I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17082

The Impact of Peer Performance and Relative Rank on Managerial Career Attainment: Evidence from College Students

Rafael P. Ribas
Breno Sampaio
Giuseppe Trevisan

JUNE 2024

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17082

The Impact of Peer Performance and Relative Rank on Managerial Career Attainment: Evidence from College Students

Rafael P. Ribas
Boise State University

Breno Sampaio
Universidade Federal de Pernambuco and IZA

Giuseppe Trevisan
Universidade Federal de Pernambuco

JUNE 2024

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Impact of Peer Performance and Relative Rank on Managerial Career Attainment: Evidence from College Students*

The ranking system within academic environments may impact future professional trajectories. Examining the influence of class rank on college students' managerial attainment is crucial for understanding some determinants of career advancement. This paper estimates the effect of a low rank in a highperforming class on the probability of college students attaining a managerial position in the future. Our data combine administrative records from a highly selective university in Brazil and employment registries. For most programs, this university divides first-year students into two classes based on their preferences and admission scores. In a regression discontinuity design, we control for students' preferences and inherent skills by comparing the last student admitted to the high-score class (the 'first class') with the first student excluded from this class, who joins the 'second class.' Results show that the last student in the first class is 10 percentage points less likely to attain a managerial position soon after graduating than a similar student in the second class. Although this effect is initially similar between genders, it diminishes for men over time while persisting for women. Overall, our study indicates that better-performing peers can hinder a student's managerial career by lowering their relative rank in the classroom.

JEL Classification: D91, I23, J16, J24, M51

Keywords: leadership, relative performance, learning environment, peer effect, ranking effect

Corresponding author:
Breno Sampaio
Universidade Federal de Pernambuco
Av. Prof. Moraes Rego
1235 - Cidade Universitária
Recife - PE, 50670-901
Brazil
E-mail: brenosampaio@ufpe.br

* We thank the helpful comments from Adam Booij, Ben Elsner, Bruno Ferman, Isabel Fernandez-Mateo, Claudio Ferraz, Ingo Isphording, Felice Klein, Cecilia Machado, Roberto Nisticò, Hessel Oosterbeek, Cristine Pinto, Erik Plug, Vladimir Ponczek, Rudi Rocha, Rodrigo Soares, Yuki Takahashi, Gabriel Ulyssea, seminar participants at Boise State University, University of Amsterdam, and conference participants at the 2nd Brazilian Meeting in Family and Gender Economics. We acknowledge provision of data from NTI/UFPE, COVEST/COPSET, and the Brazilian Ministry of Labour and Employment, and support from Dieison Casagrande, Henrique Lima, and Domingos Mendes in obtaining them.

1 Introduction

Many factors influence the likelihood of an individual attaining a managerial position, from personality traits (Judge et al., 2002) to socioeconomic background (Li, Arvey and Song, 2011). Understanding these factors is crucial for companies seeking new leaders and universities aiming to foster students' leadership skills. Among those factors, educational level and quality appear to have a significant role (Useem and Karabel, 1986; Spilerman and Lunde, 1991; Judge et al., 1995). Still, some studies consider formal education not only as a means to improve students' cognitive skills and abilities but also as an opportunity to enhance their levels of self-efficacy and confidence, their identity as a leader, and their social network, which help explain different career paths (Yang, Chawla and Uzzi, 2019; Offermann et al., 2020).

While universities may equip students with tools and opportunities to improve their leadership skills, the development of essential competencies for managerial roles can also be highly influenced by their interaction with peers. However, the impact of interacting with classmates on a student's career is not straightforward. On the one hand, better-performing peers can enrich someone's learning experience in college and professional network later (Sacerdote, 2001; Marmaros and Sacerdote, 2002; Carrell, Fullerton and West, 2009), making their skills more attractive and noticeable to employers. On the other hand, having those peers implies a lower rank for a student in the classroom. With higher-ranking peers, this student may change their perception of what it takes to be a leader, raising their standards and lowering their self-concept and aspirations (Davis, 1966; Cicala, Fryer and Spenkuch, 2017; Murphy and Weinhardt, 2020).

This paper examines how a low rank in a high-performing class versus a high rank in a low-performing class affects a student's likelihood of attaining a future managerial position. To identify the causal impact, we utilize the rule of class assignment of a highly selective university in Brazil. When students apply to a program in this university, they must inform whether they prefer to start in the fall semester (referred to as the 'first class') or in the spring (the 'second class'). All applicants then take the entrance exam together. After the exam, every applicant's score is made public, and the top-scoring applicants for each program are invited to join their preferred class. Since the two classes have the same size and the first class is oversubscribed, the class preference of lower-scoring students is ignored, and they can enroll only in the second class. This constraint on students' class choice allows us to examine students who are similar in many ways but attend different classes with different peers. By applying a regression discontinuity design (RDD), we compare the expected outcomes of the last student enrolled in the first class and the first student who could not choose their class and enrolled in the second class. The former has better-performing peers but the lowest rank within their class, whereas the latter has a higher in-class rank but with peers who have not performed as well as the first-class students on the entrance exam. We name the difference in their expected outcomes the 'last-in-class' effect.

Our results show that the last student in the first class is about 10 percentage points (p.p.) less likely to become a manager two years after their expected graduation than a similar student in the second class. This implies that better-performing peers can significantly curb a student's managerial career. When applying different specifications for our RDD, the estimates for the last-in-class effect are found to be robust, varying between -9 p.p. and -13 p.p. in the first four years after expected graduation. Furthermore, the effect is more salient in cohorts with little difference in peer performance between the first and second classes. As the difference in peer performance between classes increases, the last-in-class effect weakens.

These findings indicate that, shortly after graduation, the last-in-class effect is primarily driven by the adverse impact of a lower relative rank in the first class (versus the higher rank in the second class), which outweighs the positive effect of a higher peer performance. Five years after the expected graduation, though, the negative ranking effect becomes smaller and insignificant, while the positive effect of peer performance persists. On average, students at the bottom of the first class become as likely to attain a managerial position as similar students in the second class.

It is worth stressing that our analysis is confined to students enrolled in the same program at a highly selective university. Therefore, students in the first and second classes are more similar to each other than to students at other institutions, which may explain why the relative rank within class is the primary determinant of the last-in-class effect. Further results indicate that neither differences in work experience nor academic outcomes, such as the grade point average (GPA), time to graduation, and rank at graduation, mediate the negative effect on managerial attainment. The only standing factor explaining this effect is how a student's grades compare to their classmates'. Factors such as work experience and networking with peers appear to rather weaken the last-in-class effect over time. However, the effect decreases only for men. For low-ranking women in the first class, the last-in-class effect stays around -10 p.p. for at least six years after their expected graduation. The persistent effect on women is observed even if they attend the same program and accumulate similar work experience as low-ranking men in the first class.

The contribution of our paper is threefold. First, we present unique evidence that joining a class with better-performing peers can significantly undermine a student's managerial career due to the adverse effect of a lower rank. Some studies point out that the effect of high-performing peers in college can be negative, but they are mostly focused on short-term outcomes, such as academic performance, probability of graduation, and socio-emotional skills (e.g., Sacerdote, 2001; Booij, Leuven and Oosterbeek, 2017; Dasgupta et al., 2020; Elsner, Isphording and Zölitz, 2021). More broadly, our study also provides new insights into the literature on peer effects in the workplace (Mas and Moretti, 2009; Nanda and Sørensen, 2010; Tartari, Perkmann and Salter, 2014; Brune, Chyn and Kerwin, 2022), pointing out that the effect of co-workers' performance on an employee's career advancement can be negative due to relative comparisons.

The second contribution is the evidence that the ranking effect on managerial attainment is not necessarily channeled only through individual performance. In a context where the effects on academic outcomes are small and insignificant, we still find large and significant effects on managerial attainment. This finding is in line with previous studies pointing out that other factors besides cognitive skills and formal education affect students' career paths (Judge et al., 2002; Li, Arvey and Song, 2011; Offermann et al., 2020).

The third contribution relates to the potential attenuators of the ranking effect. We show that work experience and access to a network of high-performing peers can offset the negative effect of a lower rank. However, these factors tend to favor men more than women. As a result, a lower rank in college is particularly detrimental to women in the long run. This finding is consistent with the existence of cumulative gender disadvantages in the labor market (DiPrete and Soule, 1988; Fernandez-Mateo, 2009; Fitzsimmons, Callan and Paulsen, 2014). Given other barriers that hinder women's career advancement (Hultin and Szulkin, 1999; Foschi, 2000; Castilla, 2008), they find it harder to overcome the negative effect of a low rank in college. Our results are also consistent with gender differences in social networks, which are less favorable to women with respect to job opportunities (Yang, Chawla and Uzzi, 2019; Lindenlaub and Prummer, 2020).

2 Previous Literature

According to human capital theory (Becker, 1964), higher education is correlated with managerial attainment due to the effect of general training on individual skills, a pattern that is broadly supported by empirical evidence (e.g., Wise, 1975; Useem and Karabel, 1986; Spilerman and Lunde, 1991). Beyond fostering cognitive skills, higher education can also be pivotal in the development of a leadership identity through experiential opportunities and orientation (Komives, 2011; Offermann et al., 2020). Moreover, some studies point out that cognitive ability alone is not a sufficient determinant of managerial attainment (e.g., Fiedler, 1986; Li, Arvey and Song, 2011). Socio-emotional traits such as self-esteem, attentiveness, and interpersonal skills are found to increase managerial effectiveness and the likelihood of attaining a leadership role (George, 2000; Judge et al., 2002; Li, Arvey and Song, 2011; Hoffman and Tadelis, 2021).

Another important factor contributing to educational achievement and career success is the composition of peers in the classroom. Extensive research demonstrates that students who are surrounded by high-achieving peers tend to perform better academically (e.g., Hanushek et al., 2003; Zimmerman, 2003; Carrell, Fullerton and West, 2009). This peer effect on learning outcomes occurs for various reasons. For instance, higher-performing peers may provide better support in the learning process (Hahn et al., 2019), exert greater effort from students through competitive rivalry (Beugnot et al., 2019), create social pressure that fosters academic engagement (Bursztyn and Jensen, 2015), and encourage instructors to elevate their teaching standards (Duflo, Dupas and Kremer, 2011). In addition to the impact on academic performance, the interaction with higher-achieving peers can also enhance a student's social network, providing better job opportunities in the future (Marmaros and Sacerdote, 2002; Zimmerman, 2019).

On the other hand, the presence of better-performing peers can adversely affect a student's socio-emotional skills and career aspirations by lowering their relative rank in the classroom. In sociology, the work of Davis (1966) lays the foundation for a large body of literature on 'contextual' effects (e.g., Meyer, 1970; Nelson, 1972; Jonsson and Mood, 2008). These studies generally consider two conflicting forces shaping career aspirations. The first is the supportive effect of the environment created by high achievers. The second is the "frog pond" effect, which lowers students' aspirations as they compare their academic ability with others. In psychology, Marsh and Parker (1984) introduce a similar concept, named the 'big-fish-little-pond' effect, providing evidence that students in low-ability groups present higher self-concepts than similar students in high-ability groups.

Using data from primary and secondary schools, recent studies estimate the causal effect of a lower rank. They find that, controlling for inherent skills, a lower rank reduces students' confidence, self-esteem, and perceived abilities (Cicala, Fryer and Spenkuch, 2017; Pagani, Comi and Origo, 2021; Murphy and Weinhardt, 2020; Zarate, 2023), their probability of going to college (Elsner and Isphording, 2017), and their future earnings (Denning, Murphy and Weinhardt, 2023). A lower rank is also found to reduce test scores (Tincani, 2017; Murphy and Weinhardt, 2020; Fabregas, 2023), which is attributed to changes in self-perception (Cicala, Fryer and Spenkuch, 2017).

Closely related to the present study is the work of Elsner, Isphording and Zölitz (2021), Ribas, Sampaio and Trevisan (2020), Bertoni and Nisticò (2023), and Dasgupta et al. (2020), who estimate the effect of class ranks in college. Elsner, Isphording and Zölitz (2021) and Ribas, Sampaio and Trevisan (2020) find that a lower rank among peers increases a student's chance of switching majors. Ribas, Sampaio and Trevisan (2020) and Bertoni and Nisticò (2023) point out that an absolute increase in peer quality within the classroom can partially offset the adverse effect of a lower relative rank on academic outcomes. As regards socio-emotional skills, Dasgupta et al. (2020) show that the peer environment in selective colleges reduces students' overconfidence, extraversion, and conscientiousness due to relative rank concerns.

3 Institutional Background and Data

3.1 Institutional Background

The *Universidade Federal de Pernambuco* (UFPE) is a flagship university in the Northeastern region of Brazil and one of the top ten public institutions in the country. Fifty-seven out of 99 of its undergraduate programs offer two options for the students. They can start studying either in the first semester of the academic year (the 'first class') or in the second semester (the 'second class'). During the application to UFPE, the applicants must specify the program of study they want to enroll in and the semester they want to start.

To enter the chosen program, applicants must take an exam called *vestibular*, which has two rounds. The first round assesses students' general knowledge and eliminates about 40% of the applicants. In the second round, the remaining applicants are tested on subjects specifically required for their program. The final score is a weighted average of the first- and second-round scores. After the *vestibular*, the admissions committee (*Comissão para o Vestibular*, COVEST) sends acceptance letters to the top-scoring applicants in each program until all places in the first and second classes are taken. On average, only 10% of the applicants receive the acceptance offer, and 84% of the admitted applicants enroll at UFPE.

As regards the class assignment, the first and second classes must have the same number of students, but most of the admitted students prefer to attend the first class. Accordingly, some of the admitted students who would prefer to be in the first class can only enroll in the second. The order of preference to enroll in the first class is strictly based on the students' entrance scores. This assignment mechanism implies that there is a cutoff point to enter the first class and the median score is higher in the first class than in the second. Furthermore, after the application, students admitted to the first class cannot switch to the second class. Section A of the Online Appendix presents more institutional details.

3.2 Data Sources and Sample

For this study, we collected administrative records from 13,505 first-year students at UFPE. In this sample, 7,411 are women and 6,094 are men. Our data come from three different sources. The first is COVEST, which provides the first- and second-round scores and the final entrance score of every applicant from 2002 to 2007. Since all applicants take the same exam in the first round, their first-round score is our proxy for cognitive skills, which we use to compare students across programs. The final entrance score is the determinant of class assignment within program cohorts.

The COVEST data also include the number of times each applicant did the entrance exam in the past and a long set of socioeconomic characteristics. Given this information, we restrict our sample to applicants admitted to UFPE for the first time and enrolled in a program with two entry classes, excluding those who dropped out before the end of the first semester. We also exclude applicants already enrolled in higher education before applying to UFPE because their career aspirations tend to be less sensitive to their peers' performance. The final sample comprises 75% of the first-year students enrolled in two-class programs, representing 52% of all first-year students.

The second data source is UFPE's Academic Information System (*Sistema de Informações e Gestão Acadêmica*, SIGA), which provides information on students' enrollment, course grades, and status. The third is the Annual Social Information Report (*Relação Anual de Informações Sociais*, RAIS) from the Ministry of Labor, which contains information on every registered employee in Brazil. Using students' social security numbers (*Cadastro de Pessoa Física*, CPF), we match the COVEST sample with RAIS to obtain their four-digit occupation code (*Classificação Brasileira de Ocupação*, CBO) from 2008 to 2014.

To count the years after college, we consider that time to graduation varies from three to six years depending on the program of study. For each program, we use the year of expected graduation as the reference. To make first and second classes comparable, we also count the years after college from the month of expected graduation in each class.

With the occupation codes from RAIS, we identify whether students become middle- or top-level managers up to six years after their expected graduation. Our classification includes all roles from president and CEO to branch and department managers, but it excludes low-level positions such as assistant manager and supervisor. We consider managerial positions in for-profit companies, government agencies, and nonprofit organizations. Table S2 of the Online Appendix presents the list of occupation codes, highlighting those classified as managerial positions. The final sample is restricted to students employed by the time of the assessment. In this sample, managers earn 26% more than non-managers (Table S3, Online Appendix).

Table A1 of the Appendix presents descriptive statistics for most of the variables in our dataset. Due to students' preference for the first class, the average entrance score and first-round score are higher in the first class. The average GPA in the first semester and the graduation rate are also higher in the first class. In our sample, about 10% of the students become managers six years after their expected graduation. Although the probability of having a high-skilled occupation in the future is higher in the first class, the probability of attaining a managerial position is not.

4 Empirical Strategy

This section describes the application of two empirical models. The first model is the RDD, used to estimate the last-in-class effect on future managerial attainment. The RDD consists of estimating the relationship between the outcome (i.e., managerial attainment) and the entrance score, above and below the first-class cutoff. The discontinuity in that relationship is the difference between the predicted outcomes just above and just below the cutoff (Imbens and Lemieux, 2008). The last-in-class effect is identified by dividing the difference in the expected outcome and the difference in the probability of attending the first class (Hahn, Todd and Van der Klaauw, 2001).

The second model estimates the relationship between the last-in-class effect and the difference in peer performance between classes. This estimation has two purposes. The first is to verify whether our findings are sensitive to changes in peer performance. The second is to examine the last-in-class effect under a minimal difference in peer composition to verify whether the relative rank alone affects a student's managerial attainment.

4.1 Regression Discontinuity Design

The RDD yields a consistent estimate for the Local Average Treatment Effect (LATE) because, in theory, students who are just above and just below the cutoff are very similar in almost every aspect. The only difference between them is that the student below the cutoff was forced to attend the second class. At the first-class cutoff, the constraint on class choice is considered exogenous, so it works as an instrumental variable.

Let x_{ki} be the entrance score of student i in program k and $\underline{x}_k$ be the score of the last student joining the first class. If x_{ki} is greater than or equal to $\underline{x}_k$, then the student may go either to class one ($c = 1$) or to class two ($c = 2$) according to their initial choice. If x_{ki} is less than $\underline{x}_k$, then the student must join the second class, regardless of their class preference. This rule implies that the probability of attending the first class below the cutoff is zero, while the probability of attending the first class above the cutoff is greater than zero but less than one.

For any outcome y, the last-in-class effect refers to the difference in expected values conditional on attending the first and second classes. Since students attending these classes can be different in many pre-established characteristics, the expected values are also conditional on having an entrance score equal to the first-class cutoff:

$$\Delta y \equiv E\big(y|c=1, x=\underline{x}_k\big) - E\big(y|c=2, x=\underline{x}_k\big)$$

According to Hahn, Todd and Van der Klaauw (2001) and Imbens and Lemieux (2008), the LATE, Δy, is identified by the following fuzzy RDD estimand:

$$\Delta y = \frac{\lim_{x\downarrow\underline{x}} E\left(y|x \geq \underline{x}_k\right) - \lim_{x\uparrow\underline{x}} E\left(y|x < \underline{x}_k\right)}{\lim_{x\downarrow\underline{x}} \Pr\left(c=1|x \geq \underline{x}_k\right) - \lim_{x\uparrow\underline{x}} \Pr\left(c=1|x < \underline{x}_k\right)}. \quad (1)$$

This estimand is the ratio of two differences. The numerator is the difference between conditional expected outcomes approaching the first-class cutoff from above and from below. This difference is the sharp RDD estimand for the intention-to-treat (ITT) effect, which represents the impact of having an entrance score above the first-class cutoff. The denominator is the difference between conditional probabilities of enrolling in the first class approaching the cutoff from above and from below. In our case, notice that the probability approaching the cutoff from below is zero — i.e., $\lim_{x\uparrow\underline{x}} \Pr\left(c=1|x < \underline{x}_k\right) = 0$ — because no student below the cutoff can enroll in the first class.

A necessary condition to identify the LATE is that the difference in class enrollment (i.e., the denominator) is close enough to one so that the instrument is sufficiently strong. This condition is satisfied if students systematically prefer to enroll in the first class. Graph A of Figure 1 confirms the strength of the discontinuity in class enrollment. At the cutoff, where the standardized entrance score is zero, the probability of attending the first class is 74% from above and 0% from below. This difference gives us enough statistical power to compare the last students who had the right to attend the first class and the first students who did not have this privilege.

Although these students have nearly the same entrance score, graph B shows that those below the first-class cutoff are ranked almost 50 p.p. higher in their class than those above the cutoff. On the downside, graph C shows that the students right below the cutoff tend to join worse-performing classes than those right above. At the cutoff, the expected difference in the median first-round score of the attended class is close to 0.2 standard deviations (s.d.). Considering the discontinuities in graphs B and C, our RDD identifies the net effect of being at the bottom of a better-performing class instead of attending the second class.

Another condition to identify the LATE is that students cannot manipulate their entrance scores, and their scores do not affect their presence in the sample. Although applicants do not know the cutoff between classes and their rank when they apply to the university and choose their class, they could decline the offer as soon as the entrance scores and class rankings are disclosed (Bond et al., 2018). As a result, the density of students would be discontinuous at the cutoff, and the endogenous selection would imply that students above the cutoff are not similar to those below. To verify this issue, we run the McCrary's (2008) test for density discontinuity at the cutoff, and our results show no evidence that it is true (Figure S1, Online Appendix). We also test for discontinuities in the characteristics of students and their instructors at the cutoff and find no significant difference (Table S4, Online Appendix).[1] Therefore, the assigned class does not seem to affect the decision of students near the cutoff to enroll in the admitted program.

Regarding the outcome, we define it as a binary variable indicating whether a student has a managerial position in a certain year in the future or not. We also investigate other outcomes related to work experience and academic performance. To estimate equation (1), we use local linear regressions with triangular kernel weighting. Details on the estimation procedure are in Section B.1 of the Online Appendix. The main regressions do not include control variables or fixed effects

[1] Still, the same instructor may treat first and second classes differently. Since it comes from the interaction between teachers' and students' skills, we assume that this behavior derives from the difference in the skill distribution between classes.

since their absence does not impose restrictions on the validity of the RDD. Robust standard errors and optimal bandwidths are obtained as described by Calonico, Cattaneo and Titiunik (2014).

4.2 Regression Discontinuity Conditional to Peer Performance

Due to a rich variation in class composition across program cohorts, we can also identify the heterogeneity of the last-in-class effect with respect to peer performance. In some cohorts, the difference in classmates' scores between classes is four times as large as the average difference shown in graph C of Figure 1. In others, it is close to zero (see Figure S2, Online Appendix). By observing the difference in peer performance between classes in the same program cohort, we can examine how the last-in-class effect varies with peer quality.

Let $\Delta q_k = (q_{1k} - q_{2k})$ be the observed difference in peer performance between classes in the same program cohort, k. Then the LATE conditional to the difference in peer performance is:

$$\Delta\left(y|\Delta q_k\right) \equiv \frac{\lim_{x\downarrow \underline{x}} E\left(y|x \geq \underline{x}_k, \Delta q_k\right) - \lim_{x\uparrow \underline{x}} E\left(y|x < \underline{x}_k, \Delta q_k\right)}{\lim_{x\downarrow \underline{x}} \Pr\left(c=1|x \geq \underline{x}_k, \Delta q_k\right) - \lim_{x\uparrow \underline{x}} \Pr\left(c=1|x < \underline{x}_k, \Delta q_k\right)}. \tag{2}$$

As Δq_k decreases, Δy is still identified because the running variable, x, is standardized within program cohorts. The class performance, q_{ck}, is standardized across programs in the same year, so that students in different programs are comparable in absolute terms.

In theory, even if Δq_k is small, enrolling in the first or second class can have considerable implications for a student's relative rank, as shown in Figure 2. In more homogeneous cohorts, like cohort C, the difference in peer performance between classes is smaller than in other cohorts. Even so, the discontinuity in student's relative rank is similar across cohorts. Thus, for cohort C, the last-in-class effect should be mostly driven by the difference in relative rank. By centering our estimates on this type of cohort, we check whether the last-in-class effect is determined by the relative rank. In addition to the ranking effect, if peer performance plays a role, the LATE should change as Δq_k increases. In fact, the first derivative of Δy_k with respect to Δq_k is a lower bound for the marginal effect of peer performance (see Section B.2, Online Appendix).

In practice, the running variable and peer performance may present a strong collinearity. To avoid the problem of under-identification, we calculate the running variable using the applicants' final entrance score and the peer performance using the first-round scores. These scores are still correlated, but not mechanically. To confirm that we have enough statistical power in the first stage even when the classes are very similar, we test for the discontinuity in the assigned class under different scenarios (see Table S5, Online Appendix).

To estimate equation (2), we use local linear regressions with triangular kernel weighting. Details on the estimation procedure are in Section B.2 of the Online Appendix. Robust standard errors and optimal bandwidths are obtained as described by Calonico, Cattaneo and Titiunik (2014).

5 Results

This section presents our results in two parts. First, we investigate the average effect on managerial attainment for each year after the expected graduation from college, along with some robustness checks and the analysis of potential mediators. Then, we provide separate estimates for men and women and examine possible mechanisms that might explain the gender differences in the estimates.

5.1 The Average Last-in-Class Effect

5.1.1 The Last-in-Class Effect on Managerial Attainment

To evaluate the impact of attending the first class as opposed to the second class on students' future managerial attainment, we apply the fuzzy RDD estimator. This estimator compares the last students who entered the first class with the first students left out of the first class. The comparison is made in terms of holding or not holding a managerial position in the years following their expected graduation.

Figure 3 provides the estimated last-in-class effect on future managerial attainment. The vertical axis presents the magnitudes of the effect, and the horizontal axis has the years after the expected graduation. The years are counted from the semester that the students were supposed to graduate in their original major. Each blue dot in the figure represents a point estimate obtained from a fuzzy RDD, as shown in equation (1). The darker and lighter shaded areas represent 90% and 95% confidence intervals, respectively.

Results in this figure show neither large nor significant effects around the year of expected graduation (year zero). Two years after the expected graduation, though, students at the bottom of the first class are 10 p.p. less prone to attain a managerial position than similar students who attended the second class. This effect is significant at the 5% level and considered large given that the probability of being a manager is about 10% in the whole sample. In years three and four, the last-in-class effect fluctuates between -8 p.p. and -11 p.p., remaining significant at the 5% level. Nevertheless, the effect becomes weaker and insignificant five to six years after the expected graduation, varying between -2 p.p. and -5 p.p.

If anything, these results indicate that being at the bottom of the better-performing class prevents students from attaining a managerial position shortly after college. However, this effect appears to be only momentary, disappearing over time. In Section 5.2, we show that the long-run effect varies by gender, being more persistent for women than for men.

5.1.2 Robustness Checks

To verify the robustness of our findings, we now focus on two outcomes: having a managerial position anytime until year four and being a manager in year five. The estimated last-in-class effects on these two outcomes are shown in Table 1. Each horizontal panel of this table presents the estimated effects on a separate outcome. Each column presents the estimates using a different sample or specification. Given the combinations of outcomes on the panels and specifications on the columns, each point estimate is obtained from a separate regression. For each point estimate, this table also displays the standard errors in parentheses and the p-values in brackets.

Column (1) of Table 1 presents the results using the same sample and specification as in Figure 3. If we consider the probability of attaining a managerial position anytime until year four, the last-in-class effect jumps to -13 p.p., which is slightly higher than the effects between years two and four in Figure 3. In year five, the estimated effect is the same as before, -2 p.p.

Results in column (2) use the sample of all admitted students, including those already in college before admission. In column (3), the RDD controls for program fixed effects. In column (4), we compare only the two nearest students on each side of the cutoff for each program cohort. In column (5), we apply a broader definition of manager, which includes low-level positions, such as assistant manager and supervisor. Overall, the last-in-class effect until year four varies between -9 p.p. and -13 p.p., with all estimates being significant at the 5% level. In year five, the estimated effects vary between 3 p.p. and -7 p.p., with all estimates being insignificant at the 5% level. The only specification that shows a significant effect at the 10% level is in column (4).

We also find that our RDD estimates are robust under a series of alternative bandwidths. Around the optimal bandwidth, applied in Table 1, the effect until year four varies between -10 p.p. and -13 p.p., while the effect in year five varies between -2 p.p. and -7 p.p. (see Figure S3, Online Appendix). Therefore, the pattern displayed in Figure 3 is also found under a series of alternative samples and specifications.

5.1.3 Potential Mediators

Two possible mediators for the initial effects on managerial attainment are academic performance and work experience. In the last two columns of Table 1, we re-estimate the last-in-class effect controlling for these types of outcomes. For academic performance, we consider covariates such as GPA, semester of graduation, rank at graduation, and the probabilities of graduating on time, switching programs, and graduating in the original program.[2] For work experience, we consider

[2]See the last-in-class effect on these variables in Table S6 of the Online Appendix.

years of experience, number of previous jobs, current job tenure, low-level management experience, STEM experience, high-skilled experience, and migration to another state.[3]

In columns (6) and (7) of Table 1, we estimate the last-in-class effect controlling for academic outcomes and work experience, respectively. As observed in this table, the estimated effects remain largely unchanged, varying between −0.01 p.p. and 0.01 p.p. from the baseline model in column (1). Therefore, characteristics that employers might observe on paper, such as academic transcripts and work experience, cannot explain the effect on managerial attainment. In Section 5.2.3, we discuss why work experience is not a mediator for the negative last-in-class effect.

In terms of academic performance, Table A2 of the Appendix confirms that the last-in-class effect on GPA is small and insignificant for all the semesters in college. However, the effect on the relative rank within course sections in the first semester is large and significant at the 1% level, reducing a student's rank by 0.22 s.d. Afterwards, the effect on rank becomes gradually weaker, losing significance after the fourth semester. Accordingly, the negative effect on managerial attainment seems to correlate with students' rank in the classroom early in college, something that future employers do not directly observe. Below, we examine how students' rank and peer performance influence the last-in-class effect.

5.1.4 Sensitivity to Peer Performance

The discontinuity in class enrollment with respect to entrance scores implies significant differences in class rank and peer performance for students around the first-class cutoff (Figure 1). To verify how rank and peer performance interact, we estimate the relationship between the last-in-class effect and the difference in peer performance between classes across program cohorts. The smaller the difference in peer performance, the weaker its contribution to the last-in-class effect, leaving the class rank as the only possible determinant. Although this exercise cannot perfectly disentangle the effect of rank from the effect of peer performance, it may indicate which channel plays a dominant

[3] See the last-in-class effect on these variables in Table S7 of the Online Appendix.

role in the average last-in-class effect and whether they offset or complement each other.

Figure 4 presents the last-in-class effect (vertical axis) across various levels of the difference in peer performance between classes (horizontal axis). The graphs in Panel A show the effect on managerial attainment through the first four years after expected graduation, whereas those in Panel B show the effect in year five. We also measure peer performance in three different ways: the median score of the assigned class in the first round of the entrance exam (left-hand graphs), the 20th percentile (middle graphs), and the 80th percentile (right-hand graphs). Unlike the leave-out mean, the percentiles provide a full picture of the skill distribution and are not sensitive to individual values. In each graph, the blue dots are point estimates, and the darker and lighter shaded areas represent 90% and 95% confidence intervals, respectively.

The three measures of peer performance we use provide similar patterns. In program cohorts whose difference in peer performance between classes is close to zero, the last-in-class effect through year four (Panel A) is close to -17 p.p., which is at least as negative as the effect in other cohorts. In year five (Panel B), the effect in those cohorts is between zero and 3 p.p. Results are also similar if we consider the difference in standard deviations of the entrance score between classes and the difference between the 20th percentile in the first class and the 80th percentile in the second class (Figure S4, Online Appendix). Considering the minimal difference in peer performance between classes, the enduring negative effect on managerial attainment should be caused by the difference in students' relative rank (see Figure 2).

In Panel A of Figure 4, we also observe that an increase in peer performance in the first class tends to mitigate rather than enhance the last-in-class effect through the first four years. If the 20th percentile of the first class increases by 0.6 s.d. compared to the second class, the last-in-class effect drops from -17 p.p. to -8 p.p. In Panel B, we observe a similar relationship even though the average last-in-class effect is insignificant. In year five, students at the bottom of the first class will be 5 p.p. more likely to attain a managerial position if the absolute performance in their class is at least 0.5 s.d. larger than the performance in the second class. In both panels, the last-in-class effect is more sensitive to peer performance at the bottom of the skill distribution (the 20th centile) than at the top (the 80th centile).

This analysis indicates that, in our sample, the adverse effect of a lower relative rank dominates the positive effect of a higher peer performance in the first class. However, in the long run, the ranking effect weakens while the peer effect persists. Moreover, for the last student in the first class, an increase in the quality of peers near them has a larger positive effect than an increase at the top of the class distribution.

5.2 The Last-in-Class Effect by Gender

In this part, we present the effects on managerial attainment separated by gender, discuss some robustness checks for the effects on men and women, and examine some potential mechanisms for the gender-specific effects, such as differences in academic performance and career paths. This analysis also helps us understand why the average last-in-class effect decreases over time.

5.2.1 The Gender-Specific Effect on Managerial Attainment

Figure 5 presents the last-in-class effect on managerial attainment (vertical axis) for each year after the expected graduation (horizontal axis), splitting the sample by gender. The left-hand graph shows the effects on women, whereas the right-hand graph shows the effects on men. Each blue dot in these graphs represents a point estimate obtained from a fuzzy RDD, as shown in equation (1). The darker and lighter shaded areas represent 90% and 95% confidence intervals, respectively.

This figure indicates that neither men nor women are significantly affected before year two. Between years two and four, the effects are significant and similar between genders, varying from -6 p.p. to -11 p.p. for women and from -10 p.p. to -11 p.p. for men. However, in years five and six, the effect on men becomes positive but insignificant, while the effect on women remains negative and significant, varying from -9 p.p. to -14 p.p.

Similar to the robustness checks in Table 1, Table 2 confirms that the gender-specific effects are robust across different samples and specifications. For women, the effect on managerial attainment through the first four years varies between -11 p.p. and -15 p.p. For men, it varies from -6 p.p. to -12 p.p. In year five, the last-in-class effect on women ranges from -5 p.p. to -13 p.p., whereas the effect on men ranges between zero and 12.5 p.p. The gender differences in the RDD estimates are also robust under a series of alternative bandwidths (Figure S3, Online Appendix).

In terms of mediators, columns (6) and (7) of Table 2 show that the estimated effects on men and women do not significantly change after we control for variables related to academic performance and professional experience. Moreover, the last-in-class effects on women's and men's GPA are not significantly different from zero. However, the effects on class rank are large and significant for both genders, particularly in earlier semesters (see Table A2, Appendix). The similar effects on class rank are consistent with the similar effects on managerial attainment through the first four years after expected graduation. Therefore, regardless of students' gender and academic performance, their relative ranks early in college seem to explain the initial effect on managerial attainment.

5.2.2 Gender-Specific Sensitivity to Peer Performance

To examine the gender-specific roles of rank and peer performance in the last-in-class effect, we repeat the exercise presented in Figure 4 but split the sample by gender. Figure 6 shows the relationship between the last-in-class effect through the first four years after expected graduation and the difference in peer performance between classes. As before, we measure peer performance in three ways: the median first-round score of the class, the 20th percentile, and the 80th percentile.

For both women (top graphs) and men (bottom graphs), the last-in-class effect under a difference of 0.1 s.d. between classes is as high as or higher than the effects under larger differences. This pattern confirms that differences in relative rank are the primary driver of the initial last-in-class effect. Yet, the ranking effect appears to be higher for men than for women through the first four years. For men, under minimal differences between classes, the last-in-class effect varies between −19 p.p. and −23 p.p. For women, it varies between −12 p.p. and −16 p.p. This difference between genders is consistent with previous studies assessing short-term outcomes. These studies find that male students are more sensitive to their rank than female students (e.g., Elsner and Isphording, 2018; Ribas, Sampaio and Trevisan, 2020; Murphy and Weinhardt, 2020). A possible explanation is that men are more prone to compare themselves to classmates than women (Chevalier et al., 2009; Cooper, Krieg and Brownell, 2018).

Although the effect of a lower rank appears more detrimental to men, Figure 6 also suggests that men respond more positively to peer performance than women. As the difference in peer performance between first and second classes increases from 0.1 s.d. to 0.6 s.d., the last-in-class effect on men decreases by 9 p.p. to 13 p.p. across the three specifications. On the other hand, the effect on women only responds to an increase in the performance of low-ranking peers — i.e., those who are close to the last student in the first class. An increase from 0.1 s.d. to 0.6 s.d. in the difference of the 20th percentile lowers the last-in-class effect on women by 7 p.p. This gender-specific sensitivity to peer performance aligns with the evidence that men respond more positively to peer performance (Beugnot et al., 2019).

Figure 7 presents the relationship between peer performance and the last-in-class effect five years after expected graduation. For women, the lower relative rank in the first class appears to drive the persistent negative impact on managerial attainment, but an increase in peer performance can mitigate this effect. For men, the adverse ranking effect and the positive relationship with peer performance disappear. If anything, the effect of attending the first class on men becomes positive regardless of the difference in peer performance between classes. Despite the stronger effects on men through the first four years (Figure 6), the evidence of more persistent effects on women is in line with Denning, Murphy and Weinhardt's (2023) findings. They show that the short-term effect of ranking on academic performance is similar between genders, but the long-term effect on earnings is significant only for women.

Overall, these results suggest that the initial relative rank rather than peer performance is the primary factor explaining the negative last-in-class effect on managerial attainment for both men and women. In the long run, though, the negative effect of a low rank on men disappears. For women, the ranking effect is more persistent, but it can be mitigated by an increase in peer performance in the first class.

5.2.3 The Career Path of Managers, Network, and Type of Firms

To better understand the initial effect on managerial attainment and the decreasing effect on men, we look at the characteristics of students who were very close to the first-class cutoff and were managers in years four and five. The purpose of this descriptive analysis is not to seek out characteristics that explain future managerial positions. Rather, it is intended to rule out factors not often found among managers.

Figures 8 to 10 compare students just above and below the first-class cutoff, four and five years after the expected graduation. To reproduce the ITT estimate in our RDD, we consider only observations within 0.025 s.d. of the cutoff. In each graph, the height of stacked bars represents the proportion of managers on each side of the cutoff. These figures reveal that an increase in managerial attainment above the cutoff causes the decreasing effect on men. Namely, five years after expected graduation, male students at the bottom of the first class catch up with similar students in the second class. We do not observe the same process for women above the cutoff.

Based on their work experience before being appointed as a manager for the first time, managers are classified as being promoted within the same firm ('insider'), having formal experience and being externally hired as a manager ('outsider'), and never having a registered job before the managerial position ('first job'). Figure 8 shows that internal promotions are rare around the cutoff, suggesting that career development within companies does not mediate our results. Moreover, most of the managers in year four found their positions straight out of college.[4] On the other hand, the reversal effect on men in year five is observed among students with some formal experience.

Additional results indicate that all the male students attaining managerial positions later have experience with high-skilled work. A great part of them had a low-management position before, while most of the others had a STEM job (Figure S5, Online Appendix). Nevertheless, these characteristics do not explain the gender differences in the long run because, above the first-class cutoff, men and women are very similar regarding professional experience (Table S8, Online Appendix).

To examine the role of networks, we created a categorical variable indicating whether, while appointed as a manager, the student worked with at least one former classmate in the same firm, at least one former student from the same program, and at least one former student from the same university. Figure 9 indicates that almost all managers below the cutoff did not have a co-worker from the same university when appointed. Hence, social ties with former classmates do not appear to explain the initial effect. However, in year five, most male managers above the cutoff were appointed by a firm that also employed a former classmate. This result suggests that attending the first class can have a long-term effect through academic connections, but mostly for men.

In Figure 10, we classify students based on the proportion of female managers in their firms, excluding themselves. Below the cutoff, most female students attaining managerial positions earlier are in firms with at least 60% of the managers being women. Later, half of the male students above the cutoff are appointed as managers in firms where the share of female managers is less than 40%. As a robustness check, we also classify firms based on their gender pay gap. For students below the cutoff, the first managerial appointment happens in firms with a relatively lower pay gap. Above the cutoff, male students are appointed to managerial positions in firms with a higher pay gap between men and women (Figure S6, Online Appendix).

According to these results, promotion within companies, professional experience, and social ties

[4]Unfortunately, we do not have complete information on internships because employers only report them on RAIS if they have an employment contract with students.

with former classmates do not account for the initial effect on managerial attainment. Over time, though, men at the bottom of the first class increase their managerial attainment, catching up with similar students in the second class. In this process, we cannot rule out the role of work experience and social ties with former classmates. However, women at the bottom of the first class do not benefit from accumulating similar experience and having the same classmates.

Regarding the gender differences in the long run, we cannot ignore the possibility of gender bias in the workplace. While managers in the second class are appointed earlier in firms with more gender equality, male managers at the bottom of the first class are appointed later in firms with greater inequality. This difference in the employer type might explain why women's professional experience does not offset the last-in-class effect, making it more persistent.

We also consider three other potential mechanisms for the gender-specific effects on managerial attainment: the sorting of men and women into different programs, women's motherhood decisions, and gender differences in a personality trait such as grit. Results, detailed in Section E of the Online Appendix, indicate that the last-in-class effect on men also disappears in programs where women are more affected in the long run (Table S9, Online Appendix). Thus, differences in program choices cannot fully account for the gender-specific effects. Moreover, motherhood does not seem to explain the persistent effect on women. If anything, women at the bottom of the first class are slightly less likely to be married and have children (Table S10, Online Appendix). Finally, a lack of grit does not appear to explain the persistent effect on women because those at the bottom of the first class exhibit significantly higher grit scores than those in the second class (Table S11, Online Appendix).

6 Conclusion

This study explores the impact of a student's rank in college on their future managerial attainment, comparing those in higher-performing classes to their counterparts in lower-performing classes. Our sample consists of students from identical programs at the same university, divided into two classes based on initial test scores. Around the cutoff between these classes, we focus on students who, before enrolling in college, were very similar despite attending different classes.

Our findings reveal that ranking last in the first class leads to a significant 10 p.p. decrease in students' likelihood of attaining a managerial position shortly after graduation. However, this effect fades over time. Five years after expected graduation, students at the bottom of the first class exhibit managerial attainment levels close to their counterparts' in the second class. Although the initial impact is similar between genders, the reduction of this effect is observed solely among men. For at least six years after expected graduation, low-ranking women in the first class continue to experience the negative impact on managerial attainment.

Further examination into potential mediators indicates neither academic performance nor work experience can account for the initial effect on managerial attainment. When comparing similar students in different classes, we find no significant differences in their GPAs. Moreover, most second-class students who attained managerial positions after college had no formal experience prior to the appointment. The only significant difference between first- and second-class students lies in their ranks within classrooms.

By examining the heterogeneity of the last-in-class effect with respect to peer performance, we confirm that the negative impact of a lower rank in the first class dominates the positive effect of higher peer quality in the short run. Particularly for men, higher peer performance in the first class appears to partially offset the negative ranking effect. In the long run, though, men become less sensitive to peer and ranking effects in college. For women, the negative ranking effect continues to outweigh the positive effect of better-performing peers, resulting in lower managerial attainment.

The decreasing effects on men seems to be related to social ties with former classmates and the accumulation of relevant work experience, such as low-management positions and STEM jobs. However, the effect still persists for women who accumulate similar experience and have the same classmates. We also show that motherhood decisions or lack of grit cannot explain the persistent effect on women. A potential mechanism we cannot rule out is the gender bias in the workplace and recruiting process. Our findings suggest that low-ranking men tend to attain managerial positions later in companies with greater gender inequality.

Given our unique setting and quasi-experimental design, our study contributes to the literature in three ways. The first contribution is the causal evidence that joining a better-performing class can adversely affect a student's chances of attaining a managerial role in the future. In our context, this negative effect is primarily due to the impact of a lower rank in the classroom. Some related studies on peer interactions in college suggest a similar mechanism, but they are mostly focused on short- and medium-term effects on educational attainment and academic achievement (e.g., Elsner, Isphording and Zölitz, 2021; Bertoni and Nisticò, 2023). The second contribution is related to the mechanism. We show that the negative effect of a low rank on managerial attainment occurs even when the impact on academic outcomes is small and insignificant. This evidence reinforces the idea that other individual traits and experiences, besides academic abilities, affect students' career advancement (Judge et al., 2002; Li, Arvey and Song, 2011; Offermann et al., 2020). The third contribution relates to factors that moderate the effect over time. Our findings suggest that professional experience and connections with former classmates can attenuate the impact of a lower rank in the long run. However, these factors appear more beneficial for men than for women. Consequently, the last-in-class effect persists more among women. This conjecture aligns with the evidence of cumulative disadvantages women face in the labor market (DiPrete and Soule, 1988; Fernandez-Mateo, 2009; Fitzsimmons, Callan and Paulsen, 2014) and gender differences in social networks (Yang, Chawla and Uzzi, 2019; Lindenlaub and Prummer, 2020).

More generally, our work also provides new insights for studying peer effects in professional environments (Mas and Moretti, 2009; Nanda and Sørensen, 2010; Tartari, Perkmann and Salter, 2014; Brune, Chyn and Kerwin, 2022). The interaction between peer performance and relative rank can influence employees' career trajectories, particularly in environments where peer performance is observed. Accordingly, organizations should consider the downsides of relative rankings when designing performance evaluation systems, team structures, and leadership development programs.

Considering the context of our study, our conclusions are limited by our sample, which comprises students from a single university. It is possible that, in other contexts, the ranking effect is not as salient, especially in a sample with greater diversity and a wider range of class and institutional options. Another limitation arises in our empirical model. Even though the RDD provides a clear causal comparison between two options, it only allows us to compare being ranked last in a higher-performing class with holding a higher rank in a lower-performing class. As a result, we cannot infer the impact of other combinations of rank and peer performance. Our study is also constrained by our dataset, which contains little to no information on non-academic outcomes during college. A final limitation concerns our inability to distinguish between supply- and demand-side mechanisms for the last-in-class effect. We do not know whether low-ranking students are discouraged from applying to managerial positions or do not present the characteristics sought by employers.

Despite these limitations, our study introduces a novel factor influencing career progression. Future work should investigate the impacts of performance ranking in other settings, including graduate programs and workplace environments. In addition, some questions remain unanswered. One of these questions is on how students' ranks at different parts of the performance distribution impact their career trajectories. For instance, are top-performing candidates as sensitive to their ranks as bottom-performing candidates? Another question is on how personality traits moderate the link between rank and managerial attainment. Understanding these moderators could help improve interventions aiming to attenuate the negative consequences of peer interaction on an individual's career. Finally, future work should examine whether the impact of a low rank on managerial attainment is driven by students' self-discouragement from applying for managerial roles or by employers' perceptions of students' skills. In this regard, one may investigate what types of socio-emotional skills and experiential opportunities during school years mediate the effect of rank on managerial attainment.

References

Becker, Gary S. 1964. *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education. NBER Books*. 1 ed., New York:National Bureau of Economic Research, distributed by Columbia University Press.

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

Beugnot, Julie, Bernard Fortin, Guy Lacroix, and Marie Claire Villeval. 2019. "Gender and peer effects on performance in social networks." *European Economic Review*, 113: 207–224.

Bond, Timothy, George Bulman, Xiaoxiao Li, and Jonathan Smith. 2018. "Updating human capital decisions: Evidence from SAT score shocks and college applications." *Journal of Labor Economics*, 36(3): 807–839.

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

Brune, Lasse, Eric Chyn, and Jason Kerwin. 2022. "Peers and Motivation at Work." *Journal of Human Resources*, 57(4): 1147–1177.

Bursztyn, Leonardo, and Robert Jensen. 2015. "How Does Peer Pressure Affect Educational Investments?" *Quarterly Journal of Economics*, 130(3): 1329–1367.

Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik. 2014. "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs." *Econometrica*, 82(6): 2295–2326.

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.

Castilla, Emilio J. 2008. "Gender, Race, and Meritocracy in Organizational Careers." *American Journal of Sociology*, 113(6): 1479–1526.

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. 2017. "Self-Selection and Comparative Advantage in Social Interactions." *Journal of the European Economic Association*, 16(4): 983–1020.

Cooper, Katelyn M., Anna Krieg, and Sara E. Brownell. 2018. "Who perceives they are smarter? Exploring the influence of student characteristics on student academic self-concept in physiology." *Advances in Physiology Education*, 42(2): 200–208.

Dasgupta, Utteeyo, Subha Mani, Smriti Sharma, and Saurabh Singhal. 2020. "Effects of Peers and Rank on Cognition, Preferences, and Personality." *Review of Economics and Statistics*, 104: 587–601.

Davis, James A. 1966. "The Campus as a Frog Pond: An Application of the Theory of Relative Deprivation to Career Decisions of College Men." *American Journal of Sociology*, 72(1): 17–31.

Denning, Jeffrey T., Richard Murphy, and Felix Weinhardt. 2023. "Class Rank and Long-Run Outcomes." *Review of Economics and Statistics*, 105(6): 1426–1441.

DiPrete, Thomas A., and Whitman T. Soule. 1988. "Gender and Promotion in Segmented Job Ladder Systems." *American Sociological Review*, 53(1): 26–40.

Duflo, Esther, Pascaline Dupas, and Michael Kremer. 2011. "Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya." *American Economic Review*, 101(5): 1739–74.

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." *Economic Journal*, 131(640): 3182–3206.

Fabregas, Raissa. 2023. "Trade-Offs of Attending Better Schools: Achievement, Self-Perceptions and Educational Trajectories." *Economic Journal*, 133(655): 2709–2737.

Fernandez-Mateo, Isabel. 2009. "Cumulative Gender Disadvantage in Contract Employment." *American Journal of Sociology*, 114(4): 871–923.

Fiedler, Fred E. 1986. "The Contribution of Cognitive Resources and Leader Behavior to Organizational Performance." *Journal of Applied Social Psychology*, 16(6): 532–548.

Fitzsimmons, Terrance W., Victor J. Callan, and Neil Paulsen. 2014. "Gender disparity in the C-suite: Do male and female CEOs differ in how they reached the top?" *Leadership Quarterly*, 25(2): 245–266.

Foschi, Martha. 2000. "Double Standards for Competence: Theory and Research." *Annual Review of Sociology*, 26(1): 21–42.

George, Jennifer M. 2000. "Emotions and Leadership: The Role of Emotional Intelligence." *Human Relations*, 53(8): 1027–1055.

Hahn, Jinyong, Petra Todd, and Wilbert Van der Klaauw. 2001. "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design." *Econometrica*, 69(1): 201–209.

Hahn, Youjin, Asadul Islam, Eleonora Patacchini, and Yves Zenou. 2019. "Friendship and Female Education: Evidence from a Field Experiment in Bangladeshi Primary Schools." *Economic Journal*, 130(627): 740–764.

Hanushek, Eric A., John F. Kain, Jacob M. Markman, and Steven G. Rivkin. 2003. "Does peer ability affect student achievement?" *Journal of Applied Econometrics*, 18(5): 527–544.

Hoffman, Mitchell, and Steve Tadelis. 2021. "People Management Skills, Employee Attrition, and Manager Rewards: An Empirical Analysis." *Journal of Political Economy*, 129(1): 243–285.

Hultin, Mia, and Ryszard Szulkin. 1999. "Wages and Unequal Access to Organizational Power: An Empirical Test of Gender Discrimination." *Administrative Science Quarterly*, 44(3): 453–472.

Imbens, Guido W., and Thomas Lemieux. 2008. "Regression discontinuity designs: A guide to practice." *Journal of Econometrics*, 142(2): 615–635.

Jonsson, Jan O., and Carina Mood. 2008. "Choice by Contrast in Swedish Schools: How Peers' Achievement Affects Educational Choice." *Social Forces*, 87(2): 741–765.

Judge, Timothy A., Daniel M. Cable, John W. Boudreau, and Robert D. Bretz Jr. 1995. "An Empirical Investigation of the Predictors of Executive Career Success." *Personnel Psychology*, 48(3): 485–519.

Judge, Timothy A, Joyce E Bono, Remus Ilies, and Megan W Gerhardt. 2002. "Personality and leadership: A qualitative and quantitative review." *Journal of Applied Psychology*, 87(4): 765–780.

Komives, Susan R. 2011. "College Student Leadership Identity Development." In *Early Development and Leadership: Building the Next Generation of Leaders.* , ed. Susan E. Murphy and Rebecca Reichard, Chapter 13, 273–292. New York:Routledge.

Lindenlaub, Ilse, and Anja Prummer. 2020. "Network Structure and Performance." *Economic Journal*, 131(634): 851–898.

Li, Wen-Dong, Richard D. Arvey, and Zhaoli Song. 2011. "The influence of general mental ability, self-esteem and family socioeconomic status on leadership role occupancy and leader advancement: The moderating role of gender." *The Leadership Quarterly*, 22(3): 520–534.

Marmaros, David, and Bruce Sacerdote. 2002. "Peer and social networks in job search." *European Economic Review*, 46(4): 870–879.

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): 213–231.

Mas, Alexandre, and Enrico Moretti. 2009. "Peers at Work." *American Economic Review*, 99(1): 112–145.

McCrary, Justin. 2008. "Manipulation of the running variable in the regression discontinuity design: A density test." *Journal of Econometrics*, 142(2): 698–714.

Meyer, John W. 1970. "High School Effects on College Intentions." *American Journal of Sociology*, 76(1): 59–70.

Murphy, Richard, and Felix Weinhardt. 2020. "Top of the Class: The Importance of Ordinal Rank." *Review of Economic Studies*, 87(6): 2777–2826.

Nanda, Ramana, and Jesper B. Sørensen. 2010. "Workplace Peers and Entrepreneurship." *Management Science*, 56(7): 1116–1126.

Nelson, Joel I. 1972. "High School Context and College Plans: The Impact of Social Structure on Aspirations." *American Sociological Review*, 37(2): 143–148.

Offermann, Lynn R., Kaitlin R. Thomas, Lauren A. Lanzo, and Lindsey N. Smith. 2020. "Achieving leadership and success: A 28-year follow-up of college women leaders." *The Leadership Quarterly*, 31(4): 101345.

Pagani, Laura, Simona Comi, and Federica Origo. 2021. "The Effect of School Rank on Personality Traits." *Journal of Human Resources*, 56(4): 1187–1225.

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): 1–13.

Sacerdote, Bruce. 2001. "Peer Effects with Random Assignment: Results for Dartmouth Roommates." *Quarterly Journal of Economics*, 116(2): 681–704.

Spilerman, Seymour, and Tormod Lunde. 1991. "Features of Educational Attainment and Job Promotion Prospects." *American Journal of Sociology*, 97(3): 689–720.

Tartari, Valentina, Markus Perkmann, and Ammon Salter. 2014. "In good company: The influence of peers on industry engagement by academic scientists." *Research Policy*, 43(7): 1189–1203.

Tincani, Michela M. 2017. "Heterogeneous peer effects and rank concerns: Theory and evidence." CESifo Working Paper 6331.

Useem, Michael, and Jerome Karabel. 1986. "Pathways to Top Corporate Management." *American Sociological Review*, 51(2): 184–200.

Wise, David A. 1975. "Personal Attributes, Job Performance, and Probability of Promotion." *Econometrica*, 43(5/6): 913–931.

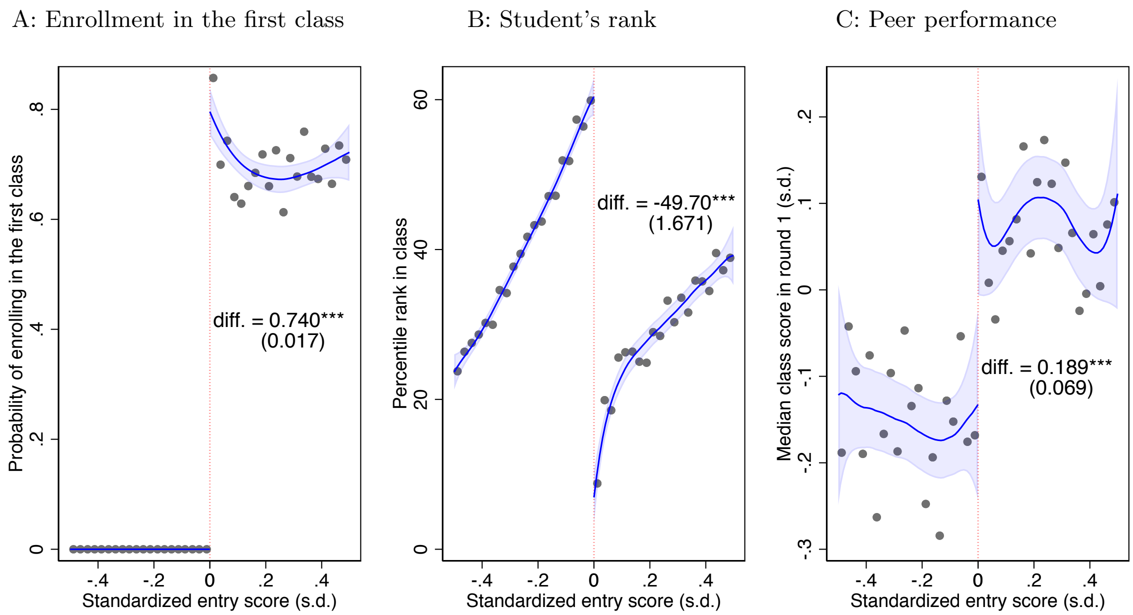
Yang, Yang, Nitesh V. Chawla, and Brian Uzzi. 2019. "A network's gender composition and communication pattern predict women's leadership success." *Proceedings of the National Academy of Sciences*, 116(6): 2033–2038.

Zarate, Román Andrés. 2023. "Uncovering Peer Effects in Social and Academic Skills." *American Economic Journal: Applied Economics*, 15(3): 35–79.

Zimmerman, David J. 2003. "Peer Effects in Academic Outcomes: Evidence from a Natural Experiment." *Review of Economics and Statistics*, 85(1): 9–23.

Zimmerman, Seth D. 2019. "Elite Colleges and Upward Mobility to Top Jobs and Top Incomes." *American Economic Review*, 109(1): 1–47.

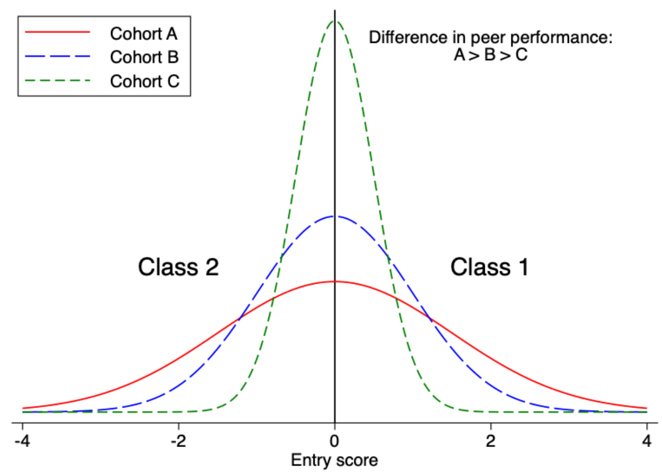
Figure 1: Relationship between Entrance Score and Enrollment in the First Class, Student's Rank, and Peer Performance



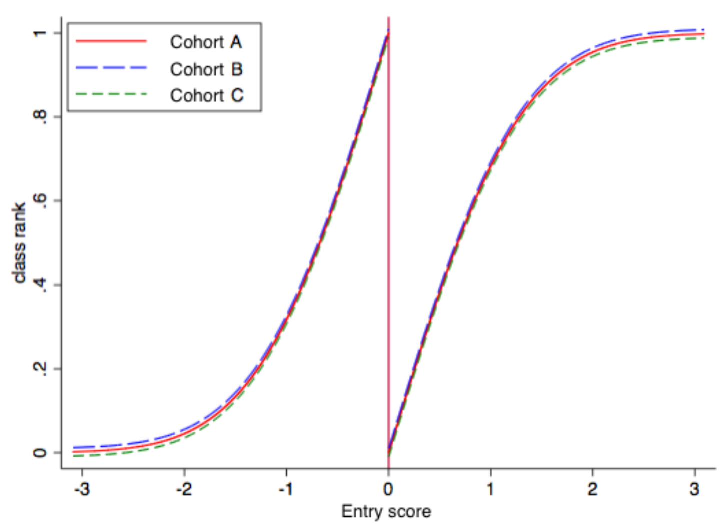
The blue line represents predicted values, the shaded area represents their 95% confidence interval, and the gray dots represent mean values within bins of 0.025 s.d. The running variable (horizontal axis) is the final entrance score, standardized by program and year using the cutoff for the first class and the standard deviation of admitted candidates. Student rank is the percentile of a student in his or her assigned class based on their final entrance score. Peer performance is measured by the median score of classmates in the first round of the entrance exam; this score is standardized by year using all the university candidates. The relationship between outcomes (vertical axis) and the running variable is estimated using locally weighted regressions with triangular kernel weights; the bandwidth is selected according to Calonico, Cattaneo and Titiunik (2014). The estimated discontinuity ("diff.") is the difference between predicted values at the cutoff, with robust standard errors in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. $N = 13{,}505$.

Figure 2: Example of Program Cohorts with Differences in Peer Performance and Student's Rank

A: Distribution of individual skills

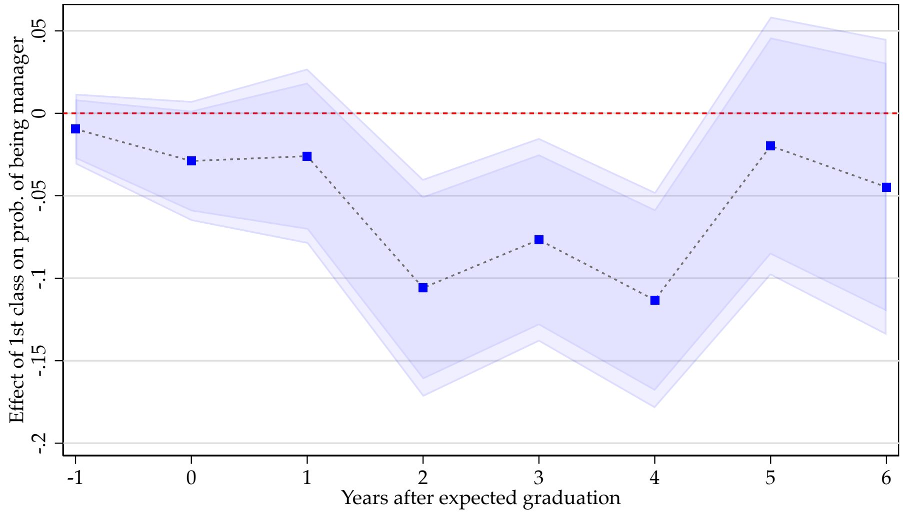


B: Difference in student's rank



This figure shows a hypothetical example of three program cohorts with different distributions of peer performance, measured by students' absolute entry score, but similar rank discontinuity between classes, measured in percentiles of the entry score within classes.

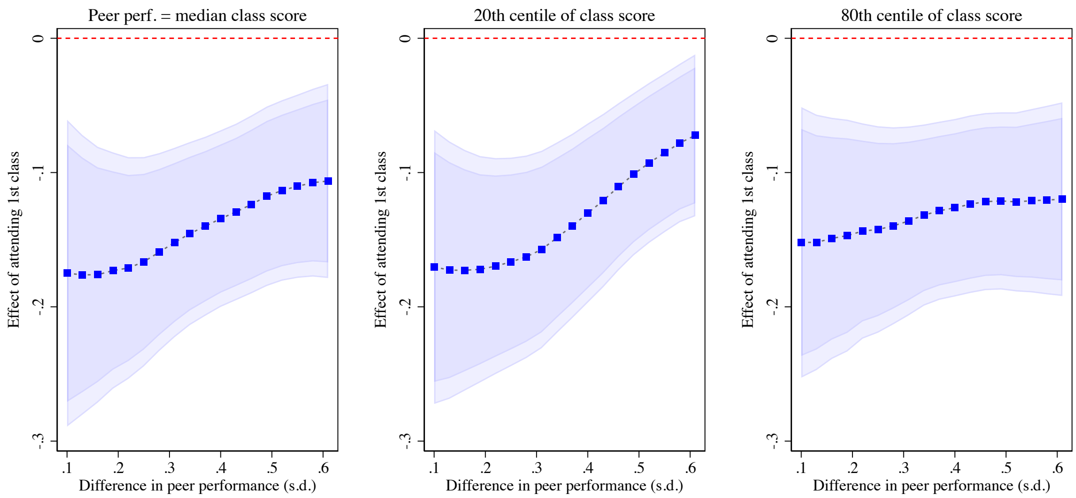
Figure 3: Last-in-Class Effect on Managerial Attainment



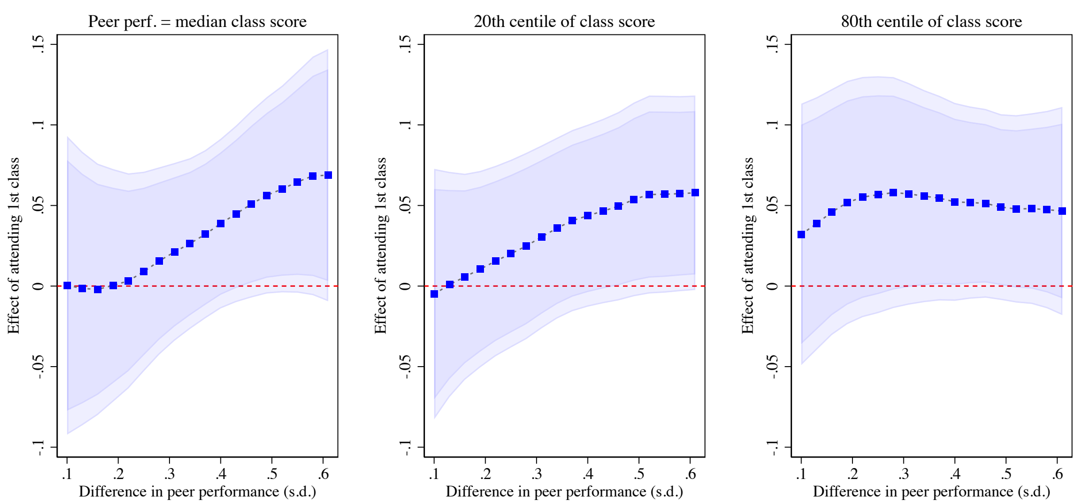
This figure presents the fuzzy regression discontinuity (FRD) for the effect of being the last in the first class on the probability of being in a management position (vertical axis) in each year after the expected graduation (horizontal axis). The blue dots represent the estimated effect and the shaded areas represents their 90% and 95% confidence intervals. The dependent variable is equal to 1 if student occupies a top- or middle-level management position, and 0 otherwise; details are in Table S2 of the Online Appendix. 'Years after expected graduation' are counted from the semester in which students are expected to graduate from their original program. Sample includes only individuals who were employed by the time of the assessment. FRDs are estimated using triangular kernels with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). N = 2,536-8,827.

Figure 4: Relationship between the Last-in-Class Effect and Difference in Peer Performance

A: Manager until four years after expected graduation

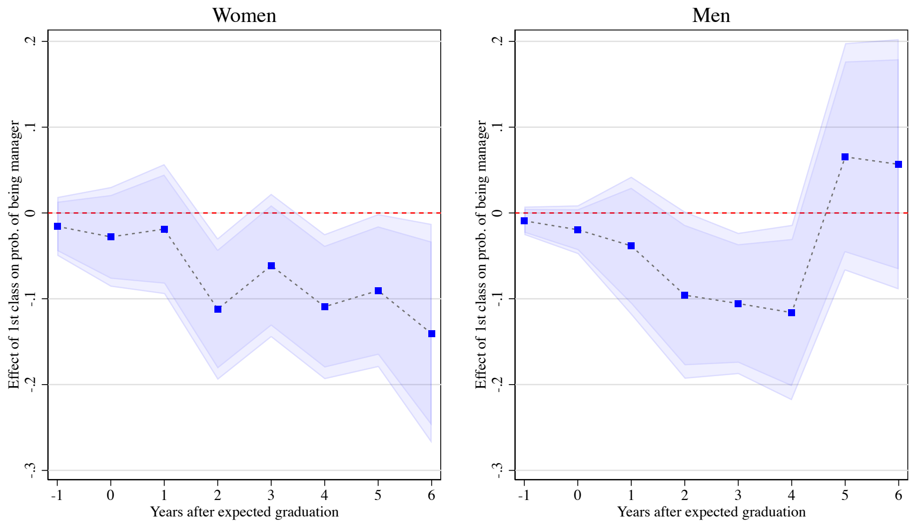


B: Becoming a manager five years after expected graduation



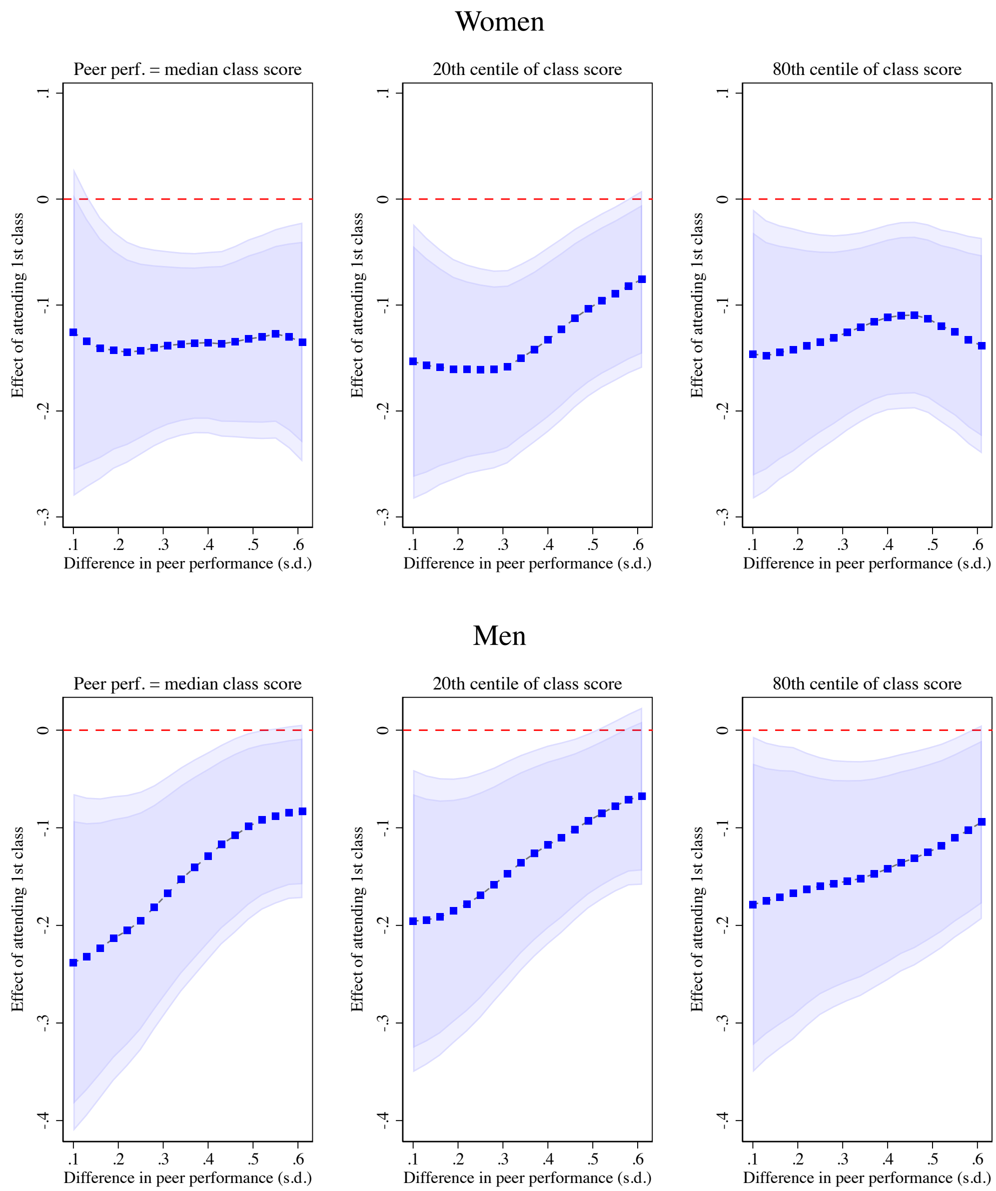
These graphs present the relationship between the last-in-class effect on managerial attainment (vertical axis) and the difference in peer performance between classes (horizontal axis). The last-in-class effect is estimated using a fuzzy regression discontinuity (FRD) design. Blue dots represent point estimates and the shaded areas represents their 90% and 95% confidence intervals. The dependent variable is equal to 1 if student occupies a top- or middle-level management position, and 0 otherwise. Panel A considers managerial attainment anytime within four years after the expected graduation. Panel B considers the probability of becoming a manager in year five. Sample includes only individuals who were employed by the time of the assessment. Peer performance is measured in three different ways: median class score in the first round of the entrance exam (left-hand graphs), 20th centile of the score in the class (middle graphs), and 80th centile of the score in the class (right-hand graphs). FRDs and their relationship with peer performance derive from locally weighted regressions with triangular kernel weights; the bandwidth is selected according to Calonico, Cattaneo and Titiunik (2014); the bandwidth for the difference in peer performance is 0.5 s.d. $N = 9{,}889$ (Panel A) and 6,695 (Panel B).

Figure 5: Last-in-Class Effect on Managerial Attainment by Gender



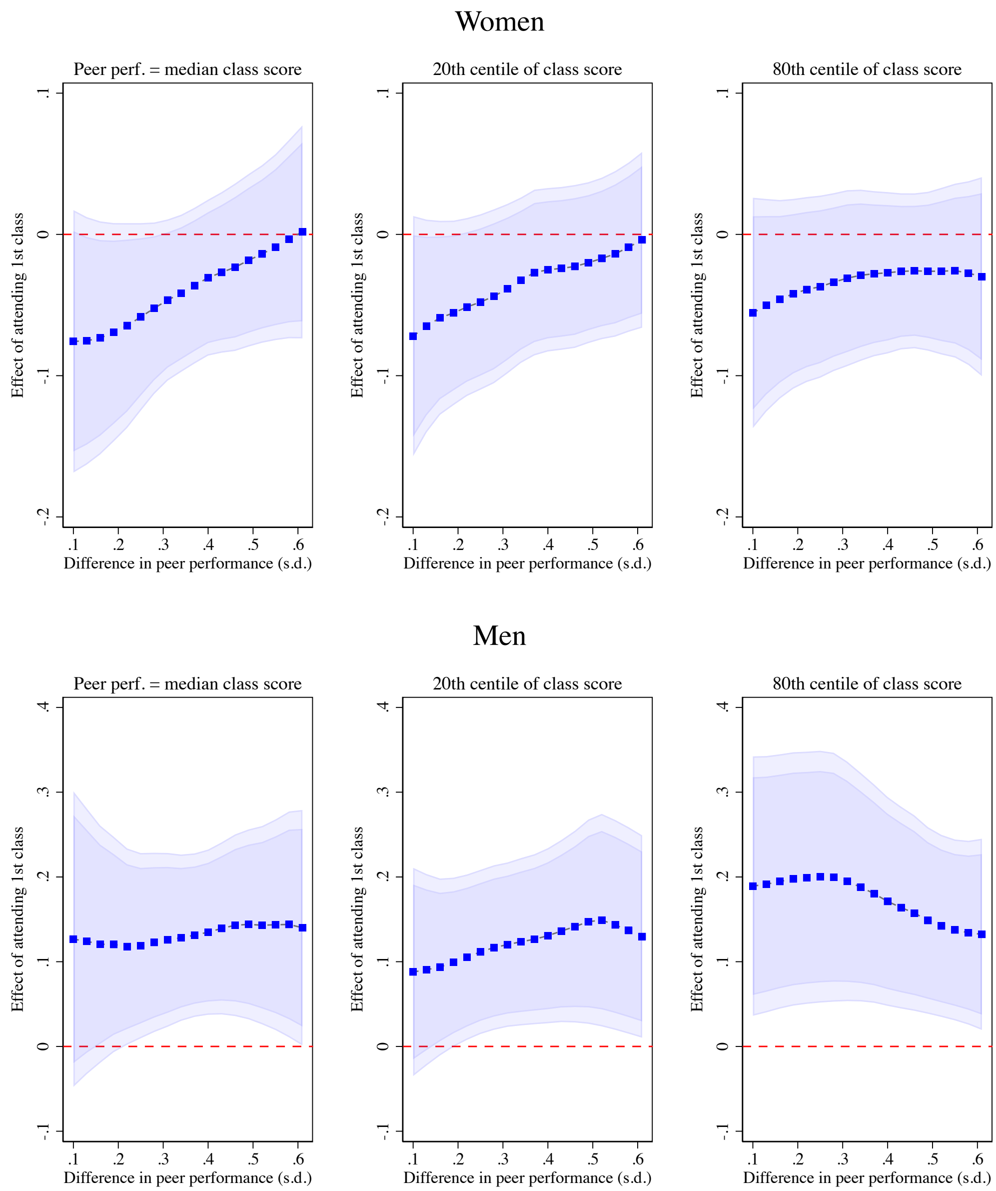
This figure presents the fuzzy regression discontinuity (FRD) for the effect of being the last in the first class on the probability of being in a management position (vertical axis) in each year after the expected graduation (horizontal axis). The blue dots represent the estimated effect and the shaded areas represents their 90% and 95% confidence intervals. The dependent variable is equal to 1 if student occupies a top- or middle-level management position, and 0 otherwise; details are in Table S2 of the Online Appendix. 'Years after expected graduation' are counted from the semester in which students are expected to graduate from their original program. Sample includes only individuals who were employed by the time of the assessment. FRDs are estimated using triangular kernels with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). N = 1,340-4,895 (women), and 1,196-3,932 (men).

Figure 6: Relationship between the Last-in-Class Effect and Difference in Peer Performance, Manager Until Four Years After Expected Graduation



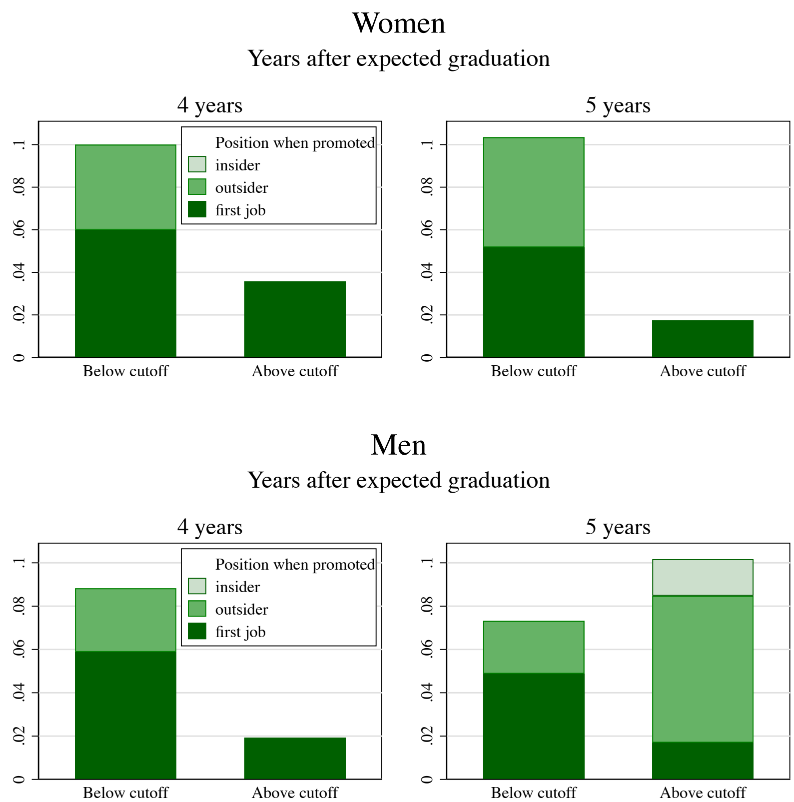
These graphs present the relationship between the last-in-class effect on the probability of being a manager anytime until four years after the expected graduation (vertical axis) and the difference in peer performance between classes (horizontal axis). The last-in-class effect is estimated using a fuzzy regression discontinuity (FRD) design. Blue dots represent point estimates and the shaded areas represents their 90% and 95% confidence intervals. The dependent variable is equal to 1 if the worker occupies a top- or middle-level management position, and 0 otherwise. Sample includes only individuals who were employed by the time of the assessment. Peer performance is measured in three different ways: median class score in the first round of the entrance exam (left-hand graphs), 20th centile of the score in the class (middle graphs), and 80th centile of the score in the class (right-hand graphs). FRDs and their relationship with peer performance derive from locally weighted regressions with triangular kernel weights; the bandwidth is selected according to Calonico, Cattaneo and Titiunik (2014); the bandwidth for the difference in peer performance is 0.5 s.d. N = 5,641 (women) and 4,532 (men).

Figure 7: Relationship between the Last-in-Class Effect and Difference in Peer Performance, Becoming a Manager Five Years After Expected Graduation



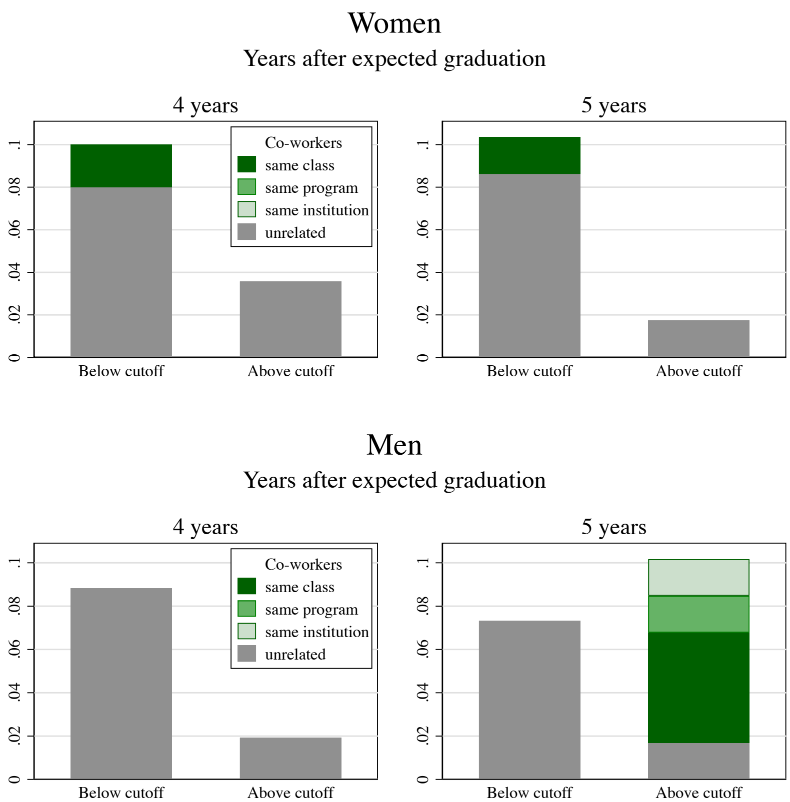
These graphs present the relationship between the last-in-class effect on the probability of being a manager anytime five years after the expected graduation (vertical axis) and the difference in peer performance between classes (horizontal axis). The last-in-class effect is estimated using a fuzzy regression discontinuity (FRD) design. Blue dots represent point estimates and the shaded areas represents their 90% and 95% confidence intervals. The dependent variable is equal to 1 if the worker occupies a top- or middle-level management position, and 0 otherwise. Sample includes only individuals who were employed by the time of the assessment and were not managers in the previous year. Peer performance is measured in three different ways: median class score in the first round of the entrance exam (left-hand graphs), 20th centile of the score in the class (middle graphs), and 80th centile of the score in the class (right-hand graphs). FRDs and their relationship with peer performance derive from locally weighted regressions with triangular kernel weights; the bandwidth is selected according to Calonico, Cattaneo and Titiunik (2014); the bandwidth for the difference in peer performance is 0.5 s.d. $N = 4{,}045$ (women) and 3,255 (men).

Figure 8: Proportion of Managers Below and Above the First-Class Cutoff by Type of Promotion



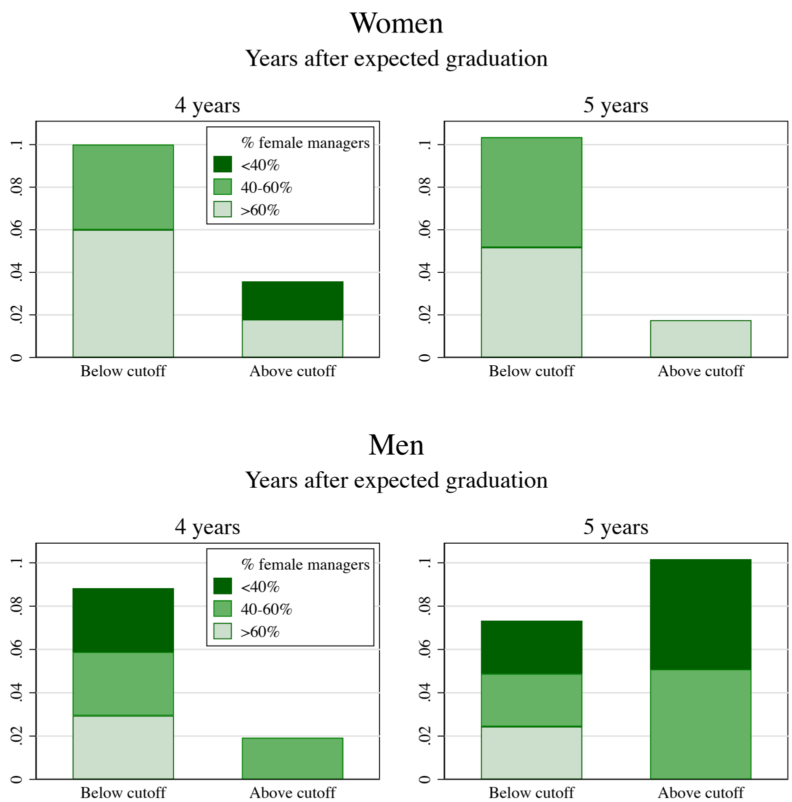
This figure presents the proportion of managers four and five years after the expected graduation among students who were just below and above the first-class cutoff. Managers are classified based on their previous occupation, before their first promotion. 'Insiders' are those promoted for a company that they had worked at before. 'Outsiders' are those who had a formal job and were externally hired as a manager. 'First job' represents those who never had a registered job before becoming a manager. Sample includes only individuals who were employed by the time of the assessment and were within 0.025 s.d. of the cutoff. $N = 159$ (women) and 136 (men).

Figure 9: Proportion of Managers Below and Above the First-Class Cutoff by Academic Connections



This figure presents the proportion of managers four and five years after the expected graduation among students who were just below and above the first-class cutoff. Managers are classified based on presence of at least one co-worker from the same class, program, or institution when they became managers for the first time. Sample includes only individuals who were employed by the time of the assessment and were within 0.025 s.d. of the cutoff. $N = 159$ (women) and 136 (men).

Figure 10: Proportion of Managers Below and Above the First-Class Cutoff by Share of Female Managers



This figure presents the proportion of managers four and five years after the expected graduation among students who were just below and above the first-class cutoff. Managers are classified based on the percentage of women among other managers in the firm that promoted them. Sample includes only individuals who were employed by the time of the assessment and were within 0.025 s.d. of the cutoff. $N = 159$ (women) and 136 (men).

Table 1: Last-in-Class Effect on Managerial Attainment

	Baseline	All students	Fixed-effect	Matched pairs	Incl. low-management	Controls for graduation	Controls for experience
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Manager until 4 years after	-0.130	-0.131	-0.120	-0.089	-0.093	-0.130	-0.131
	(0.032)	(0.030)	(0.031)	(0.033)	(0.044)	(0.032)	(0.032)
	[0.000]	[0.000]	[0.000]	[0.006]	[0.034]	[0.000]	[0.000]
N. of obs.	*10,173*	*11,557*	*10,173*	*646*	*10,173*	*10,173*	*10,173*
Manager 5 years after	-0.020	-0.024	-0.007	-0.070	0.033	-0.018	-0.020
	(0.040)	(0.038)	(0.038)	(0.039)	(0.056)	(0.040)	(0.040)
	[0.608]	[0.529]	[0.847]	[0.071]	[0.558]	[0.642]	[0.622]
N. of obs.	*7,300*	*8,379*	*7,300*	*496*	*7,300*	*7,300*	*7,300*

This table presents the fuzzy regression discontinuity (FRD) estimates for the last-in-class effect on the probability of being a manager. 'Years after' are counted from the semester in which students are expected to graduate from their original program. The sample includes only individuals who were employed by the time of the assessment. Except for column (2), the sample excludes students who had been enrolled in higher education before the application. Except for column (4), FRDs are estimated using triangular kernels with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). In column (4), FRDs are estimated using two observations from each side of the cutoff for each program cohort. Except for column (5), the dependent variable is equal to 1 if student occupies a top- or middle-level management position, and 0 otherwise; details are in Table S2 of the Online Appendix. In column (5), the dependent variable is equal to 1 if student occupies a low-, middle-, and top-level management position, and 0 otherwise. Estimates in column (3) control for program fixed effects. Estimates in column (6) control for variables related to college graduation: graduated, years after graduation, graduated in original program, graduated in the fall, GPA at graduation, and rank at graduation. Estimates in column (7) control for observed experience: years of experience, number of jobs, current tenure, low-level management experience, STEM experience, high-skilled experience, and migration to another state. Robust standard errors are in parentheses, and p-values are in brackets.

Table 2: Last-in-Class Effect on Managerial Attainment by Gender

	Baseline (1)	All students (2)	Fixed-effect (3)	Matched pairs (4)	Incl. low-management (5)	Controls for graduation (6)	Controls for experience (7)
Women							
Manager until 4 years after	-0.133	-0.146	-0.120	-0.129	-0.113	-0.133	-0.134
	(0.042)	(0.041)	(0.040)	(0.038)	(0.061)	(0.042)	(0.042)
	[0.002]	[0.000]	[0.003]	[0.001]	[0.067]	[0.002]	[0.001]
N. of obs.	*5,641*	*6,195*	*5,641*	*598*	*5,641*	*5,641*	*5,641*
Manager 5 years after	-0.090	-0.103	-0.074	-0.129	-0.048	-0.095	-0.085
	(0.046)	(0.045)	(0.044)	(0.043)	(0.068)	(0.046)	(0.046)
	[0.047]	[0.022]	[0.097]	[0.002]	[0.475]	[0.039]	[0.063]
N. of obs.	*4,045*	*4,476*	*4,045*	*461*	*4,045*	*4,045*	*4,045*
Men							
Manager until 4 years after	-0.119	-0.104	-0.106	-0.057	-0.066	-0.124	-0.123
	(0.047)	(0.042)	(0.046)	(0.042)	(0.072)	(0.047)	(0.047)
	[0.012]	[0.013]	[0.022]	[0.179]	[0.362]	[0.008]	[0.009]
N. of obs.	*4,532*	*5,362*	*4,532*	*588*	*4,532*	*4,532*	*4,532*
Manager 5 years after	0.064	0.058	0.077	-0.003	0.125	0.063	0.054
	(0.067)	(0.061)	(0.063)	(0.051)	(0.090)	(0.066)	(0.068)
	[0.337]	[0.341]	[0.220]	[0.957]	[0.166]	[0.343]	[0.424]
N. of obs.	*3,255*	*3,903*	*3,255*	*454*	*3,255*	*3,255*	*3,255*

This table presents the fuzzy regression discontinuity (FRD) estimates for the last-in-class effect on the probability of being a manager. 'Years after' are counted from the semester in which students are expected to graduate from their original program. The sample includes only individuals who were employed by the time of the assessment. Except for column (2), the sample excludes students who had been enrolled in higher education before the application. Except for column (4), FRDs are estimated using triangular kernels with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). In column (4), FRDs are estimated using two observations from each side of the cutoff for each program cohort. Except for column (5), the dependent variable is equal to 1 if the worker occupies a top- or middle-level management position, and 0 otherwise; details are in Table S2 of the Online Appendix. In column (5), the dependent variable is equal to 1 if the worker occupies a low-, middle-, and top-level management position, and 0 otherwise. Estimates in column (3) control for program fixed effects. Estimates in column (6) control for observed experience: years of experience, number of jobs, current tenure, low-level management experience, STEM experience, high-skilled experience, and ever migrated. Estimates in column (7) control for variables related to college graduation: graduated, years after graduation, graduated in original program, graduated in the fall, and GPA at graduation. Robust standard errors are in parentheses, and p-values are in brackets.

Table A1: Descriptive Statistics

	All				Women				Men			
	1st class		2nd class		1st class		2nd class		1st class		2nd class	
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Standardized entrance score	1.128	0.889	0.061	0.829	1.105	0.886	0.034	0.813	1.156	0.891	0.095	0.847
Standardized round 1 score	0.301	0.974	-0.142	0.970	0.196	0.954	-0.265	0.960	0.425	0.983	0.012	0.960
Student's rank in class	0.457	0.276	0.464	0.279	0.448	0.274	0.454	0.277	0.467	0.277	0.476	0.281
Average std. course grade*	-0.099	0.738	-0.095	0.736	-0.015	0.686	-0.009	0.693	-0.205	0.786	-0.209	0.775
GPA*	7.642	1.287	7.473	1.239	7.925	1.014	7.717	0.975	7.285	1.490	7.148	1.460
Number of courses taken*	5.387	1.057	5.277	1.154	5.453	1.103	5.272	1.209	5.307	0.991	5.283	1.082
Number of absences*	0.850	3.993	0.637	3.155	0.614	3.182	0.517	2.623	1.135	4.776	0.789	3.712
Switched programs	0.063	0.243	0.043	0.203	0.044	0.205	0.028	0.165	0.086	0.280	0.062	0.242
Tried to enter another program	0.143	0.350	0.109	0.312	0.118	0.322	0.083	0.276	0.173	0.378	0.141	0.348
Graduated on time	0.487	0.500	0.463	0.499	0.580	0.494	0.573	0.495	0.377	0.485	0.325	0.469
Delay in graduation (years)	1.411	1.115	1.425	1.119	1.303	0.990	1.280	0.974	1.572	1.261	1.667	1.291
Ever graduated	0.758	0.428	0.734	0.442	0.834	0.372	0.824	0.381	0.670	0.470	0.622	0.485
Dropped out	0.222	0.416	0.239	0.426	0.155	0.362	0.162	0.368	0.301	0.459	0.334	0.472
4 years after expected graduation												
Employed	0.649	0.477	0.675	0.469	0.654	0.476	0.675	0.468	0.643	0.479	0.674	0.469
High-skilled occupation	0.608	0.488	0.586	0.493	0.623	0.485	0.629	0.483	0.590	0.492	0.531	0.499
Manager**	0.074	0.262	0.088	0.283	0.075	0.263	0.093	0.291	0.073	0.261	0.081	0.273
5 years after expected graduation												
Employed	0.691	0.462	0.723	0.447	0.695	0.460	0.724	0.447	0.686	0.464	0.723	0.447
High-skilled occupation	0.643	0.479	0.604	0.489	0.655	0.475	0.641	0.480	0.629	0.483	0.556	0.497
Manager**	0.089	0.284	0.093	0.291	0.092	0.288	0.095	0.293	0.085	0.279	0.091	0.288
6 years after expected graduation												
Employed	0.723	0.448	0.745	0.436	0.733	0.442	0.744	0.437	0.710	0.454	0.747	0.435
High-skilled occupation	0.665	0.472	0.626	0.484	0.682	0.466	0.661	0.474	0.644	0.479	0.581	0.494
Manager**	0.092	0.290	0.101	0.301	0.097	0.296	0.101	0.301	0.087	0.281	0.100	0.300
Covariates												
Woman	0.541	0.498	0.556	0.497	-	-	-	-	-	-	-	-
Age	20.43	3.814	20.76	4.018	20.32	3.259	20.71	3.699	20.55	4.376	20.82	4.385
White	0.585	0.493	0.533	0.499	0.577	0.494	0.526	0.499	0.595	0.491	0.541	0.499
Living in Pernambuco	0.911	0.285	0.916	0.278	0.904	0.294	0.911	0.284	0.919	0.272	0.921	0.269
From public high school	0.206	0.405	0.248	0.432	0.212	0.409	0.256	0.437	0.199	0.400	0.237	0.425
Employed at application	0.132	0.339	0.175	0.380	0.112	0.315	0.158	0.365	0.155	0.362	0.195	0.396
Number of previous applications	2.006	0.951	2.076	0.957	2.091	0.965	2.140	0.957	1.908	0.924	1.997	0.952
Both parents with college degree	0.293	0.455	0.233	0.423	0.269	0.444	0.199	0.399	0.320	0.467	0.275	0.446
Neither parents with college degree	0.440	0.496	0.516	0.500	0.483	0.500	0.562	0.496	0.392	0.488	0.460	0.498
Instructor characteristics*												
Female instructors	0.411	0.231	0.393	0.244	0.463	0.216	0.429	0.242	0.352	0.233	0.347	0.240
40+ year-old instructors	0.693	0.269	0.688	0.260	0.735	0.263	0.733	0.247	0.646	0.269	0.632	0.266
Assistant professors	0.436	0.277	0.435	0.242	0.469	0.280	0.472	0.237	0.398	0.269	0.388	0.240
Associate or full professors	0.382	0.287	0.353	0.272	0.346	0.277	0.328	0.267	0.423	0.291	0.383	0.275
Instructor quality*,***												
Dropout rate	-0.039	0.025	-0.042	0.023	-0.034	0.019	-0.039	0.020	-0.045	0.030	-0.047	0.026
Failure rate	-0.013	0.016	-0.013	0.017	-0.010	0.012	-0.011	0.015	-0.016	0.019	-0.015	0.020
Number of observations	2,752-6,608		2,830-6,897		1,462-3,577		1,567-3,834		1,290-3,031		1,263-3,063	

*In the first semester. **Variable is equal to 1 if student occupies a top- or middle-level management position, and 0 otherwise; details are in Table S2 of the Online Appendix. ***Instructor quality is calculated by a three-way fixed-effect model described in Section C.5 of the Online Appendix. The sample comprises candidates admitted to a program with two entry classes and attending a higher education institution for the first time; it excludes those who dropped out of the program before the end of the first term.

Table A2: Last-in-Class Effect on Academic Performance

	All		Women		Men	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Standardized GPA						
1th semester	-0.066	[0.458]	-0.006	[0.954]	-0.158	[0.329]
	(0.089)		(0.108)		(0.161)	
2th semester	-0.085	[0.321]	-0.028	[0.797]	-0.192	[0.220]
	(0.086)		(0.108)		(0.156)	
3th semester	-0.076	[0.392]	-0.022	[0.843]	-0.201	[0.211]
	(0.088)		(0.110)		(0.160)	
4th semester	-0.062	[0.496]	0.004	[0.972]	-0.203	[0.204]
	(0.091)		(0.113)		(0.160)	
5th semester	-0.036	[0.698]	0.030	[0.794]	-0.173	[0.289]
	(0.093)		(0.114)		(0.163)	
6th semester	-0.045	[0.630]	0.018	[0.874]	-0.189	[0.268]
	(0.093)		(0.113)		(0.171)	
7th semester	-0.036	[0.697]	0.038	[0.736]	-0.205	[0.233]
	(0.093)		(0.114)		(0.171)	
8th semester	-0.019	[0.839]	0.055	[0.632]	-0.183	[0.279]
	(0.094)		(0.115)		(0.169)	
Class rank per course section						
1th semester	-0.224	[0.001]	-0.222	[0.007]	-0.218	[0.060]
	(0.070)		(0.082)		(0.116)	
2th semester	-0.181	[0.003]	-0.176	[0.019]	-0.196	[0.055]
	(0.061)		(0.075)		(0.102)	
3th semester	-0.132	[0.028]	-0.131	[0.082]	-0.140	[0.164]
	(0.060)		(0.075)		(0.100)	
4th semester	-0.125	[0.037]	-0.102	[0.155]	-0.166	[0.096]
	(0.060)		(0.072)		(0.100)	
5th semester	-0.092	[0.122]	-0.078	[0.260]	-0.123	[0.214]
	(0.059)		(0.070)		(0.099)	
6th semester	-0.077	[0.172]	-0.071	[0.281]	-0.109	[0.278]
	(0.056)		(0.066)		(0.101)	
7th semester	-0.059	[0.284]	-0.048	[0.466]	-0.103	[0.297]
	(0.055)		(0.066)		(0.099)	
8th semester	-0.047	[0.387]	-0.037	[0.561]	-0.092	[0.336]
	(0.054)		(0.064)		(0.096)	
Number of observations	9,923-10,504		5,674-5,913		4,249-4,591	

This table presents the fuzzy regression discontinuity (FRD) for the last-in-class effect on academic performance in each academic term. Academic performance is measured by two variables: standardized GPA, which is standardized by the distribution of GPAs from students in the same program and academic progress, but not necessarily in the same cohort; and the average class rank per course section, which comes from the final grade in each course standardized by the distributions of scores in the same course, section, and semester. FRDs are estimated using triangular kernels with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). Robust standard errors are in parentheses, and p-values are in brackets.

Online Appendix to "The Impact of Peer Performance and Relative Rank on Managerial Career Attainment: Evidence from College Students"

Rafael P. Ribas, Breno Sampaio, and Giuseppe Trevisan

June 6, 2024

A Institutional Background

The *Universidade Federal de Pernambuco* (UFPE) is a flagship university in the Northeastern region of Brazil and one of the top ten institutions in the country. According to the Ministry of Education, UFPE has always had the highest evaluations in the Northern and Northeastern regions of Brazil since 1995. In addition to its high quality and reputation, it is a public university and does not charge tuition fees. As a result, UFPE is the top choice for almost every high school student in the state of Pernambuco.

A.1 Admissions Policy

About 95% of its undergraduate students are admitted through an exam, called *vestibular*, which is held only once a year.[1] Some 68% of the candidates are students who have recently graduated from high school. Half of them are taking the *vestibular* for the first time, and the other half are retaking it because they were not admitted the year before. The minority are candidates who came from other institutions or study programs (12%), graduated from the adult education program (2.5%), or have not studied for a while (17.5%). In fact, anyone with a high school diploma or equivalent can apply to the university; the chances of being accepted depend uniquely on the test score.

The admission process in Brazil requires candidates to choose their study program (major) when they apply. That is, they are not admitted to the university as a whole, but to a particular undergraduate program offered by the institution. They cannot apply to multiple programs in the same year. To switch majors, the student has to retake the *vestibular* and compete for a place in the new program. A very few students, less than 5%, are able to skip this process and join a program that is short of non-freshman students.

The *vestibular* has two rounds. The first one assesses students' general knowledge and eliminates about 40% of the candidates.[2] In the second round, the remaining candidates

[1] In 2015, all programs began to adopt the new national entrance process (the Unified Selection System, SISU) to public universities in Brazil, ending institution-specific exams.

[2] Since 2010, the first round has been replaced by the National High School Exam (ENEM), which has a

are tested in Portuguese, a foreign language, and three other subjects that are particularly required for the major. The final score is a weighted average of the first- and second-round scores. Finally, each program admits those candidates with the best final scores until all the places are taken. On average, only 10% of the original candidates per program are admitted.

A.2 Class Assignment

Fifty-seven out of 99 programs offer two options for the freshmen. They can start studying either in the first semester (called the "first class" hereafter) or in the second semester of the academic year (called the "second class"). Table S1 presents the list of programs, indicating those with two classes. These classes must have the same number of students. Despite delaying graduation for at least half a year, starting later does not change a student's curriculum because all the required courses are offered every semester. Most importantly, students starting in different terms will have different classmates even though they attend the same institution. In their first term, students in the same class take all courses together and do not interact academically with students from the other class.

In those programs, candidates are required to reveal their class preference before taking the entrance exam. In practice, about 70% of the admitted students prefer to attend the first class. Given the limited number of places, the order of preference is strictly based on their final entrance score. Once the first class is full, the remaining students have to join the second class, regardless of their initial choice. The final classification of candidates, organized by class and major, is fully disclosed by the admissions committee (*Comissão para o Vestibular*, COVEST) through its website and printed in the newspapers. Candidates cannot switch classes after the final classification is revealed, or even after the application.

Despite the initial class assignment, course retention forces first-class students to attend classes with second-class students, and vice versa. To keep our instrument valid, we analyze the effect of the initial assignment instead of the actual class composition. The bias created

similar structure.

by mixing classes should pull our estimates towards zero.

B Estimation Procedures

B.1 Standard Regression Discontinuity

To estimate equation (1), we use locally weighted regression (LWR) with triangular kernel weights, as follows. Set $Y = [y_1 \ \dots \ y_n]'$, $C = \left[\mathbf{1}(c_1 = 1) \ \dots \ \mathbf{1}(c_n = 1)\right]'$, and $X = \left[(1, x_1 - \underline{x}) \ \dots (1, x_n - \underline{x})\right]'$, where n is the number of observations. Also set $W_- = \text{diag}\big(\mathbf{1}(x_1 < \underline{x})\, k_1, \dots, \mathbf{1}(x_n < \underline{x})\, k_n\big)$ and $W_+ = \text{diag}\big(\mathbf{1}(x_1 \geq \underline{x})\, k_1, \dots, \mathbf{1}(x_n \geq \underline{x})\, k_n\big)$, where diag(.) denotes a diagonal matrix and $k_i = \max\Big[0, \big(1 - |x_i - \underline{x}|\,/b\big)\Big]$ is a triangular kernel weight, with a chosen bandwidth b.

First, we estimate the following LWR estimator on each side of the cutoff:

$$\hat{\mu}_-^z = (1 \ \ 0)\left(X'W_-X\right)^{-1} X'W_-Z,$$
$$\hat{\mu}_+^z = (1 \ \ 0)\left(X'W_+X\right)^{-1} X'W_+Z.$$

Then the estimator for the net effect of the first class is:

$$\widehat{\Delta y} = \frac{\hat{\mu}_+^y - \hat{\mu}_-^y - \hat{B}^y\,(b, b^*)}{\hat{\mu}_+^c - \hat{\mu}_-^c - \hat{B}^c\,(b, b^*)}. \tag{B.1}$$

where b is the optimal main bandwidth and b^* is the optimal pilot bandwidth. The bias estimator, $\hat{B}^z(.)$, adjusts the LWR estimates for a large, MSE-optimal bandwidth. See Calonico, Cattaneo and Titiunik (2014) for details of the bias correction and robust variance.

B.2 Conditional Regression Discontinuity

B.2.1 Estimator

To estimate equation (2), first we set $XQ = \left[(1, x_1 - \underline{x}, \Delta q_1) \ \dots (1, x_n - \underline{x}, \Delta q_n)\right]'$ and $V_-^u = \text{diag}\big(\mathbf{1}(x_1 < \underline{x})\, k_1 h_1^u, \dots, \mathbf{1}(x_n < \underline{x})\, k_n h_n^u\big)$ and $V_+^u = \text{diag}\big(\mathbf{1}(x_1 \geq \underline{x})\, k_1 h_1^u, \dots, \mathbf{1}(x_n \geq \underline{x})\, k_n h_n^u\big)$, where $h_i^u = \max\Big[0, \big(1 - |\Delta q_i - u|\,/d\big)\Big]$ is a triangular kernel weight, with a chosen bandwidth d. Then, for a chosen value u, we apply the following LWR estimator:

$$\hat{\eta}^z_-(u) = (1 \;\; 0 \;\; u)\left(XQ'V^u_-XQ\right)^{-1} XQ'V^u_-Z,$$
$$\hat{\eta}^z_+(u) = (1 \;\; 0 \;\; u)\left(XQ'V^u_+XQ\right)^{-1} XQ'V^u_+Z.$$

Hence, the estimator for Δy conditional on Δq is:

$$\widehat{\Delta y}(\Delta q = u) = \frac{\hat{\eta}^y_+(u) - \hat{\eta}^y_-(u) - \hat{B}^y(u, b, b^*)}{\hat{\eta}^c_+(u) - \hat{\eta}^c_-(u) - \hat{B}^c(u, b, b^*)}. \tag{B.2}$$

Given an arbitrary bandwidth d for the difference in peer quality, bandwidths b and b^* are calculated using the following MSE-optimal estimators:

$$b = \left[\frac{\hat{V}_1}{4\hat{B}_1^2 + \hat{R}_1}\right]^{1/5} n^{-1/5} \quad \text{and} \quad b^* = \left[\frac{5\hat{V}_2}{2\hat{B}_2^2 + \hat{R}_2}\right]^{1/5} n^{-1/5}, \tag{B.3}$$

where for $q = 1, 2$, $\hat{V}_q = \mathcal{V}_q(\hat{\eta}^y_+) + \mathcal{V}_q(\hat{\eta}^y_-)$, $\hat{B}_q = \mathcal{B}_q(\hat{\eta}^y_+) - \mathcal{B}_q(\hat{\eta}^y_-)$, and $\hat{R}_q = \mathcal{R}_q(\hat{\eta}^y_+) + \mathcal{R}_q(\hat{\eta}^y_-)$. Functions $\mathcal{V}_q(.)$, $\mathcal{B}_q(.)$ and $\mathcal{R}_q(.)$ are specified by Calonico, Cattaneo and Titiunik (2014).

B.2.2 Interpretation

Let y_{kci} be the outcome of interest of student i in class c of program k. This outcome is a function of each student's rank, r_{kci}, and peer quality, q_{kc}. To simplify our setting, we assume no time variation. But in practice we also exploit the fact that the class composition within programs changes every year. Then suppose that the outcome is a function of these explanatory variables in the following way:

$$y_{kci} = B(r_{kci}) + \Gamma(q_{kc}) + u_{kci} \tag{B.4}$$

where $B(.)$ and $\Gamma(.)$ are monotonic continuous functions.

For any outcome z, Δz represents the expected difference between classes for the last student in the first class. Then from equation (B.4), the net effect of the first class is given by:

$$\Delta y = \beta\,\Delta r + \gamma\,\Delta q, \tag{B.5}$$

where $\beta = \left[B(\bar{r}_1) - B(\bar{r}_2)\right]/\Delta r$, with $\bar{r}_c = E\big(r|c, x = \underline{x}_k\big)$, and $\gamma = \left[\Gamma(\bar{q}_1) - \Gamma(\bar{q}_2)\right]/\Delta q$, with $\bar{q}_c = E\big(q|c, x = \underline{x}_k\big)$.

Unlike Δr, which is a fuzzy estimand, Δq_k is observed for each program (every year). Even though its effect can be specific per student, its value is not specific to those close to the cutoff — i.e., $E\big(q|k, c, x\big) = E\big(q|k, c\big)$. The difference in peer quality between classes is common to all students in the same program. Hence, for a given difference Δq_k, the fuzzy discontinuity is given by:

$$\begin{aligned}\Delta y_k\left(\Delta q_k\right) &= \frac{\lim_{x\downarrow\underline{x}} E\left(y|x \geq \underline{x}_k, \Delta q_k\right) - \lim_{x\uparrow\underline{x}} E\left(y|x < \underline{x}_k, \Delta q_k\right)}{\lim_{x\downarrow\underline{x}} \Pr\left(c = 1|x \geq \underline{x}_k, \Delta q_k\right)} \\ &= E\left(\beta_k|\Delta q_k\right) \cdot \Delta r_k(\Delta q_k) + \gamma_k \cdot \Delta q_k \end{aligned} \tag{B.6}$$

where $\beta_k = \left[B(\bar{r}_{k1}) - B(\bar{r}_{k2})\right]/\Delta r_k$, with $\bar{r}_{kc} = E\big(r|c, x = \underline{x}_k, \Delta q_k\big)$, and $\gamma_k = \left[\Gamma(q_{k1}) - \Gamma(q_{k2})\right]/\Delta q_k$. For programs in which classes are similar ($\Delta q_k = 0$), this fuzzy discontinuity depends only on the first term on the right-hand side (the rank effect).

By estimating the relationship between $(\Delta y_k, \Delta r_k)$ and Δq_k, we not only approximate the rank effect at $\Delta q_k = 0$ but also verify how the net effect, Δy_k, changes with a higher peer quality in the first class. From equation (B.6), consider that

$$\frac{d\Delta y_k}{d\Delta q_k} = E\left(\beta_k|\Delta q_k\right)\frac{d\Delta r_k}{d\Delta q_k} + \Delta r_k \frac{dE\left(\beta_k|\Delta q_k\right)}{d\Delta r_k}\frac{d\Delta r_k}{d\Delta q_k} + \gamma_k. \tag{B.7}$$

Note that Δr_k is negative because the last student in the first class should always increase their rank by moving to the second class. Moreover, $d\Delta r_k/d\Delta q_k$ is negative because the wider the gap between the two classes, the sharper the discontinuity in the student's rank. If we assume that $B(.)$ is weakly monotonic, then $d\Delta y_k/d\Delta q_k > 0$ implies that $\gamma_k > 0$. That is, $d\Delta y_k/d\Delta q_k$ provides a lower bound estimator for the marginal effect of peer quality, γ_k.

C Data Sources and Sample

Our data come from four different sources. The first is the admissions committee (COVEST), which provides information on every applicant from 2002 to 2007. The second is UFPE's

Academic Information System (*Sistema de Informações e Gestão Acadêmica*, SIGA), which provides information on students' enrollment, grades and status. The third is the Annual Social Information Report (*Relação Anual de Informações Sociais*, RAIS) from the Ministry of Labor, which contains information on every registered employee in Brazil. The last comes from a telephone survey, carried out in 2015, that interviewed a sample of students who entered UFPE between 2002 and 2006.

C.1 Applications and Entrance Score

The COVEST data include the test scores from the first and second rounds and the final entrance score. Since all candidates take the same exam in the first round, the round 1 score is our proxy for cognitive skills, which is used to compare students across programs. Although this score is an average of scores per subject, such as History and Chemistry, Ribas, Sampaio and Trevisan (2020) show that it is strongly correlated with all the subject scores, and no correlation between subject scores is found to be negative — i.e., subject scores are not substitutes.[3] The round 1 score is standardized by year using the mean and standard deviation of all the candidates. We also use the round 1 score to assess "peer quality," measured by the median score in the class and other quantiles. Unlike the leave-out mean, the quantiles provide a full picture of the distribution of skills and are not sensitive to individual values.

The final score is the determinant of class assignment and relative rank. We standardize this variable by program and year using the first-class cutoff — i.e., the final score of the last student in the first class — and the standard deviation of admitted candidates' scores. To rank students per class, we use the percentiles of the final score. The last student in a class has a rank equal to zero, while the first student's rank equals one.

The COVEST data also include the number of times each candidate took the entrance exam in the past, their previous score(s), previous studies, and a long list of characteris-

[3] We do not use the subject scores in our analysis because they are available only for 2005.

tics, such as age, gender, race, employment, and parents' education. On the basis of this information, we restrict our sample to candidates who are admitted by UFPE for the first time and join a program with two classes. Moreover, the sample excludes students who were admitted through a process other than the *vestibular* or had been attending another higher education institution. It is worth mentioning that students' rank and peer quality were measured before the sample was restricted.

C.2 College Enrollment and Transcripts

SIGA provides detailed information on all students enrolled in 2002-2014, regardless of when they enter and leave the institution. Variables include students' academic status (active, graduated or dismissed), the number of missed sessions in each course enrolled, and the final grade of every course taken at the university. These grades are used to calculate students' grade point average (GPA), failure rate, dropout rate, and standardized grade by course. Based on the students' status, we also verify whether they switch programs before graduating. Students who did not enroll in any course in the first semester are excluded.

This source also contains the characteristics of all instructors, such as gender, age, and academic position. To assess instructors' unobserved characteristics, we estimate instructor-specific parameters related to dropout and failure rates in their courses (see Section C.5). Since each student takes several courses at the same time, with different instructors, all these variables are averaged per semester.

C.3 Future Occupation

In Brazil, every registered firm is legally required to annually report every worker employed in the previous year, with information about salary, number of months worked, and type of occupation. This information is available on RAIS. Using students' social security number (*Cadastro de Pessoa Física*, CPF), we match the two previous data sources with RAIS to obtain their occupation for every year from 2002 to 2014.

Then, we construct two variables: whether the student was employed for at least a month; and whether she, if employed, had a middle- or top-level management position. Table S2 presents the list of occupation codes, highlighting those classified as management positions. The final variables are constructed for each year after the students' expected graduation. These years are counted from the month in which a student should end the initially chosen program. Any delay due to personal reasons, including the decision to start a new study program, or unforeseen circumstances, such as strikes, are not taken into account.

C.4 Telephone Survey

In 2015, a telephone survey was conducted with UFPE alumni to collect information regarding their professional history and family. The sample comes from a universe of 11,813 alumni who entered the university between 2002 and 2014. The sampling process was stratified by gender, year of admission, and study program, with a target size of 2,490 interviews. Using 25 interviewers, the survey took eight weeks to complete. Every time a sampled subject did not respond the call, he or she was replaced by another random subject within the same stratum. In total, 32,834 calls were made until 2,490 subjects were interviewed. From this sample, we are able to match 1,373 alumni with our sample, which represents 10% of the 2002-2007 cohorts.

On average, the interviews took 12 minutes each. The questionnaire includes questions on previous and current occupations, marital status, number of children, and individual grit. The latter was assessed by reading eight statements to the subject and asking her whether they sound: 1) "very much like her," 2) "mostly like her," 3) "somewhat like her," 4) "not much like her," and 5) "not like her at all" (Duckworth et al., 2007). In our analysis, we consider that subjects strongly agree with the statement if they check option 1), and agree if they check either option 1) or 2). Subjects strongly disagree with the statement if they check option 5), and disagree if they check either option 4) or 5). Following Duckworth et al., we also construct the grit scale, which is the sum of answered numbers divided by eight. For half of the questions, the numbers are reversed.

C.5 Instructor Quality

To construct measures of instructors' quality, we apply the following procedure. Consider the performance of student i in course s, taught by instructor p, y_{isp}, as a function of the individual fixed effect, γ_i, course fixed effect, γ_s, and instructor fixed effect, γ_p:

$$y_{isp} = \gamma_i + \gamma_s + \gamma_p + \varepsilon_{isp} \tag{C.1}$$

where $\varepsilon_{isp} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$.

The parameter of instructor quality, γ_p, is identified because some instructors teach multiple courses and some courses are taught by multiple instructors. This parameter is estimated through three steps.

The first step is to subtract the average outcome per course from the student's observed performance:

$$\hat{y}_{ip}(s) = y_{isp} - \frac{\sum_i 1(i \in N_s) \cdot y_{isp}}{\sum_i 1(i \in N_s)} \qquad \text{for all } s = 1, ..., S. \tag{C.2}$$

where N_s is the set of students who took course s.

The second step is to average $\hat{y}_{ip}(s)$ per student:

$$\bar{\hat{y}}_i = \frac{\sum_s 1(i \in N_s) \cdot \hat{y}_{ip}(s)}{\sum_s 1(i \in N_s)}. \tag{C.3}$$

Let $N_{s,p}$ be the subset of students who attended course s with instructor p. Then the estimator for the instructor fixed effect is given by:

$$\hat{\gamma}_p = \frac{\sum_s \sum_i 1(i \in N_{s,p}) \cdot \left[\hat{y}_{ip}(s) - \bar{\hat{y}}_i\right]}{\sum_s \sum_i 1(i \in N_{s,p})}. \tag{C.4}$$

In our study, this informartion is used to verify whether instructors' quality is similar between classes. See Tables A1 and S4.

C.6 Descriptive Statistics

Table A1 presents descriptive statistics for most of the variables in our dataset. Due to the class assignment, described above, both the final entrance score and round 1 score are, on average, higher in the first class. The average GPA in the first academic term and the graduation rate are also higher in the first class, which confirms that it indeed has better students.

D A Model of Class Composition and Career Decisions

Consider a continuum of individuals who have to make a decision about their careers by the end of high school. Individual i has to choose either among K high-skilled careers or one that does not require a college degree, denoted by $k = 0$. This decision is reversible and individuals may change their career paths later on, but at a cost. Skill level s_i is known by individual i, but it is distributed according to an unknown function $F(s)$.

For $k = 0$, individuals can immediately find a job, but for $k > 0$ individuals must spend one period in college before going to the market. After college, individual i's utility in career k is given by:

$$u_i^k = v_i^k + w^k \, p\Big(h_i^k, h_{-i(k)}^k\Big) \, ,$$

where v_i^k is the individual taste for career k, w^k is the lifetime salary in this career, $p\Big(h_i^k, h_{-i(k)}^k\Big)$ is the probability of finding a job, h_i^k is the k-specific human capital accumulated by i, and $h_{-i(k)}^k$ denotes the quantiles of human capital among those who choose career k, excluding i. All individuals have their own taste for each high-skilled career, $\big\{v_i^1, \ldots, v_i^K\big\}$, which is independently drawn, but they do not know it until they go to college.

The probability of finding a job in career k is increasing in h_i^k, $\partial_1 p > 0$, and nonincreasing in $h_{-i(k)}^k$, $\partial_2 p \leq 0$. Based on its curvature, we define two types of career: those in which most workers succeed, and those in which only a few workers succeed. One may think of $p(.)$ not as the probability of employment, but as the distribution function of salaries.

Definition 1. *A career is* highly competitive *if the probability is convex in the individual human capital, $\partial_{11}\, p \geq 0$, and an increase in peers' ability reduces the individual return, $\partial_{12}\, p \leq 0$. A career is* less competitive *if the probability is concave in the individual human capital, $\partial_{11}\, p \leq 0$, and an increase in peers' ability increases the individual return, $\partial_{12}\, p \geq 0$.*

The human capital is a function of inherited skills, s_i, the effort applied during the study program, e_i^k, and the skill distribution of classmates, $s_{-i(c)}$:

$$h_i^k = h^k\left(e_i^k, s_i, s_{-i(c)}\right).$$

For every k, we assume that $\partial_1 h^k$, $\partial_2 h^k > 0$, and $\partial_{11} h^k < 0$. We also assume that peer quality increases human capital, $\partial_3 h^k > 0$, the return of effort (learning), $\partial_{13} h^k \geq 0$, and hence the probability of finding a job, $\partial_1 p\, \partial_3 h^k > 0$. Given this human capital production function, peer effect is defined as:

Definition 2. Peer effect *is the direct effect that peer skills, $s_{-i(c)}$, have on the accumulation of human capital and on its derivatives.*

With $K + 1$ options in hand, an individual's initial decision is based on the expected value of each career path. However, individuals do not know the true distribution of skills in the population and, as a result, the distribution among those who choose each career, F^k. Thus their initial decision is based on the belief that individual skills in their chosen career follow a prior distribution, $s_{-i(k)} \sim \tilde{F}_i^k$. Likewise, individuals also believe that the skill distribution of classmates is not different from the population of workers in k, so $s_{-i(c)} \sim \tilde{F}_i^k$. This prior distribution is randomly drawn among individuals, but it also depends on their initial information set I_i — i.e., how accurate their prior is. Let $\mathcal{I}$ represent all the existent information. If $I_i = \mathcal{I}$, then $\tilde{F}_i^k \to F^k$. If $I_i = \emptyset$, then individuals are clueless about the distribution of $s_{-i(k)}$ and heavily influenced by any new information.

During college, effort has a marginal disutility equal to γ. Given $\tilde{F}_i^k$ for every k =

$1, \ldots, K$, individual's problem is to choose k and $\{e^k\}_{k=1}^{K}$ so that their value function is

$$\begin{aligned} V_i &= \max_{k,\{e^k\}} \left\{ V_i^0, V_i^1, \ldots, V_i^K \right\} \\ &= \max_{k,\{e^k\}} \left\{ w^0, \theta \tilde{E}_i\big(w_i^1\big) - \gamma e_i^1, \ldots, \theta \tilde{E}_i\Big(w_i^K\Big) - \gamma e_i^K \right\}. \end{aligned} \tag{D.5}$$

where $\theta \in (0,1)$ is a discount factor. $\tilde{E}_i\big(w_i^k\big)$ is individual i's subjective expectation of their future salary, which is given by:

$$\tilde{E}_i\Big(w_i^k\Big) = w^k p\left[h^k\Big(e_i^k, s_i, \tilde{F}_i^{k^{-1}}\Big), \tilde{F}_i^{k^{-1}}\right] = w^k \tilde{p}_i^k\left[\tilde{h}_i^k\Big(e_i^k\Big)\right],$$

where $\tilde{p}_i^k(.)$ and $\tilde{h}_i^k(.)$ are subjective functions derived from s_i and $\tilde{F}_i^k$. That is, the subjective expectation of the future salary depends on how the individuals see themselves in comparison to their envisaged peers.

After $k > 0$ is chosen, students get to know their classmates' skills, $s_{-i(c)}$, and this information is incorporated in the posterior distribution $\hat{F}_i^k$. If $s_{-i(c)} \geq \tilde{F}_i^{k^{-1}}$, then $\hat{F}_i^{k^{-1}} \geq \tilde{F}_i^{k^{-1}}$ as long as $I_i \subsetneq \mathcal{I}$. If $I_i = \emptyset$, then $\hat{F}_i^{k^{-1}} = s_{-i(c)}$. Since $s_{-i(c)}$ is known, there is no longer any uncertainty regarding $h_i^k(.)$. In college, students also learn about their taste for the chosen career, v_i^k. With these adjustments, students face new decisions: how much their effort should change, and whether they should drop out of college (D), switch careers (S) or graduate (G). Their new value function is:

$$\hat{V}_i^k = \max_{\{D,S,G\},e^k} \left\{ V_i^0,\ \theta V_i^{k'},\ \theta v_i^k + \theta w^k \hat{p}_i^k\left[h_i^k\Big(e_i^k\Big)\right] - \gamma e_i^k \right\} \tag{D.6}$$

where $V_i^{k'} = \max\left\{V_i^1, \ldots, V_i^{k-1}, V_i^{k+1}, \ldots, V_i^K\right\}$, which is given and does not vary with v_i^k and $s_{-i(c)}$ — i.e., neither their program nor their classmates provide any information on the value of other careers. Given the revelation of $s_{-i(c)}$, we define another effect:

Definition 3. Ranking effect *is the direct effect that peer skills, $s_{-i(c)}$, have on the subjective probability of being employed and on its derivatives.*

Suppose student i is randomly assigned either to class 1 or to class 2, with $\big(s_{-i(1)} \cup s_{-i(2)}\big) = F^{k^{-1}}$, $\big(s_{-i(1)} \cap s_{-i(2)}\big) = \emptyset$ and $s_{-i(1)} \geq s_{-i(2)}$. That is, the distribution of students in the program is equal to the true distribution of skills in the career, no student attends the two classes at the same time, and at least one student in class 1 has better skills than the rank-equivalent student in class 2. From the model above, we extract the following propositions.

Proposition 1. *The ranking effect increases (reduces) the student's probabilities of switching careers in class 1 (class 2). The peer effect has the opposite consequence. Therefore, the net effect of going to the better class is ambiguous.*

Proof. From value function (D.6), given the initial choice for career k, the probability of switching careers is given by:

$$\Pr(S) = \Pr\left\{\theta V_i^{k'} \geq \theta v_i^k + \theta w^k \hat{p}_i^k\left[h_i^k\left(e_i^k, s_{-i(c)}\right)\right] - \gamma e_i^k\right\} \tag{D.7}$$

$$= \Pr\left\{v_i^k \leq V_i^{k'} + \gamma e_i^k/\theta - w^k \hat{p}_i^k\left[h_i^k\left(e_i^k, s_{-i(c)}\right)\right]\right\}$$

$$\propto \gamma e_i^k/\theta - w^k \hat{p}_i\left[h_i^k\left(e_i^k, s_{-i(c)}\right), s_{-i(c)}\right], \tag{D.8}$$

where e_i^k is given by the first-order condition:

$$w^k \frac{\partial \hat{p}_i}{\partial h}\left[h_i^k\left(e_i^k, s_{-i(c)}\right), s_{-i(c)}\right] \frac{\partial h_i^k}{\partial e}\left(e_i^k, s_{-i(c)}\right) - \frac{\gamma}{\theta} = 0. \tag{D.9}$$

Then differentiating (D.8) with respect to $s_{-i(c)}$ and with condition (D.9), we have:

$$\frac{\partial \Pr(S)}{\partial s_{-i(c)}} \propto -\frac{\partial \hat{p}_i}{\partial s_{-i(c)}}\left[h_i^k\left(e_i^k\right), s_{-i(c)}\right] - \frac{\partial \hat{p}_i}{\partial h}\left[h_i^k\left(e_i^k, s_{-i(c)}\right), s_{-i(c)}\right] \frac{\partial h_i^k}{\partial s_{-i(c)}}\left(e_i^k, s_{-i(c)}\right). \tag{D.10}$$

From Definition 3, $\partial \hat{p}_i / \partial s_{-i(c)}$ is a ranking effect and the first term on the RHS of (D.10) is non-negative. That is, an increase in peer skills should, if anything, reduce the subjective probability of finding a job in k and hence increase the probability of switching programs.

From Definition 2, $\partial h_i^k / \partial s_{-i(c)}$ is a peer effect and the second term on the RHS of (D.10) is non-positive. That is, an increase in peer skills should, if anything, increase human capital, which increases the subjective probability of finding a job in k and hence reduces the probability of switching careers. ∎

Proposition 2. *If the career is highly competitive, then the ranking effect reduces (increases) this student's effort in class 1 (class 2), decreasing (increasing) their true expected salary. The peer effect has the opposite consequence. Therefore, the net benefit of going to the better class is ambiguous.*[4]

Proof. Given k, the second order condition for an optimal e_i^k is:

$$\partial_{ee}\hat{V}_i^k = \frac{\partial^2 \hat{p}_i}{\partial h^2}\left[h_i^k\left(e_i^k\right)\right] \cdot \left[\frac{\partial h_i^k}{\partial e}\left(e_i^k, s_{-i(c)}\right)\right]^2 + \frac{\partial \hat{p}_i}{\partial h}\left[h_i^k\left(e_i^k\right)\right] \cdot \frac{\partial^2 h_i^k}{\partial e^2}\left(e_i^k, s_{-i(c)}\right) < 0. \quad \text{(D.11)}$$

By differentiating (D.9) with respect to $s_{-i(c)}$, we have:

$$\begin{aligned}\frac{\partial e_i^k}{\partial s_{-i(c)}} &= \left(-\partial_{ee}\hat{V}_i^k\right)^{-1}\left[\frac{\partial h_i^k}{\partial e}\frac{\partial^2 \hat{p}_i}{\partial h \partial s_{-i(c)}} + \frac{\partial h_i^k}{\partial e}\frac{\partial^2 \hat{p}_i}{\partial h^2}\frac{\partial h_i^k}{\partial s_{-i(c)}} + \frac{\partial \hat{p}_i}{\partial h}\frac{\partial^2 h_i^k}{\partial e \partial s_{-i(c)}}\right] \\ &\propto \frac{\partial h_i^k}{\partial e}\frac{\partial^2 \hat{p}_i}{\partial h \partial s_{-i(c)}} + \frac{\partial h_i^k}{\partial e}\frac{\partial^2 \hat{p}_i}{\partial h^2}\frac{\partial h_i^k}{\partial s_{-i(c)}} + \frac{\partial \hat{p}_i}{\partial h}\frac{\partial^2 h_i^k}{\partial e \partial s_{-i(c)}}. \end{aligned} \quad \text{(D.12)}$$

From Definition 3, $\partial^2 \hat{p}_i / \partial h \partial s_{-i(c)}$ is a ranking effect, which is non-positive if the career is highly competitive (Definition 1). Thus, the first term on the RHS of (D.12) is non-positive — i.e., an increase in peer skills should, if anything, reduce the perceived return of human capital and hence reduce effort. In less competitive careers, $\partial^2 \hat{p}_i / \partial h \partial s_{-i(c)} \geq 0$ and the implied effect on effort is non-negative.

From Definition 2, $\partial h_i^k / \partial s_{-i(c)}$ and $\partial^2 h_i^k / \partial e \partial s_{-i(c)}$ are peer effects. If the career is highly competitive (Definition 1), then $\partial^2 \hat{p}_i / \partial h^2 \geq 0$ and the second term on the RHS of (D.12) is non-negative. That is, an increase in peer skills should increase human capital and, if anything, its perceived return and hence increase effort. In less competitive careers, $\partial^2 \hat{p}_i / \partial h^2 \leq 0$ and the implied effect on effort is non-positive — i.e., peer quality substitutes effort. As long as a higher peer quality improves learning, $\partial^2 h_i^k / \partial e \partial s_{-i(c)} > 0$, then the third term is positive.

[4] If the career is less competitive, then the ranking effect increases the student's effort and future salary in class 1. The peer effect on effort is ambiguous because a better peer quality improves learning, but it also substitutes effort. However, the peer effect increases the future salary in class 1.

For the same student, the effect of $s_{-i(c)}$ on the true expected salary is:

$$\frac{\partial E\left(w_i^k\right)}{\partial s_{-i(c)}}\left(e_i^k, s_{-i(c)}\right) = w^k \frac{\partial p}{\partial h}\left(\frac{\partial h_i^k}{\partial e}\frac{\partial e_i^k}{\partial s_{-i(c)}} + \frac{\partial h_i^k}{\partial s_{-i(c)}}\right)$$
$$\propto \left(\frac{\partial h_i^k}{\partial e}\right)^2 \frac{\partial^2 \hat{p}_i}{\partial h \partial s_{-i(c)}} - \frac{\partial^2 h_i^k}{\partial e^2}\frac{\partial \hat{p}_i}{\partial h}\frac{\partial h_i^k}{\partial s_{-i(c)}} + \frac{\partial h_i^k}{\partial e}\frac{\partial \hat{p}_i}{\partial h}\frac{\partial^2 h_i^k}{\partial e \partial s_{-i(c)}} \tag{D.13}$$

The second and third terms on the RHS of (D.13), representing the peer effect, are positive as long as it exists. The first term, representing the ranking effect, is negative only in highly competitive careers. Therefore, the peer quality can make students in class 1 better off due to the peer effect, but it can also make them worse off due to the ranking effect. ■

Note that Proposition 1, related to career changes, does not depend on how competitive the career is, but Proposition 2, which is related to effort, does. Therefore, the ranking effects on the applied effort and career decisions are not necessarily related.

E Other Potential Mechanisms for Gender-Specific Effects

We also consider three other potential mechanisms for the gender-specific effects on managerial attainment: the sorting of men and women into different programs, women's motherhood decisions, and gender differences in a personality trait such as grit.

E.1 Gender Sorting into Programs of Study

In Table S9, we verify whether the gender differences in the last-in-class effect are related to the type of study program. This table shows that the more competitive the admissions process, the more pronounced and persistent the effect on women. Namely, high-achieving women are more sensitive to the class assignment in the short and long run. In the long run, though, both men and women are more affected by their lower ranks in programs with lower failure rates. A possible explanation is that in difficult programs, the class composition changes more often, so students' initial class matters less. Still, even in those programs the initial negative effect disappears for men but not for women.

We also check whether the gender differences could be explained by program choices. For women, we still observe a negative effect in programs with a higher share of male students. For men, we also observe the reversal effect in programs with a larger presence of women. Therefore, our results do not appear to be explained by gender differences in program choices.[5]

E.2 Effect on Motherhood Decisions

Another possible reason women in the first class do not attain a managerial position later is that they dedicate more time to their families, investing less in their careers (Bertrand, Goldin and Katz, 2010). To examine this mechanism, we estimate the last-in-class effect on the number of maternity leaves while employed, the number of children, and the probability of being married. Whereas the first outcome comes from the employment records (RAIS), the two others come from a telephone survey carried out in 2015 — i.e., nearly 10 years after they applied to college. Details about this survey are in Section C.4.

Table S10 shows that for women none of those outcomes are significantly affected by the class assignment. If anything, women at the bottom of the first class are less likely to be married and have children. For those who never became managers until year five, the probability of a maternity leave is slightly higher in the first class, but the difference between classes is not significant. Therefore, dedication to family does not seem to be a reason women in the first class do not catch up with the others.

E.3 Effect on Grit

Through the telephone survey, we also gathered self-reported data on students' dedication and perseverance a decade after their college admission (see Section C.4). Using these responses, we computed a 'grit' score as proposed by Duckworth et al. (2007).

[5] Other studies find that gender composition affects career aspirations (e.g., Dasgupta, Scircle and Hunsinger, 2015; Zölitz and Feld, 2021; Brenøe and Zölitz, 2020). Our result suggests that this effect does not interact with the effect of class assignment that we find.

Table S11 presents the estimated last-in-class effect on the 'grit' score. We find that, if anything, women at the bottom of the first class present a higher grit score than those in the second class. For men, the last-in-class effect is negative and insignificant. Still, compared to their counterparts with higher rank, the managerial attainment of low-ranking women is more affected in the long run than the low-ranking men's. Therefore, differences in grit levels does not appear to explain the gender-specific effects on managerial attainment.

References

Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz. 2010. "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors." *American Economic Journal: Applied Economics*, 2(3): 228–255.

Brenøe, Anne Ardila, and Ulf Zölitz. 2020. "Exposure to More Female Peers Widens the Gender Gap in STEM Participation." *Journal of Labor Economics*, 38(4): 1009–1054.

Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik. 2014. "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs." *Econometrica*, 82(6): 2295–2326.

Cattaneo, Matias D., Michael Jansson, and Xinwei Ma. 2019. "Simple Local Polynomial Density Estimators." *Journal of the American Statistical Association*, forthcoming: 1–7.

Dasgupta, Nilanjana, Melissa McManus Scircle, and Matthew Hunsinger. 2015. "Female peers in small work groups enhance women's motivation, verbal participation, and career aspirations in engineering." *Proceedings of the National Academy of Sciences*, 112(16): 4988–4993.

Duckworth, Angela L., Christopher Peterson, Michael D. Matthews, and Dennis R. Kelly. 2007. "Grit: Perseverance and passion for long-term goals." *Journal of Personality and Social Psychology*, 92(6): 1087–1101.

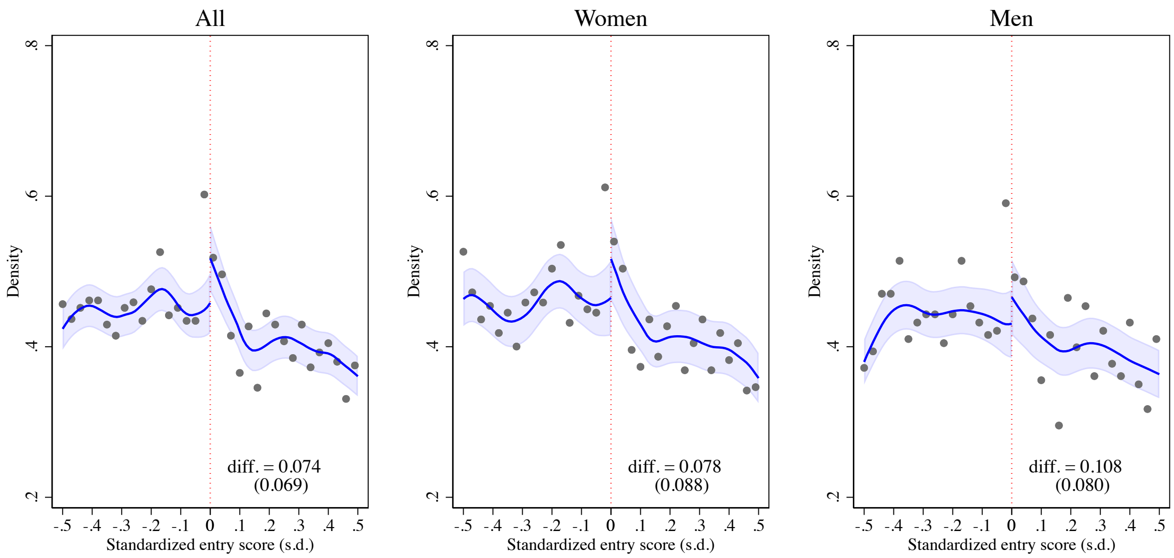
McCrary, Justin. 2008. "Manipulation of the running variable in the regression discontinuity design: A density test." *Journal of Econometrics*, 142(2): 698–714.

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): 1–13.

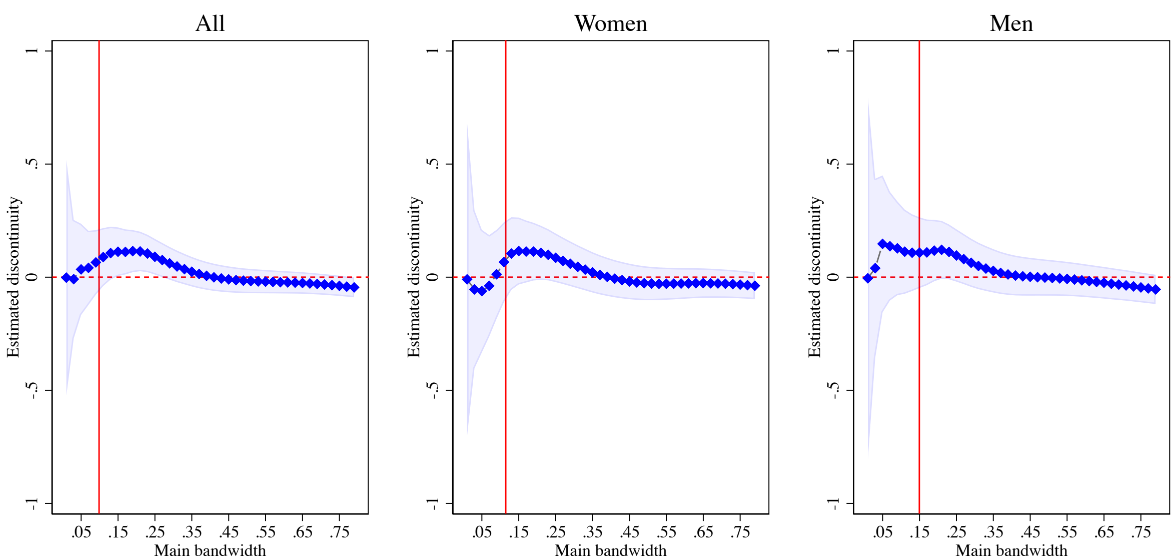
Zölitz, Ulf, and Jan Feld. 2021. "The Effect of Peer Gender on Major Choice in Business School." *Management Science*, 67(11): 6963–6979.

Figure S1: Test for Density Discontinuity at the Cutoff for the First Class

A: Discontinuity under the optimal bandwidth

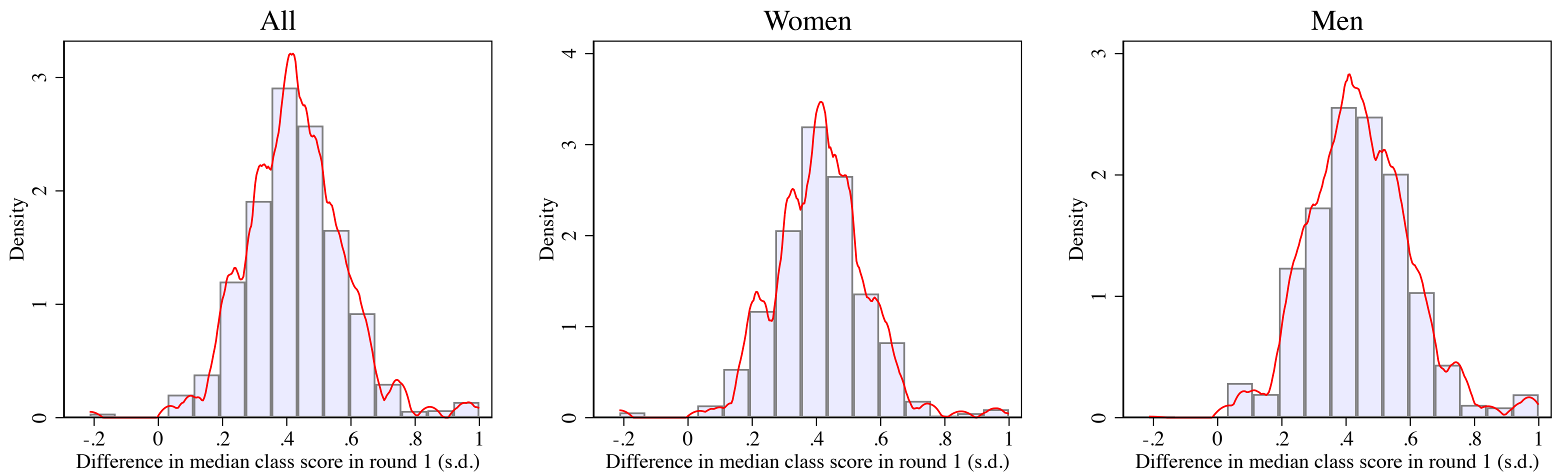


B: Discontinuity under different bandwidths



This figure presents the test for density discontinuity (McCrary, 2008). In panel (a), the blue line represents the estimated density, the shaded area represents its 95% confidence interval, and the gray dots represent the mean density within bins of 0.025 s.d. The running variable (standardized entry score), in the horizontal axis, is the final score used for admission to the study program; it is standardized by program and year using the cutoff for the first class and the s.d. of candidates admitted to the program. The estimated discontinuity ("diff.") is calculated using the estimator proposed by Cattaneo, Jansson and Ma (2019), with robust standard error in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. In panel (b), the estimated discontinuity (vertical axis) is obtained under several bandwidths (horizontal axis). The vertical line indicates the main bandwidth used in panel (a). N = 13,505 (all students), 7,411 (women), 6,094 (men).

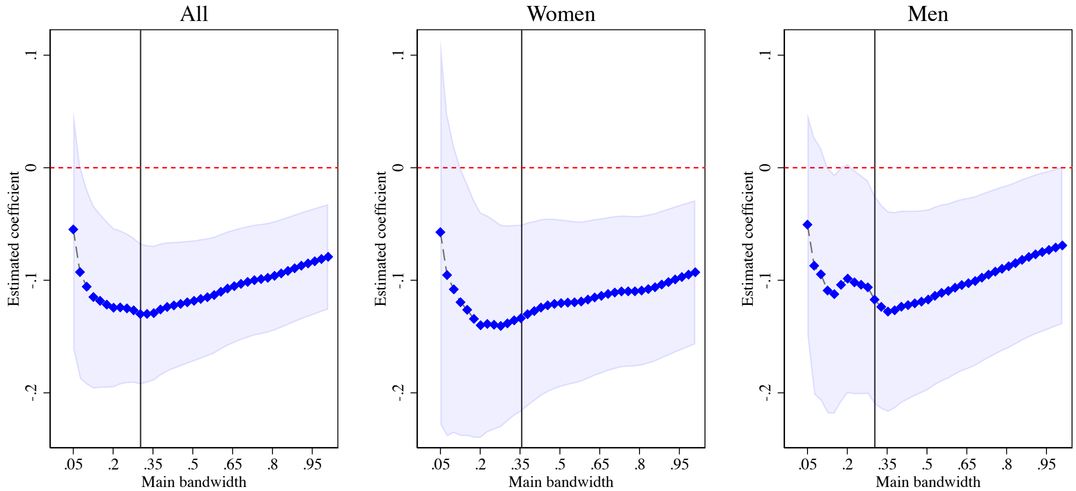
Figure S2: Distribution of Differences in Peer Performance between Classes



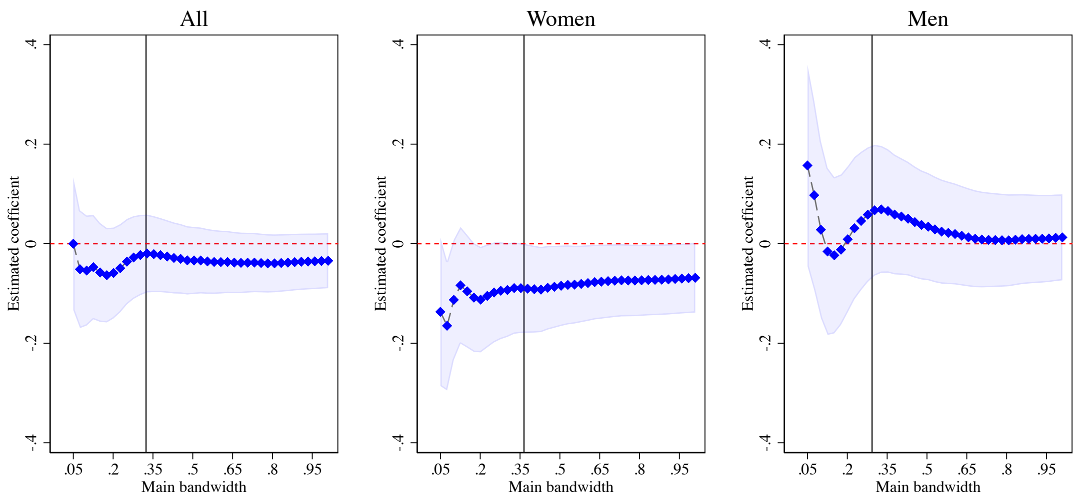
This figure presents the histograms for differences in peer performance between classes in the same program in the same year. Peer performance is measured by the median score of classmates in the first round of the entrance exam; this score is standardized by year using the mean and standard deviation of all the university candidates. The distribution in the left-hand graph is weighted by the total number of students. The graph in the middle is weighted by the number of female students. The right-hand graph is weighted by the number of male students. $N = 13{,}505$ (all students), 7,411 (women), 6,094 (men).

Figure S3: Last-in-Class Effect on Managerial Attainment under Different Bandwidths

A: Manager until four years after expected graduation



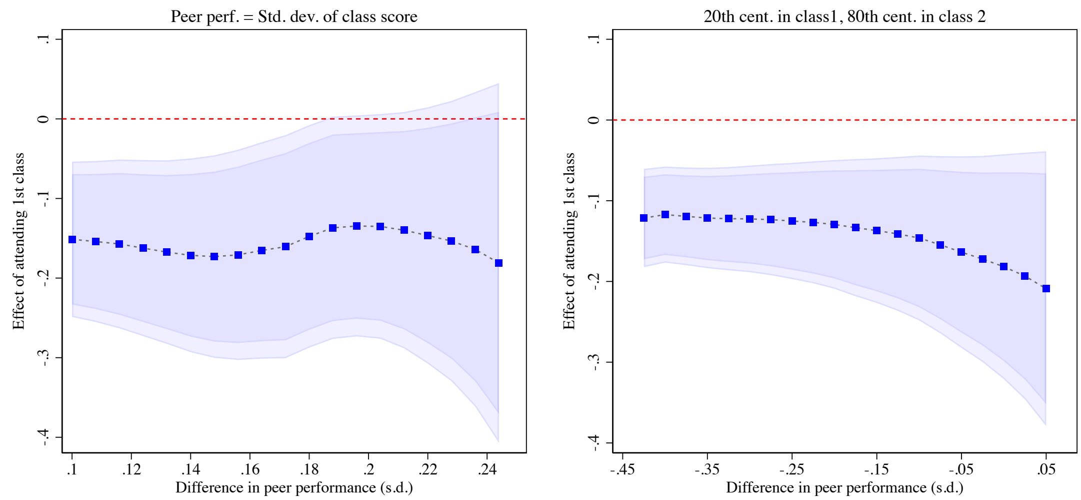
B: Becoming a manager five years after expected graduation



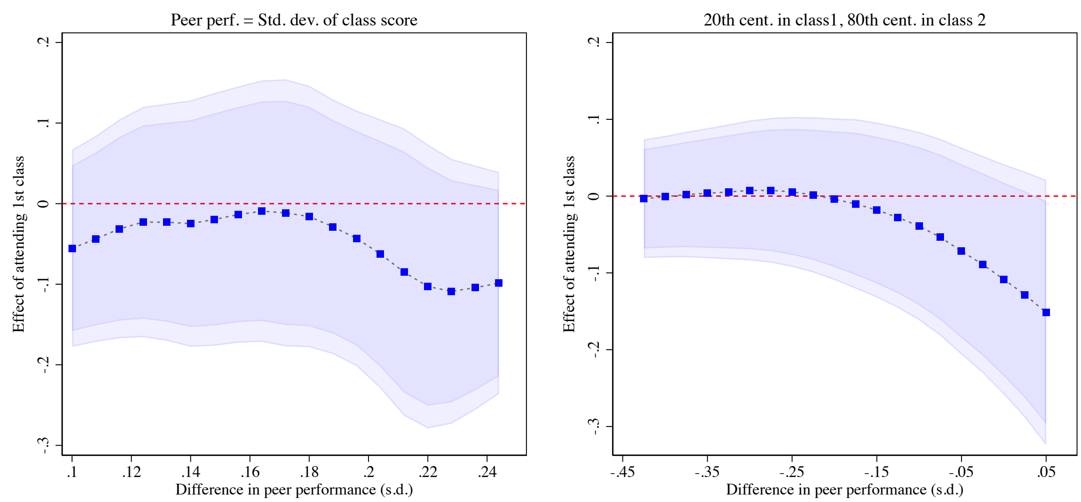
This figure presents the fuzzy regression discontinuity estimates (vertical axis), as in column (1) of Table 1, but using several bandwidths (horizontal axis). The shaded area represents the robust confidence interval at the 95% level. Functions are estimated using triangular kernel. The vertical line indicates the main bandwidth obtained with the procedure proposed by Calonico, Cattaneo and Titiunik (2014). N = 10,173 and 7,300 (all students), N = 5,641 and 4,045 (women), and 4,532 and 3,255 (men).

Figure S4: Relationship between the Last-in-Class Effect and Difference in Class Score Distribution

A: Manager until four years after expected graduation

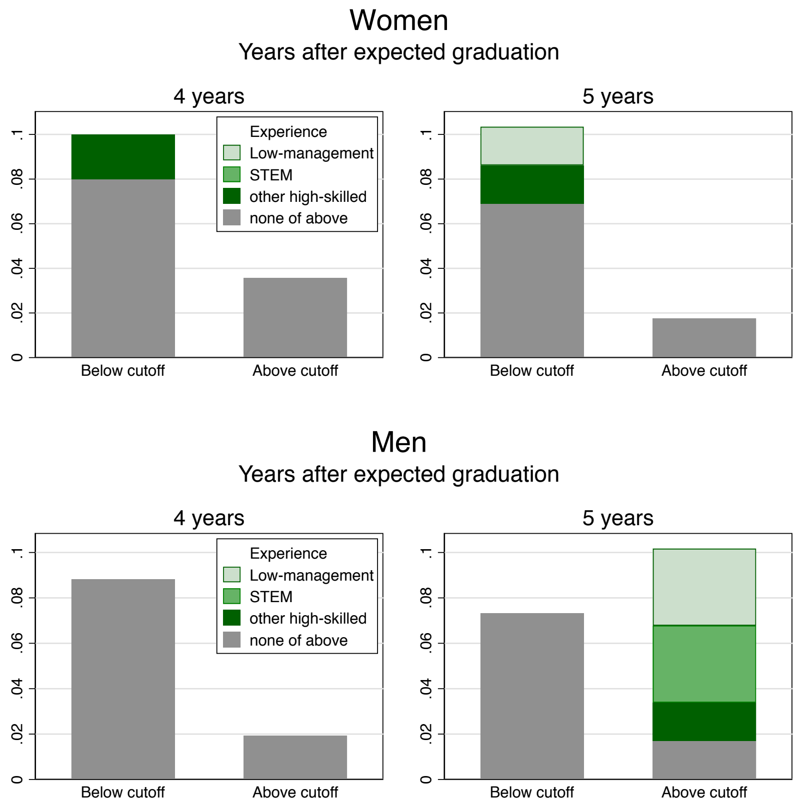


B: Becoming a manager five years after expected graduation



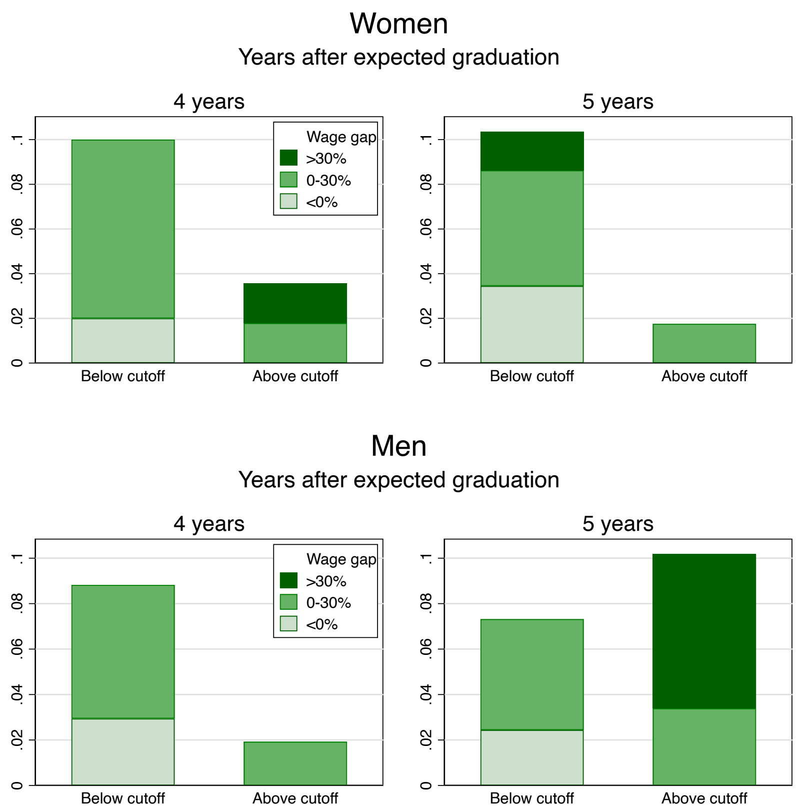
These graphs present the relationship between the last-in-class effect on managerial attainment (vertical axis) and the difference in peer performance between classes (horizontal axis). The last-in-class effect is estimated using a fuzzy regression discontinuity (FRD) design. Blue dots represent point estimates and the shaded areas represents their 90% and 95% confidence intervals. The dependent variable is equal to 1 if student occupies a top- or middle-level management position, and 0 otherwise. Panel A considers managerial attainment anytime within four years after the expected graduation. Panel B considers the probability of becoming a manager in year five. Sample includes only individuals who were employed by the time of the assessment. Peer performance is measured in two different ways: standard deviation of the class score in the first round of the entrance exam (left-hand graphs), and 20th centile of the score in class 1 and 80th centile of the score in class 2 (right-hand graphs). FRDs and their relationship with peer performance derive from locally weighted regressions with triangular kernel weights; the bandwidth is selected according to Calonico, Cattaneo and Titiunik (2014); the bandwidth for the difference in peer performance is 0.5 s.d. N = 9,889 (Panel A) and 6,695 (Panel B).

Figure S5: Proportion of Managers Below and Above the First-Class Cutoff by Professional Experience



This figure presents the proportion of managers four and five years after the expected graduation among students who were just below and above the first-class cutoff. Managers are classified based on their previous experience, before their first promotion. Sample includes only individuals who were employed by the time of the assessment and were within 0.025 s.d. of the cutoff. $N = 159$ (women) and 136 (men).

Figure S6: Proportion of Managers Below and Above the First-Class Cutoff by Gender Pay Gap

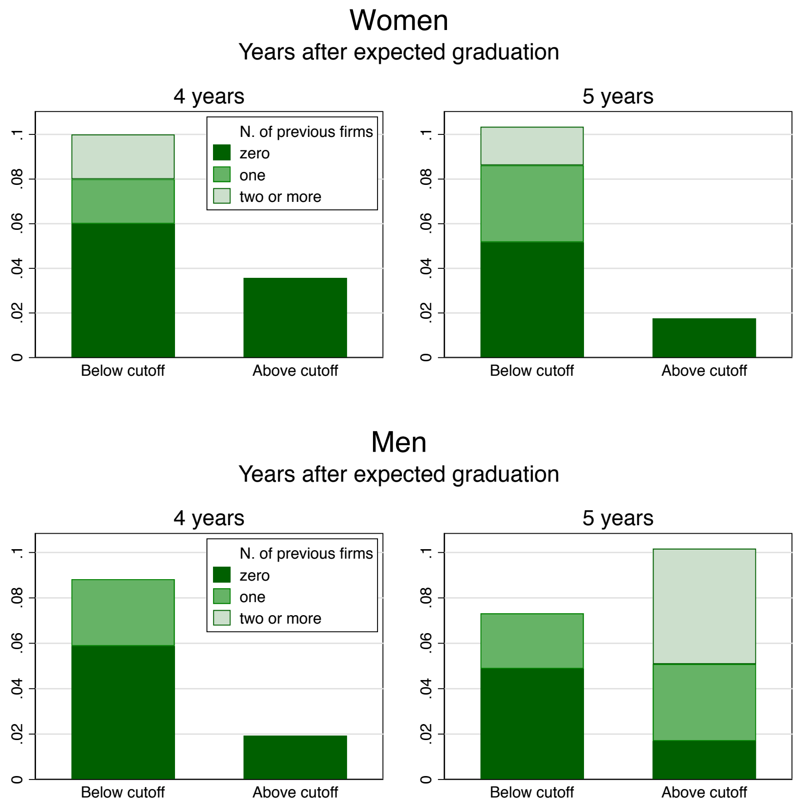


This figure presents the proportion of managers four and five years after the expected graduation among students who were just below and above the first-class cutoff. Managers are classified based on the gender pay gap in the firm that promoted them. Gender pay gap is calculated by the difference in the average log salary between men and women, controlling for education and position. Sample includes only individuals who were employed by the time of the assessment and were within 0.025 s.d. of the cutoff. $N = 159$ (women) and 136 (men).

Figure S7: Proportion of Managers Below and Above the First-Class Cutoff by Time to Graduation

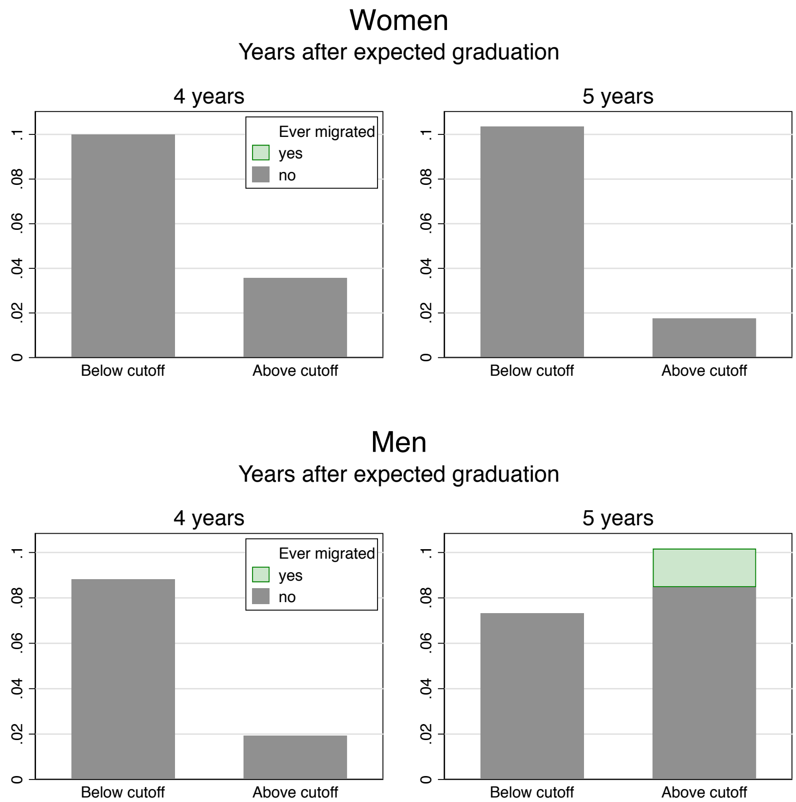
This figure presents the proportion of managers four and five years after the expected graduation among students who were just below and above the first-class cutoff. Managers are classified based on how long it took for them to graduate, if they graduated up to four and five years after the expected graduation. Sample includes only individuals who were employed by the time of the assessment and were within 0.025 s.d. of the cutoff. $N = 159$ (women) and 136 (men).

Figure S8: Proportion of Managers Below and Above the First-Class Cutoff by Number of Previous Jobs



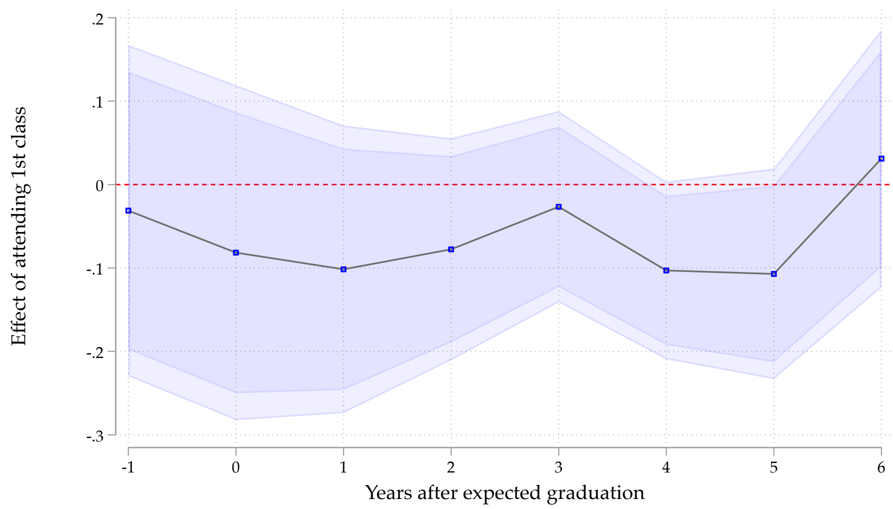
This figure presents the proportion of managers four and five years after the expected graduation among students who were just below and above the first-class cutoff. Managers are classified based on the number of formal jobs they had before they became managers. Sample includes only individuals who were employed by the time of the assessment and were within 0.025 s.d. of the cutoff. $N = 159$ (women) and 136 (men).

Figure S9: Proportion of Managers Below and Above the First-Class Cutoff by Migration Status



This figure presents the proportion of managers four and five years after the expected graduation among students who were just below and above the first-class cutoff. Managers are classified based on whether they ever migrated to a different state or not. Sample includes only individuals who were employed by the time of the assessment and were within 0.025 s.d. of the cutoff. $N = 159$ (women) and 136 (men).

Figure S10: Last-in-Class Effect on the Probability of Working for a Large Firm



This figure presents the fuzzy regression discontinuity (FRD) for the effect of being the last in the first class on the probability of working for a firm with 1,000 employees or more (vertical axis) in each year after the expected graduation (horizontal axis). The blue dots represent the estimated effect and the shaded areas represents their 90% and 95% confidence intervals. 'Years after expected graduation' are counted from the semester in which students are expected to graduate from their original program. Sample includes only individuals who were employed by the time of the assessment. FRDs are estimated using triangular kernels with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). $N = 2,536\text{-}8,827$.

Table S1: All Regular Undergraduate Programs Offered by UFPE

Undergraduate Program	Two classes	Undergraduate program	Two classes
Accounting	✓	Library Science	
Actuarial Science[**]		Linguistics and Literature	✓
Archaeology[**]		Marine Engineering[**]	
Architecture	✓	Marketing	
Audiophonology		Materials Engineering[**]	
Audiovisual Communication[**]		Mathematics	
Automation Engineering[**]		Mathematics Education	
Biology	✓	Mathematics Education (CAA)[**]	
Biology (CAV)		Mechanical Engineering	✓
Biology - Medical Sciences		Media Communication	
Biology Education		Medicine	✓
Biomedical Engineering		Mining Engineering	✓
Biomedicine	✓	Museology[**]	
Business Administration	✓	Music (Instrument)	
Business Administration (CAA)	✓	Music (Vocal)	
Cartographic Engineering		Music Education	✓
Chemical Engineering	✓	Nursing	✓
Chemistry		Nursing (CAV)	✓
Chemistry Education		Nutrition	✓
Chemistry Education (CAA)[**]		Nutrition (CAV)	✓
Civil Engineering	✓	Occupational Therapy	✓
Civil Engineering (CAA)	✓	Oceanography[**]	
Computational Engineering	✓	Pedagogy	✓
Computational Science	✓	Pedagogy (CAA)	✓
Dance[**]		Pharmacy	✓
Dental Medicine	✓	Philosophy[**]	
Design		Philosophy Education[**]	
Design (CAA)	✓	Physical Activity and Sports[*]	
Economics		Physical Activity and Sports (CAV)[**]	
Economics (CAA)	✓	Physical Education[*]	
Electrical Engineering	✓	Physical Education (CAV)[**]	
Electronics Engineering	✓	Physics	
Energy Engineering[**]		Physics Education (CAA)[**]	
Engineering[**]		Physics Education	
Food Engineering[**]		Physiotherapy	✓
Geography		Political Science[**]	
Geography Education		Production Engineering[**]	
Geology	✓	Production Engineering (CAA)	
Graphic Arts		Psychology	✓
History	✓	Public Health (CAA)[**]	
History Education	✓	Secretarial Science	✓
Hotel Management		Sign Language Education	✓
Industrial Chemistry		Social Sciences	
Information Management[**]		Social Science Education	
Information Systems[**]		Social Service	✓
Journalism		Statistics	
Language Education (French)[**]		Theater	
Language Education (English)[**]		Tourism Management	✓
Language Education (Spanish)	✓	Visual Arts[**]	
Law	✓		

✓denotes the programs with two entry classes. [*]Physical Activity and Physical Education are not included because their ranking is not determined by cognitive skills only. [**]Not included in the sample because the program did not exist before 2008. CAA and CAV are campi located in other cities.

Table S2: Management Positions in the Brazilian Classification of Occupations (CBO)

Codes	Description (in Portuguese)	Manager	Codes	Description (in Portuguese)	Manager
0101-05 to 0312-10	Forças armadas, policiais e		2413-05 to 2413-40	Tabeliões e registradores	
	bombeiros militares		2422-05 to 2422-50	Membros do Ministério Público	
1111-05 to 1111-20	Senadores, deputados, vereadores		2423-05	Delegados de polícia	
1112-05 to 1112-55	Dirigerentes gerais do poder executivo		2424-05 to 2424-10	Defensores públicos	
1113-05 to 1113-40	Magistrados		2511-05 to 2531-25	Profissionais das ciências sociais,	
1114-05 to 1114-15	Dirigentes do serviço público	✓		humanas, comportamentais e	
1115-05 to 1115-10	Gestores públicos			administrativas	
1130-05 to 1130-15	Dirigentes de povos indígenas	✓	2532-05 to 2532-25	Gerentes de comercialização e	✓
1141-05 to 1144-05	Dirigentes de organizações políticas,	✓		consultoria bancária	
	sociais e sem fins lucrativos		2533-05	Corretores de valores e ativos financeiros	
1210-05 to 1238-05	Diretores de empresas e de instituições	✓	2541-05 to 2544-20	Auditores e fiscais de tributos	
	de intermediação financeira		2611-05 to 2611-10, 2611-20 to 2611-40	Profissionais do jornalismo (exceto	
1311-05 to 1313-20	Diretores e gerentes de organizações	✓		diretores de redação)	
	não-governamentais e de serviços		2611-15	Diretores de redação	✓
	pessoais, sociais, culturais e públicos		2612-05 to 2615-30	Profissionais da informação, arquivistas,	
1411-05 to 1427-05	Gerentes de produção, de obras, de	✓		museólogos, e da escrita	
	operações, administrativos, financeiros		2616-05 to 2616-25	Editores	✓
	de recursos humanos, de marketing,		2617-05 to 2618-20	Profissionais de comunicação	
	de comercialização, de suprimentos,			audio-visuais	
	de tecnologia da informação, de		2621-05 to 2621-35	Produtores artísticos e culturais	✓
	de pesquisa e desenvolvimento e de		2622-05 to 2622-20	Diretores de espetáculos e afins	✓
	manutenção		2623-05 to 2623-25	Cenógrafos	
2011-05 to 2041-05	Pesquisadores e peritos criminais		2623-30	Diretor de arte	✓
2111-05 to 2149-35	Profissionais das ciências naturais e		2624-05 to 2628-30	Outros profissionais artístico-culturais	
	exatas, engenheiros (exceto		2629-05	Designers de interiores	
	agropecuários e de alimentos),		2631-05	Ministro de culto religioso	
	arquitetos e urbanistas		2631-10 to 2631-15	Missionários e teólogos	
2151-05 to 2151-50	Oficiais de convés	✓	2711-05 to 2711-10	Chefes de cozinha e afins	
2152-05 to 2152-20	Oficiais de máquinas da marinha	✓	3001-05 to 3422-10	Técnicos de nível médio (exceto gerentes	
	mercante		(except 3423-05, 3425-20, 3425-25,	de serviço de transporte de passageiros e	
2153-05 to 2153-15	Profissionais da pilotagem aeronáutica		3426-05 e 3532-35)	cargas e chefe de serviços bancários)	
2211-05 to 2253-25	Biólogos, engenheiros agropecuários		3423-05	Chefes de serviço de transporte rodoviário	✓
	e de alimentos, profissionais da saúde e		3425-20	Gerentes de administração de aeroportos	✓
	da educação física		3425-25	Gerentes de empresa aérea em aeroportos	✓
2311-05 to 2394-05	Profissionais da educação com formação		3426-05	Chefe de estação portuária	✓
	técnica ou superior		3532-35	Chefes de serviços bancários	✓
2410-05 to 2410-40	Advogados		4101-05 to 9922-25	Níveis de competência 2 (básico) e	
2412-05 to 2412-35	Procuradores e advogados públicos			1 (não qualificado)	

✓denotes the range of occupational codes comprising top- and middle-level managers in the 2002 edition of the Brazilian Classification of Occupations (*Classificação Brasileira de Ocupações*, CBO).

Table S3: Wage Premium of Management Position

	Dependent variable: log annual earnings							
	(1)		(2)		(3)		(4)	
Manager	0.229	[0.000]	0.242	[0.000]	0.170	[0.000]	0.205	[0.000]
	(0.025)		(0.025)		(0.040)		(0.039)	
Woman	-0.253	[0.000]	-0.192	[0.000]	-0.261	[0.000]	-0.197	[0.000]
	(0.017)		(0.017)		(0.018)		(0.017)	
Manager × Woman					0.103	[0.043]	0.064	[0.192]
					(0.051)		(0.049)	
Number of observations	29,681		29,679		29,681		29,679	
Controls (education, age, experience)	✓		✓		✓		✓	
Year dummies	✓		✓		✓		✓	
Industry fixed effects			✓				✓	

This table presents the log-linear regression of students' annual earnings on position and gender. In these regressions, we control for education, age, experience, and year. In models (2) and (4), we also control for industry fixed effects. Robust standard errors clustered at the student level are in parentheses, and p-values are in brackets.

Table S4: Balance of Covariates at the Cutoff for the First Class

	All		Women		Men	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Woman	-0.012	[0.743]				
	(0.037)					
Age	-0.020	[0.946]	0.349	[0.328]	-0.485	[0.309]
	(0.291)		(0.357)		(0.477)	
White	0.045	[0.344]	-0.014	[0.837]	0.139	[0.098]
	(0.048)		(0.070)		(0.084)	
Living in Pernambuco	0.011	[0.607]	-0.029	[0.301]	0.069	[0.024]
	(0.021)		(0.028)		(0.031)	
From public high school	-0.011	[0.784]	-0.065	[0.230]	0.051	[0.372]
	(0.040)		(0.054)		(0.057)	
Employed at application	-0.036	[0.237]	-0.018	[0.641]	-0.055	[0.203]
	(0.030)		(0.039)		(0.043)	
Number of previous applications	0.013	[0.862]	0.134	[0.197]	-0.117	[0.270]
	(0.077)		(0.104)		(0.106)	
Both parents with college degree	-0.031	[0.337]	-0.036	[0.382]	-0.007	[0.874]
	(0.032)		(0.042)		(0.046)	
Neither parents with college degree	0.008	[0.834]	0.016	[0.760]	0.009	[0.871]
	(0.040)		(0.051)		(0.056)	
Instructor characteristics						
Female instructors	0.007	[0.730]	0.013	[0.618]	0.001	[0.967]
	(0.021)		(0.026)		(0.029)	
40+ year-old instructors	0.011	[0.604]	0.002	[0.941]	0.028	[0.412]
	(0.022)		(0.027)		(0.034)	
Assistant professors	0.007	[0.732]	-0.014	[0.586]	0.035	[0.233]
	(0.020)		(0.026)		(0.029)	
Associate or full professors	-0.006	[0.808]	0.006	[0.848]	-0.019	[0.582]
	(0.023)		(0.030)		(0.034)	
Instructor quality						
Dropout rate	0.003	[0.069]	0.001	[0.581]	0.005	[0.120]
	(0.002)		(0.002)		(0.003)	
Failure rate	-0.000	[0.907]	-0.001	[0.490]	0.001	[0.604]
	(0.002)		(0.002)		(0.002)	
Number of observations	5,582-13,505		3,029-7,411		2,553-6,094	

This table presents the regression discontinuity (RD) estimates for all covariates observed at application and the characteristics of instructors in the first semester. Instructor quality is calculated by a three-way fixed-effect model described in Section C.5. RDs are estimated using triangular kernel with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). Robust standard errors are in parentheses, and p-values are in brackets.

Table S5: Discontinuities in the First-Class Enrollment by Difference in Peer Performance and Heterogeneity

Difference in peer heterogeneity (s.d.)	Difference in peer performance (s.d.)														
	All					**Women**					**Men**				
	Δ=0	Δ=.175	Δ=.350	Δ=.525	Δ=.700	Δ=0	Δ=.175	Δ=.350	Δ=.525	Δ=.700	Δ=0	Δ=.175	Δ=.350	Δ=.525	Δ=.700
Δ=-.20	0.749	0.778	0.800	0.834	0.866	0.807	0.825	0.839	0.859	0.884	0.638	0.685	0.724	0.786	0.833
	(0.049)	(0.037)	(0.033)	(0.035)	(0.041)	(0.061)	(0.047)	(0.042)	(0.047)	(0.056)	(0.064)	(0.050)	(0.044)	(0.045)	(0.052)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Δ=-.10	0.717	0.738	0.753	0.782	0.812	0.769	0.781	0.790	0.810	0.836	0.616	0.657	0.691	0.740	0.783
	(0.040)	(0.028)	(0.023)	(0.025)	(0.031)	(0.050)	(0.036)	(0.030)	(0.033)	(0.043)	(0.053)	(0.038)	(0.032)	(0.032)	(0.039)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Δ=0	0.702	0.713	0.724	0.747	0.776	0.736	0.746	0.755	0.778	0.808	0.620	0.646	0.670	0.705	0.742
	(0.036)	(0.025)	(0.019)	(0.020)	(0.026)	(0.045)	(0.032)	(0.025)	(0.026)	(0.036)	(0.049)	(0.035)	(0.027)	(0.027)	(0.033)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Δ=.10	0.707	0.715	0.725	0.744	0.768	0.732	0.743	0.754	0.774	0.802	0.626	0.648	0.668	0.697	0.730
	(0.039)	(0.027)	(0.020)	(0.019)	(0.025)	(0.050)	(0.035)	(0.026)	(0.026)	(0.035)	(0.054)	(0.038)	(0.029)	(0.026)	(0.031)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Δ=.20	0.714	0.720	0.727	0.741	0.758	0.737	0.750	0.763	0.782	0.809	0.619	0.635	0.651	0.677	0.704
	(0.048)	(0.035)	(0.028)	(0.026)	(0.030)	(0.059)	(0.044)	(0.035)	(0.033)	(0.041)	(0.068)	(0.051)	(0.040)	(0.034)	(0.037)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

This table presents the discontinuity in the enrollment in the first class as a function of differences (Δ) in peer performance and heterogeneity between classes in the same program in the same year. Peer performance is measured by their median classmate's first-round score and peer heterogeneity is measured by the within-class standard deviation of first-round scores. Functions are estimated using triangular kernel with the bandwidth selection procedure adapted from Calonico, Cattaneo and Titiunik (2014). Robust standard errors are in parentheses, and p-values are in brackets.

Table S6: Last-in-Class Effect on Academic Outcomes

	All		Women		Men	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Switched programs	0.027	[0.211]	0.030	[0.212]	0.023	[0.550]
	(0.022)		(0.024)		(0.039)	
Ever graduated	-0.029	[0.457]	-0.044	[0.335]	-0.012	[0.871]
	(0.039)		(0.046)		(0.075)	
Graduated on time	-0.054	[0.302]	-0.119	[0.076]	0.050	[0.586]
	(0.053)		(0.067)		(0.091)	
Delay in graduation (years)	-0.003	[0.981]	0.159	[0.241]	-0.442	[0.144]
	(0.131)		(0.136)		(0.303)	
Graduated in original program	-0.034	[0.189]	-0.017	[0.492]	-0.042	[0.434]
	(0.026)		(0.025)		(0.053)	
Graduated in the fall	-0.279	[0.000]	-0.324	[0.000]	-0.203	[0.021]
	(0.056)		(0.070)		(0.088)	
Final GPA (standardized by graduation class)	-0.014	[0.906]	-0.043	[0.759]	0.005	[0.977]
	(0.115)		(0.139)		(0.179)	
Number of observations	7,998-13,505		4,965-7,411		3,033-6,094	

This table presents the fuzzy regression discontinuity (FRD) for the effect of being last in the first class on academic outcomes. ‘Switched programs’ is equal to 1 if the student starts a new program at UFPE, and 0 otherwise. ‘Ever graduated’ is equal to 1 if the student is observed to graduate at UFPE, and 0 otherwise. ‘Graduated on time’ is equal to 1 if the student concludes the program in a timely manner, and 0 otherwise. ‘Delay in graduation’ is the number of years above the regular duration of the original program. ‘Graduated in original program’ is equal to 1 if the student finished the original program, and 0 otherwise. ‘Graduated in the fall’ is equal to 1 if the student graduated in June, and 0 if graduated in December. ‘Final GPA’ is the grade point average of students at graduation, standardized by the distribution of GPAs of other students graduating in the program and semester. FRDs are estimated using triangular kernels with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). Robust standard errors are in parentheses and p-values are in brackets.

Table S7: Last-in-Class Effect on Work Experience

	Employed	Years of experience	Number of jobs	Job tenure	Low-manag. experience	STEM experience	High-skilled experience	Migration
Year −1	-0.074	-0.523	-0.186	0.163	0.015	0.022	0.071	0.127
	(0.041)	(0.239)	(0.076)	(0.636)	(0.052)	(0.020)	(0.063)	(0.064)
	[0.075]	[0.028]	[0.015]	[0.798]	[0.779]	[0.266]	[0.258]	[0.048]
Year 0	-0.031	-0.596	-0.112	-0.092	-0.003	0.041	0.064	0.145
	(0.043)	(0.264)	(0.085)	(0.589)	(0.048)	(0.025)	(0.058)	(0.063)
	[0.481]	[0.024]	[0.187]	[0.876]	[0.949]	[0.101]	[0.270]	[0.020]
Year 1	-0.061	-0.640	-0.127	-0.205	-0.004	0.020	0.036	0.146
	(0.046)	(0.288)	(0.099)	(0.500)	(0.047)	(0.025)	(0.058)	(0.059)
	[0.184]	[0.026]	[0.198]	[0.682]	[0.929]	[0.418]	[0.538]	[0.014]
Year 2	-0.051	-0.722	-0.228	-0.827	-0.022	-0.007	-0.042	0.076
	(0.047)	(0.311)	(0.115)	(0.432)	(0.039)	(0.025)	(0.054)	(0.046)
	[0.270]	[0.021]	[0.047]	[0.056]	[0.567]	[0.777]	[0.437]	[0.098]
Year 3	-0.052	-0.770	-0.216	-0.676	-0.043	0.026	-0.050	0.070
	(0.047)	(0.332)	(0.127)	(0.379)	(0.041)	(0.027)	(0.052)	(0.047)
	[0.263]	[0.020]	[0.089]	[0.074]	[0.286]	[0.333]	[0.338]	[0.136]
Year 4	0.005	-0.718	-0.153	-0.492	-0.061	0.022	-0.049	0.042
	(0.043)	(0.350)	(0.138)	(0.345)	(0.041)	(0.030)	(0.050)	(0.046)
	[0.904]	[0.040]	[0.267]	[0.153]	[0.137]	[0.468]	[0.328]	[0.363]
Year 5	0.021	-0.543	-0.034	-0.846	-0.012	0.052	0.060	0.023
	(0.052)	(0.386)	(0.191)	(0.423)	(0.042)	(0.036)	(0.059)	(0.053)
	[0.685]	[0.160]	[0.858]	[0.045]	[0.769]	[0.143]	[0.309]	[0.666]
Year 6	-0.006	-0.937	-0.035	-1.093	-0.009	0.090	0.025	-0.022
	(0.054)	(0.523)	(0.253)	(0.588)	(0.052)	(0.046)	(0.063)	(0.057)
	[0.910]	[0.073]	[0.891]	[0.063]	[0.865]	[0.048]	[0.697]	[0.696]
N. of observations	7,685-13,505	7,685-13,505	7,685-13,505	3,681-10,351	3,681-10,351	3,681-10,351	3,681-10,351	3,681-10,351

This table presents the fuzzy regression discontinuity (FRD) for the effect of being last in the first class on labor outcomes for each year after the expected graduation in the original program. 'Employed' is equal to 1 if the student was employed any time in the last 12 months, and 0 otherwise. 'Years of experience' is the number of cumulative years working as a registered employee. 'Number of jobs' is the number of different firms the student had worked for. 'Job tenure' is the number of years working for the current firm. 'Low-management experience' is equal to 1 if the student had ever worked as a low-level manager, such as assistant manager and supervisor, and 0 otherwise. 'STEM experience' is equal to 1 if the student had ever worked in a STEM job, and 0 otherwise. 'High-skilled experience' is equal to 1 if the student had ever had a high-skilled occupation, and 0 otherwise. 'Migration' is equal to 1 if the student had ever been employed in a state other than Pernambuco, and 0 otherwise. FRDs are estimated using triangular kernels with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). Robust standard errors are in parentheses and p-values are in brackets.

Table S8: Work Experience Five Years After Expected Graduation, Women and Men Above the First-Class Cutoff

	Average		Difference
	Women	Men	(1) − (2)
	(1)	(2)	(3)
Years of experience	3.473	3.406	0.068
	(0.279)	(0.262)	(0.383)
			[0.860]
Had 2 or more previous jobs	0.605	0.590	0.015
	(0.040)	(0.042)	(0.058)
			[0.791]
Low-management experience	0.138	0.137	0.001
	(0.028)	(0.029)	(0.041)
			[0.971]
STEM job experience	0.039	0.187	-0.148
	(0.016)	(0.033)	(0.037)
			[0.000]
Other high-skilled experience	0.329	0.230	0.099
	(0.038)	(0.036)	(0.052)
			[0.061]
Co-workers from the same class	0.309	0.460	-0.151
	(0.038)	(0.042)	(0.057)
			[0.008]
Ever migrated	0.217	0.173	0.044
	(0.034)	(0.032)	(0.046)
			[0.340]
Ever had maternity leave	0.039	0.000	0.039
	(0.016)	(0.000)	(0.016)
			[0.013]
Manager 5 years after (%)	0.658	7.194	-6.536
	(0.658)	(2.200)	(2.296)
			[0.005]
Number of observations	*152*	*139*	

This table presents the gender difference in work experience five years after the expected graduation. Sample only includes students who were above and within 0.1 s.d. from the first-class cutoff, were employed in year five, and had never been managers up until then. Columns (1) and (2) show the mean of observed characteristics, including the dependent variable (at the bottom). Column (3) shows the difference in these means. Robust standard errors are in parentheses, and p-values are in brackets.

Table S9: Last-in-Class Effect on Managerial Attainment by Type of Study Program

		Type of study program					
		Competition for admission		Difficulty of the curriculum		Share of men	
	All	High	Low	Hard	Easy	High	Low
Women							
Manager until 4 years after	-0.133	-0.173	-0.084	-0.149	-0.094	-0.175	-0.107
	(0.042)	(0.069)	(0.047)	(0.078)	(0.054)	(0.073)	(0.049)
	[0.002]	[0.012]	[0.077]	[0.055]	[0.079]	[0.017]	[0.029]
N. of obs.	*5,641*	*2,613*	*3,028*	*2,090*	*2,617*	*2,435*	*3,206*
Manager 5 years after	-0.090	-0.117	-0.045	-0.059	-0.166	-0.059	-0.095
	(0.046)	(0.072)	(0.056)	(0.075)	(0.072)	(0.076)	(0.057)
	[0.047]	[0.106]	[0.422]	[0.431]	[0.021]	[0.442]	[0.095]
N. of obs.	*4,045*	*1,981*	*2,064*	*1,346*	*1,812*	*1,683*	*2,362*
Men							
Manager until 4 years after	-0.119	-0.121	-0.126	-0.110	-0.166	-0.109	-0.144
	(0.047)	(0.069)	(0.065)	(0.061)	(0.096)	(0.054)	(0.079)
	[0.012]	[0.079]	[0.052]	[0.072]	[0.086]	[0.044]	[0.069]
N. of obs.	*4,532*	*2,287*	*2,245*	*1,786*	*1,971*	*2,442*	*2,090*
Manager 5 years after	0.065	0.096	0.040	0.063	-0.009	0.057	0.083
	(0.068)	(0.095)	(0.091)	(0.086)	(0.105)	(0.086)	(0.100)
	[0.334]	[0.314]	[0.664]	[0.464]	[0.931]	[0.510]	[0.406]
N. of obs.	*3,255*	*1,732*	*1,523*	*1,146*	*1,391*	*1,864*	*1,391*

This table presents the fuzzy regression discontinuity (FRD) estimates for the last-in-class effect on the probability of being a manager. The dependent variable is equal to 1 if student occupies a top- or middle-level management position, and 0 otherwise; details are in Table S2 of the Online Appendix. 'Years after' are counted from the semester in which students are expected to graduate. Sample includes only individuals who were employed by the time of the assessment. The sample is also split by type of study program at the median value of the following variables: 'competition for admission,' defined as the program cohort's median score in the first round of the entrance exam; 'difficulty of the curriculum,' defined as the average course failure rate in the program; and the 'share of men' admitted to the program. FRDs are estimated using triangular kernels with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). Robust standard errors are in parentheses, and p-values are in brackets.

Table S10: Last-in-Class Effect on Marriage, Children, and Maternity Leave

	All women		Non-manager women	
	Whether have (dummy)	Number of	Whether have (dummy)	Number of
Ever being married	-0.100		-0.131	
	(0.183)		(0.194)	
	[0.585]		[0.499]	
N. of obs.	*766*		*673*	
Children	-0.223	-0.125	-0.162	-0.123
	(0.273)	(0.182)	(0.276)	(0.199)
	[0.415]	[0.493]	[0.556]	[0.537]
N. of obs.	*760*	*760*	*667*	*667*
Maternity leaves until 4 years after	-0.028	0.009	-0.005	0.033
	(0.036)	(0.041)	(0.035)	(0.039)
	[0.440]	[0.827]	[0.885]	[0.392]
N. of obs.	*5,743*	*5,743*	*5,169*	*5,169*
Maternity leaves until 5 years after	-0.007	-0.010	0.025	0.036
	(0.043)	(0.047)	(0.044)	(0.046)
	[0.871]	[0.826]	[0.567]	[0.431]
N. of obs.	*4,682*	*4,682*	*4,104*	*4,104*

This table presents the fuzzy regression discontinuity (FRD) estimates for the last-in-class effect on outcomes related to women's family in the future. The first two outcomes are assessed through a telephone survey in 2015 — i.e., 9 to 13 years after they applied to the university. In the FDR model, we control for year of admission to the university. The last two outcomes were assessed four and five years after their expected graduation in the original program. For these two outcomes, the sample only includes students who had ever had a formal job up to the assessment. In the last two columns, we restrict the samples to students who had never been managers up to the assessment. For children and maternity leaves, we estimated the effect on the probability of having at least one (dummy) and on the total number. FRDs are estimated using triangular kernels with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). Robust standard errors are in parentheses, and p-values are in brackets.

Table S11: Last-in-Class Effect on the 8-Item Grit Scale

	All	Women	Men
Grit score	0.101	0.342	-0.290
	(0.134)	(0.200)	(0.223)
	[0.453]	[0.087]	[0.192]
N. of obs.	*1,331*	*787*	*544*

This table presents the fuzzy regression discontinuity (FRD) estimates for the last-in-class effect on grit score. Grit is measured using eight statements, which varies from 1 (least grit) to 5 (most grit) according to Duckworth et al. (2007). The assessment was made through a telephone survey in 2015 — i.e., 9 to 13 years after they applied to the university. FRDs are estimated using triangular kernels with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). In the regressions, we also control for year of admission to the university. Robust standard errors are in parentheses, and p-values are in brackets.