Class rank, job preferences and career prospects

Águeda Solís Alonso*

This version: April 2026
Click here for the latest version

Abstract

Using university administrative data matched with census student surveys, this paper studies the effects of class rank on job preferences, labor market prospects, and early career outcomes. I find that being top of the class increases academic orientation, pushing graduates to pursue further education and to postpone labor market entry. Quantitatively, a one-decile increase in class rank (roughly 2–4 positions) reduces labor market participation by 1.4 percentage points one year after graduation, raises PhD enrollment by 0.6 percentage points, and lowers reservation wages by 0.8%. Higher-ranked students are willing to accept worse pecuniary conditions in exchange for jobs that align better with their studies, suggesting a role for intrinsic motivation. Effects are stronger for males and peer groups with higher average ability, indicating that peer competition influences rank effects. The weaker response of female graduates to relative rank signals also helps explain gender gaps in transitions into PhD studies and early-stage research careers.

Keywords: rank, peer effects, higher education, prospects
JEL codes: I21, I26, J24

---

*University of Trento, solisalonso.agueda@gmail.com.
I am indebted to the Student Services office of the University of Turin for providing access to the data. I thank Ainoa Aparicio-Fenoll, Pietro Biroli, Mariana Blanco, Marina Della Giusta, Paul Devereux, Maria Laura Di Tommaso, Luca Facchinello, Luca Favero, Patricia Funk, Giacomo Gallegati, Giovanni Mastrobuoni, Elie Murard, Daniela Piazzalunga, Matteo Ploner, Chiara Pronzato, Tommaso Sartori, Giuseppe Sorrenti, Alessio Tomelleri, Juan Vargas and audiences at seminars at the Collegio Carlo Alberto, the OECD Centre for Local Development, and the Applied Microeconomics Workshop in Bolzano for useful comments and discussions.

1 Introduction

"There is no quality in this world that is not what it is merely by contrast. Nothing exists in itself."
— Herman Melville

Information on quality or performance is usually presented to us in the form of rankings. Whether it is about sports teams classifications, financial performance of firms, song charts, university rankings or peer-reviewed journals, comparisons and ranks emerge naturally and inevitably among groups, and are key to our understanding of ability and success. Rankings are particularly salient in educational contexts, where individuals interact frequently for extended periods of time, and constantly receive signals about their own performance and that of their peers through tests, evaluations, and grades. Moreover, students often face choices regarding educational investments and career choices under uncertainty about their payoffs, increasing the scope to rely on these signals to form beliefs about their ability.

This paper provides new causal evidence on how a student's rank among their Master's peers influences their career prospects and choices. I focus on Master's programs, where peers constitute a natural and well-defined reference group: class sizes are typically small, which limits endogenous sorting into smaller groups, and study plans are largely standardized, so that students follow most classes together.

I construct a measure of relative ability based on prior academic performance and exploit quasi-random variation in the distribution of ability across classes. Causal identification relies on the comparison of individuals with the same predetermined ability, in classes with the same average ability, who end up in different relative positions because of differences in the ability distribution of their respective peers. Identification rests on the assumption that these effects are homogeneous across classes, as is common in the previous literature (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020; Elsner, Isphording and Zölitz, 2021).

I combine administrative records with pre-graduation and post-graduation surveys for ten cohorts of Master's graduates from a large Italian university. A distinctive feature of the data is the availability of mandatory pre-graduation surveys, which capture students' career prospects, job search intentions, reserve wages, and job preferences. This allows me to examine outcomes that are typically unobserved in administrative sources. The paper yields three main findings.

First, higher class rank substantially increases academic orientation, pushing graduates to pursue further education and to postpone entry into the labor market. Students who rank higher have better grades, are more likely to graduate with distinction, express interest in doctoral studies, and delay entry into the labor market. Moving up by one decile within the class distribution, which corresponds roughly to surpassing two peers in the average class, reduces the probability of employment one year after graduation by 1.4 percentage points, while increasing PhD enrollment by 0.6 percentage points. These effects are robust to allowing for class heterogeneity, sorting, measurement error correction, and alternative ability measures.

Second, the response to relative rank is strongly heterogeneous by gender. The probability of pursuing a PhD rises by 1 percentage point per rank decile among male graduates, compared to 0.4 among females. Despite being overrepresented in tertiary education, females are consistently less likely to enroll in doctoral studies. I find that this gender gap is not explained by differences in ability or field of study, suggesting that men's and women's educational aspirations respond differently to relative position within the peer group.

Third, rank affects career preferences and job valuation. Higher-ranked students are more willing to accept more precarious types of contracts, such as internships, apprenticeships, or freelancing, and lower wages, in exchange for jobs more aligned with their studies. This pattern is consistent with intrinsic motivation as a key channel through which rank shapes career choices. In contrast, I find little evidence for alternative mechanisms proposed in prior work, such as external responses from families or educational institutions, or updated expectations about returns (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020; Elsner, Isphording and Zölitz, 2021; Pagani, Comi and Origo, 2021).

This study relates to the literature on the effects of academic rank, a specific type of peer effect that is a function of both individuals' own level of ability and that of their peers. Rank effects were first studied and identified by Cicala, Fryer and Spenkuch (2018) and Murphy and Weinhardt (2020), who established the fact that, independent of the effect of absolute ability, relative ability during school has an impact on future outcomes. This pattern has also been discussed in other disciplines under the name of "big fish-little pond effect" (Marsh and Parker, 1984), arguing that students form beliefs about ability based on a comparison group, and that this self-concept affects educational and labor outcomes through motivation and effort. Since the establishment of this branch of the literature, rank effects have been identified in a variety of contexts and outcomes.[1] Closer to the current study is the

[1]In particular, rank effects have been shown to impact academic performance and learn-

subset of works that examine rank effects in higher education, which have mostly focused on short-term outcomes related to academic performance and attainment. Relative position among peers has been documented to have positive effects on credit attainment (Bertoni and Nisticò, 2023), academic performance and degree attainment (Payne and Smith, 2020), and time to graduation and occupational prestige (Ribas, Sampaio and Trevisan, 2020), as well as having significant effects on subject and major choice (Elsner, Isphording and Zölitz, 2021).

This paper makes two major contributions. First, it expands the literature on rank effects by identifying impacts on job preferences, previously unexplored due to data limitations in administrative sources, and on doctoral enrollment. By linking survey and administrative data, I demonstrate that rank not only predicts academic performance but also fundamentally shapes career aspirations and the decision to pursue research-oriented trajectories. My results complement the finding that higher relative ability in education stages as early as elementary school can impact long-term earnings (Denning, Murphy and Weinhardt, 2023; Del Bono, Holford and Sartori, 2025), suggesting that rank-induced accumulation of human capital and delayed labor market entry may help explain effects on earnings later in life.

More broadly, this study deepens our understanding on belief formation and gender differences in self-assessment by focusing on the largely unexplored decision to pursue a PhD[2]. This paper is the first to study how relative ability in a peer group shapes the decision to enter the doctoral track, which constitutes the gateway to academic and research careers. My findings reveal that beliefs shaped by relative ability substantially influence the decision to apply for a PhD, and that these beliefs operate more strongly for men than for women. In doing so, this paper highlights a previously

ing (Megalokonomou and Zhang, 2024; Carneiro et al., 2025), selection into school tracks and college majors (Goulas, Griselda and Megalokonomou, 2024; Delaney and Devereux, 2021), and even affect outcomes beyond education such as behavioral traits (Pagani, Comi and Origo, 2021; Del Bono, Holford and Sartori, 2025) or risky behaviours (Elsner and Isphording, 2018; Comi et al., 2021). See Delaney and Devereux (2022) for a review of the literature.

[2]Prior work, mostly focused on the transition to graduate studies, shows that students' expected returns, correlated with beliefs on their own ability, affect decisions to obtain further schooling (Boneva, Golin and Rauh, 2022) and that providing accurate information on performance can influence both university (Goulas and Megalokonomou, 2021) and major choices (Li and Xia, 2024). Previous studies have also documented that women tend to exhibit lower confidence in their performance (Chevalier et al., 2009; Exley and Nielsen, 2024) and in both absolute and relative ability (Bordalo et al., 2019), and have examined gender attrition in specific fields (Owen, 2023) and later academic stages (Bagues, Sylos-Labini and Zinovyeva, 2017).

undocumented mechanism in the formation of academic career aspirations, and contributes with new evidence on gendered belief dynamics at the point of entry into academia.

The remainder of this paper is structured as follows: Section 2 introduces the setting, Section 3 presents the data and the identification strategy, Section 4 discusses the results, Section 5 explores potential mechanisms, Section 6 addresses some sensitivity checks, and finally Section 7 concludes.

2 Setting

This paper evaluates the effect of academic rank on educational investments, labor supply and job preferences in the context of a public university in North Western Italy, the University of Turin. Primarily located in the fourth most populous city of Italy, this is a relatively large university with around 80,000 enrolled students, which offers degrees in all disciplines except for engineering.

Like most public universities in Italy, the university under analysis is a non-selective institution, with generally non-competitive admission requirements and relatively low tuition fees[3], which results in a high heterogeneity in terms of the socio-economic background of the students, and a composition of students which is very similar to the national average. Despite some mobility, especially from the South of the country to the central area or the North, geographical position largely determines the choice of university. As such, around 70% of students are legal residents of the region before starting their university degrees. Moreover, the university accrues 60% of the university students in the region, thus having a central role in the local labor market.

Tertiary education in Italy is mostly organized in 3-year Bachelor's degrees and 2-years Master's degrees, or single-cycle degrees, usually lasting for 5 years and equivalent to a Master's (common for subjects such as law, medicine, or pharmacy). Possibly because of the low economic and academic entry barriers, around two-thirds of Bachelor's graduates complete further education (OECD, 2020), a figure in line with, yet slightly higher than, other OECD countries. For this reason, Master's Degrees are the relevant qualification to study the transition into the labor market in this context.

[3]According to the Italian Ministry of University and Research, around one-third of students is exempt from paying tuition, with fees being proportional to family wealth. For those who do pay them, the average tuition fee was 1281 euro in the academic year 2022/2023, representing 3% of the average household earnings.

Like in most European countries, students enroll in a specific field of study and follow a standard study plan. As per law mandate, at least 50% of the degree credits are common within each program (Ministero dell'Istruzione, dell'Università e della Ricerca, 2004). All students registered for a given course share a class, such that the relevant peer group in this context comprises the cohort of students undertaking the same Master's program.

Programs are typically small, with a median size of 18 students, and an average of 38. Small class sizes limit the scope for endogenous sorting into smaller peer networks, and mitigate concerns of bias that can result from errors in the measurement of the relevant peer group (Carrell, Fullerton and West, 2009). A related concern is that students may select into a Master's program partly based on prior acquaintances from their Bachelor's degree, which could introduce pre-existing social ties that confound peer effects. This concern is unlikely to be severe in this setting: among students for whom information about Bachelor's degree, institution, and graduation year is available,[4] approximately half share at least one Master's classmate who attended the same Bachelor's program. However, the share of peers with overlapping Bachelor's background remains low, averaging 6% across the full sample and 12% when restricting to those with at least one such overlap, suggesting that pre-existing ties constitute only a minor component of the peer group.

3 Empirical strategy

3.1 Data

The source of data for the analysis is a combination of administrative and survey data on Master's graduates compiled by the AlmaLaurea university consortium.

Every year, the consortium conducts graduates' profile surveys among the newly graduated regarding their experience during the studies and their career plans, and surveys former graduates one, three, and five years after graduation about their entry into the labor market and their employment conditions. This data is then combined with administrative records regarding their academic performance and demographic data (gender, age, province of residence, parental occupation and educational attainment, and

[4] This information was integrated into the Master's Graduate Profile data starting from 2013.

secondary education results).

I follow ten cohorts of graduates from all the Master's degrees offered by the institution between 2008 and 2018, which amounts to 49,179 individuals across 243 different degree programs. The graduates' profile survey is a mandatory step in the graduation request procedure, ensuring a census coverage, and although there is no formal requirement to fulfill them after receiving the degree, response rates remain significantly high one year after graduation, with 82.23% of the surveyed responding.

The main outcomes used in this paper are variables measured both at graduation and one year afterward. At graduation, I analyze variables related to academic performance during the Master's degree, such as GPA, and graduation with Honors (*Cum Laude*), as well as academic orientation, defined as their expressed interest in pursuing doctoral studies. I also study career prospects, measured by a set of Likert scale variables measuring their preferences for different job characteristics and their willingness to accept a specific type of employment contract. Moreover, I study earnings prospects, measured by the survey item "what is the minimum monthly wage that you would be willing to accept for full-time employment?", which was introduced in the survey in 2015. I also investigate how these prospects and further education intentions map into real outcomes, by looking into self-reported enrollment into a PhD and average monthly earnings one year after graduating.

Table 1 reports summary statistics for the sample.

Table 1: Descriptive Statistics

	(1) All		(2) Above class median		(3) Below class median		(4) Difference in means	
Variable	N	Mean	N	Mean	N	Mean	Difference	P-value
Gender: Female	49,179	0.63	22,523	0.69	26,656	0.58	0.116	0.000
First-generation university graduate	46,437	0.65	21,450	0.67	24,987	0.64	0.035	0.000
Academic highschool	49,167	0.81	22,520	0.80	26,647	0.81	-0.001	0.692
Academic highschool - humanities	49,167	0.19	22,520	0.19	26,647	0.20	-0.008	0.019
Academic highschool - sciences	49,167	0.46	22,520	0.42	26,647	0.50	-0.082	0.000
Highschool diploma grade	47,776	83.35	22,523	92.86	25,253	74.88	17.978	0.000
Social class: burgeoise	34,771	0.26	16,034	0.24	18,737	0.28	-0.040	0.000
Social class: middle class	34,771	0.33	16,034	0.33	18,737	0.32	0.013	0.009
Social class: lower burgeoise	34,771	0.21	16,034	0.21	18,737	0.20	0.015	0.001
Social class: working class	34,771	0.19	16,034	0.20	18,737	0.18	0.021	0.000
Resident in the region	49,179	0.78	22,523	0.78	26,656	0.78	-0.006	0.104
Resident in a different region	49,179	0.21	22,523	0.22	26,656	0.20	0.024	0.000
Age at graduation	49,179	26.71	22,523	26.24	26,656	27.10	-0.863	0.000
Duration of studies (in years)	49,179	3.62	22,523	3.52	26,656	3.70	-0.176	0.000
GPA (1-30 scale)	49,107	27.34	22,500	27.82	26,607	26.94	0.880	0.000
Graduated with Cum Laude	49,179	0.33	22,523	0.45	26,656	0.23	0.223	0.000
Reserve wage	17,560	1288.80	8,132	1264.45	9,428	1309.80	-45.346	0.000
Wants to pursue further education	46,236	0.43	21,382	0.44	24,854	0.42	0.021	0.000
Wants to do a PhD	46,437	0.10	21,450	0.11	24,987	0.10	0.016	0.000
Is doing a PhD	40,343	0.05	18,806	0.06	21,537	0.04	0.017	0.000
Working	40,419	0.56	18,837	0.56	21,582	0.57	-0.017	0.001
Average monthly earnings(t+1)	22,059	1130.62	10,158	1119.64	11,901	1139.99	-20.345	0.006
Gap between reservation and actual wage	7,325	-94.20	3,391	-81.72	3,934	-104.96	23.239	0.094
Job search (in months)	15,138	2.82	6,928	2.79	8,210	2.85	-0.065	0.206

Note: Table includes the number of observations and mean for key individual characteristics, including Highschool diploma grade, the measure of ability used throughout this paper, and main outcome variables. Columns (2) and (3) report the same statistics broken down by whether the individual is above/below his classmates' median ability, while column (4) presents the difference in means between the previous columns and the p-value associated with a two-sided mean comparison test.

3.2 Measuring ability

An ideal measure of human capital should be salient enough so that individuals have some understanding of where they stand in relation to their peer group. At the same time, to allow for comparison and ranking across individuals, it should be standardized and not easily manipulated or confounded by unobservable characteristics. In practice, the generally available measures of ability introduce a trade-off between salience and standardization: grades are highly salient, but may not be comparable across schools or instructors, while standardized tests, if available, may not be salient to students, particularly if they are low-stakes. With these considerations, I leverage the high-school diploma grade, also known as *maturità* (maturity diploma) or *Esame di Stato* (State Exam), as my preferred measure of ability.

At the end of secondary education, three months before University enrollment, students take a national standardized exam that grants access to tertiary education. The exam consists of three written tests and an oral examination. One of the written tests, common to all students, is on Italian language, while the second one is specific to the high school track followed (for instance, Greek or Latin for the humanities track, math or physics for the scientific track), and the last one is specific to the singular high-school, as it depends on the expertise of the teachers who have been selected to be part of the examining commission. The first and second exams are written centrally at the Ministry of Education and are the same for all students who have followed the same high school track.

In Italy, following a non-academic high school track does not preclude enrollment in tertiary education. Nevertheless, the representation of technical and professional (non-academic) tracks is minor: 83% of the students come from academic tracks, while around 15% come from technical, and less than 2% from professional tracks. Among academic tracks, the scientific one is the most common (47%), followed by the humanities track (20%). Given this high concentration of academic tracks, and the fact that there are marked differences in academic performance across tracks, the fact that university students may come from different types of high-school and thus their exams might have been different is likely to play a minor role in the calculation of the rank variable[5].

Grading of the tests is done by a committee, specific to each class, com-

[5] Both class rank and class-by-high-school-type ranks are highly correlated (0.70), even more so for academic high-school graduates, which represent the majority of university students. Further proof of this can be found in Table A.2 in Annex A.4, where I test the robustness of my results to using a high-school-type specific measure of rank.

posed of an equal number of teachers from the high school and external ones (typically three from each side during the period under study; however, due to reforms over the years, this number is reduced to two in some cohorts). Internal commissioners are chosen by the high school, while external commissioners are allocated by the Ministry of Education based on their availability and their geographical proximity. The Ministry of Education also appoints the headmaster of a different high school to act as president of the committee and ensure the evaluation criteria are applied objectively and fairly across students.

The final grade is obtained by adding the scores in the three written tests (up to 15 points each, 45 in total), the score of the oral examination (up to 30 points), and up to 25 points which are determined from the grades of the last three years of education. The final grade is expressed in a 100-points scale, with a minimum passing grade of 60, and it is typically published on each high school's scoreboard. Hence, students know both how they scored, and how they scored relative to peers from the same high school. This public disclosure, together with the national media coverage of results, expands the reference group to which students compare themselves, possibly generating a shock to their relative ability beliefs.

Passing the exam is a prerequisite not only for accessing higher education but also for the vast majority of jobs. While the grade is not used in the admission process in universities, which implement their own entry tests in degrees with limited amount of seats, economic benefits such as scholarships, university fee reductions and vouchers for the purchase of cultural goods and services are determined on the basis of having a high mark (typically never lower than 90/100). When it comes to employment opportunities, until 2015 there were also minimum grade requirements for accessing public employment, ranging from 70 to 80. Since then, although no longer a requirement, extra points are awarded to candidates in a wide array of public calls for vacancies in the public sector, the police and armed forces, and in private companies with public ownership. Given the high-stakes nature of the exam, it has considerable social and psychological salience, making it suitable as a measure to capture perceived relative ability[6].

Since grading depends on the committees, and a part of the score is

[6] While information on perceived rank is not available, and hence it is not possible to empirically test the relation between rank based on this metric and perceived rank, a number of papers find a strong and positive correlation between perceived and actual rank (Pagani, Comi and Origo, 2021; Elsner and Isphording, 2017; Yu, 2020), suggesting that students are able to form an accurate idea of their rank through interaction with their peers, even when they are not provided with explicit information.

based on high school grades, it is not a fully standardized score, raising concerns about its validity to make comparisons across individuals. Random measurement error would introduce attenuation biases in the estimation, giving as a result lower bound estimates. When it comes to nonrandom error, given that high school grades are established by different teachers across three years, and that the grading committees include members external to the high-school, concerns should be limited. Although there is a widespread perception that grading standards are more lenient in the South of the country, I do not find evidence of systematic differences within my sample between local students and students who come from a different region, who represent around one-fifth of the sample.

Proof of the validity of the diploma grade as a measure of ability is its high correlation with academic performance during the master (0.72), which is also highly significant (S.E. of 0.008). Nevertheless, in Section 6, I explore the sensitivity of my results to systemic measurement error, and to leveraging two alternative measures of ability: academic performance at the current (Master's) and previous (Bachelor's) degree, potentially more salient at labor market entry than high-school diploma, albeit less standardized[7].

3.3 Identifying rank effects

This paper aims at identifying the effects of class rank on prospects and short-term labor market outcomes by exploiting variation in peer composition.

I use the high-school diploma grade to compute student's relative ability among their university peers. This measure is generally taken three years before Master's students start interacting with each other. While I have no information on high-school attended, it is likely that the Master's peer group differs substantially from the high-school peer group, reducing concerns about reflection and interference from class-level shocks.

In order to compute a rank measure that is comparable across classes with different sizes, I compute the percentile rank measure:

[7]Nation-wide mandatory standardized testing of mathematical and language competences during primary and secondary education was introduced in academic year 2008-2009, and hence only existing for cohorts that graduate university after 2017. Moreover, individual results of these tests are not disclosed to students, reducing their salience and their relevance as measures of ability. Finally, since these are low-stakes tests with no consequences for the test-taker, it may be rational to exert less effort than in a regular graded school examination, making it unclear that they are intrinsically superior measures of academic ability.

$$Rank_{dch} = \frac{n_{dch} - 1}{N_{dc} - 1}$$

Where n_{dch} stands for the position of individuals with ability level h from degree d in cohort c (or class dc, since, commonly, all students taking a course are together in the same class). Ties are not corrected for, meaning that n_{dc} reflects the number of people in the same class who have a strictly higher ability level plus one, and those with the same level share a rank. N_{dc} stands for class size. The resulting number ranges from zero to one, with zero representing the highest ranked student (the one with the highest ability), and one the lowest ranked student. To improve the interpretability of the model results, I multiply $Rank_{dch}$ by minus ten. The associated coefficient can then be interpreted as the effect of going up by one decile in the peer ability distribution.

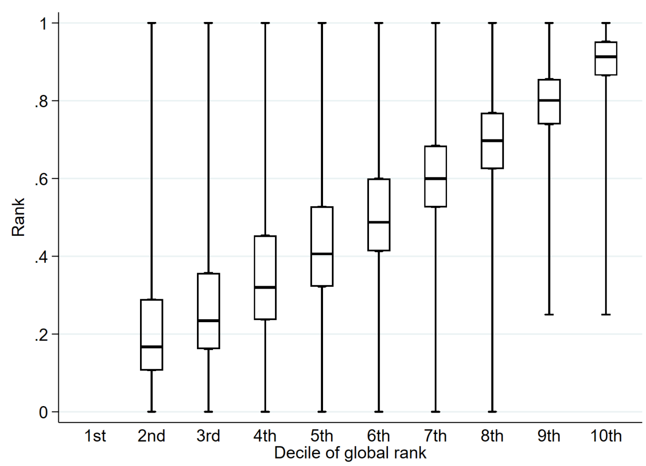
The identification strategy relies on comparing students with the same underlying ability who end up in different rank positions because of quasi-random variation in their peer groups. The first requisite then is that there is sufficient variation in rank conditional on ability. Figure 1 plots the relation between class and global (considering the full sample) ranks. As expected, there is a positive relationship between both, with students that rank high among their peers being more likely to rank high in the overall ability distribution. Nevertheless, conditional on ability, there is substantial variation in relative rank, with students on the 2nd to 8th decile of the global distribution ranking in all positions of their class distribution. In particular, the standard deviation of rank controlling for measured ability is of 1.33, which for the average class of size 38 translates into a variation of around 5 positions in the class ranking, and for the median class with 18 students, into a variation of 2 positions approximately.

Table 2: Raw and Residual Variation of Rank

	Mean	SD
Ability rank	-4.57	3.08
Residual rank, net of measured ability	0.00	1.33

Note: Table reports descriptive statistics for class rank, before and after removing the effect of measured ability.

Figure 1: Local vs. global rank



Note: Figure reports the relationship between the local rank (defined at the class level) and the global ability rank (across all degrees and cohorts). The horizontal borders of the boxes indicate the 25th and 75th quintile respectively, while the line inside the box indicates the median. Brackets indicate the minimum and the maximum value of the local rank, by global rank deciles.

To properly isolate the causal effect of rank from the influence of ability and other potential confounders, such as degree and cohort factors, these elements have to be properly accounted for in the empirical estimation. The first and most obvious confounder is individual absolute ability. In order to properly isolate the effect of *relative* ability from that of *absolute* ability, I flexibly control for my measure of ability through a third-order polynomial to account for its high correlation with class rank, as is common in the literature (Delaney and Devereux, 2022; Elsner and Isphording, 2017).

Additionally, identification requires addressing two additional challenges: distinguishing rank effects from other peer effects, and accounting for potential sorting of individuals into certain degrees or cohorts.

Because ranking high among peers and having low-skilled classmates can be seen as two sides of the same coin (Bertoni and Nisticò, 2023), assumptions need to be imposed on peer effects in order to identify class rank effects. Denoting the relationship between outcomes and rank as

$$Y_{dch(i)} = \alpha + \beta R_{dch(i)} + v_{dch(i)} \tag{1}$$

where $R_{dch(i)}$ stands for our rank measure and $v_{dch(i)}$ for the error term, which depend on the degree (d), cohort (c) and ability level ($h(i)$) of the individual i. The error term includes any possible peer effects, or other class-level effects related to instructors or different factors. Identification requires restrictions on $v_{dch(i)}$, and hence on the sort of peer and class effects that are assumed in the model.

In this paper, I assume the error term can be summarized by an additive class (dc) effect and an additive ability effect, so that $E(v_{dch(i)}|d, c, h) = \gamma_{h(i)} + \theta_{dc}$. This assumption allows for cohort-varying effects within a particular degree and for peer effects different than rank effects, but implies that peer effects are assumed to be homogeneous across different types of classes.

It is important to note that including class (degree-by-cohort) fixed effects is not equivalent to exploiting within-class variation for identification. Two students with identical ability levels can hold different ranks depending on the ability distribution of their peers. Conditional on own ability, rank therefore varies across classes. Class fixed effects absorb differences in mean ability across peer groups, but leave intact this cross-group variation in rank conditional on ability, which is the source of identification for the causal rank effect.

Identification of β in Equation 1 comes from variation in higher moments of the ability distribution. I compare students with the same level of ability who have different rank positions because they are in peer groups with the same average level of ability (absorbed by the degree-by-cohort fixed effect), but with differences in variance, skewness, etc.. For an illustrative example, see Figure A.1 in Appendix A.1.

The identifying assumption would be violated if peer effects are heterogeneous across class characteristics such as average ability or ability variance. Imposing a weaker assumption, while allowing for these heterogeneities, reduces the identifying variation and obscures its interpretation[8]. For this reason, estimations following different versions of this assumption have been relegated to a series of sensitivity checks in Section 6.

Additionally, causal identification requires quasi-random assignment of individuals to peer groups. Violations of this assumption have been classified by the previous literature (see Denning, Murphy and Weinhardt (2023)) into active and passive sorting. Active sorting happens if individuals choose their classes on the basis of rank, perhaps because they have a preference for ranking high among their peers (for status reasons), while passive sorting would arise if students are sorted into degrees on the basis of characteristics such as gender or social background that, even if unrelated to their rank, could introduce spurious correlations between academic rank and outcomes.

Active sorting requires that the students have perfect information on what their rank position would be at a given Master's program, in a given starting year. In practice, this is difficult: given the across-cohort variation that exists even within programs, it would not be possible to perfectly predict what the actual rank would be even if previous cohorts' ability distribution was known (see Figure A.2 in Annex A.1). Passive sorting, on the other hand, would happen if students with certain characteristics were systematically more likely to be in classes with certain characteristics (for instance, if students coming from less privileged backgrounds consistently enrolled in degrees where average ability is lower).

In the presence of active or passive sorting, rank effects would be inconsistently estimated. In order to check for the presence of sorting, I run several regressions to assess the relationship between rank and students' observable characteristics, controlling for own ability and class fixed effects:

$$X_{idc} = \alpha + \beta R_{idc} + f(H_i) + \sigma_{dc} + e_{idc} \tag{2}$$

Results, displayed in Table 3, do not suggest evidence of sorting. Un-

[8] Under this assumption, identification comes from comparing variation in rank position across classes with similar distributions, hence restricting variation to small differences that leave overall distribution unchanged.

der the assumption that unobservable characteristics behave the same way, sorting should not be a concern in this setting.

Table 3: Randomisation check: Effect of Rank on Individual-Level Characteristics

	(1) Gender: Female	(2) Age at graduation	(3) Resident in the region	(4) Academic hs - humanities	(5) Academic hs - sciences
Rank	-0.00	-0.03	-0.00	0.00	0.00
	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)
	(6) Social class: burgeoise	(7) Social class: lower burgeoise	(8) Social class: middle class	(9) Social class: working class	(10) First-gen
Rank	-0.00	-0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: Table displays the effect of class ability rank on individual characteristics, after controlling for a third-degree polynomial of the ability measure and class fixed effects. Clustered standard errors are reported between parentheses.

Additionally, because class rank is a function of the distribution of ability in the peer group, testing for systematic correlation between individual characteristics and features of the peer ability distribution (such as the median, the variance, the skewness and the kurtosis), can be informative on the presence of sorting. Results of these analyses, collected in Appendix A.2, largely confirm the absence of evidence of sorting in this setting.

I include controls for individual characteristics in my baseline model to improve the precision of my estimates. In Section 6 I discuss the sensitivity of my estimates to the exclusion of these controls, and I implement alternative identification strategies that deal with potential sorting.

With the previous considerations, my preferred specification to estimate the causal effects of class rank on aspirations, job preferences and short-term labor market outcomes is the following:

$$Y_{dch} = \alpha + \beta R_{dch} + f(H) + \gamma' \mathbf{X} + \sigma_{dc} + e_{dch} \tag{3}$$

Where Y_{dch} represents one of the outcomes described in Subsection 3.1, $f(H)$ is a third-order polynomial of the baseline ability measure, $\mathbf{X}$ stands for a set of individual characteristics such as gender, age at graduation, parental education and region of residence, and σ_{dc} are degree-by-cohort (class) fixed effects. The main coefficient of interest is β, which should be interpreted as the average causal effect of moving up by one decile in the

Table 4: Rank effects on academic performance and motivation and labour supply

Panel A: at graduation				
	(1) GPA (18-30 scale)	(2) Graduated Cum Laude	(3) Wants to do a PhD	(4) Reserve wage
Rank	0.047***	0.015***	0.008***	-7.12*
	(0.008)	(0.003)	(0.002)	(3.95)
N	47,124	47,169	47,169	19,005
R^2	0.467	0.212	0.215	0.204
Panel B: one year after graduation				
	(5) Employment	(6) PhD enrollment	(7) Avg. monthly earnings	
Rank	-0.014***	0.006***	-6.79	
	(0.003)	(0.002)	(4.32)	
N	37,900	37,837	20,490	
R^2	0.148	0.219	0.271	

Note: Table displays the coefficients associated to class rank for separate regressions, together with the associated sample size (N), and the adjusted R-squared. Outcomes are variables related to academic performance and motivation and labor supply. Columns (1) - (3) reflect outcomes measured at graduation, while columns (4) - (6) refer to outcomes measured one year after. All regressions control for a third-degree polynomial of the ability measure, individual controls (gender, age at graduation, region of residence and parental educational attainment) and class fixed effects. Clustered standard errors are reported between parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

class ability rank. Standard errors are clustered at the class level, the level at which rank is determined.

4 Results

4.1 Educational investments and labor supply

Table 4 reports my main estimates of the effect of class rank on academic performance, motivation and labor participation based on Equation 3. In order to make sense of the magnitude of these effects, it is useful to put into perspective what a decile represents in this sample. In an average class with 38 students, each rank decile represents roughly 4 positions, hence moving up one decile typically means outperforming about 4 more classmates.

Results show that ranking one decile closer to the top of the class translates into an improvement of 0.047 points (in a 30-points scale) in grade point average,[9] which at the same time increases the probability of graduating with Latin Honors (*Cum Laude*) by 1.5 percentage points. These improvements in academic performance are accompanied by increases in the self-reported interest in pursuing further studies, in particular a doctoral degree, an interest that appears to largely materialize one year after, with an increase of 0.6 percentage points in the probability of being enrolled into these type of studies, and a decrease of 1.4 percentage points in the probability of being employed. While a one-decile improvement in class rank induces graduates' willingness to accept lower salaries, with a fall of 7.12 euros in their reservation wage, this difference is not reflected in actual monthly earnings, for which the coefficient is similar in size (-6.79), but statistically indistinguishable from zero.

Estimates of the effect of rank on grades are qualitatively in line with previous findings, albeit relatively lower in magnitude. Differences in setting, measurement of human capital, timing of measurement of key variables, and specification are the potential driving forces behind the divergences. The 0.047 points increase in GPA represents 0.049 standard deviations, a third of the effect of 0.149 found by Denning, Murphy and Weinhardt (2023) for primary students in Texas (US) five years after ability measurement (same lapse as in this case). Closer to my estimates are those of Elsner, Isphording and Zölitz (2021), who find class rank in a specific subject increases grades in follow-up courses by 0.0403 standard deviations, or Payne and Smith (2020)'s documented effect of 0.083 standard deviations one year after entering university in Ontario, suggesting that class rank effects may have a greater impact on earlier stages of education. The exception to this pattern is Ribas, Sampaio and Trevisan (2020), who, relying on a different identification strategy based on a discontinuity in class assignment rules, find an effect of 0.336 standard deviations among the students of a Brazilian elite university.

On the other hand, the null effect on average monthly earnings contrasts with Denning, Murphy and Weinhardt (2023) and Dadgar (2026)'s positive estimates. Divergence with Denning, Murphy and Weinhardt (2023) could be explained by differences between the US and Italy in the labor market prospects of recent graduates, or by differences in the sample of interest. While they study all elementary school students, my analysis is focused on Master's degree graduates, a more selected sample in which variation in

[9] This increase in academic performance seems to not be mechanically driven by Professors grading on a curve and artificially inflating the grades of top students, since the effect of class rank on standardized GPA (3% of a standard deviation) is statistically and economically significant.

labor market outcomes might not be as marked. Regarding Dadgar (2026) instead, in this case earnings are measured in the mid-to-late thirties, a sample roughly ten years older than mine, hence likely driving this difference.

While rank effects on educational attainment have been found in different contexts (Payne and Smith, 2020; Elsner and Isphording, 2017; Dadgar, 2026; Denning, Murphy and Weinhardt, 2023), to the best of my knowledge, no effects on willingness to pursue doctoral studies or actual PhD enrollment have been documented before.

4.2 Job preferences

The previous results, in line with the existing literature, show that a higher rank fosters academic performance and educational attainment, documenting a new margin, doctoral enrollment.

This section delves into previously unexplored effects of class rank, job preferences. My census graduate survey data allows me to explore the effects on job preferences along two dimensions: job aspects deemed important, and acceptable forms of employment.

I investigate the impact on priorities when looking for a job. Graduates are asked to rate in a scale from 1 (not important at all) to 5 (very important) the importance of earnings, career progression, stability and security, acquisition of professional skills, coherence with studies, match with cultural interests, independence and autonomy, and free time for choosing a job. Based on the answers to these questions, I create three preference indexes: match with interests (coherence with studies and match with cultural interests), pecuniary conditions (earnings, career progression, stability and security and acquisition of professional skills), and flexibility (independence and autonomy and free time) [10].

Students who rank one decile higher among their peers than other students with similar levels of ability and observable characteristics report that coherence with studies is more important for them when choosing their future job. Although small in magnitude (around 1% of a standard deviation), this effect is statistically significant at the 10% level, and it's the only statistically significant difference in job preferences. The effects of class rank on the importance of pecuniary factors and flexibility on the job, although statistically indistinguishable from zero, are negative.

Secondly, I leverage a set of questions about graduates' willingness to accept different types of labor contracts. Results, displayed in Table A.5

[10] Estimates for the effects of class rank on the individual items are collected in Table 5 in Appendix A.5

Table 5: Rank effects: importance of aspects of a job

	(1) Pecuniary index	(2) Match index	(3) Flexibility index
Rank	-0.008	0.009*	-0.005
	(0.006)	(0.005)	(0.006)
N	46,374	46,310	46,261
R^2	0.105	0.118	0.068

Note: Table displays the coefficients associated to class rank for separate regressions, together with the associated sample size (N), and the adjusted R-squared. Dependent variables are standardized indexes based on the self-reported importance of different aspects of a job, measured in a scale ranging from 1 (not important at all) to 5 (very important). All regressions control for a third-degree polynomial of the ability measure, individual controls (gender, age at graduation, region of residence and parental educational attainment) and class fixed effects. Clustered standard errors are reported between parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

in Appendix A.5, confirm the previously documented patterns: graduates with a better relative performance are willing to trade earnings and secure employment conditions in exchange for having jobs that match their interests and their studies, expressing a higher willingness to accept more precarious sorts of employment, such as internships, apprenticeships, or project-based collaborations.

In Appendix A.5, I additionally explore the effects of class rank on job satisfaction and reported skill use at the job.

4.3 Gender heterogeneity

The previous subsections describe the finding that class rank induces changes in academic performance, academic motivation, job preferences, and the decision to postpone labor market entry. A related relevant question then is whether these effects differ between males and females. The evidence provided by the existing literature has so far been mixed, with some studies finding stronger effects for males (Bertoni and Nisticò, 2023; Murphy and Weinhardt, 2020; Elsner, Isphording and Zölitz, 2021), and others documenting statistically similar patterns (Denning, Murphy and Weinhardt, 2023; Payne and Smith, 2020).

In this context, the results presented in Table 6 show that the effects of class rank on academic performance and motivation are consistently larger for males than for females. The differences are statistically significant for GPA, interest in pursuing a PhD, and actual PhD enrollment, where the estimates for males more than double those for females. Only for reservation wages are the differences not statistically significant. These findings indicate that males react more strongly to rank signals than females, suggesting that differential responses to peer comparison may contribute to the observed drop in the share of women transitioning from Master's to Doctoral education.

Figure 2 further reflects the existence of differences in the magnitude of effects of class rank on job preferences, although qualitative patterns remain similar for both genders. The first sub-figure shows that the increase in the importance of job-studies coherence is mostly driven by male graduates. For females, a higher rank translates also into a raise in the importance of the match between studies and job, albeit smaller, and, differently than males, accompanied by a decrease in the importance given to the stability and security aspect of the job. In line with this, class rank affects males' preferences regarding employment types to a lesser extent than females', while females show a higher willingness to accept some forms of formative contracts (insertion contracts) and temporary employment relationships (project-based collaborations).

Some back-of-the-envelope calculations might be useful to understand the contribution of this differential response to the gap in academic aspirations. If females' response to class rank had the same intensity as males' (that is, if their marginal effect on interest in a PhD was 1 percentage point instead of 0.6), the share of females in the potential pool of PhD applicants (assuming people who report being interested in doing a PhD actually apply for admission) would increase by 5 percentage points, roughly 534 people, representing a 20% increase of the baseline. Assuming that PhD selection committees don't have a preference for candidates of one gender conditional on their quality, and that the total number of available funded PhD positions is fixed, the share of females enrolled in a PhD would increase by approximately 8 percentage points, closing around two-thirds of the gap between the share of female PhD students (50%) and the share of female Master's Degrees graduates (63%).

This *leakage* of women from higher education into doctoral training is not driven by females graduating from fields for which there are few PhD positions available: STEM, the only field in which female representation is not majoritarian (46% of students), represented 19% of the total amount of PhD positions available in the period 2015-2019 (Ministero dell'Università e della Ricerca , MUR). Moreover, the results are statistically similar in the

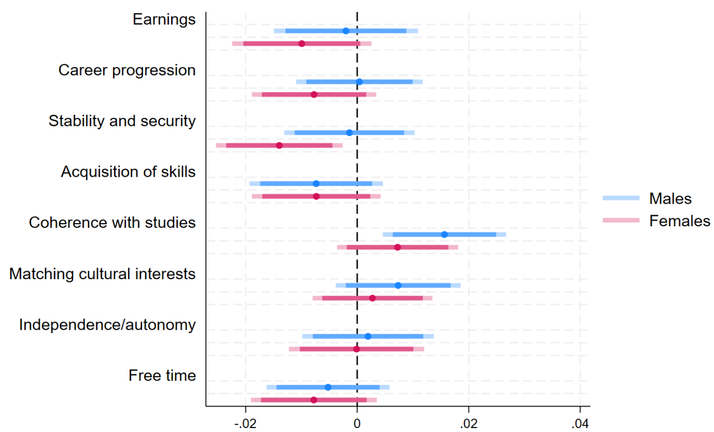
Table 6: Rank effects on academic performance and motivation and labour supply, by gender

Panel A: at graduation				
	(1) GPA (18-30 scale)	(2) Graduated Cum Laude	(3) Wants to do a PhD	(4) Reserve wage
Gender: Male × Ability rank	0.063***	0.017***	0.010***	-5.79
	(0.008)	(0.003)	(0.002)	(4.05)
Gender: Female × Ability rank	0.036***	0.013**	0.006***	-8.08*
	(0.008)	(0.003)	(0.002)	(4.17)

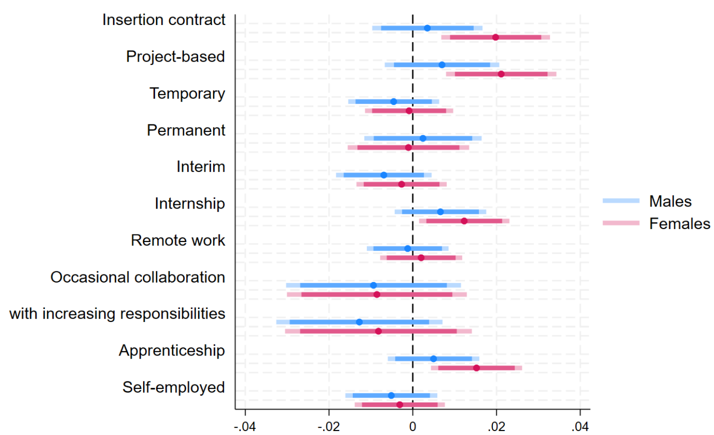
Panel B: one year after graduation			
	(5) Employment	(6) PhD enrollment	(7) Avg. monthly earnings
Gender: Male × Ability rank	-0.017***	0.010***	-8.98*
	(0.003)	(0.002)	(4.69)
Gender: Female × Ability rank	-0.012***	0.004**	-5.47
	(0.003)	(0.002)	(4.37)

Note: Table displays the coefficients associated to class rank for separate regressions. The main explanatory variable, *rank*, is interacted with an indicator for graduates' gender. Outcomes are variables related to academic performance and motivation and labor supply. Columns (1) - (4) reflect outcomes measured at graduation, while columns (5) - (7) refer to outcomes measured one year after. Reserve wage is only available for cohorts who graduated after 2014. All regressions control for a third-degree polynomial of the ability measure, individual controls (gender, age at graduation, region of residence and parental educational attainment) and class fixed effects. Clustered standard errors are reported between parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Figure 2: Rank effects: job preferences, by gender



(a) Aspects of a job



(b) Employment types

Note: Figures show estimates and associated 95% and 90% Confidence Intervals for the relationship between class rank and job preferences, estimated following Equation 3, and interacting class rank with an indicator for gender. Each coefficient and associated CI reflect estimates for separate regressions in which the dependent variables are survey items measuring the importance of different aspects of a job, or willingness to accept contract types, measured in a scale from 1 to 5, which have been standardized with respect to each gender's mean and standard variation.

most male-dominated field (STEM) and the most female-dominated field (Humanities), as shown in Figure A.5 in Annex A.3.

The gender gap in doctoral enrollment is, however, sensitive to the academic environment to which students are exposed. Exploiting variation in the gender composition of faculty across disciplines and academic years, drawn from administrative data on the gender breakdown of Italian university personnel published by the Ministry of Universities and Research (Ministero dell'Università e della Ricerca , MUR), I find that the share of female professors plays a meaningful role, but only for women. Males show no significant differences in either their willingness to enroll in a PhD program or their actual enrollment rates depending on whether they are exposed to a higher or lower share of female faculty. By contrast, females are significantly more likely to express interest in and pursue doctoral training when the proportion of female professors in their discipline exceeds the sample median (25%). These findings are consistent with a role-model mechanism, where female students might be discouraged from entering academic careers in part by the relative absence of same-gender representation among faculty. Results of this analyses are shown in Figure XXX in Annex A.3.

The finding that males respond more strongly to rank information aligns with hypotheses derived from behavioral and labor economics. If beliefs about ability and expected returns influence educational choices[11], and if males and females interpret rank differently, asymmetric effects on academic aspirations and career choices are expected.

Prior studies indicate that females rely less on peer comparison to form beliefs about their own ability (Chevalier et al., 2009), and that women tend to update their beliefs less in response to positive feedback and more to negative feedback[12]. These mechanisms could explain the smaller observed responsiveness of female students to rank-induced motivation.

Gender differences in preferences and perceived job characteristics may also contribute [13].If females perceive the academic career as risky, competitive, or lacking work-life balance, they may be less inclined to pursue a PhD. Moreover, anticipated discrimination can be an additional discouraging fac-

[11]See Boneva, Golin and Rauh (2022); Belfield et al. (2020); Boneva and Rauh (2017)

[12]See Möbius et al. (2022) and Shastry, Shurchkov and Xia (2020), and Bordalo et al. (2019); Coffman, Collis and Kulkarni (2024) on stereotype-dependent updating.

[13]Prior research has highlighted gender differences in attitudes towards risk and competition (Cortes and Pan, 2018; Niederle and Vesterlund, 2007), relative importance of earnings versus pro-social aspects of jobs (Lepinteur and Nieto, 2025), valuation of non-wage characteristics such as commuting time or work-life balance (Fluchtmann et al., 2024), or in the intensity of these preferences (Lordan and Pischke, 2022)

tor (Lepage, Li and Zafar, 2025).

The observed gender gap in PhD enrollment fits within a broader pattern of attrition of women along the academic career path. Females, despite being over-represented in higher education, and at the top of the grades distribution, are less likely to continue their education towards a doctoral degree. In Italy, the percentage of females with a Master's Degree that enroll in a PhD is 18% , which is 24 percentage points below the same share for males. This makes the transition from Master's Degrees to Doctoral Degrees the stage towards an academic career in which the drop in the share of females is the most pronounced: the percentage of females falls from roughly 70% at the Master degree level to 50% at the doctoral stage, followed by the transition from Assistant Professor to Professor, in which the share of females falls from 46% to 36%[14].

While earlier work has extensively analyzed gender disparities in academic promotions (Bosquet, Combes and Garcia-Penalosa, 2013; Ginther and Kahn, 2004, 2009), particularly in the Italian context (De Paola and Scoppa, 2015; De Paola, Ponzo and Scoppa, 2015; Bagues, Sylos-Labini and Zinovyeva, 2017; Zinovyeva and Bagues, 2015), the determinants of the decision to pursue doctoral studies, and the possible gender differences in this choice remain understudied[15].

These results presented here show that self-perception, shaped by peer comparison, influences selection into the doctoral track. Moreover, they suggest a role for differential reactions to ability signals by gender, rather than differences in ability itself, in explaining the smaller predisposition of females toward academic careers. While the estimates on Figure 2 are based on standardized measures within gender, and hence take into account baseline gender differences in the strength and the variation of preferences, further tests on the role of different preferences versus differences in the formation and updating of beliefs based on peer comparison are not possible with the available data. Further research is needed to answer this question and help formulate effective policies that contribute to fixing the *leaky pipeline* in academia.

[14] Figures are slightly different in other European countries, with females being generally less over-represented in higher education. The corresponding fall at the Doctoral stage is of 11 pp, slightly below the drop at the transition to Professorship (14 pp). However, data from the European Commission (Commission, for Research and Innovation, 2021) confirm the pattern that the PhD is the stage at which female underrepresentation in academia starts. See Appendix A.3.

[15] Previous research has linked the decision to pursue a PhD with the prestige of the Master's-granting institution (Estevan and Santos, 2025) or unfavorable labor market conditions (Bedard and Herman, 2008; Johnson, 2013).

5 Mechanisms

Why does class rank affect academic aspirations and career preferences? Students with similar ability but with a higher relative position may be more confident and motivated, and thus put more effort into studying and make more ambitious career choices.

My findings suggest a trade-off between pecuniary conditions after the Master's, and job-studies match, which together with the rise in PhD enrollment in detriment of labor market entry, are consistent with class rank having an effect through these intrinsic motivation factors, which have received the greatest amount of support from the existing literature (Elsner and Isphording, 2017; Elsner, Isphording and Zölitz, 2021; Murphy and Weinhardt, 2020; Pagani, Comi and Origo, 2021).

The postponement of labor market entry and the decision to acquire further education would also be compatible with rank effects acting through inter-temporal preferences, making graduates more willing to trade off immediate pecuniary conditions in exchange for better prospects after completing doctoral studies. Nevertheless, the negative and statistically insignificant effects of class rank on the reported importance of career progression and skill acquisition (see Table 5) are not supportive of this channel.

Moreover, the existing literature has proposed several alternative explanations underlying the effects, such as competitive preferences, changes in beliefs on returns, or external responses from the family or the educational environment.

First, top students may have a higher preference for competition, be it driven by a pursuit of self-improvement, or by a concern to preserve their relative position in the class. Testing whether rank estimates are larger in contexts where students face higher levels of competition provides suggestive support for the hypothesis that competitive preferences may play a role in the results. Competition for being the best student is arguably more pronounced in classes with high-skilled peers, and the higher willingness to compete of males with respect to females is a consistent finding of the competitiveness literature (Niederle and Vesterlund, 2007; Buser, Niederle and Oosterbeek, 2014; Flory, Leibbrandt and List, 2015). Thus, if competition plays a role in rank effects, we should observe larger effects in classes with higher average ability and classes with a higher proportion of males. Table 7 collects the results of these heterogeneity analyses and confirms this intuition. Point estimates for labor participation, PhD enrollment and academic performance are consistently higher in classes with an average ability in the top quartile of the global distribution and those with a high proportion of males. The differences are statistically significant in both cases for the PhD enrollment estimates.

Similarly, if there are gender differences in willingness to compete, one would expect that comparison with same-sex peers would be more salient for males as well, regardless of peer ability or gender composition. The last two rows in Table 7 reflect the result of substituting the unique class rank by gender-specific class ranks, and largely confirm the previous two analyses.

Table 7: Mechanisms: competitiveness

	Employment	PhD enrollment	GPA	Cum Laude	Want to do a PhD	Reserve wage	Avg. monthly earnings
Rank (baseline estimates)	-0.014***	0.006***	0.047***	0.015***	0.008***	-7.12*	-6.79
	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)	(3.95)	(4.32)
Rank×Low peer ability	-0.007*	0.002	0.052***	0.009**	0.007***	1.48	-12.91**
	(0.004)	(0.002)	(0.011)	(0.004)	(0.002)	(6.77)	(5.86)
Rank×High peer ability	-0.017***	0.009***	0.052***	0.019***	0.008***	-14.95***	-8.52*
	(0.004)	(0.002)	(0.009)	(0.003)	(0.002)	(5.01)	(5.14)
Rank×Low male ratio	-0.011**	0.005*	0.025**	0.010**	0.007**	-10.49*	0.29
	(0.004)	(0.003)	(0.011)	(0.004)	(0.003)	(6.09)	(5.78)
Rank×High male ratio	-0.011***	0.011***	0.047***	0.012***	0.012***	-6.21	-5.04
	(0.004)	(0.003)	(0.010)	(0.003)	(0.003)	(5.49)	(5.85)
Gender Rank×Female	-0.004*	-0.001	0.013**	0.006***	-0.000	-5.20	-4.34
	(0.002)	(0.001)	(0.006)	(0.002)	(0.001)	(3.24)	(3.31)
Gender Rank×Male	-0.009***	0.005***	0.038***	0.009***	0.003**	-3.77	-7.99**
	(0.002)	(0.001)	(0.006)	(0.002)	(0.002)	(3.34)	(3.56)

Note: Table reports estimates of class rank effects on the outcomes of interest for different types of classes, categorized according to their average ability measure, and by its gender composition, and using gender-specific rank measures. The *Low* and *High* categories refer to classes in which the average ability or the proportion of female students is either in the first or the last quartile of the overall distribution.

Second, class rank could have an effect through perceived returns from education. If students infer from their rank that they are highly-skilled, they may also adjust their perceptions of their returns to work and to further education and decide to continue their studies.

To test this channel, I look at whether the results differ depending on the opportunity costs associated with pursuing a PhD. I classify degrees into high-opportunity-cost-degrees and low-opportunity-cost ones based on the average earnings of their graduates. Incentives to pursue a PhD would be higher in degrees with low average earnings, suggesting that if this is a relevant channel, we would expect to observe that rank effects are stronger in these programs. Results, displayed in Table 8, suggest little heterogeneity based on this dimension, and provide little support for the hypothesis of the adjustment of perceived returns.

Table 8: Mechanisms: expectations on returns

	Employment	PhD enrollment	GPA	Cum Laude	Want to do a PhD	Reserve wage	Avg. monthly earnings
Rank (baseline estimates)	-0.014***	0.006***	0.047***	0.015***	0.008***	-7.12*	-6.79
	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)	(3.95)	(4.32)
Rank×Low opp. cost	-0.012***	0.003	0.029**	0.012***	0.004	-4.35	-6.95
	(0.004)	(0.002)	(0.012)	(0.004)	(0.002)	(6.39)	(6.15)
Rank×High opp. cost	-0.013***	0.001	0.057***	0.013***	0.001	-7.15	-11.71*
	(0.004)	(0.002)	(0.012)	(0.004)	(0.002)	(5.13)	(6.25)

Note: Table reports estimates of class rank effects on the outcomes of interest for different types of degrees, categorized on the basis of graduates' average earnings. The *Low* and *High* categories refer to degree programs in which the average earnings of their graduates is either in the first or the last quartile of the overall distribution.

Third, class rank could trigger an external response from parents, who may decide to increase their investments in their children, or from the academic environment, making additional or different resources available to the best-ranked students. I leverage the available information on parental education and occupation to discern the possible mediator role of parental response. More educated and wealthy households may have a higher degree of awareness and involvement on their children's education (Houtenville and Conway, 2008; Cobb-Clark, Salamanca and Zhu, 2019; Kalil, Ryan and Corey, 2012) and more capacity to react to information about their performance (Graetz, Öckert and Skans, 2023). In this sense, I run two heterogeneity analyses by interacting the main variable of interest, *rank*, first with an indicator for social class based on parental occupation, and then with an indicator for whether at least one of the parents has achieved tertiary education. Nevertheless, it is unlikely that parents play a substantial role at this stage, given that they are probably unaware of their child's rank, and less influential than at earlier stages of education. In line with this, the outcomes for which rank effects diverge the most are those related to academic performance, GPA and the probability of graduating with honors, while for outcomes related to employment and further studies choices, rank effects seem not to depend on household economic or educational background.

Table 9: Mechanisms: parental involvement

	Employment	PhD enrollment	GPA	Cum Laude	Want to do a PhD	Reserve wage	Avg. monthly earnings
Rank (baseline estimates)	-0.014***	0.006***	0.047***	0.015***	0.008***	-7.12*	-6.79
	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)	(3.95)	(4.32)
Rank×working class	-0.016***	0.005**	0.021**	0.006*	0.005*	-10.58**	-5.67
	(0.004)	(0.002)	(0.010)	(0.003)	(0.002)	(5.30)	(5.81)
Rank×middle class	-0.018***	0.008***	0.042***	0.012***	0.007***	-5.51	-9.34
	(0.004)	(0.002)	(0.009)	(0.003)	(0.002)	(4.90)	(5.77)
Rank×lower burgeoise	-0.013***	0.005**	0.043***	0.013***	0.006**	-5.49	-7.25
	(0.004)	(0.002)	(0.010)	(0.003)	(0.002)	(5.03)	(5.72)
Rank×burgeoise	-0.020***	0.009***	0.055***	0.018***	0.008***	-11.17**	-10.38*
	(0.004)	(0.002)	(0.009)	(0.003)	(0.002)	(4.91)	(5.98)
Rank×first-gen	-0.017***	0.006***	0.037***	0.010***	0.006**	-6.10	-8.53
	(0.004)	(0.002)	(0.010)	(0.003)	(0.002)	(5.22)	(5.38)
Rank×no first-gen	-0.018***	0.008***	0.051***	0.016***	0.008***	-10.64**	-8.61
	(0.004)	(0.002)	(0.009)	(0.003)	(0.002)	(4.79)	(5.79)

Note: Table reports estimates of class rank effects on the outcomes of interest for different types of individuals, categorized on the basis of their household background and the educational attainment of their parents.

Although my data does not contain information about the specific university resources available for differently-ranked students, I perform two tests to tease out the possible role of the university, and in particular of Professors, in class rank effects. First, I explore outcomes related to satisfaction with the studies, which are part of the graduation survey, and hence available for the entire sample. I find some weak evidence (reported in Table A.6 in Appendix A.5) that relative position positively affects satisfaction with the Degree, and that this increase is driven by a positive valuation of Professors rather than peers.

Relatedly, there could be concerns that the increased probability of being enrolled into a PhD could simply reflect that PhD admission committees use cohort rank as a measure of candidates' performance, since rank information is likely available to them. For those who continue their studies in the same department, there is presumably some overlap between Professors who teach at the Master Degree's and Professors who sit in the PhD admissions committee. Although 64% of students enroll in a different university, information on rank may be disclosed in recommendation letters, which are often required in the PhD admission process, and hence potentially available even for other departments and universities. While this mechanism cannot be fully ruled out, I argue that it is unlikely that this is the sole driver of this effect, given that I also find an increase in the intentions of pursuing doctoral studies before graduation.

Nevertheless, I provide an additional check in the fashion of Elsner, Isphording and Zölitz (2021). I modify my preferred specification and include the Master's Degree graduation mark as a control. If rank effects persist after controlling for the graduation mark, this is indicative of rank having an independent effect on PhD enrollment beyond acting as a proxy for quality for committees[16]. This analysis is presented in Table 10, and shows that the estimate for PhD enrollment remains unchanged when including performance in the Master's as a control.

Table 10: Mechanisms: University selection

	Employment	PhD enrollment	GPA	Cum Laude	Want to do a PhD	Reserve wage	Avg. monthly earnings
Rank (baseline estimates)	-0.014***	0.006***	0.047***	0.015***	0.008***	-7.12*	-6.79
	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)	(3.95)	(4.32)
Rank (controlling for final mark)	-0.014***	0.006***	0.027***	0.010***	0.007***	-7.14*	-7.20*
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(3.95)	(4.31)

Note: Table reports the baseline estimates of class rank effects on the outcomes of interest, and a comparison with the estimates after including the Master's Degree final mark as a control.

To summarize, the mechanisms for which I find a greater amount of support with the available data are competitiveness and motivation and effort, in line with previous findings of the related literature (Elsner and Isphording, 2017; Elsner, Isphording and Zölitz, 2021; Murphy and Weinhardt, 2020; Pagani, Comi and Origo, 2021). My results are also consistent with Professors having an influence on the effects, although evidence of that mechanism is weaker.

6 Robustness checks

In this section, I test the sensitivity of my results to alternative identifying assumptions proposed by the literature, and to some critical issues related to the measurement of the main variable, class rank.

[16]Given that graduation marks are affected by rank, the inclusion of this variable as a control introduces post-treatment or bad control bias (Angrist and Pischke, 2009), hence the interpretation of the rank coefficient is no longer causal

Table 11: Sensitivity to different specifications

	Employment	PhD enrollment	GPA	Cum Laude	Want to do a PhD	Reserve wage	Avg. monthly earnings
Baseline estimates	-0.014***	0.006***	0.047***	0.015***	0.008***	-7.12*	-6.79
	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)	(3.95)	(4.32)
Additive degree and cohort effects							
Degree and Cohort F.E.s	-0.009***	0.005***	0.018**	0.006**	0.007***	-7.97**	0.27
	(0.003)	(0.001)	(0.007)	(0.002)	(0.002)	(3.78)	(3.55)
+ Individual characteristics	-0.009***	0.005***	0.021***	0.006**	0.007***	-6.85*	-1.93
	(0.003)	(0.001)	(0.007)	(0.002)	(0.002)	(3.72)	(3.55)
+ Class ability	-0.012***	0.006***	0.043***	0.014***	0.008***	-7.35*	-6.98*
	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)	(3.99)	(4.24)
+ Class heterogeneity	-0.012***	0.006***	0.043***	0.014***	0.008***	-7.35*	-6.90
	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)	(3.99)	(4.24)
Parametric functions of class and ability							
H×class ability, H×class heterogeneity	-0.009***	0.005***	0.033***	0.018***	0.009***	-1.92	6.79
	(0.003)	(0.002)	(0.010)	(0.003)	(0.002)	(4.76)	(4.65)
H×class distribution types	-0.011***	0.007***	0.047***	0.021***	0.009***	-1.75	-2.57
	(0.003)	(0.002)	(0.006)	(0.003)	(0.002)	(4.44)	(4.52)
Global H decile dummies	-0.012***	0.006***	0.051***	0.014***	0.007***	-8.07**	-5.84
	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)	(4.01)	(4.56)
Measurement of Rank							
Using Bachelor's grades	-0.000	0.011***	0.003	0.017***	0.014***	-4.38	-9.19*
	(0.004)	(0.002)	(0.011)	(0.004)	(0.003)	(4.69)	(5.28)
Using Master's grades	-0.002	0.007***	-	0.025***	0.008***	-22.42***	-10.42**
	(0.003)	(0.002)	-	(0.003)	(0.002)	(5.21)	(4.28)
Based on standardized measure	-0.014***	0.006***	0.035***	0.008**	0.009***	-6.77	-7.59
	(0.004)	(0.002)	(0.010)	(0.003)	(0.002)	(5.22)	(5.38)

Note: Table reports estimates of class rank effects on the outcomes of interest across different model specifications.

I start by substituting degree-by-cohort fixed effects by separate degree and cohort fixed effects, effectively assuming that the error term in Equation 1 is composed by additive degree, cohort and ability effects. While this is a stronger assumption than the one used in my preferred specification, as it imposes the absence of effects of class-specific factors different than rank, comparing both still gives a useful intuition on which variables might be important for teasing out selection and other confounding effects from causal rank effects.

This specification tends to either leave estimates practically unchanged, as it is the case for interest in PhD and PhD enrollment, or provide downward-biased estimates for the rest of the variables. This suggests that there are peer effects in place for the affected outcomes, and that these peer effects have an opposite effect than that of rank.

Adding individual characteristics (gender, age at graduation, parental education and region of residence) as controls to the model does not affect the estimates. As discussed in Subsection 3.3, this confirms the little potential for concerns of selection into peer groups. On the other hand, adding average class ability as a control systematically brings the estimates closer to the baseline, making both sets of estimates statistically indistinguishable. This is in line with the findings of Bertoni and Nisticò (2023), evidencing that ranking high among peers and the average ability of peers are two sides of the same coin, and that average peer quality is an important confounder.

Turning into a weaker identifying assumption instead, I introduce parametric functions of class and ability effects into the model, allowing for heterogeity in rank effects across class characteristics. I start by replicating Bertoni and Nisticò (2023)'s approach by introducing interactions of my measure of ability with the class mean and the class variance. Estimates on the probability of employment, GPA and reserve wage slightly shrink in size, while PhD intentions and actual enrollment remain practically unchanged, and the effect on average monthly wages, while still statistically non-significant, changes sign and becomes positive. This suggests that, while PhD-related outcomes may not be responsive to class characteristics, the rest of outcomes may be.

Next, I follow Denning, Murphy and Weinhardt (2023) and categorize classes according to their ability distribution, creating 16 types by dividing the sample according to mean and variance quartiles. Conclusions are similar to the previous exercise, with point estimates being statistically indistinguishable from the baseline model.

The last specification check regards the flexible inclusion of ability effects to correctly account for its high correlation with the main variable of interest. In this sense, following Murphy and Weinhardt (2020), I substitute the third-order polynomial used in the baseline estimates with an indicator variable for each decile of the global ability distribution. Again, estimates remain practically unaltered.

Next, I test the sensitivity of my estimates to aspects related to the measurement of rank: the timing of measurement and the potential threat of multiplicative error in the measurement of ability.

There is a trade-off between employing measures of ability that are measured before or after the peer group forms. While innate ability should remain more or less constant across the life cycle, rank can plausibly affect human capital accumulation. If rank affects human capital and human capital affects rank contemporaneously, this could introduce a reflection problem (Manski, 1993), which favors measures that precede peer group formation. On the other hand, measures of ability that are taken after the peer group forms have the advantage that they might be more salient, as students are more aware of the current performance of their classmates, revealed through repeated evaluations, than of their past performance. Since perceived rank is what determines self-concept and behavior changes instead of actual rank, using a contemporary or a more recent measure may be more accurate. I propose two alternative measures of ability based on academic performance: the final grade achieved in the previous degree attained (Bachelor's Degree), and GPA of the Master's degree in course. In both cases, estimates on self-reported interest in PhD studies and actual enrollment remain unchanged, whereas the detrimental effect of class rank on employment becomes smaller and statistically insignificant. Effects on reserve and actual wages increase in size and become statistically significant when using current academic performance, with a decile increase translating into a fall of 22.42 euro in reserve wages, and a fall of 10.42 euro on average monthly earnings one year after graduation. When using Bachelor's grades, the effect on reservation wage falls in magnitude and loses significance, while the impact on actual earnings remains negative (9.19 euro) and statistically significant at the 10% level. Overall, the robustness of the results across ability measures reinforces the validity of high-school diploma grade as a measure of internalized relative ability. While the stronger wage effects observed when using contemporary academic performance suggest that baseline estimates might be conservative, this more salient measure risks contamination from endogenous reflection, suggesting that the true effect of rank likely lies between the estimates derived from pre-peer group and contemporary measures of ability.

Multiplicative measurement error occurs when the measurement error increases with distance from the average. In this context, because the sample includes only those who graduate, and not the entirety of the enrolled, and rank has been shown by the literature to impact graduation (Ribas, Sampaio and Trevisan, 2020; Dadgar, 2026), class rank is consistently overestimated. The overestimation of the explanatory variable can not be measured because of lack of information on the drop-outs[17]. Nevertheless, this error introduces a downward bias in the estimates, underestimating the true effect size. Instead, measurement error for the ability measure could happen for instance if teachers grade on a curve, favoring the high achievers. In this case, in order to correct for multiplicative measurement error, I follow Murphy and Weinhardt (2020): I standardize the ability measure into a uniform distribution, I construct the class rank variable based on the standardized ability measure,

[17] According to data based on the national student registry (ANVUR, 2018), the drop-out rate at the Master's degree level in Italy is of 5.9%, in line with estimates from other OECD countries (OECD, 2019)

and I re-run my preferred specification. Results, captured in the last row of Table 11, show that, while GPA, probability of graduating Cum Laude, and reserve wage point estimates shift downwards, GPA and reserve wage estimates are statistically indistinguishable from baseline estimates, and the effect on Cum Laude graduation remains statistically significant. The rest of the estimates remain unchanged. The results suggest that original estimates are modestly downward-biased due to multiplicative measurement error, particularly in GPA, Cum Laude probability, and reserve wage. However, since the corrected estimates remain statistically significant and most other outcomes are unaffected, the magnitude of mismeasurement appears limited and does not affect the core findings.

I also address concerns that rank effects may be non-linear. I substitute the continuous rank variable for decile indicators, and I plot the baseline effect against the estimates for each decile. Results, shown in Figure A.7 in the Appendix, do not suggest important non-linearities.

Finally, I address concerns that results might be driven by residual endogenous characteristics not captured by the ability polynomial or individual controls, such as selection into specific degrees.

Following the logic of the re-centered instrument proposed by Borusyak, Caceres Bravo and Hull (2025), I "re-center" rank by controlling for the expected rank position conditional on Master's program choice, which absorbs the component of rank that is mechanically determined by own ability and program-specific characteristics (the endogenous part of rank). This way, I isolate the variation in rank that arises purely from the luck of cohort assignment (the exogenously-determined part of rank). Results remain statistically similar across most outcomes, with the effect on current academic performance and reserve wages being slightly larger, suggesting that if anything, the baseline estimates are conservative. Further details on the construction of the expected rank and the full set of results are provided in Appendix A.4.1.

Further sensitivity checks based on the building of the rank variable and the peer group used to define it can be found in Table A.2 in Appendix A.4. P-values adjusted for Multiple Hypothesis Testing, following Romano and Wolf (2005) are also collected in Appendix A.4.

7 Conclusion

This paper provides new causal evidence on how relative ability within university cohorts shapes students' educational aspirations, job preferences, and early career outcomes. Leveraging a unique dataset that combines administrative records with pre- and post-graduation survey responses for ten cohorts of Master's graduates at a large Italian university, I exploit quasi-random variation in peer composition to isolate the causal effect of relative ability rank.

The results demonstrate that class rank is an important determinant of students' post-graduate choices and motivations. Higher-ranked students are more likely to pursue doctoral studies, delay entry into the labor market, and accept less secure employment in exchange for positions better aligned with their field of study. These patterns indicate that intrinsic motivation and academic self-concept, shaped by relative performance, play a pivotal role in career decision-making.

The influence of rank is particularly pronounced in settings characterized by stronger peer competition, such as male-dominated or higher-ability cohorts, underscoring the role of social comparison and competitiveness as key behavioral mechanisms. Moreover, the muted response among female students suggests that gender differences in the interpretation of rank signals contribute to the persistent underrepresentation of women in doctoral and research careers, even among equally high-achieving graduates.

By documenting how rank shapes not only academic attainment but also career aspirations and early labor market behavior, this paper broadens the scope of the rank effects literature beyond performance outcomes. It also contributes to the study of belief formation and gender gaps in academic trajectories by uncovering a novel mechanism through which relative standing influences the transition into research-oriented careers.

These findings open several promising avenues for future research. First, using high-school grades as a proxy for ability captures a policy-relevant dimension of student performance. At the same time, grades also reflect non-cognitive traits such as persistence, effort, or ambition, and family resources, which may influence both rank and educational and career outcomes. Future research that combines these measures with standardized cognitive tests and separates the effects of cognitive ability from those of non-cognitive skills could shed new light on the mechanisms linking relative performance, self-perception, and subsequent human capital investment and career choices.

Second, research should also examine whether the pecuniary–match trade-off identified in this study translates into improved career trajectories or higher job satisfaction in the medium term. Understanding whether early preferences for job–study alignment ultimately yield better long-run outcomes would provide valuable insight into the efficiency and persistence of rank-driven career choices.

Third, findings underscore the importance of understanding how students interpret rank-related signals, and how these perceptions interact with preferences and stereotypes in shaping academic trajectories. Future work should explore how interventions such as feedback framing, exposure to role models, mentoring, or career counseling might mitigate differential reactions to academic rank and support the academic and labor market outcomes of underrepresented groups.

References

Angrist, Joshua D, and Jörn-Steffen Pischke. 2009. *Mostly harmless econometrics: An empiricist's companion.* Princeton University Press.

ANVUR. 2018. "Sintesi del Rapporto Biennale sullo Stato del Sistema Universitario e della Ricerca 2018." Agenzia Nazionale di Valutazione del Sistema Universitario e della Ricerca (ANVUR), Roma.

Bagues, Manuel, Mauro Sylos-Labini, and Natalia Zinovyeva. 2017. "Does the gender composition of scientific committees matter?" *American Economic Review*, 107(4): 1207–1238.

Bedard, Kelly, and Douglas A Herman. 2008. "Who goes to graduate/professional school? The importance of economic fluctuations, undergraduate field, and ability." *Economics of Education Review*, 27(2): 197–210.

Belfield, Chris, Teodora Boneva, Christopher Rauh, and Jonathan Shaw. 2020. "What drives enrolment gaps in further education? the role of beliefs in sequential schooling decisions." *Economica*, 87(346): 490–529.

Bertoni, Marco, and Roberto Nisticò. 2023. "Ordinal rank and the structure of ability peer effects." *Journal of Public Economics*, 217: 104797.

Boneva, Teodora, and Christopher Rauh. 2017. "Socio-economic gaps in university enrollment: The role of perceived pecuniary and non-pecuniary returns."

Boneva, Teodora, Marta Golin, and Christopher Rauh. 2022. "Can perceived returns explain enrollment gaps in postgraduate education?" *Labour Economics*, 77: 101998.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer. 2019. "Beliefs about gender." *American Economic Review*, 109(3): 739–773.

Borusyak, Kirill, Mauricio Caceres Bravo, and Peter Hull. 2025. "Estimating Demand with Recentered Instruments."

Bosquet, Clément, Pierre-Philippe Combes, and Cecilia Garcia-Penalosa. 2013. "Gender and competition: evidence from academic promotions in France." CESifo Working Paper.

Buser, Thomas, Muriel Niederle, and Hessel Oosterbeek. 2014. "Gender, competitiveness, and career choices." *The Quarterly Journal of Economics*, 129(3): 1409–1447.

Carneiro, Pedro, Yyannu Cruz-Aguayo, Francesca Salvati, and Norbert Schady. 2025. "The effect of classroom rank on learning throughout elementary school: experimental evidence from Ecuador." *Journal of Labor Economics*, 43(2): 433–466.

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

Chevalier, Arnaud, Steve Gibbons, Andy Thorpe, Martin Snell, and Sherria Hoskins. 2009. "Students' academic self-perception." *Economics of Education Review*, 28(6): 716–727.

Cicala, Steve, Roland G Fryer, and Jörg L Spenkuch. 2018. "Self-selection and comparative advantage in social interactions." *Journal of the European Economic Association*, 16(4): 983–1020.

Cobb-Clark, Deborah A, Nicolas Salamanca, and Anna Zhu. 2019. "Parenting style as an investment in human development." *Journal of Population Economics*, 32(4): 1315–1352.

Coffman, Katherine, Manuela R Collis, and Leena Kulkarni. 2024. "Stereotypes and belief updating." *Journal of the European Economic Association*, 22(3): 1011–1054.

Comi, Simona, Federica Origo, Laura Pagani, and Marco Tonello. 2021. "Last and furious: Relative position and school violence." *Journal of Economic Behavior & Organization*, 188: 736–756.

Commission, European, Directorate-General for Research, and Innovation. 2021. *She figures 2021 – Gender in research and innovation – Statistics and indicators.* Publications Office.

Cortes, Patricia, and Jessica Pan. 2018. "Occupation and gender." *The Oxford handbook of women and the economy*, 425–452.

Dadgar, Iman. 2026. "The effect of ordinal rank in school on educational achievement and income in Sweden." *Economics of Education Review*, 110: 102737.

Delaney, Judith M, and Paul J Devereux. 2021. "High school rank in math and English and the gender gap in STEM." *Labour Economics*, 69: 101969.

Delaney, Judith M, and Paul J Devereux. 2022. "Rank effects in education: What do we know so far?" *Handbook of Labor, Human Resources and Population Economics*, 1–24.

Del Bono, Emilia, Angus Holford, and Tommaso Sartori. 2025. "Beyond Test Scores: How Academic Rank Shapes Long-Term Outcomes." *arXiv preprint arXiv:2510.11973*.

Denning, Jeffrey T, Richard Murphy, and Felix Weinhardt. 2023. "Class rank and long-run outcomes." *Review of Economics and Statistics*, 105(6): 1426–1441.

De Paola, Maria, and Vincenzo Scoppa. 2015. "Gender discrimination and evaluators' gender: evidence from Italian academia." *Economica*, 82(325): 162–188.

De Paola, Maria, Michela Ponzo, and Vincenzo Scoppa. 2015. "Gender differences in attitudes towards competition: Evidence from the Italian scientific qualification." IZA Discussion Papers.

Elsner, Benjamin, and Ingo E Isphording. 2017. "A big fish in a small pond: Ability rank and human capital investment." *Journal of Labor Economics*, 35(3): 787–828.

Elsner, Benjamin, and Ingo E Isphording. 2018. "Rank, sex, drugs, and crime." *Journal of Human Resources*, 53(2): 356–381.

Elsner, Benjamin, Ingo E Isphording, and Ulf Zölitz. 2021. "Achievement rank affects performance and major choices in college." *The Economic Journal*, 131(640): 3182–3206.

Estevan, Fernanda, and Kelly Santos. 2025. "Does It Matter Which Institution You Choose? A Case Study of Brazilian Graduate Admissions." *Journal of Human Capital*, 19(4): 000–000.

Exley, Christine L, and Kirby Nielsen. 2024. "The gender gap in confidence: Expected but not accounted for." *American Economic Review*, 114(3): 851–885.

Flory, Jeffrey A, Andreas Leibbrandt, and John A List. 2015. "Do competitive workplaces deter female workers? A large-scale natural field experiment on job entry decisions." *The Review of Economic Studies*, 82(1): 122–155.

Fluchtmann, Jonas, Anita M. Glenny, Nikolaj A. Harmon, and Jonas Maibom. 2024. "The Gender Application Gap: Do Men and Women Apply for the Same Jobs?" *American Economic Journal: Economic Policy*, 16(2): 182–219.

Ginther, Donna K, and Shulamit Kahn. 2004. "Women in economics: moving up or falling off the academic career ladder?" *Journal of Economic perspectives*, 18(3): 193–214.

Ginther, Donna K, and Shulamit Kahn. 2009. "Does science promote women? Evidence from academia 1973-2001." In *Science and engineering careers in the United States: An analysis of markets and employment.* 163–194. University of Chicago Press.

Goulas, Sofoklis, and Rigissa Megalokonomou. 2021. "Knowing who you actually are: The effect of feedback on short-and longer-term outcomes." *Journal of Economic Behavior & Organization*, 183: 589–615.

Goulas, Sofoklis, Silvia Griselda, and Rigissa Megalokonomou. 2024. "Comparative advantage and gender gap in STEM." *Journal of Human Resources*, 59(6): 1937–1980.

Graetz, Georg, Björn Öckert, and Oskar Nordström Skans. 2023. "Parental Education and the Responses to Higher SAT Scores." *Journal of Human Resources.*

Houtenville, Andrew J, and Karen Smith Conway. 2008. "Parental effort, school resources, and student achievement." *Journal of Human resources*, 43(2): 437–453.

Johnson, Matthew T. 2013. "The impact of business cycle fluctuations on graduate school enrollment." *Economics of Education Review*, 34: 122–134.

Kalil, Ariel, Rebecca Ryan, and Michael Corey. 2012. "Diverging destinies: Maternal education and the developmental gradient in time with children." *Demography*, 49(4): 1361–1383.

Lepage, Louis-Pierre, Xiaomeng Li, and Basit Zafar. 2025. "Anticipated Discrimination and Major Choice." National Bureau of Economic Research.

Lepinteur, Anthony, and Adrìan Nieto. 2025. "All about the money? The gendered effect of education on industrial and occupational sorting." *Labour Economics*, 102670.

Li, Hongyan, and Xing Xia. 2024. "Grades as signals of comparative advantage: How letter grades affect major choices." *Journal of Economic Behavior & Organization*, 227: 106717.

Lordan, Grace, and Jörn-Steffen Pischke. 2022. "Does Rosie like riveting? Male and female occupational choices." *Economica*, 89(353): 110–130.

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

Marsh, Herbert W, and John W Parker. 1984. "Determinants of student self-concept: Is it better to be a relatively large fish in a small pond even if you don't learn to swim as well?" *Journal of Personality and Social Psychology*, 47(1): 213.

Megalokonomou, Rigissa, and Yi Zhang. 2024. "How good am I? Effects and mechanisms behind salient rank." *European Economic Review*, 170: 104870.

Ministero dell'Istruzione, dell'Università e della Ricerca. 2004. "Modifiche al regolamento recante norme concernenti l'autonomia didattica degli atenei, approvato con decreto del Ministro dell'università e della ricerca scientifica e tecnologica 3 novembre 1999, n. 509." Art. 10. Entrata in vigore: 27 novembre 2004.

Ministero dell'Università e della Ricerca (MUR). 2020. "Dati per bilancio di genere." *https://dati-ustat.mur.gov.it/dataset/dati-per-bilancio-di-genere*, Ultimo aggiornamento disponibile nel 2023.

Möbius, Markus M, Muriel Niederle, Paul Niehaus, and Tanya S Rosenblat. 2022. "Managing self-confidence: Theory and experimental evidence." *Management Science*, 68(11): 7793–7817.

Murphy, Richard, and Felix Weinhardt. 2020. "Top of the class: The importance of ordinal rank." *The Review of Economic Studies*, 87(6): 2777–2826.

Niederle, Muriel, and Lise Vesterlund. 2007. "Do women shy away from competition? Do men compete too much?" *The Quarterly Journal of Economics*, 122(3): 1067–1101.

OECD. 2015. *Frascati Manual 2015: Guidelines for Collecting and Reporting Data on Research and Experimental Development. The Measurement of Scientific, Technological and Innovation Activities*, Paris:OECD Publishing.

OECD. 2019. *Education at a Glance 2019: OECD Indicators.* Paris:OECD Publishing.

OECD. 2020. "Tertiary graduation rate in Italy, 2020." Accessed on 28/08/2024, 16:55 CEST.

Owen, Stephanie. 2023. "College major choice and beliefs about relative performance: An experimental intervention to understand gender gaps in STEM." *Economics of Education Review*, 97: 102479.

Pagani, Laura, Simona Comi, and Federica Origo. 2021. "The effect of school rank on personality traits." *Journal of Human Resources*, 56(4): 1187–1225.

Payne, A Abigail, and Justin Smith. 2020. "Big fish, small pond: The effect of rank at entry on postsecondary outcomes." *Southern Economic Journal*, 86(4): 1475–1509.

Ribas, Rafael P, Breno Sampaio, and Giuseppe Trevisan. 2020. "Short-and long-term effects of class assignment: Evidence from a flagship university in Brazil." *Labour Economics*, 64: 101835.

Romano, Joseph P, and Michael Wolf. 2005. "Exact and approximate stepdown methods for multiple hypothesis testing." *Journal of the American Statistical Association*, 100(469): 94–108.

Shastry, Gauri Kartini, Olga Shurchkov, and Lingjun Lotus Xia. 2020. "Luck or skill: How women and men react to noisy feedback." *Journal of Behavioral and Experimental Economics*, 88: 101592.

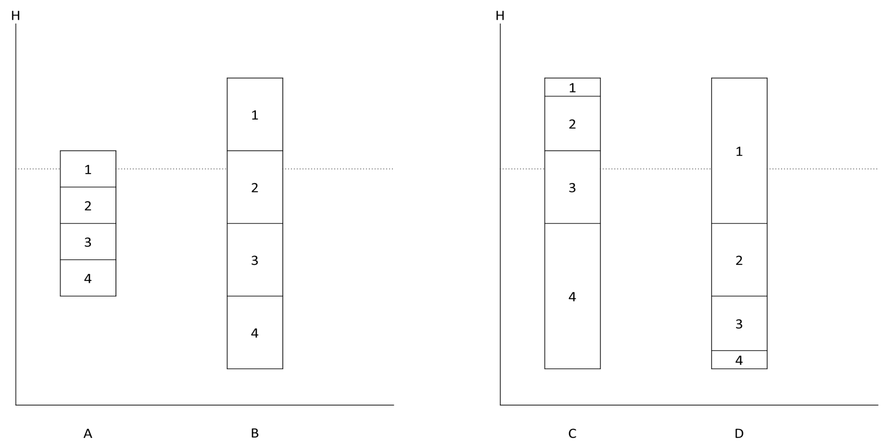
Yu, Han. 2020. "Am I the big fish? The effect of ordinal rank on student academic performance in middle school." *Journal of Economic Behavior & Organization*, 176: 18–41.

Zinovyeva, Natalia, and Manuel Bagues. 2015. "The role of connections in academic promotions." *American Economic Journal: Applied Economics*, 7(2): 264–292.

A Appendix

A.1 Identifying variation

Figure A.1: Identifying variation

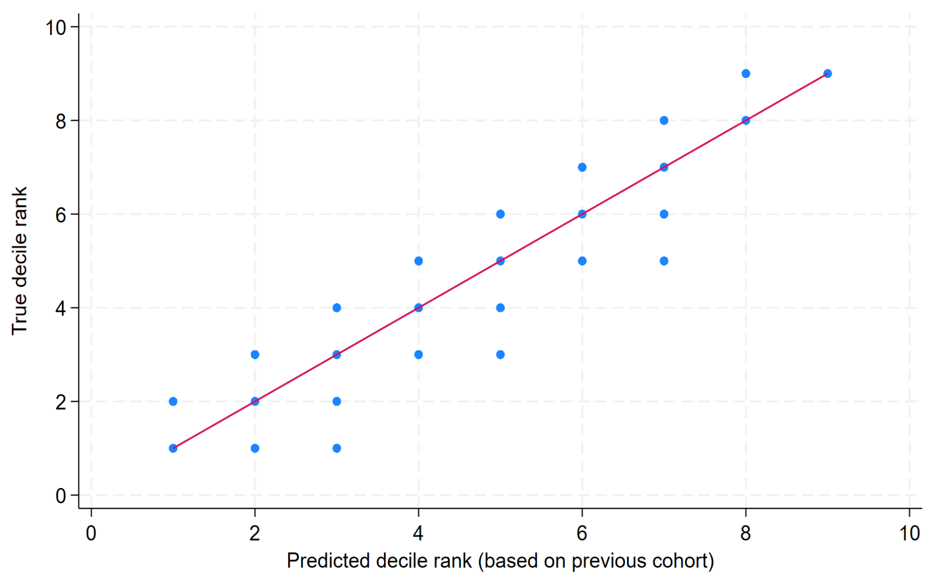


(a)

(b)

Note: Figure shows four examples (A, B, C, and D) of ability distributions within a class, with the numbers referring to the quartiles of the distribution. Panel A presents a case in which two classes have the same average level of human capital and a different variance. Panel B presents a situation in which the two classes have the same variance, but the distribution is centered differently, with class C being skewed towards higher levels of ability, and class D being skewed towards the lower end of the distribution. In both cases, a student would end up having a different relative position with respect to her peers, even if her ability level remains constant.

Figure A.2: Predicted versus true percentile



Note: The figure plots each student's predicted percentile based on the previous cohort's score distribution against their true percentile within their own cohort. Deviations from the 45 degree line indicate rank-prediction error arising from across-cohort differences in ability distributions.

A.2 Validity of the identification strategy

To test the absence of systematic correlation between individual characteristics and characteristics of the peer ability distribution, which could point at sorting of individuals into peer groups and introduce endogenous correlation between rank position and outcomes, thus violating the identifying assumptions, I run the following regressions:

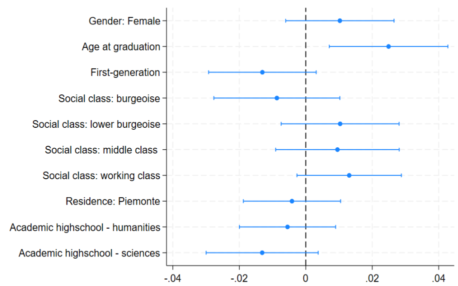
$$X_{idc} = \alpha + \gamma f(\overline{H}_{dc-i}) + f(H_{idc}) + +\sigma_{dc} + e_{idc} \tag{4}$$

Where $f(\overline{H}_{dc-i})$ stands for different moments of the (leave-one-out) peer group ability distribution: mean, median, variance, skewness, and kurtosis. A γ statistically different than zero would point at individuals with certain characteristics being more likely to end up in certain groups.

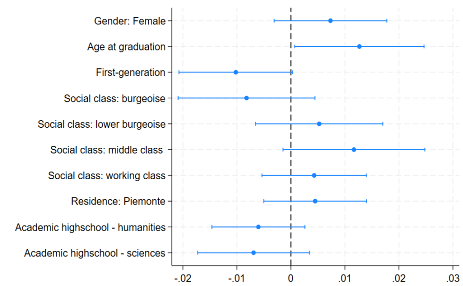
Figure A.3 displays estimates for γ in a series of regressions in which the dependent variables, X_{idc} represent individual pre-determined characteristics available in the data: gender, age at graduation, and indicators for first-generation University graduate status, parental occupation, province of residence and type of high school pursued.

Estimates largely suggest statistically insignificant relationships between individual characteristics and peer ability, thus supporting the assumption of no sorting. Few exceptions suggest relationships that, although statistically significant, are small and not significant from an economic point of view, e.g. a unit increase in mean peer ability is associated with a 0.03 increase in the age at graduation (roughly 11 days), or a unit increase in peer ability variance is associated with a 0.02 increase in the probability of having completed a scientific high-school (4% of the sample mean).

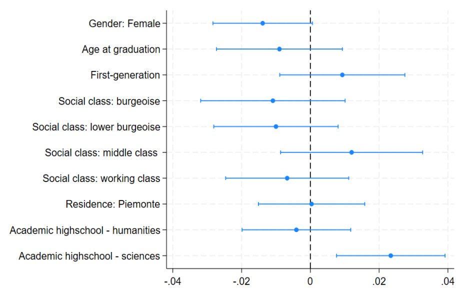
Figure A.3: Balance checks: Individual Characteristics and Peer Ability Distribution



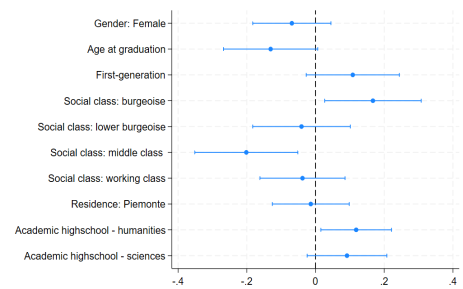
(a) Mean



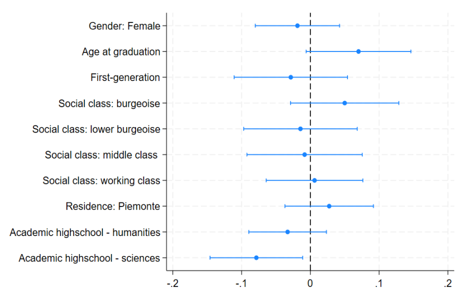
(b) Median



(c) Variance



(d) Skewness

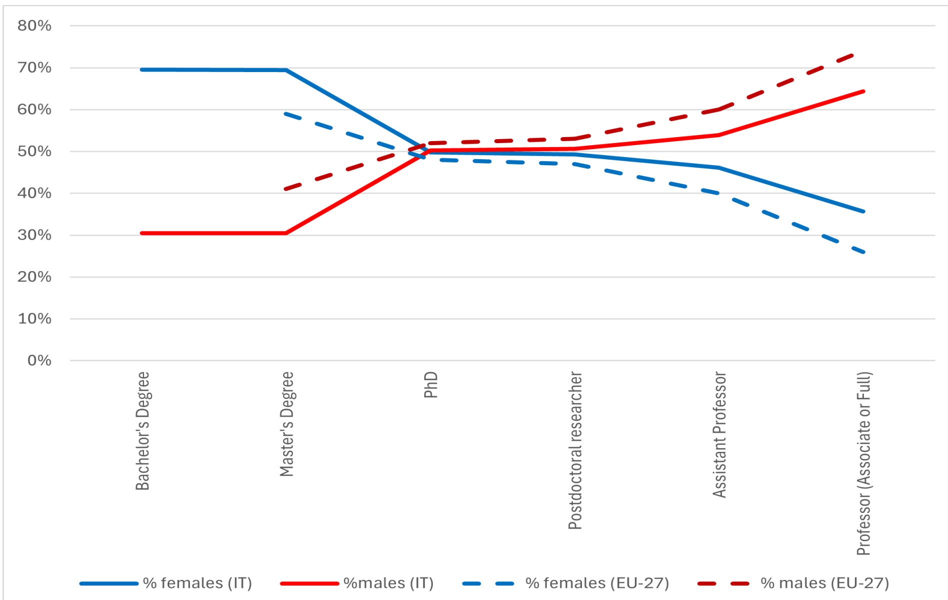


(e) Kurtosis

Note: Figures plot the correlation between individual pre-determined characteristics and different features of the leave-one-out peer ability distribution, conditional on a third-order polynomial of individual ability and peer group fixed effects. Standard errors are clustered at the degree-cohort group level.

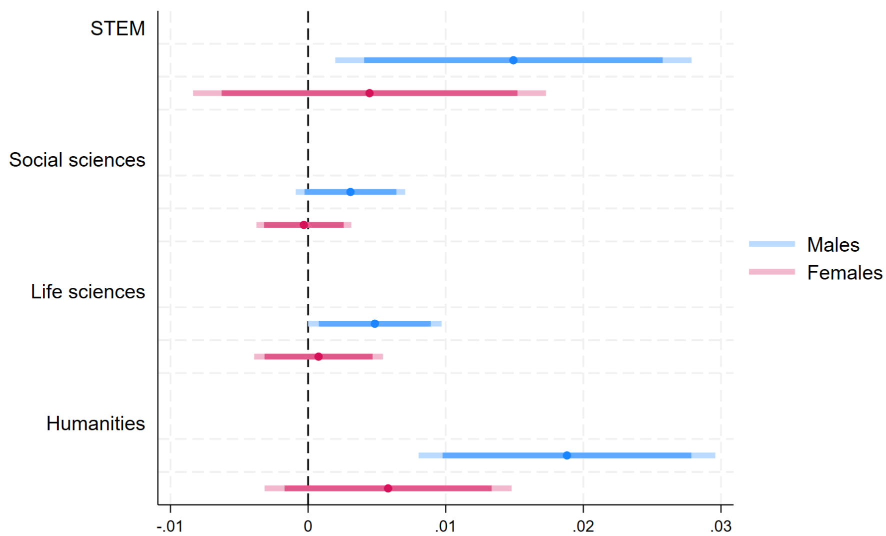
A.3 The *Leaky pipeline* in Italy and in Europe

Figure A.4: Gender composition and career progression in the academic profession



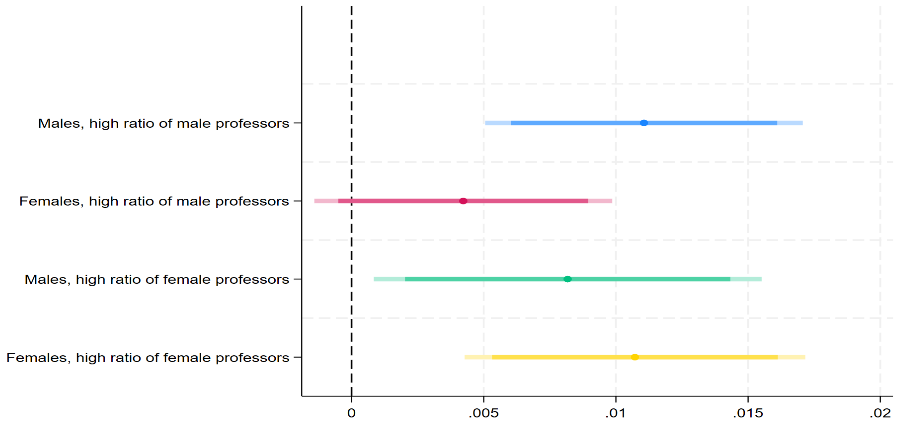
Note: Figure shows the share of females and males in all stages of the academic career, since post-mandatory tertiary education, until Professorship. Figures from Italy are taken from the Gender balance time series data of the Ministry of Universities and Research (Ministero dell'Università e della Ricerca , MUR) and refer to the year 2020, while figures for EU-27 are taken from the 2021 edition of the *She Figures* report (Commission, for Research and Innovation, 2021).

Figure A.5: Rank effects on PhD enrollment, by field and gender

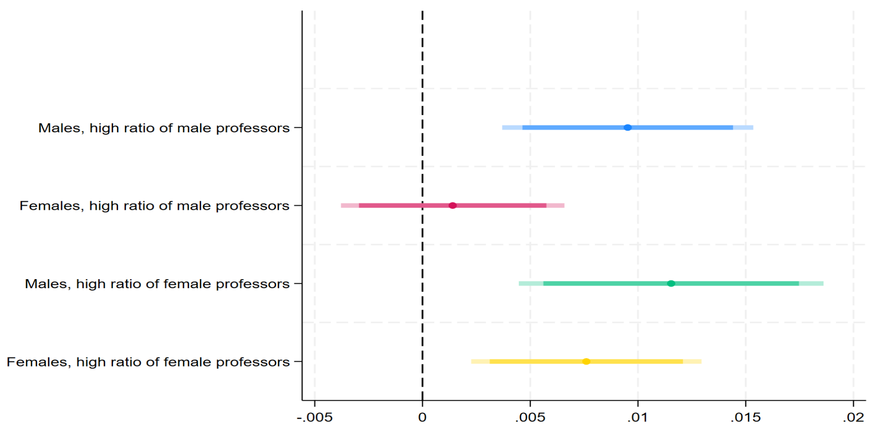


Note: Figure shows estimates (and associated Confidence Intervals) for the effects of class rank on the probability of being enrolled in a PhD one year after graduation, by broadly-defined field of study, and gender.

Figure A.6: Rank effects on interest in a PhD and PhD enrollment, by gender and exposure to female professors



(a) Interest in doctoral studies



(b) Enrollment in PhD one year after graduation

Note: Figure plots estimates and 95% Confidence Intervals for the effect of class rank on the probability of expressing interest in doctoral studies and on actual PhD enrollment one year after graduation, separately by gender and by level of exposure to female professors. Each graduate is matched to a measure of the share of full professors who are female based on their Master's program's scientific discipline (classified according to OECD (2015)) and the academic year of enrollment. A discipline-year cell is defined as having a high ratio of female professors if the percentage of female full professors exceeds the sample median (25%).

A.4 Additional robustness checks

A.4.1 Re-centered Rank Exercise

The re-centered rank is constructed in two steps. In the first step, I compute an expected value for rank for each student: the rank they would have obtained had they attended every other cohort of the same degree program. Formally, for each student i enrolled in degree d and cohort c, I compute the ordinal rank of i's high school grade h_i within each alternative cohort (d, c'), for all $c \neq c$. Following the same normalisation used for the baseline rank variable, the ordinal rank of student i in cohort (d, c') is defined as the number of students in that cohort with a high school grade strictly above h_i, divided by the cohort size:

$$\tilde{r}_{i,dc'} = \frac{\#\{j \in (d, c') : h_j > h_i\} - 1}{N_{i,dc'} - 1}$$

Where $N_{i,dc'}$ is the total number of students enrolled in degree d in cohort c'. This is scaled by -10 to match the baseline rank variable, so that 0 corresponds to the top student and 10 to the bottom. The hypothetical rank $\tilde{R}_i$ is then obtained by averaging $\tilde{r}_{i,dc'} \times (-10)$ across all alternative cohorts $c' \neq c$:

$$\tilde{R}_i = \frac{1}{T_d - 1} \sum_{c' \neq c} \tilde{r}_{i,dc'} \times (-10)$$

Where T_d is the total number of cohorts observed for degree d.

In the second step, I re-center the baseline rank variable by including $\tilde{R}_i$ as a control in the regression:

$$Y_{idc} = \alpha + \beta R_{idc} + \delta \tilde{R}_i + \phi_{dc} + e_{idc} \tag{5}$$

$\tilde{R}_i$ absorbs the component of rank that is mechanically determined by own ability and degree program characteristics, leaving only the variation in rank that arises from the idiosyncratic ability composition of the cohort a student happened to attend.

The logic of this exercise follows Borusyak, Caceres Bravo and Hull (2025), who show that when a treatment or instrument combines exogenous shocks with potentially endogenous exposure, omitted variable bias is governed by the conditional expectation of the treatment given the endogenous components. Adjusting for this conditional expectation isolates the exogenous component. In the present context, class rank combines own ability and degree choice (the endogenous component) with the peer ability distribution (the cohort-specific shock). The hypothetical rank serves as the conditional expectation of rank given own ability, and controlling for it removes the endogenous ability component, isolating the variation that comes from the luck of cohort assignment.

Table A.1 reports the baseline results and the results using this re-centered rank approach.

Table A.1: Sensitivity to re-centering Rank

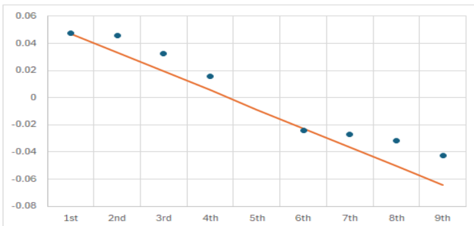
	Employment	PhD enrollment	GPA	Cum Laude	Want to do a PhD	Reserve wage	Avg. monthly earnings
Baseline estimates	-0.014***	0.006***	0.047***	0.015***	0.008***	-7.12*	-6.79
	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)	(3.95)	(4.32)
Re-centered Rank estimates							
Re-centered Rank	-0.013***	0.009***	0.151***	0.023***	0.008***	-16.79***	-0.03
	(0.004)	(0.002)	(0.043)	(0.003)	(0.003)	(5.41)	(5.11)
$\tilde{R}_i$	0.011***	-0.005**	0.533***	0.024***	-0.003	8.37	-3.49
	(0.004)	(0.002)	(0.043)	(0.004)	(0.003)	(5.92)	(5.44)
Re-centered Rank estimates (without degree-by-cohort fixed effects)							
Re-centered Rank	-0.008	0.014***	0.285***	0.031***	0.017***	11.15	31.90***
	(0.006)	(0.003)	(0.090)	(0.004)	(0.003)	(7.48)	(6.60)
$\tilde{R}_i$	0.004	-0.009**	0.404***	0.017***	-0.012	-21.09**	-39.65***
	(0.007)	(0.003)	(0.104)	(0.005)	(0.004)	(8.63)	(7.56)

Note: Table reports estimates of class rank effects on the outcomes of interest following the Baseline model (Equation 3) and coefficients of the Re-centered Rank approach (Equation 5) described in Appendix A.4.1.

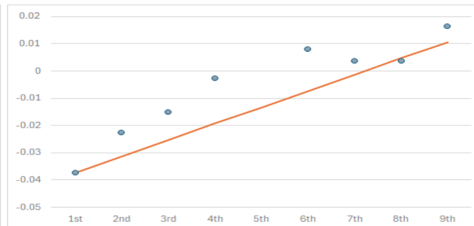
The stability of results across specifications supports the interpretation that rank effects are not driven by residual selection into Master's degree programs or other endogenous characteristics correlated with ability, but reflect the causal effect of relative standing within a cohort estimated by exploiting quasi-random across-cohort variation.

A.4.2 Non-linearities in Rank effects

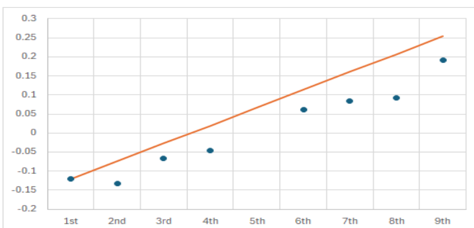
Figure A.7: Linear versus decile-specific rank effects



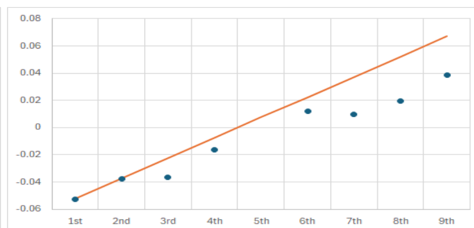
(a) Employment



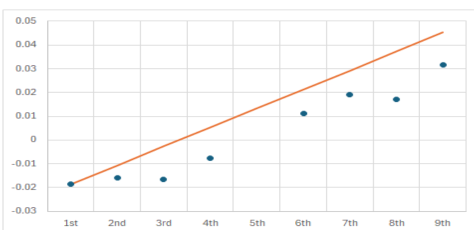
(b) PhD enrollment



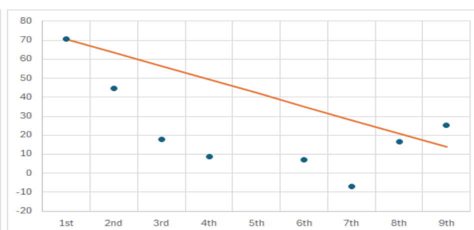
(c) GPA



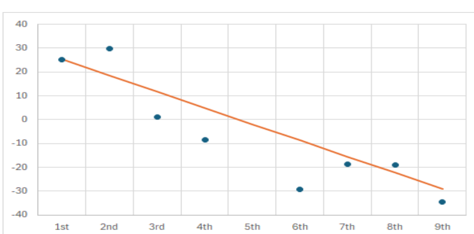
(d) Cum Laude



(e) Want to do a PhD



(f) Reserve wage



(g) Avg. monthly earnings

Note: Figures plot the baseline effect, depicted as the red sloped line, against estimates for each decile, obtained by substituting the continuous rank variable for decile indicators.

A.4.3 Robustness to Rank variable construction

Table A.2: Sensitivity to different Rank specifications

	Employment	PhD enrollment	GPA	Cum Laude	Want to do a PhD	Reserve wage	Avg. monthly earnings
Baseline estimates	-0.014***	0.006***	0.047***	0.015***	0.008***	-7.12*	-6.79
	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)	(3.95)	(4.32)
Using track rank	-0.009**	0.003*	0.030***	0.004	0.009***	-2.85	-5.92
	(0.004)	(0.002)	(0.010)	(0.003)	(0.002)	(5.39)	(5.15)
Using starting year to define cohort	-0.012***	0.005***	0.050***	0.017***	0.006***	-4.90	-7.57*
	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)	(3.53)	(4.17)
Using high-school type to define peer group	-0.011***	0.005***	0.007	0.006***	0.006**	-2.14	0.28
	(0.002)	(0.001)	(0.008)	(0.002)	(0.001)	(2.90)	(3.09)

Note: Table reports estimates of class rank effects on the outcomes of interest across different specifications of the main explanatory variable, $Rank_{hdc}$. The second row represents the results when switching from a "field" rank (number of people with a higher ability, plus one) to a "track" rank (number of people with a lower ability, plus one). The third row represents instead the main results when changing the cohort variable used to define the peer group, instead of the year of graduation, using the year of start of studies, calculated as the difference between graduation year and duration of studies. The fourth row represents the results when using specific high-school track ranks within each class instead of a unique class rank as main explanatory variable.

A.4.4 Multiple Hypothesis Correction

Table A.3: Romano-Wolf adjusted p-values

	(1) Model p-value	(2) Resample p-value	(3) Romano-Wolf p-value
Is working	0.000	0.010	0.010
Is doing a PhD	0.001	0.010	0.010
GPA	0.000	0.010	0.010
Cum Laude	0.307	0.228	0.485
Wants to do a PhD	0.002	0.010	0.010
Reserve wage	0.046	0.010	0.030
Average monthly earnings	0.103	0.050	0.139
Importance of match aspects in a job	0.080	0.020	0.089
Importance of pecuniary aspects in a job	0.474	0.347	0.485
Importance of flexibility aspects in a job	0.322	0.198	0.485

Note: Table reports corrected p-values for the estimates in Table 4 and 5 following Romano and Wolf (2005). Resample p-values come from a bootstrap procedure with 100 replications with clustering at the peer group level.

A.5 Additional results

Table A.4: Rank effects: importance of aspects of a job

	(1) Earnings	(2) Career progression	(3) Stability and security	(4) Gaining skills
Rank	-0.005	-0.004	-0.006	-0.003
	(0.005)	(0.005)	(0.005)	(0.003)
N	46,273	46,219	46,150	46,169
R^2	0.059	0.108	0.049	0.029
	(5) Coherence with studies	(6) Cultural interests	(7) Independence and autonomy	(8) Free time
Rank	0.009*	0.004	0.001	-0.008
	(0.005)	(0.005)	(0.005)	(0.006)
N	46,190	46,042	46,109	46,094
R^2	0.095	0.064	0.028	0.035

Note: Table displays the coefficients associated to class rank for separate regressions, together with the associated sample size (N), and the adjusted R-squared. Dependent variables are self-reported importance of different aspects of a job, measured in a scale ranging from 1 (not important at all) to 5 (very important).All regressions control for a third-degree polynomial of the ability measure, individual controls (gender, age at graduation, region of residence and parental educational attainment) and class fixed effects. Clustered standard errors are reported between parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Table A.6: Rank effects on satisfaction with studies

	(1) Overall	(2) With Professors	(3) With peers	(4) Would choose same degree and same university
Rank	0.011**	0.010*	0.004	0.004*
	(0.005)	(0.005)	(0.005)	(0.002)
N	46,931	46,906	46,786	46,917
R-squared(adj.)	0.061	0.061	0.025	0.045

Note: Table reports estimates of class rank effects on measures of satisfaction with the Master's Degree program. Outcomes (1)-(3) are measured following a Likert scale from 1 (definitely not) to 4 (definitely yes). Outcome (4) is an indicator variable based on a survey item in which the respondent is asked Looking backwards, would you have enrolled again?, with possible answers being Yes, same degree and university/Yes, same university but different degree/Yes, same degree but different university/Yes, different degree and university/I would not enroll in a Master's Degree.

Table A.5: Rank effects: willingness to accept employment types

	(1) Insertion	(2) Project-based	(3) Temporary	(4) Interim
Rank	0.016*	0.022**	-0.017	-0.034
	(0.008)	(0.010)	(0.032)	(0.039)
N	29,550	31,083	47,169	47,169
R^2	0.088	0.076	0.035	0.036
	(5) Part-time	(6) Full-time	(7) Internship	(8) Remote work
Rank	-0.021	-0.021	0.014*	0.004
	(0.032)	(0.021)	(0.007)	(0.036)
N	47,169	47,169	45,241	47,169
R^2	0.039	0.032	0.105	0.044
	(9) Occasional collaboration	(10) Increasing responsibilities	(11) Apprenticeship	(12) Self-employment
Rank	-0.098	-0.098	0.015**	-0.027
	(0.101)	(0.090)	(0.007)	(0.035)
N	14,183	16,086	45,140	47,169
R^2	0.054	0.047	0.118	0.038

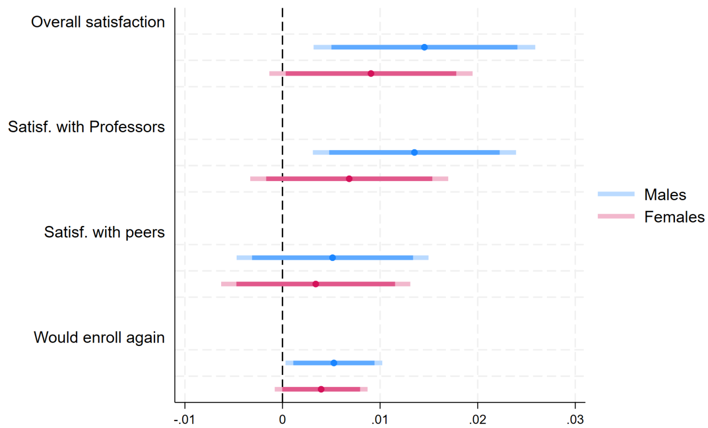
Note: Table displays the coefficients associated to class rank for separate regressions, together with the associated sample size (N), and the adjusted R-squared. Dependent variables are self-reported willigness to accept different types of employment contracts, measured in a scale ranging from 1 (very unlikely) to 5 (very likely).All regressions control for a third-degree polynomial of the ability measure, individual controls (gender, age at graduation, region of residence and parental educational attainment) and class fixed effects. Clustered standard errors are reported between parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Table A.7: Rank effects on job satisfaction and skill use

Panel A: job satisfaction			
	(1)	(2)	
	Job satisfaction (1-10)	High (>8) satisf.	
Rank	-0.009	-0.002	
	(0.017)	(0.004)	
N	19295	19295	
R-squared(adj.)	0.002	0.000	
Panel B: use of skills at job			
	(3)	(4)	(5)
	High use of skills	Limited use of skills	No use of skills
Rank	-0.004	0.003	0.001
	(0.004)	(0.004)	(0.003)
N	21177	21177	21177
R-squared(adj.)	0.002	0.000	0.003
Panel C: perceived efficacy of Master's degree for job			
	(6)	(7)	
	Effective/very effective	Little or not at all effective	
Rank	-0.006*	0.002	
	(0.004)	(0.003)	
N	20714	20714	
R-squared(adj.)	0.002	0.003	
Panel D: Master's degree needed for job			
	(8)	(9)	(10)
	Degree needed	Degree useful	Not required nor useful
Rank	-0.008**	0.008**	0.000
	(0.004)	(0.004)	(0.003)
N	21177	21177	21177
R-squared(adj.)	0.002	0.002	0.002

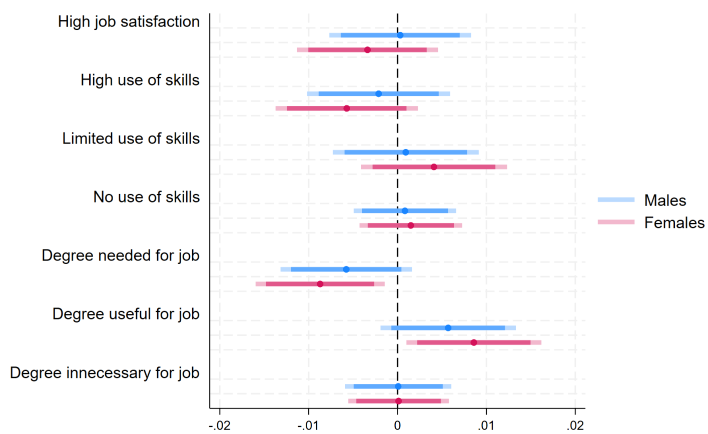
Note: Table reports estimates of class rank effects on self-reported measures of job satisfaction, use of skills acquired at the Master's degree on their job, perceived match between the studies and the job, and whether the Master's degree was necessary or useful for the job.

Figure A.8: Satisfaction with studies, by gender



Note: Figure plots coefficients for class rank and associated Confidence Intervals for regressions in which the dependent variables are measures of satisfaction with the completed degree.

Figure A.9: Job satisfaction and skill use, by gender



Note: Figure plots coefficients for class rank and associated Confidence Intervals for regressions in which the dependent variables are self-reported measures of job satisfaction, use of skills at the job and match between the studies and the job.