of rank effects by Murphy and Weinhardt (2020).

In the empirical analysis, we estimate the effect of a student’s ordinal rank in first-year sections on contemporaneous performance and longer-run outcomes. Regressions are based on the following equation:

$$y_{isct} = \beta r_{isct} + f(gpa_{i,t-1}) + \mathbf{X}_i' \boldsymbol{\gamma} + \boldsymbol{\delta}_{sct} + \varepsilon_{isct}. \quad (2)$$

The dependent variable y_{isct} 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 .⁸ Therefore, each section is nested in a unique period-course combination. We regress this outcome on the student’s percentile rank within section s , $r_{isct} \in [0,1]$, which is a function of the student’s own predetermined GPA measured at the end of period $t - 1$ as well as the distribution of the student’s own predetermined GPA in section s . To isolate the effect of rank for a given level of achievement, we control for a function of predetermined GPA. In our preferred specification, we include a third-order polynomial,

⁸ We run all our main specifications at the student-course level, as this replicates the hypothetical experiment wherein students are randomly assigned to sections *within* courses. For comparison, we also perform an analysis at the student level, whereby the regressor is a student’s average rank. The results, which are available upon request, confirm our main results at the student-section level.

although we later show robustness checks with polynomials of different orders as well as more flexible controls based on decile dummies. The vector \mathbf{X}_i controls for predetermined individual characteristics, namely age, gender, and indicators for nationality (Dutch, German, or other). In addition, we follow Murphy and Weinhardt (2020) and Elsner and Isphording (2017) by conditioning on section fixed effects δ_{sct} . These fixed effects are central to our identification strategy, as they absorb all average differences in observable and unobservable characteristics between sections. Importantly, this includes any peer group characteristic that is the same for all students within a section, for example, the mean ability or the variance in ability.

The error term ε_{isct} captures all determinants of the outcome that are not captured by other regressors. Given the likely cross-sectional dependence of error terms, it is necessary to adjust the standard errors for clustering. Two dimensions of dependence are particularly important. First, we observe each student multiple times, and the error terms of the same student are likely correlated. Second, students are assigned to sections within the same course, which means that the error terms may have a course-specific component and therefore may be correlated within courses. We account for these correlations by adjusting the standard errors for two-way clustering at the student and course level.⁹ In Appendix Table A3, we also present standard errors with one-way clustering at various levels, which are consistently smaller than the two-way clustered standard errors.

5.2. Identification

⁹ When referring to the course level, we implicitly refer to unique cohort-term-course combinations; for example, the grades in Microeconomics in the second term of the starting cohort in 2008.

Identifying variation. Our coefficient of interest, β , measures the marginal impact of a higher 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 centres 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, 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 after controlling for mean differences across sections. Table A4 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.

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:

$$cov(\varepsilon_{isct}, r_{isct} | f(gpa_{i,t-1}), \mathbf{X}_i, \boldsymbol{\delta}_{sct}) = 0. \quad (3)$$

In our setting, the validity of this assumption is plausible for two reasons. First, by conditioning on section fixed effects $\boldsymbol{\delta}_{sct}$, we eliminate all potential confounders at the peer group level. This is

important because we aim 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 these direct effects are eliminated by the fixed 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, which is a potential source of bias in studies based on non-random assignment.

Quasi-random assignment of the ordinal rank. To confirm that our measure of the ordinal rank is as good as randomly assigned, in Table 2 we perform balancing tests in which we regress student characteristics on the ordinal rank, a third-order polynomial in GPA, as well as various sets of fixed effects. None of the coefficients is statistically significant, which is consistent with the random assignment of students to sections and supports the assumption of strict exogeneity of rank conditional on GPA and section fixed effects.

[Table 2 here]

Challenges to identification. Despite the random assignment, two challenges to identification remain. One is functional form, as strict exogeneity only holds if the specification error – a component of ε_{isct} – is uncorrelated with a student's rank. A second challenge is measurement error in the ability variable,

which may lead to spurious rank effects. We address both challenges in robustness checks in the next section.

6. Main Results

6.1. Ordinal Rank and Student Performance

We first estimate the effect of rank on contemporaneous performance in the first year. Table 3 displays the estimated effects of the ordinal rank on four measures of performance. This and the following tables report coefficients from separate regressions of the dependent variables shown in the column headers on the ordinal rank, adjusted for a third-order polynomial in predetermined GPA, individual characteristics, and the fixed effects listed at the bottom. Each coefficient represents the marginal effect of an increase in a student's ordinal rank within a section, holding constant individual achievement and mean peer achievement as well as all other factors that are constant across all members of a section. Because of the standardization, the coefficients are to be interpreted as the effect of a one standard deviation increase in the ordinal rank – an increase of about 12 percentiles, or about 1.4 rank position in a section of 12 students.

Column (1) shows that a higher ordinal rank significantly reduces the likelihood of dropping out of the course. A one standard deviation increase in the ordinal rank reduces dropout risk by 2.3 percentage points. Similarly, an increase in the rank by one standard deviation increases the likelihood of passing the course by 3.2 percentage points, which is equivalent to about 5% of the mean (column 2). Columns (3) and (4) reveal economically and statistically significant effects of the ordinal rank on performance. A one standard deviation increase in the ordinal rank increases the grade at the end of the course by 6.7% of a standard deviation and the standardised grade in a follow-up course by 4% of a standard deviation. The effect of rank on standardised grades is similar in magnitude to the effect

found by Murphy and Weinhardt (2020) for secondary school children in England. Moreover, the effect of rank appears to be more important than spillovers of higher average peer ability or an instructor with a higher value-added. In the same setting, Feld and Zölitz, (2017) estimate that a one standard deviation increase in the average peer GPA causes an increase of 1.26% of a standard deviation in student grades. An instructor with a one standard deviation higher value-added increases students' grades by 2% of a standard deviation (Salamanca *et al.* forthcoming).

Despite differences in the setting and the extent of peer exposure, our main finding – an increase in performance of around 7% for a one standard deviation increase in rank – is in the same ballpark as recent results by Murphy and Weinhardt (2020), who study rank effects in British primary and secondary schools. In their setting, a one standard deviation increase in rank based on standardised test scores in primary school increases test scores at ages 14–16 by about 8% of a standard deviation. Denning *et al.* (2019) find similar-sized effects for students in that same age group in Texas. It is perhaps surprising that the short-term exposure to a peer group at a Dutch business school leads to similar rank effects as the year-long exposure to school peers in Britain or Texas. One explanation for the similarity in effect sizes may lie in the uncertainty about one's own ability, which is particularly high at the beginning of college (Arcidiacono *et al.* 2016). During this period, the signal contained in one's ordinal rank may play a particularly important role. Results of Bertoni and Nisticò (2019) suggest that the effects of rank at the beginning of college can be even larger if peer groups stay together for a longer period. They use data from an experiment at the University of Amsterdam, where peer groups stay together for the entire first year, and find a much larger rank effect: a one standard deviation increase in rank increases math test scores by 25% of a standard deviation.

Our second finding – that a high rank in a given subject increases the probability of majoring

in that subject – is also in line with the earlier literature. Although the effect sizes are difficult to compare across settings, both Murphy and Weinhardt (2020) and Denning *et al.* (2019) show that changes in the ordinal rank early in a student’s career affect later specialisation choices.

Given that a rank effect is a specific type of peer effect, our results can be compared to those in the literature identifying “classical” peer spillovers in similar settings. Feld and Zölitz (2017) find positive but small peer spillovers in the same setting: having peers of a one standard deviation–higher ability improves own performance by 1.26% of a standard deviation. This suggests that a person’s ordinal rank within a peer group is more important for performance and choices than the average peer ability. However, given our research design, it is not possible to separately identify peer and rank effects, as the average peer quality and a person’s rank are the result of the same random assignment. Both are mechanically correlated, which is why one cannot estimate separate causal effects in the same regression as well as determine which effect is stronger.¹⁰ Disentangling both effects is possible in a regression discontinuity design, as demonstrated by Ribas *et al.* (2020). The authors exploit the fact that the change in ordinal rank at an admission cutoff to an advanced study programme is constant across years – a student is either the highest ranked in the weak group or the lowest rank in the strong group – whereas the difference in average peer ability varies from year to year. They find that negative performance effects due to a lower rank outweigh the positive spillovers from having better peers. A comparison of the substantial rank effects we find in this paper with the moderate peer effects by Feld and Zölitz (2017) points in a similar direction.

¹⁰ Note that this does not imply that peer and rank effects cannot be identified at all. Most papers identify the effect of the ordinal rank by controlling for peer quality through peer group fixed effects. Likewise, as pointed out by Bertoni and Nisticò (2019), studies that seek to estimate the causal effect of average peer quality on individual outcomes should control for a person’s ordinal rank, as they would otherwise obtain biased estimates.

The binned scatter plot in Figure 3 sheds further light on the functional relationship between within-section rank and performance. The regression line is equivalent to the coefficient in column (3) of Table 3. While the relationship is not fully linear – there appears to be a plateau in the middle of the distribution of ranks – the dots are close to the regression line, ruling out strong non-linearities. This relationship is closer to the linear one found for secondary school students (Murphy and Weinhardt, 2020) than the non-linear relationships found in experiments that emphasise the importance of being ranked first or last (Kuziemko *et al.*, 2014; Gill *et al.*, 2019).

[Table 3 here]

[Figure 3 here]

6.2. *Dynamic Effects*

After documenting a strong positive effect of rank on performance, we explore how students respond to *changes* in their rank. If the ordinal rank is a signal for ability, changes in the rank may induce students to update their beliefs about their own ability and adjust their effort.

We begin by testing to what extent earlier ranks are more – or less – important than later ranks. On the one hand, uncertainty about one’s own ability might be larger at the early stages, in which case an early rank would have a larger effect. On the other hand, a student might first have to understand the new college setting to adequately process information provided by the rank. In that case, we would expect later ranks to have a larger effect. In Table 4, we interact the rank with an indicator for the first period in which we observe a student’s rank.¹¹ The results suggest that the

¹¹ Because we construct the rank based on predetermined GPA, the first period in which we observe the rank is the second teaching period.

effect of rank is about half the size in the first observed period compared to later periods. The effect on follow-up grades materializes in later periods only.

[Table 4 here]

In a further step, we analyse whether students respond to large changes in their rank and whether the responses differ between positive and negative changes. We base the analysis on the difference between student i 's rank in section s in period t and the student's average rank in both sections in the previous period $t - 1$, $\Delta r_{isct} = r_{isct} - \bar{r}_{isc,t-1}$.¹² From the distribution of rank changes Δr_{isct} , we construct indicators for *strong increases* and *strong decreases*. We classify a change as a *strong increase* if it lies in the top quartile of the distribution of changes and a *strong decrease* if it lies in the bottom quartile.

Table 5 presents the results of regressions of performance outcomes on the indicators for strong increases or decreases in rank. The omitted category is rank changes in the second or third quartile of the distribution of Δr_{isct} , which represent no or small changes in the ordinal rank. The controls are identical to those in our main specification in Table 3. The effects on dropout risk and course passing, shown in columns (1) and (2), have the expected signs but are small and statistically insignificant. Columns (3) and (4), in contrast, reveal strong asymmetric responses of performance to changes in rank. A strong increase in rank raises the grade in a given course as well as in a follow-up course by around 6% of a standard deviation. The effect of a strong decrease in rank is

¹² Because of the lag term in Δr_{isct} , we can only analyse rank changes in the third and fourth teaching periods of the first year. For each student in the sample, we observe four rank changes: two in period 3 relative to period 2 and two in period 4 relative to period 3. This explains the lower number of observations in Table 5.

smaller – around 3% of a standard deviation – and statistically insignificant.

[Table 5 here]

We further explore whether positive and negative signals have a cumulative effect, that is, whether students respond differentially to receiving multiple positive or negative signals. For this purpose, we restrict the estimation sample to the fourth teaching period of the first year – the last period in which we observe a student’s rank – such that for each student we observe four rank changes.¹³ We then regress the standardised grade on indicators for the cumulative number of positive and negative signals a student receives. The omitted category is students whose rank remained stable in all sections in periods 3 and 4. The controls are the same as in Table 3.

The results in Figure 4 point to an effect of accumulated positive and negative signals. Every additional positive signal leads to an increase in performance. This relationship holds for up to three positive signals, whereas a fourth positive signal has no significant additional effect on performance. Similarly, every additional negative signal has a negative effect, although the effect is less pronounced than for positive signals. Given the confidence intervals, we cannot exclude that the additional effects beyond the first negative signal are zero.¹⁴ Overall, Figure 4 confirms the

¹³ The cumulative number of negative and positive signals that a student can receive in the first year is bounded between -4 and +4. In period 2, the first period in which a student’s rank can be computed, a comparison to a pre-period is not possible. In both periods 3 and 4, the student takes two courses each and therefore is assigned to two sections. In each section, we observe a change in rank relative to the average pre-period rank. Restricting the sample to the fourth teaching period only ensures that we observe the same number of signals for all student-section combinations. We obtain similar results when we include student-section combinations in the third period.

¹⁴ Given that the number of signals results from the sampling distribution of ranks, large numbers of positive or negative rank changes are not as likely to occur as small numbers. The share of observations with four positive

asymmetric effects found in Table 5. Students respond more strongly to positive than to negative signals.

[Figure 4 here]

6.3. Robustness Checks

Functional form: The causal identification of the rank effect crucially depends on correctly specifying the functional form of the relationship between absolute GPA and the outcome. To ensure that the effect of rank is not confounded by the direct effect of absolute achievement on performance and choices, it is vital to correctly specify the effect of absolute achievement. In Appendix Table A5, we assess the robustness of our results to different parametric and non-parametric controls for absolute GPA. We parametrically control for GPA with polynomials up to the fourth order and show alternative specifications in which we semi-parametrically control for GPA with decile dummies. The estimated effects prove robust to the different specifications, which suggests that our results are not driven by specification errors.

Multiplicative measurement error. As pointed out by Murphy and Weinhardt (2020), non-standard multiplicative measurement error in the normally distributed ability measure may lead to spurious rank effects. This problem can be circumvented through a transformation of the ability measure into a uniform distribution and the construction of the ordinal rank based on the transformed measure. Appendix Table A6 displays our main regression results based on the transformed achievement measure and the same parametric and semi-parametric controls for GPA as in Appendix Table A5. The results are similar to our main results, both in terms of size and statistical significance.

signals or four negative signals is below 1% for each. The share without significant changes in rank is 44%.

Inference. We adjust the standard errors for two-way clustering at the student and course level because: i) we observe each student multiple times in the sample, and hence their error terms may not be independent, and ii) students are randomised into sections within the same course. Because grading occurs at the course level, the error terms within a course may be correlated. In Appendix Table A3, we show that our adjustment is conservative in the sense that it produces larger standard errors compared to one-way clustering at the section, course, or student levels.

7. Additional Results

7.1. Effect of Rank on Specialisation Choices and Long-Run Outcomes

Besides having a strong positive effect on contemporaneous performance, a student's rank may also affect longer-run outcomes by, for example, changing beliefs about one's success in a given specialisation. To examine longer-term effects, we focus on specialisation choices and long-run outcomes such as study satisfaction or earnings. Specialisation choices within business and economics are presumably less consequential than the decision to go to college or the choice of whether to study art history or engineering. Nonetheless, the literature has shown that major choices lead to earnings differences, if, for example, choosing a major affects the subsequent choice of occupation (Arcidiacono, 2004) or if the major choice reflects an investment in job-specific human capital (Wiswall and Zafar, 2015). In our setting, shortly after graduation, finance majors earn EUR 57,000, whereas marketing majors earn EUR 43,000 per year.

One channel through which a student's rank may affect major choices is changing beliefs about the comparative advantages of some fields versus others. If, for example, a student is highly ranked in quantitative methods but ranks low in introductory microeconomics, she might believe that

she has a comparative advantage in quantitative over theoretical content. The effect on beliefs may sway students in their later major choices, above and beyond the direct effect of rank on performance.

To estimate the impact of rank on specialisation choices, we construct four indicators: i) a binary indicator for whether a student chooses any follow-up course to the respective first-year course, ii) the number of follow-up courses a student chooses, iii) an indicator for whether a student chooses any elective with a high math intensity, and iv) an indicator for whether a student graduates in a related major. As long-run outcomes, we use: i) an indicator for whether a student graduated within four years, ii) a retrospective measure of study satisfaction on a scale from 1 to 10, and iii) log earnings.

When estimating the effect of the ordinal rank on these outcomes, the treatment varies at the student-course level whereas the outcome only varies at the student level. This means that if we observe a student in six courses, the same outcome is observed six times. In this set-up, the coefficients represent the effect of a higher rank in *one* course on the outcome.

Columns (1)–(4) of Table 6 show that the ordinal rank significantly affects specialisation choices. A one standard deviation increase in rank increases the probability of taking a follow-up course in a related subject by 1.2 percentage points and increases the number of follow-up courses by 1.9 percentage points. Similarly, in column (3), we find a strong effect on the probability of graduating in a related major. An increase in rank by one standard deviation increases this probability by 2.2 percentage points. Column (4) shows a large and statistically significant effect on the probability of choosing electives with a high math intensity. For a one standard deviation increase in rank, the choice probability increases by 3.1 percentage points.

The effect of rank on long-run outcomes, shown in columns (5)–(7), is less clear-cut than the effect on choices. While we find a significant positive effect on the probability of graduation, we find neither significant effects on study satisfaction nor earnings. The insignificant effect on earnings

should be interpreted with caution, as the earnings data is much noisier than the data on performance and choices. The earnings data are based on a non-random subsample and are self-reported, which means that they are likely subject to measurement error and selective misreporting. However, as shown in Appendix Table A2, the probability of responding is unrelated to rank.

[Table 5 here]

7.2. Gender Differences in Rank Effects

In Table 7, we explore whether the effect of rank on performance and choices differs by gender. The literature documents a significant gender gap in the willingness to compete (Niederle and Vesterlund, 2007; Andersen *et al.*, 2013; Sutter and Glätzle-Rützler, 2014). Along similar lines, several pieces of evidence show that male students are more likely than female students to rely on within-classroom comparisons to shape their beliefs about their relative ability (Chevalier *et al.*, 2009; Kuyper *et al.*, 2011; Cooper *et al.*, 2018). If female students indeed dislike competing and male students are more likely to rely on classroom comparisons, one may expect the ordinal rank to be less important to women than to men. This notion is confirmed by Murphy and Weinhardt (2020), who show that male secondary students are more responsive to their rank compared to female students.

To test for gender differences in students' responses to their ordinal rank, we re-estimate our main specification and interact the rank with an indicator for female. The results in Table 7 point to significant gender differences. In general, female students show a weaker response than male students. With respect to first-year performance (Panel A), the effect of rank on dropout is one-third smaller for female compared to male students. Gender differences in the effect on grades and follow-up grades

are statistically insignificant but point in the same direction. For third-year choices (Panel B), the differences are more pronounced. The effects on the likelihood of choosing a follow-up course, the number of follow-up courses, and on choosing a math-intensive elective are about twice as large for male as for female students. Taken together, these results confirm the higher responsiveness of male students to within-classroom comparisons found in the previous literature.

[Table 7 here]

We analyse a second channel through which gender may interact with ordinal rank, namely, a student's reference group. Rather than comparing themselves to all students in a section, students may compare themselves to peers with similar characteristics, such as gender. To test whether a student's rank within her same-gender group is indeed a better predictor for performance than her overall rank, we construct a student's same-gender rank as the percentile rank among all section peers of the same gender. However, the results in Appendix Table A7 indicate that the same-gender rank has no additional effect over and above the overall rank.¹⁵ We can thus reject a hypothesis that rank comparisons among same-gender peers are more important than comparisons among all peers.

7.3. Mechanisms

In this section, we use data from two additional sources to shed light on potential mechanisms that may explain why rank affects performance and choices.

¹⁵ Note that using this alternative and more narrow definition of a peer group also implies a smaller group size and higher residual variation in ranks, as shown in Table A4.

Evidence from course evaluations. Our first data source is course evaluations, which are short online surveys that students complete at the end of each teaching period. Using these evaluations, we construct three outcome variables: i) students' perception of the quality of their section peers, ii) students' self-reported study hours, and iii) 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 (see Appendix Table A8 for details). We construct the indices based on the first principal component of the respective questions and standardise each index to mean zero and a standard deviation of one. The outcomes are proxies for several mechanisms that may explain the effect of rank on performance and choices. The perceived quality of peers provides us with indirect information on how students evaluate their peers in relation to their own perceived ability and, therefore, can be seen as a proxy for a student's beliefs. Another important mechanism is effort, for which self-study hours are a proxy. Finally, perceived quality of teachers is informative about potential effects running through teachers' being responsive to a student's rank. For example, students with higher rank may receive more attention from the instructor or perform better if instructors teach to the top of the class.

Table 8 displays the estimated effects of rank on the proxies for mechanisms. Column (1) shows that a higher rank induces students to give a *lower* rating to their peer interactions in the course. One potential interpretation of this result could be that more highly ranked students view themselves as more able compared to their peers and, consequently, see interactions with less able peers as less fruitful. In column (2), we find a positive, albeit small and statistically insignificant, effect of rank on study hours. This suggests that if the overall effect is driven by effort, it is not driven by the extensive margin, that is, how many hours a student studies. In column (3) we find economically and statistically insignificant effects for teacher evaluations.

[Table 8 here]

Direct evidence on beliefs. Our second data source is a compulsory survey of first-year students that contains more direct evidence on beliefs. The survey was run in three cohorts two weeks after the start of their first teaching period. After taking a compulsory statistics entry test and learning their grade, students had to take a short survey that, among other questions, asked them about their expected grade on the module *Quantitative Methods*. We use the expected grade as an outcome that proxies for beliefs. We construct a student's rank within their sections in the first teaching period based on their statistics entry score.

The results of this analysis are displayed in Table 9. As a benchmark, column (1) shows the effect of the ordinal rank on standardised grades at the end of teaching period 1. Reassuringly, the effect of the rank based on the statistics score on standardised grades is similar in magnitude to the effect of rank based on GPA in Table 3. In column (2), we estimate the effect of the ordinal rank on expected grades. A one standard deviation increase in the ordinal rank increases expected grades by 4.7% of a standard deviation, which is about 40% of the effect of rank on actual grades. This result provides direct evidence that the ordinal rank shapes a student's beliefs, which may in turn affect performance.

[Table 9 here]

These results are in line with earlier work by Murphy and Weinhardt (2020) and Elsner and Isphording (2017). The former show that an increase in rank by one standard deviation increases students' subject-specific confidence by 6% of a standard deviation. The latter find that an increase

in the percentile rank by 10 percentage points significantly increases the likelihood that a student believes he or she is more intelligent than the average. Compared to these estimates, we find a smaller effect in this paper. Nonetheless, this result corroborates the hypothesis that rank effects operate through a student's self-confidence.¹⁶

8. Conclusion

In this paper, we present evidence that a student's ordinal rank in a peer group affects performance and specialisation choices in college. By exploiting the repeated random assignment of students to teaching sections at a Dutch business school, we find that students who, by chance, rank higher in their section perform better in centrally graded exams, are more likely to choose related follow-up courses, and have a higher graduation probability. We also document responses to rank changes that are consistent with asymmetric belief updating. Students' performance improves in response to strong increases in their rank while remaining stable in response to strong decreases. Finally, based on survey data, we show that the effect of rank on performance and choices partly operates through shifting expectations. Students who by chance had a higher rank have higher expectations about their future grades.

These findings provide important insights into the decision-making of college students. Our results suggest that students – who may be unsure about their relative ability and preparedness for

¹⁶ More broadly, these results relate to the literature on the big-fish-in-a-little-pond (BFLP) theory, which has a long tradition in psychology (see Fang *et al.* 2018 for a systematic review). However, the effect sizes are not readily comparable with the estimated rank effects in Murphy and Weinhardt (2020) and Elsner and Ispording (2017) and related studies. BFLP effects are typically estimated from the negative correlation between own academic self-concept and average peer ability while holding own ability constant. As such, many studies do not explicitly separate the effect of the ordinal rank from the mechanically related confounding effect of average peer quality.

different study specialisations – 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 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. A promising avenue for future research is to design interventions that reduce the noise and help students to make better-informed career choices.

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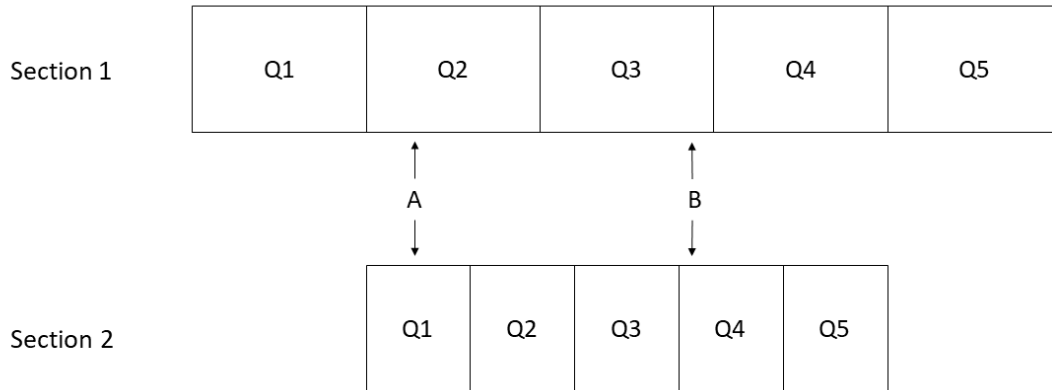
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FIGURES AND TABLES

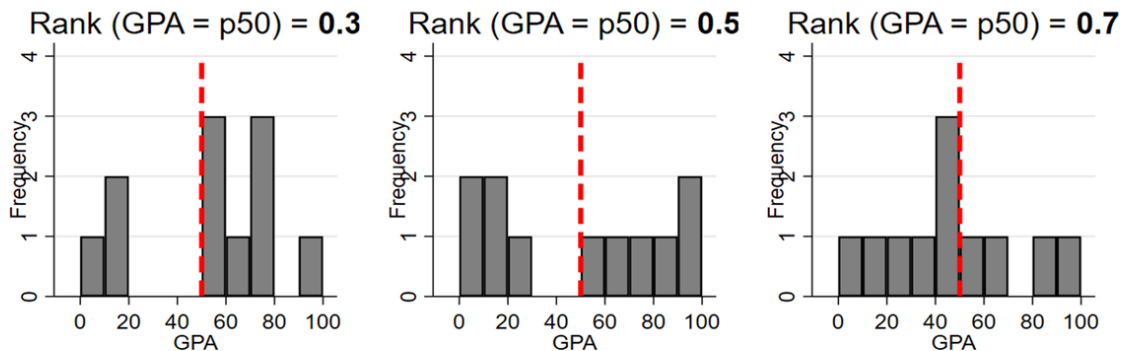
FIGURES

Figure 1: Variation in Rank

A. Different ranks with similar absolute ability and constant section mean

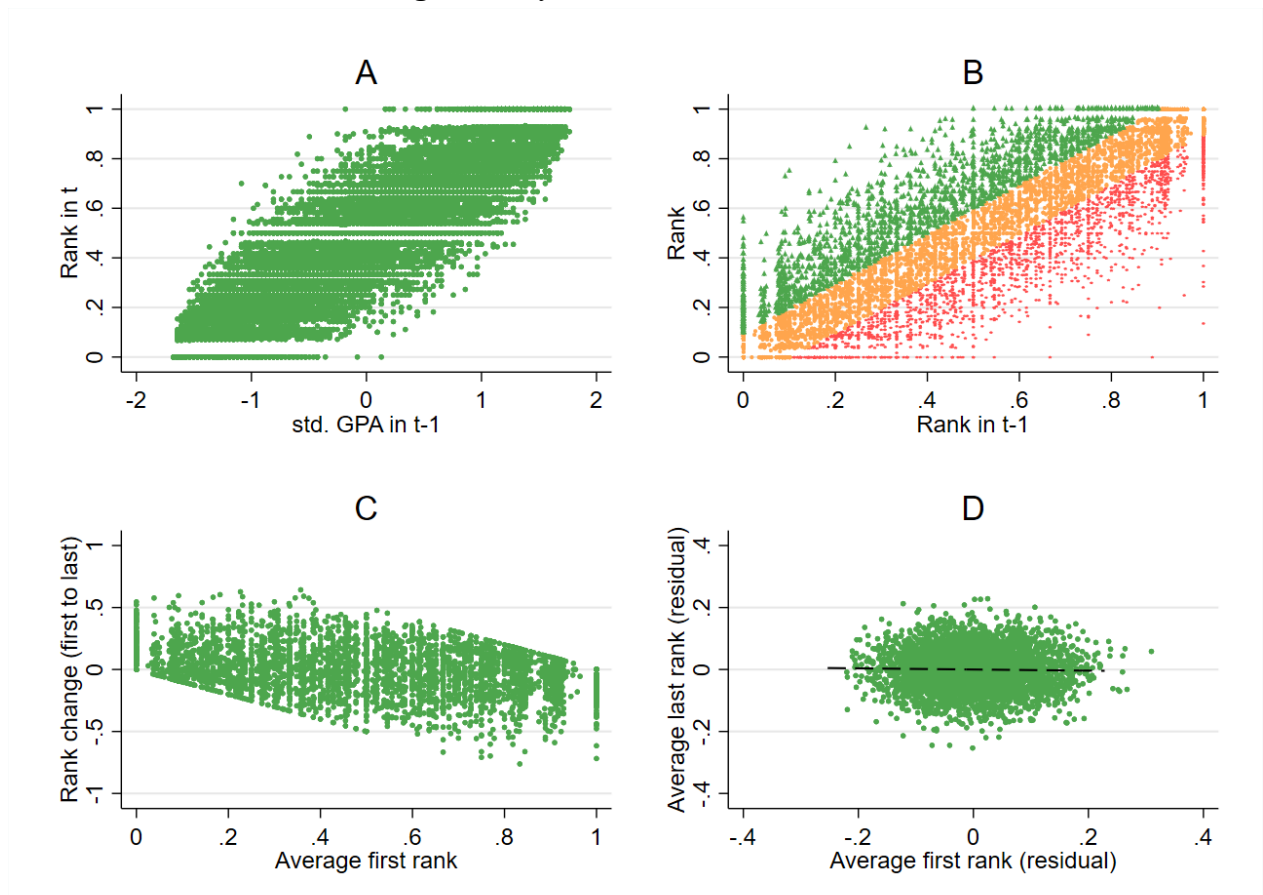


B. Empirical examples



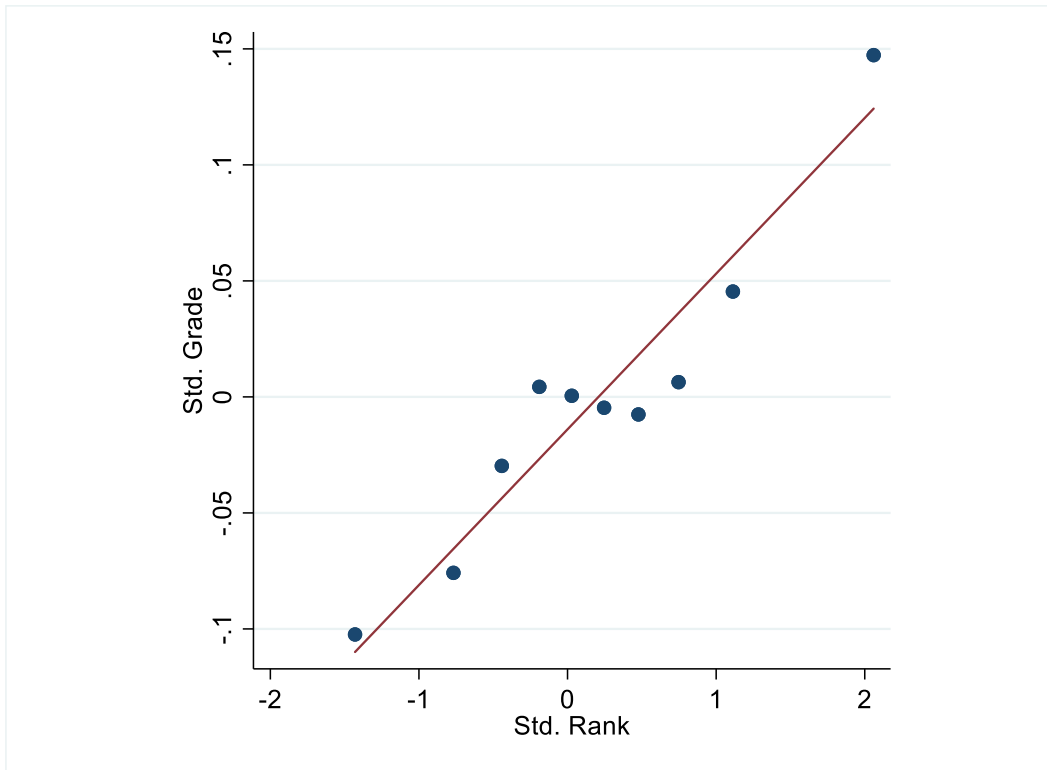
NOTE— This figure illustrates the sources of variation used in the identification of the rank effect. Panel A shows how percentile ranks of students A and B would differ if they were assigned to Sections 1 and 2. Both sections only differ in the variance but not in the mean of the section’s achievement distribution. With unchanged ability, student A would receive a higher rank in Section 1 than in Section 2. Student B would receive a lower rank in Section 1 than in Section 2. Panel B displays three exemplary sections from our data. All three sections are of similar mean ability (between 45th and 55th percentile among all sections in the sample). Dependent on the section’s exact shape of the achievement distribution, a student of median achievement may end up with different ranks between the 30th and 70th percentile.

Figure 2: Dynamic Variation in Rank



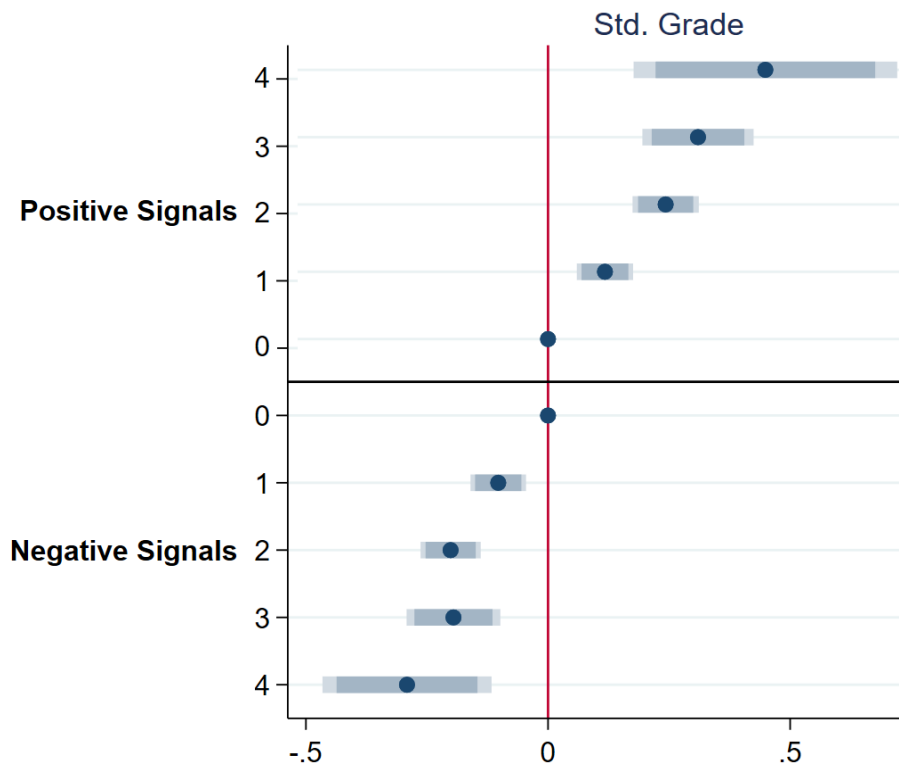
NOTE—This figure illustrates the variation in ordinal ranks within and across teaching periods. Panel A displays the variation in rank in period t for a given GPA measured in $t - 1$ after controlling for section fixed effects. Panel B displays variation in rank in a given section in t compared to a student's average rank in $t-1$. The different colours mark changes in ranks by quartile. Green symbols indicate strong upward changes (top quarter of the distribution of rank changes), orange symbols indicate neutral ranks (second and third quartiles) and red symbols indicate strong downward changes (bottom quartile). Panel C shows how these upward and downward changes lead to a mechanical convergence between average ranks in the first and last periods. Students who are initially assigned a low rank more likely experience upward rank changes, and vice versa. Panel D shows that after conditioning on absolute GPA in the first and last periods, this mechanical correlation vanishes entirely.

Figure 3: Non-linear Effect of Rank on Student Performance



NOTE—This graph displays the relationship between the standardised rank within a section and the standardised grade in a given course. We condition on the same control variables and fixed effects as in Table 3.

Figure 4: Impact of Accumulated Positive and Negative Signals



NOTE—The graph displays the coefficients and confidence intervals from a regression of standardised grades on dummy variables for the number of positive and negative rank changes in the first year. Each observation is a student-section combination in the fourth teaching period. The regression includes section fixed effects and a third-order polynomial in first-term GPA. Rank changes are defined the same way as in Table 5. The number of signals refers to the number of positive or negative rank changes a student has experienced in teaching terms 3 and 4. Horizontal bars indicate 95% and 99% confidence intervals, respectively, based on standard errors clustered at the student and course level.

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	16.190	32.980
<hr/>					
Panel B: Student Performance					
GPA (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	9,228	6.625	1.767	1	10
<hr/>					
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
<hr/>					
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
Section size	23,526	12.590	1.460	9	16

NOTE— Descriptive statistics of estimation sample. “Sd” refers to the standard deviation of the respective variable. Earnings are in EUR 1,000. 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) Rank	(2) Rank
Female	-0.0075 (0.031)	0.0237 (0.040)
Dutch	0.0047 (0.024)	0.0287 (0.025)
German	0.0211 (0.027)	-0.0576 (0.041)
Exchange student	0.0011 (0.001)	0.0009 (0.002)
Age	0.1532 (0.094)	0.1295 (0.131)
Parallel course FE	YES	YES
Section FE	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 student and course levels, are displayed in parentheses. N = 23,694. *** p<0.01, ** p<0.05, * p<0.1

Table 3: The Impact of Rank on Performance

	(1)	(2)	(3)	(4)
	Course dropout	Passed course	Std. grade	Std. follow-up grade
Std Rank	-0.0227*** (0.003)	0.0321*** (0.004)	0.0666*** (0.007)	0.0403*** (0.010)
Observations	23,694	23,694	21,976	9,470
R-squared	0.222	0.435	0.602	0.477
Mean dependent variable	0.072	0.704	-0.002	-0.005
Section FE	YES	YES	YES	YES
Parallel course 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 standardised section rank. All regressions control for gender, age, nationality, and a third-order polynomial in GPA. Robust standard errors, clustered at the student and course levels, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Early vs. Later Ranks

	(1)	(2)	(3)	(4)
	Course dropout	Passed course	Std grade	Std follow-up grade
Std Rank * First Period	0.0086** (0.004)	-0.0023 (0.006)	-0.0331** (0.015)	-0.0507*** (0.016)
Std Rank	-0.0247*** (0.003)	0.0326*** (0.004)	0.0748*** (0.009)	0.0485*** (0.011)
Observations	23,694	23,694	21,976	9,470
R-squared	0.223	0.435	0.604	0.479
Mean dependent variable	.0723	.7038	-.0017	-.0045
Parallel course FE	YES	YES	YES	YES
Section FE	YES	YES	YES	YES

NOTE— This table displays regressions at the student-section level of the outcomes listed above on the standardized rank and its interaction with an indicator for the first period in which students observe their GPA, that is, the second term. All regressions control for gender, age, nationality, a third-order polynomial in GPA, as well as the fixed effects listed at the bottom. Robust standard errors, clustered at the student and course levels, are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Rank Changes

	(1)	(2)	(3)	(4)
	Course dropout	Passed course	Std. grade	Std. follow-up grade
Rank Up	-0.0011 (0.006)	0.0126 (0.008)	0.0559*** (0.019)	0.0653** (0.025)
Rank Down	0.0081 (0.007)	-0.0151 (0.011)	-0.0320 (0.022)	0.0347 (0.030)
Observations	13,839	13,839	12,762	6,743
R-squared	0.257	0.455	0.602	0.476
Mean dependent variable	0.078	0.710	0.055	-0.025
Parallel course FE	YES	YES	YES	YES
Section FE	YES	YES	YES	YES

NOTE— All models include third-order polynomials of current and past GPA, controls for gender, age, and nationality, and the fixed effects listed at the bottom. *Rank Up* is an indicator that equals one if a student’s change in rank relative to the previous term is in the top quartile of all rank changes. *Rank Down* is an indicator for the bottom quartile of all rank changes. The reference category includes rank changes in the second and third quartiles. Robust standard errors, clustered at the student and course levels, are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: The Impact of Rank on Specialisation Choice and on Longer-Run Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Taking follow-up course	Number of follow-up courses	Graduating in related subject major	Taking math electives	Graduation	Study satisfaction	Log earnings
Std. Rank	0.0123*** (0.003)	0.0190*** (0.007)	0.0223*** (0.005)	0.0311*** (0.005)	0.0512*** (0.006)	0.0042 (0.024)	-0.0124 (0.025)
Observations	23,790	23,790	23,790	23,790	13,729	8,205	6,251
R-squared	0.339	0.347	0.442	0.396	0.387	0.212	0.319
Mean dependent variable	0.242	0.365	0.488	0.474	0.695	8.074	10.235
Parallel course FE	YES	YES	YES	YES	YES	YES	YES
Section FE	YES	YES	YES	YES	YES	YES	YES

NOTE—Each cell reports the point estimate from a separate OLS regression of the outcome listed at the top on the standardised section rank. The outcome varies at the student-level whereas most regressors vary at the student-section level. All regressions control for gender, age, nationality, a third-order polynomial in GPA, and the fixed effects listed at the bottom. The number of observations in column (5) is lower than in the previous columns as we limit the estimation sample to students who could have graduated over the time span that we observe them. The number of observations in columns (6) and (7) is lower than in the previous column due to non-response to the graduate survey. Robust standard errors, clustered at the student and course levels, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Gender Differences in the Impact of Rank

	(1)	(2)	(3)	(4)
Panel A: Performance	Course dropout	Passed course	Std. grade	Std. follow-up grade
Female * Std. Rank	0.0078*** (0.002)	-0.0005 (0.002)	-0.0063 (0.005)	-0.0133 (0.008)
Std. Rank	-0.0253*** (0.003)	0.0323*** (0.004)	0.0693*** (0.007)	0.0440*** (0.010)
Observations	23,790	23,790	22,068	9,519
R-squared	0.222	0.435	0.602	0.476
Mean dependent variable	0.072	0.704	-0.002	-0.003
Parallel course FE	YES	YES	YES	YES
Section FE	YES	YES	YES	YES
Panel B: Specialisation Choices	Taking follow-up course	Number of follow-up courses	Taking math electives	Graduating in related subject major
Female * Std. Rank	-0.0061*** (0.002)	-0.0135*** (0.003)	-0.0138*** (0.004)	-0.0070 (0.004)
Std. Rank	0.0144*** (0.004)	0.0236*** (0.007)	0.0359*** (0.005)	0.0247*** (0.005)
Observations	23,790	23,790	23,790	23,790
R-squared	0.339	0.347	0.397	0.442
Mean dependent variable	0.242	0.365	0.474	0.488
Parallel course FE	YES	YES	YES	YES
Section 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 standardised section rank. All regressions control for gender, age, nationality, and a third-order polynomial in GPA. Robust standard errors, clustered at the student and course levels, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Mechanisms – Evidence from Student Course Evaluations

	(1)	(2)	(3)
	Peer interaction index	Study hours	Teacher evaluation index
Std. Rank	-0.0192* (0.011)	0.0369 (0.108)	0.0066 (0.011)
Observations	7,423	6,902	7,245
R-squared	0.376	0.286	0.606
Mean dependent variable	-0.041	11.925	-0.055
Parallel course FE	YES	YES	YES
Section FE	YES	YES	YES

NOTE— Dependent variables in columns (1) and (3) are indices based on the first principal components of several underlying variables described in the paper. The indices are standardised to mean zero and a standard deviation of one. The dependent variable in column (2) is students’ self-reported study hours. All regressions control for gender, age, nationality, and a third-order polynomial in GPA. Robust standard errors, clustered at the student and course levels, are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Effect of Rank on Expectations and Performance

	(1)	(2)
	Std. grade	Std. expected grade
Std. Rank	0.0474** (0.017)	0.0269** (0.011)
Observations	2,304	1,993
R-squared	0.278	0.281
Parallel course FE	YES	YES
Section FE	YES	YES

NOTE— The regressions are based on the first-term performance and grade expectations of three incoming cohorts. All regressions include controls for gender, age, nationality, a third-order polynomial in the statistics entry test, and the fixed effects listed at the bottom. Expected grades are measured with the question “What do you think your exam grade will be for the course Quantitative Methods 1?”. Robust standard errors, clustered at the student and course levels, are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

APPENDIX

A.1. Identifying Variation

Table A4 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 11. 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: Mapping of Courses into Follow-Up Courses and Majors

(1)	(2)	(3)
First Year Course	Follow-Up Courses	Related Major Subject
Accounting	Finance and Accounting, Management Accounting, Auditing, Internal Control and AIS, International Financial Accounting	Accounting
Economics and Business	Behavioural 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 Management, 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 Behaviour, Services Marketing, Comparative ss Strategy, Management, Organizational Behaviour, 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 and Environmental Entrepreneurship, Managerial Economics, Marketing and SCM, International Business	Organization / Marketing
Microeconomics	Understanding Society, Industrial Organization, Behavioural Economics, Public Economics, International Competition Policy, Institutions, Behaviour and Welfare, Design of Tax Systems, Economic Psychology, Economics and Sociology, Game Theory and Economics, Information, Markets and Organizations, Institutions, Behaviour 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 A2: Test for Selective Survey Response

	(1)
	Response
Std. Rank	0.0036 (0.004)
Female	0.0683*** (0.012)
GPA	0.0320** (0.015)
Age	0.0048 (0.004)
Dutch	-0.0904*** (0.017)
German	-0.0289* (0.015)
Observations	23,501
R-squared	0.193
Parallel Course FE	YES
Section FE	YES

NOTE— All regressions additionally control for a third-order polynomial in GPA and the fixed effects listed at the bottom. Robust standard errors, clustered at the student and course levels, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Inference Under Alternative Adjustments for Clustering

	(1)	(2)	(3)	(4)
	Course dropout	Passed course	Std. grade	Std. follow-up grade
Std. Rank	-0.0227***	0.0321***	0.0666***	0.0403***
SE Clustering at the Student and Course Level	(0.003)	(0.004)	(0.007)	(0.010)
Standard Errors: Alternative Clustering Options				
SE Clustering at the Section Level	(0.002)	(0.003)	(0.005)	(0.009)
SE Clustering at the Course Level	(0.003)	(0.004)	(0.006)	(0.009)
SE Clustering at the Student Level	(0.002)	(0.003)	(0.005)	(0.010)
Robust SE - No Clustering	(0.002)	(0.003)	(0.005)	(0.009)

NOTE— All regressions control for a third-order polynomial in GPA and the same fixed effects as in Table 3. Standard errors based on different adjustments for clustering are reported in parentheses. The significance stars are based on standard errors clustered at the student and course levels. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Variation in Rank Conditional on GPA 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 Conditional on GPA	0.1392	0.1212	0.0901

NOTE— Column (2) includes fixed effects on the level of the course, that is, the level of randomization. Column (3) additionally includes fixed effects for sections as well as the respective characteristic that defines the peer group in which we calculate the rank. When conditioning on ability, we include a third-order polynomial of GPA. Robust standard errors, clustered at the student and course levels, are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Main Results – Robustness to Alternative Functional Forms

Functional Forms for Ability:	(1) First- order polynomials of GPA	(2) Second- order polynomials of GPA	(3) Third- order polynomials of GPA	(4) Fourth- order polynomials of GPA	(5) GPA deciles
Dependent Variable:					
Course Dropout	-0.0156*** (0.003)	-0.0197*** (0.003)	-0.0227*** (0.003)	-0.0227*** (0.003)	-0.0099*** (0.003)
Passed Course	0.0271*** (0.004)	0.0331*** (0.004)	0.0321*** (0.004)	0.0323*** (0.004)	0.0219*** (0.004)
Std. Grade	0.0652*** (0.007)	0.0629*** (0.007)	0.0666*** (0.007)	0.0664*** (0.007)	0.0734*** (0.009)
Std. Follow-Up Grade	0.0467*** (0.010)	0.0451*** (0.010)	0.0403*** (0.010)	0.0405*** (0.010)	0.0616*** (0.013)

NOTE— Each coefficient is the result of a separate regression at the student-section level of the outcomes listed on the left on the standardised rank. In columns (1)–(4) we control parametrically for GPA with the polynomials listed above. In column (5) we control flexibly for GPA using decile dummies. All regressions include controls for gender, age, and nationality as well as course-year, parallel course, and section fixed effects. Robust standard errors, clustered at the student and course levels, are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Main Results Robustness Check Using a Percentalised Ability Measure

	(1)	(2)	(3)	(4)	(5)
Functional Forms for Ability:	First- order polynomials of GPA	Second-order polynomials of GPA	Third- order polynomials of GPA	Fourth- order polynomials of GPA	GPA Deciles
Dependent Variable:					
Course Dropout	-0.0064** (0.003)	-0.0082*** (0.002)	-0.0027 (0.002)	-0.0034 (0.002)	-0.0077*** (0.002)
Passed Course	0.0094** (0.004)	0.0116*** (0.003)	0.0085** (0.003)	0.0089** (0.003)	0.0160*** (0.003)
Std. Grade	0.0448*** (0.008)	0.0429*** (0.008)	0.0271*** (0.008)	0.0269*** (0.008)	0.0539*** (0.007)
Std. Follow-Up Grade	0.0319*** (0.011)	0.0301*** (0.011)	0.0263** (0.011)	0.0246** (0.010)	0.0451*** (0.010)

NOTE— Each coefficient is the result of a separate regression at the student-section level of the outcomes listed on the left on the standardised and percentalised rank. The rank is based on a student’s percentalised GPA. In columns (1)–(4) we control parametrically for percentalised GPA with the polynomials listed above. In column (5) we control flexibly for percentalised GPA using decile dummies. All regressions include controls for gender, age, and nationality as well as course-year, parallel course, and section fixed effects. Robust standard errors, clustered at the student and course level, are displayed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A7: Overall Rank and Same Gender Rank

	(1)	(2)	(3)	(4)
	Course dropout	Passed course	Std. grade	Std. follow-up grade
Std. Rank	-0.0231*** (0.003)	0.0294*** (0.004)	0.0651*** (0.007)	0.0385*** (0.012)
Std. Same Gender Rank	0.0005 (0.002)	0.0040 (0.003)	0.0022 (0.006)	0.0027 (0.009)
Observations	23,694	23,694	21,976	9,470
R-squared	0.222	0.435	0.602	0.477
Mean Dependent Variable	0.072	0.704	-0.002	-0.005
Parallel Course FE	YES	YES	YES	YES
Section FE	YES	YES	YES	YES

NOTE— All regressions include controls for gender, age, nationality, a third-order polynomial in GPA as well as the fixed effects listed at the bottom. Robust standard errors, clustered at the student and course levels, are displayed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A8: List of Course Evaluation Questions

Question	Index
How many hours per week on 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 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

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