Can Better Peers Signal Less Success? The Disruptive Effect of Perceived Rank on Career Investment*

Rafael P. Ribas†

Breno Sampaio‡

Giuseppe Trevisan§

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Abstract

Is being among the best always the best? We estimate the effect of perceived rank in college and show that being last among the best increases the willingness to switch careers and reduces the likelihood of having a more prestigious occupation. To do so, we exploit a discontinuity in the class assignment in a flagship university in Brazil that sends the median student to either a better or a worse class in the same major program. Since the skill difference between classes varies within and between programs, we find that the ranking effect can be cancelled out by a high increase in peer quality. Our findings imply that the perceived rank sends a misleading signal, making similar students in the same program take distinct decisions and have different long-term outcomes. Higher parental education and stronger convictions about future earnings reduce the influence of this signal.

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†Finance Group, University of Amsterdam, e-mail: r.perezribas@uva.nl.

‡Department of Economics, Universidade Federal de Pernambuco, e-mail: brenorsampaio@gmail.com.

§Department of Economics, Universidade Federal de Pernambuco, e-mail: giuseppe.trevisan@gmail.com.

1 Introduction

It is well documented that being among better peers may improve the learning experience and productivity.[1] Peer's ability, however, can also work as a signal for what the candidate must possess to be successful in a certain career. The better the individuals choosing the same career, the lower the perceived return on this investment. On the other hand, having a natural advantage over other candidates can boost motivation and increase interest in more prestigious jobs.[2] In psychology, this event is named the 'big-fish-little-pond' effect (Marsh and Parker, 1984), in reference to the fact that students in low-ability schools present higher self-concepts than those in high-ability schools.[3] In terms of career decisions, this effect could play not only against the benefit of having better peers but also against the return on joining elite institutions.[4]

In this paper we attempt to estimate the effect of perceived rank on career change, earnings and occupation. To establish causality, we properly control for individual skills, institutional differences and the distribution of peers' ability by exploiting the mechanism of class assignment in a major flagship university in Brazil. In most of its undergraduate programs, students are assigned to one of two different classes, which we name 'first' and 'second.' The candidates must choose both the program that they want to study and their preferred class before they take the entrance exam. The priority order in the class assignment is entirely based on their test score. After the choices are made and the exam is taken, students' rank and class assignment are publicly disclosed. While most of the best candidates

[1] See, for instance, Sacerdote (2001); Zimmerman (2003); Carrell, Fullerton and West (2009); Imberman, Kugler and Sacerdote (2012); Booij, Leuven and Oosterbeek (2017) for evidence of peer effects in the classroom and Falk and Ichino (2006); Mas and Moretti (2009); Jackson and Bruegmann (2009); Azoulay, Graff Zivin and Wang (2010); Waldinger (2011); Herbst and Mas (2015); Cornelissen, Dustmann and Schönberg (2017) for evidence in the workplace.

[2] For instance, studies on school starting age show the short- and long-term benefits of early maturity (Bedard and Dhuey, 2006; McEwan and Shapiro, 2008; Dhuey and Lipscomb, 2008; Elder and Lubotsky, 2009; Black, Devereux and Salvanes, 2011; Bedard and Dhuey, 2012; Fredriksson and Öckert, 2014).

[3] See also Marsh (1987, 1991); Marsh and Hau (2003); Marsh, Köller and Baumert (2001); Zeidner and Schleyer (1999).

[4] This is in line with the claim by Arcidiacono, Lovenheim and Zhu (2015) and Arcidiacono and Lovenheim's (2016) that under certain conditions, affirmative action can harm minority students due to their poor fit with the school.

go to the first class, some students are forced to attend the second class.

This arrangement allows us to compare similar candidates who are either at the bottom of the better class or at the top of the worse class. The comparison reveals that those at the bottom are more likely to try a different program and delay their graduation. In the future, these students will also have a lower chance of getting a prime occupation, such as manager or public servant, and the least productive will earn less at the start of their career. For women, the motivation given by a higher rank is found to help them to break the glass ceiling in job promotions (Bertrand and Hallock, 2001; Babcock et al., 2017). The same woman is 13 percentage points (p.p.) more likely to be a manager in the future if she attends the second class.

The empirical identification of the ranking effect is challenging for many reasons. First, rank and skills are by definition perfectly correlated. Accordingly, we control for cognitive skills by applying a regression discontinuity (RD) design with the test scores. Second, both perceived rank and actual skills may determine the students' choice of school and the quality of teaching. We deal with institutional differences by comparing classes in the same programs and years. Third, students' rank is also correlated with peer quality, so their effects could simply cancel each other out. In addition to the standard RD design, we use the variation across program cohorts to estimate the nonlinear relationship between discontinuities and differences in the distribution of peers' ability. As the difference in peer distribution between classes moves to zero, the only remaining difference at the cutoff of test scores is in students' rank.

This relationship indicates that the effects of ranking on the willingness to switch majors, delay graduation, and future occupation can be mitigated by an increase in peer quality. We find, however, a distinction between genders, as suggested by Buser, Niederle and Oosterbeek (2014) and Almås et al. (2016) in this type of study. For women, the ranking effect on decisions in college is so weak that a small increase in peer quality brings the net effect of attending the first class close to zero. Yet the net effect on their likelihood of being a manager is still strongly driven by their rank. A 10 percentile (pctl) increase in their rank raises this likelihood by 4.6 p.p. For men, the ranking effect on early changes is much stronger and cancelled out only by an abnormal difference in peer quality. A 10 pctl drop in their rank increases by 4.6 p.p. the chance of switching programs; it decreases by 9.3 p.p. the chance of graduating at the proper time and by 8.2 p.p. the likelihood of being a public servant.

Our findings are consistent with recent studies that investigate the effect of class ranking in primary and secondary schools. Overall, these studies find that a lower perceived rank diminishes students' grades (Murphy and Weinhardt, 2016; Tincani, 2017), self-esteem (Cicala, Fryer and Spenkuch, 2016; Fabregas, 2017), and probability of attending college (Elsner and Isphording, 2017). Our work adds a new piece of evidence by showing that the perceived rank also induces career changes after students have enrolled in college and has consequences for their future occupation. According to Zafar (2011), Arcidiacono, Hotz and Kang (2012), and Stinebrickner and Stinebrickner (2012, 2014), students who are poorly matched in their programs adjust their optimistic beliefs and are more likely to drop out of the program. In our model, however, we show that the perceived rank creates a false inference that students are poorly matched in their programs and careers. That is, the updating of a student's expectation is not necessarily towards the true value.[5]

In addition to the main findings, the analysis with subsamples reveals that the discouragement about completing a program is not necessarily related to absolute academic performance.[6] For instance, men's decision to switch majors is more sensitive to their rank in programs that have an easier curriculum and higher participation by women. Yet the effect on course failure is higher in other programs. Furthermore, access to better information makes the ranking effect weaker. Most of the academic and labor outcomes are less affected if both parents have a college degree. Similarly, the ranking effect is less pronounced among

[5]Other related studies show that a lower perception of social rank reduces well-being (e.g., Wood et al., 2012; Daly, Boyce and Wood, 2015; Perez-Truglia, 2016; Bottan and Perez-Truglia, 2017).

[6]Using an alumni survey, we also find no evidence that students' rank affects their personality traits in the long run. Results are available upon request.

candidates who choose their major on the basis of market opportunities and prestige, rather than other motives such as self-fulfillment and the program's reputation. These candidates are assumed to have a stronger conviction about their future earnings, making them less likely to update their choices in light of the new information (Hastings et al., 2016).

Although candidates are unaware of the cutoff between classes when they apply to the university, they could decline an offer as soon as the test scores and class order are revealed (Bond et al., 2017). To verify this type of selection bias, we run the McCrary's (2008) test and find no evidence of missing students on either side of the threshold. In addition, we find that all the students' observable characteristics are balanced at the cutoff. Likewise, we test for observable and unobservable differences between the instructors in these classes and find no significance. Another concern is that our findings are driven by an arbitrary measure of peer quality, by peer heterogeneity, and by the selected bandwidths. Accordingly, we run several other models in which we control for peer heterogeneity, we change the measure of peer quality, and we vary the bandwidths around the MSE-optional value. All the results are robust to any of these changes. The last concern is related to the starting date of the two classes, which are five months apart. We estimate the effect of this delay on the academic outcomes of first-class students by using an unexpected strike in the university. If anything, the delay reduced the student's commitment to the program. Thus, the ranking effect may be underestimated due to the enforced delay in our RD design.

The present study is related to the evidence that students update the perceived return of schooling and career investment when they receive new signals (Jensen, 2010; Wiswall and Zafar, 2015; Hoxby and Turner, 2015). Although the broader evidence is that these signals are ineffective (Nguyen, 2008; Bettinger et al., 2012; Hastings, Neilson and Zimmerman, 2015; Busso et al., 2017), the way that the information is provided matters (Kling et al., 2012; French and Oreopoulus, 2017). In this regard, students' perceived rank can considerably distort their subjective expectation. The evidence that a lower perceived rank has disruptive effects on academic performance may also explain why peer effects are found to be heterogeneous and sometimes harmful to disadvantaged candidates (Lavy, Silva and Weinhardt, 2012; Lavy, Paserman and Schlosser, 2012; Carrell, Sacerdote and West, 2013; Feld and Zölitz, 2017). Similarly, the benefit of joining a more selective school could be null if students see themselves at the bottom of the ability distribution (e.g., Dale and Krueger, 2002; Ockert, 2010; Hastings, Neilson and Zimmerman, 2013; Abdulkadiroğlu, Angrist and Pathak, 2014; Kirkeboen, Leuven and Mogstad, 2016; Heinesen, 2018; Hoekstra, Mouganie and Wang, 2018).[7] In addition to controlling for individual skills and institutional differences, our empirical strategy provides unique evidence of the relationship between peer quality and perceived rank.

The remainder of the paper is organized as follows. Section 2 presents a theory of the way in which the ranking effect coexists with the effect of peer quality. Section 3 describes the university's admissions policy and the rule of class assignment. Section 4 details the sample and data sources and presents the descriptive statistics. In section 5, we describe our empirical strategy. Section 6 presents all the findings, along with robustness tests. Section 7 concludes the paper.

2 Theoretical Framework

To understand the potential effects of class assignment on short-term decisions and long-term earnings, we present a simple model of career investment in the context of peer effects and unobserved skill distribution. Unlike the models proposed by Zafar (2011), Arcidiacono, Hotz and Kang (2012), Stinebrickner and Stinebrickner (2012, 2014), and Wiswall and Zafar (2015), this model explicitly considers the role of classmates' skills on the decision to switch programs and drop out of college. As in Breen and García-Peñalosa (2002), students' beliefs are assumed to be updated according to a Bayes' rule.

[7] A non-exhaustive list of studies on the short- and long-term effects of selective schools includes Hoekstra (2009); Berkowitz and Hoekstra (2011); Zimmerman (2014); Dobbie and Fryer Jr (2014); Goodman, Hurwitz and Smith (2017); Canaan and Mouganie (2018).

Consider a continuum of individuals who have to make a decision about their careers by the end of high school.[8] Individual i is endowed with a set of skills, represented by a single variable s_i, and has to choose either among K study programs (majors) or a career 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 in the population 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 expected utility in career k is given by:

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

where v_i^k is the individual taste for career k, w^k is the lifetime salary in this career, $p\left(h_i^k, h_{-i(k)}^k\right)$ 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, $\left\{v_i^1, \ldots, v_i^K\right\}$, which is independently drawn, but they do not know it until they go to college.

While the probability of finding a low-skilled job ($k = 0$) is one, the probability of finding a high-skilled one ($k > 0$) depends on the individual human capital, h_i^k, and on the human capital of others who choose the same career, $h_{-i(k)}^k$. The probability function is increasing in h_i^k, $\partial_1 p > 0$, and nonincreasing in $h_{-i(k)}^k$, $\partial_2 p \leq 0$. Based on the curvature of the probability function, we define two types of career: those in which most workers have a high probability of finding a job, and those in which only a few workers have this high probability.[9]

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*

[8]This decision might have to be made earlier in countries that adopt tracking systems, such as the Netherlands and Sweden, or later in countries such as the United States. However, the decision time does not change the functioning of our model.

[9]One may think of $p(.)$ not as the probability of employment per se, but as the cdf of salaries.

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, $s_{-i(c)}$:

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

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, $\partial_1 p\, \partial_3 h^k > 0$.[10] Given this human capital production function, our definition of peer effect is the following:

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.*

During college, effort has a marginal disutility equal to γ. Since $\partial_{11} h^k < 0$, every student's effort will be at the optimal level. Then we rewrite the probability function such that:

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

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. If $I_i \to \infty$, then $\tilde{F}_i^k \to F^k$. If $I_i = 0$, then individuals are clueless about the distribution of $s_{-i(k)}$ and heavily influenced by any new information. Before college, their subjective expectation for v_i^k is zero, $\tilde{E}_i\big(v_i^k\big) = 0$.

[10] The composition of peers can affect future earnings not only through its direct effect on individual ability but also through the social ties that are created among classmates (e.g., Black, Devereux and Salvanes, 2013; Shue, 2013; Laschever, 2012; Kramarz and Skans, 2014).

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

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

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

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

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 $I_i < \infty$. If $I_i = 0$, then $\hat{F}_i^{k^{-1}} = s_{-i(c)}$. Since $s_{-i(c)}$ is known, there is no longer any uncertainty regarding $h_i^k(.)$ anymore. 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 programs (S) or graduate (G). Their new value function is:

$$\hat{V}_i^k = \max_{\{D,S,G\},e^k} \left\{ V_i^0,\ \theta V_i^{k'},\ \theta v_i^k + \theta w^k \hat{p}_i^k \left[h_i^k\left(e_i^k\right)\right] - \gamma e_i^k \right\} \tag{2}$$

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 $\left(s_{-i(1)} \cup s_{-i(2)}\right) = F^{k^{-1}}$, $\left(s_{-i(1)} \cap s_{-i(2)}\right) = \emptyset$ 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 predictions. Proofs of these propositions are in the Appendix.

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

Proposition 2. *Given the choice k, 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.*[11]

Proposition 3. *The larger the initial information set, I_i, the lower the influence of the ranking effect on effort and career change. The peer effect does not depend on I_i.*

3 Institutional Background

3.1 University Admission Policy

The *Universidade Federal de Pernambuco* (UFPE) is the major flagship university in the Northeast of Brazil and one of the top ten institutions in the country.[12] 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 of almost every high school student in the state of Pernambuco,

[11] 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.

[12] According to the Ministry of Education, UFPE has always had the highest evaluations in the Northern and Northeastern regions of Brazil since the evaluation system was created in 1995.

regardless of their social class and career choice. Due to the intense competition, the seats are filled by the very best students, and only 26% of the admitted candidates reject the offer.

About 95% of its undergraduate students are admitted through an exam, called *vestibular*, which is held only once a year.[13] 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 consists of 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 university cannot use other criteria, such as age, curriculum, or previous studies, to rank and admit candidates.[14]

The admission process in Brazil, as in the United Kingdom, requires candidates to choose their 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. Moreover, almost no institution in Brazil offers a minor degree, but some programs offer elective study tracks after admission. 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. Thus, starting a new program implies a substantial delay in graduation and hence less work experience.

The *vestibular* has two rounds and assesses applicants in the following subjects: Mathematics, Portuguese, a foreign language (English, French or Spanish), Literature, History, Geography, Physics, Chemistry, and Biology. In the first round, candidates take one test per subject and their score is the average of all these tests. Since 2010, the first round has been replaced by the National High School Exam (ENEM), which has a similar structure

[13] 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.

[14] Starting in 2013, UFPE has adopted an affirmative action policy that gives quotas to candidates from public high schools, indigenous candidates, and Afro-descendants.

and is aimed at assessing candidates' general knowledge. This round eliminates about 40% of the candidates. In the second round, the remaining candidates 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. Only 10% on average of the original candidates per program are admitted. Some programs, however, are more competitive than others. For instance, Law usually admits less than 5% of the candidates, whereas Mathematics admits almost 30% of the candidates.

3.2 Class Assignment

Fifty-seven out of 99 undergraduate programs offer two options for the freshmen.[15] They can start studying either in the first semester (called the 'first class' hereafter), right after the entrance exam, or in the second semester of the academic year (called the 'second class'). Table A1 in the Appendix presents the list of programs, indicating those with two entry 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 those programs, candidates are required to reveal their class preference before taking the entrance exam. In practice, almost 70% of the admitted students prefer to attend the first class. Given the limited number of seats, the order of preference is strictly based on their final entrance score. Accordingly, 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 admission committee (*Comissão para o Vestibular*, COVEST) through its website and printed in the newspapers.

[15] This number does not include special programs, such as those focused on distance learning and high school teachers without a college degree.

However, candidates cannot switch classes after the final classification is revealed. Figure 1 shows how this process creates a discontinuity in the relationship between entrance score and assignment to a class.

Figure 1 About Here

This arrangement allows us to compare the last student who had the right to join the first class and the first student who did not have this privilege. Although they had essentially the same final entrance score, the latter is ranked higher in her own class than the former. On the downside, the higher rank is accompanied by worse peers. Nevertheless, the difference in peer quality between classes also varies across major cohorts.

Despite the initial class assignment, course retention forces first-class students to attend classes with second-class students, and vice versa. For instance, a first-class student who fails a required course in the first semester will attend this course with the second class in the second semester. Likewise, a second-class student who fails in her first semester will attend a course with first-class students who join the program a year later. Therefore, the initial assignment is not sustained and classes tend to be more mixed throughout the program. In addition, students who are at least halfway through the program may attend elective courses at any time, even with students from other departments. To keep our instrument valid, we analyze the effect of the initial assignment instead of the actual class composition. The bias created by mixing classes should pull our estimates towards zero. Another concern is that first and second classes may differ not only in terms of peer quality, but also in terms of teaching. Although most of the undergraduate instructors teach the same course every semester, any teaching discrepancy could compromise our analysis. We further check whether these differences are locally balanced in our setting.

4 Data and Descriptive Statistics

4.1 Data Sources and Sample

Our data come from three different sources. The first is the admission committee (COVEST), which provides information on every university applicant from 2002 to 2012. The second data source is UFPE's Academic Information System (*Sistema de Informações e Gestão Acadêmica*, SIGA), which provides information on students' enrollment, grades and status. The third source 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.

Our sample of applicants ends in 2012 because since 2013 the university has adopted an affirmative action policy. This new policy affected the composition of classes and students' initial ranking. Since we perform a peer effect analysis, we also exclude cohorts (program-year) in which at least one class has fewer than 15 freshmen. That is, we keep only cohorts with a large enough number of students in both classes so that the ranking is meaningful.[16]

4.1.1 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. To eliminate time effects from the distribution of the round 1 scores, we standardize it by year using the mean and variance of all the candidates' scores. We also use the standardized round 1 score to assess 'peer quality,' measured by the median score in the class, and 'peer heterogeneity,' measured by the standard deviation within a class.

The final score is the determinant of class assignment (the running variable). We standardize this variable by program and year using the first-class cutoff — i.e., the final score

[16]The inclusion of small cohorts adds noise to our estimates, but the estimated magnitudes do not change.

of the last student in the first class — and the standard deviation of admitted candidates' scores. For the treatment variable, we use the percentiles of the final score to order students per class. 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 did the entrance exam in the past, their previous score(s), motivation to enter the program, previous studies, and a long list of characteristics, 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 are admitted through a process other than the *vestibular* and who are more than 21 years old.[17] The final sample comprises 55% of the freshman students enrolled in two-class programs, representing 41% of all UFPE freshmen. It is worth mentioning that students' rank and peer quality were measured before the sample was restricted.

4.1.2 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 in the university.[18] These grades are used to calculate students' 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 from the sample.

Another set of information from SIGA contains the grade and status (attended or not) of all the students in the first midterm exam of mandatory courses, and the characteristics of all instructors, such as gender, age and academic position. To assess instructors' unobserved

[17]Almost 75% of the candidates are 21 years old or younger.
[18]For 2002, we have only information on academic status.

characteristics, we estimate instructor-specific parameters related to dropout and failure rates in their courses (see details in the Appendix). Since each student takes several courses at the same time, with different instructors, all these variables are averaged per semester.

4.1.3 Earnings and Occupation

In Brazil, every registered firm is legally required to annually report every worker formally employed in the previous year, with information about salary, number of months worked, admission and dismissal dates, 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 earnings and occupation for every year from 2002 to 2014.

The final variables are constructed for each year after the students' expected graduation in their initially chosen program. The sample from RAIS faces a restriction because the younger the cohort, the lower the number of years available after the expected graduation. For instance, the 2002 cohort can be observed up to nine years after the expected graduation, while the 2010 cohort can be observed for one year at most. Table 1 shows how the sample of students decreases as we move further into the future. At the same time, the further we move, the higher the probability of those students being employed. A year after the expected graduation, less than 35% of the students in our sample are formally employed. Five years later, the employment rate is higher than 70%.

Table 1 About Here

From RAIS, individual earnings are calculated as the sum of all salaries in 12 months, deflated to December 2014 using the Extended Consumer Price Index (IPCA). The 12 months are counted from the first month after the expected graduation, which is either January or July. As regards employment and occupation, we construct three variables: whether the student was employed for at least a month; whether the student, if employed, had a management position (excluding supervisors); and whether the student, if employed, worked as a public servant. Public service is considered a prestigious occupation for highly-skilled workers in Brazil, given that it offers job stability and a generous pension plan.

4.2 Descriptive Statistics

Table 2 presents descriptive statistics for all 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 two years and the rate of graduation are also higher in the first class, which confirms that it has indeed better students. However, these students, particularly the men, are also more likely to give up and join another program. In general, the contrast in GPA and graduation rate between classes is higher for men than for women. Furthermore, the average round 1 scores of the women are lower overall. Despite prevailing at UFPE, this difference indicates that women are more likely to enroll in less competitive programs. Nonetheless, their GPA is higher and they have a higher chance of graduating and a lower probability than men of switching majors.

Table 2 About Here

The covariates also confirm that most of the students are white or come from private high schools, and just 9% were already working at the time of the application. The greater part of the disadvantaged students are in the second class — i.e., this has a greater proportion of black students, from public high schools, with less parental education, and who work and study at the same time. Therefore, the simple comparison between classes can be misleading because of the differences in the students' characteristics.

5 Empirical Strategy

In general, estimating peer effects is challenging because individuals are selected into groups by their unobserved skills. In addition to the biased selection, estimating ranking effects is even more difficult because the order of students depends on their peers' skills. Even if students were randomly assigned to different peer groups, a higher quality of peers would be associated with a lower rank. To deal with these identification problems, we use UFPE's rule of class assignment and the variation in skills distribution across program cohorts.

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}. These variables depend not only on the program k, chosen by the student, but also on the class assignment, which can be either $c = 1$ for those in the first class or $c = 2$ for those in the second class. 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:

$$y_{kci} = B(r_{kci}) + \gamma\, q_{kc} + u_{kci} \tag{3}$$

where $B(.)$ is a monotonic continuous function and $u_{kci} = \nu_k + \mu_i + \varepsilon_{kci}$. The identification problem is that we cannot observe the same student in two different classes, so all variables on the right hand side are correlated with the error term u_{kci} because of μ_i.

Hence, we consider that for each program, the last student joining the first class is very similar to the first student out of the first class. 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 $x_{ki} \geq \underline{x}_k$, then the student can choose between classes 1 and 2. But if $x_{ki} < \underline{x}_k$, then the student must join the second class, which implies that $\Pr\left(c = 1 | x < \underline{x}_k\right) = 0$, as shown in Figure 1.

The compliance with the entrance score is not perfect and some highly skilled students may join the second class. In this case, for any variable z, the expected difference between classes for the last student in the first class is given by the following fuzzy estimand:

$$\Delta z \equiv E\big(z|c=1, x=\underline{x}_k\big) - E\big(z|c=2, x=\underline{x}_k\big) \\ = \frac{\lim_{x\downarrow\underline{x}} E\left(z|x \geq \underline{x}_k\right) - \lim_{x\uparrow\underline{x}} E\left(z|x < \underline{x}_k\right)}{\lim_{x\downarrow\underline{x}} \Pr\left(c=1|x \geq \underline{x}_k\right)}. \tag{4}$$

Then from equation (3), the *net effect of the first class* is given by:

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

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 the net (naive) ranking effect given by the fuzzy estimand is:

$$\frac{\Delta y}{\Delta r} = \beta + \gamma \frac{\Delta q}{\Delta r}. \tag{6}$$

Both effects identified by the discontinuity in the class assignment depend on the difference in peer quality, which would cancel out the ranking effect according to Propositions 1 and 2.

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 programs in which classes are similar ($\Delta q_k = 0$), we can calculate the marginal *ranking effect* as follows:

$$\left.\frac{\Delta y_k}{\Delta r_k}\right|_{\Delta q=0} = \frac{\lim_{x\downarrow\underline{x}} E\left(y|x \geq \underline{x}_k, \Delta q_k=0\right) - \lim_{x\uparrow\underline{x}} E\left(y|x < \underline{x}_k, \Delta q_k=0\right)}{\lim_{x\downarrow\underline{x}} E\left(r|x \geq \underline{x}_k, \Delta q_k=0\right) - \lim_{x\uparrow\underline{x}} E\left(r|x < \underline{x}_k, \Delta q_k=0\right)} \\ = E\left(\beta_k|\Delta q_k=0\right) \tag{7}$$

where $\beta_k = \left[B(\bar{r}_{k1}) - B(\bar{r}_{k2})\right]/\Delta r_k$, with $\bar{r}_{kc} = E\big(r|c, x=\underline{x}_k, \Delta q_k=0\big)$. In other words, if classes are very similar, the only effect remaining is the one from each student's rank.

By estimating the relationship between $(\Delta y_k, \Delta r_k)$ and Δq_k, we not only isolate the ranking 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. Consider that

$$\frac{d\Delta y_k}{d\Delta q_k} = \gamma + E\left(\beta_k|\Delta q_k\right)\frac{d\Delta r_k}{d\Delta q_k} + \Delta r_k \frac{dE\left(\beta_k|\Delta q_k\right)}{d\Delta r_k}\frac{d\Delta r_k}{d\Delta q_k}. \tag{8}$$

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 (see Table 3). If we assume that $B(.)$ is weakly monotonic, then $d\Delta y_k/d\Delta q_k > 0$ implies that $\gamma > 0$. That is, $d\Delta y_k/d\Delta q_k$ provides a lower bound estimator for the peer effect, γ.

The estimation of this relationship is possible because the peer quality is not measured by the entrance score (running variable) itself, but rather by a cognitive score that is comparable across programs. Since the entrance score is specific by program, it does not tell anything about how similar the classes are in comparison to those in other programs. In addition, the difference in peer quality, Δq_k, varies sufficiently across program cohorts, as we show in Figure 4. To verify the robustness of our findings, we also estimate the relationship between fuzzy discontinuities and the difference in the standard deviation of skills between classes, forcing it to be zero. Details on the estimation procedures are in the Appendix. Robust standard errors and optimal bandwidths are obtained as described by Calonico, Cattaneo and Titiunik (2014).

6 Results

Our results are presented as follows. First, we verify how much the mechanism of class assignment affects students' rank and peer quality and test whether it is manipulated by candidates. Second, we present the estimated effect of ranking on the willingness to change majors and on academic performance. Third, we present the long-term effects on earnings and occupation. Then we investigate some mechanisms that may explain our main findings. Finally, we provide some additional tests to certify the validity of our results.

6.1 First-Stage Estimates and Manipulation Test

UFPE's rule for class assignment creates two types of exogenous variation at the cutoff: rank and peer quality. The first panel of Figure 2 shows the discontinuity in students' rank at the entrance score cutoff. The last student to the right of the cutoff is indeed expected to be at the very bottom of her class, while the first student to the left of the cutoff is expected to be at the top. In spite of the imperfect compliance with the final score, the ranking difference between these students is of 35 pctl for men and 39 pctl for women.

FIGURE 2 ABOUT HERE

The difference in ranking at the cutoff is simply the consequence of having classes at different levels. However, the pool of students could be so homogeneous that the class difference would be irrelevant. The second panel of Figure 2 shows that the expected difference in peer quality is significant. For both genders, the median classmate's round 1 score is around 0.21 s.d. higher and the variability in peers' scores is about 0.03 s.d. higher to the right of the cutoff than to the left. Therefore, students who just miss the cut for the first class fall into a significantly worse and more homogeneous class.

If students anticipated the disadvantage of either being the worst student in the first class or falling into the second class, they could decline the offer of a place and the sample would suffer from a biased selection. To verify if such a behavior occurs, Figure 3 presents the density of enrolled students, separately estimated for both sides of the cutoff. A visual inspection suggests that the density is continuous at the cutoff. To formally test this continuity, we also apply the Cattaneo, Jansson and Ma's (2017) version of McCrary's (2008) test.[19] This test does not indicate evidence of missing students on either side of the cutoff.

FIGURE 3 ABOUT HERE

Everything so far suggests that some students are restricted from choosing their class,

[19] Cattaneo, Jansson and Ma's (2017) test is not sensitive to the choice of bin width. Results for the original McCrary's test are available upon request.

which creates a exogenous variation in rank and peer quality at the cutoff. To separate these two components, we also exploit the fact that the difference in peer quality between classes varies across programs and over time. Figure 4 shows that facing almost no difference in peer quality is not rare. Although the mean difference in the median peer's score between classes is 0.37 s.d., for 9% of females and 5% of males, this difference is less than or equal to 0.1 s.d. Thus, the lower tail of these distributions should be fat enough to provide accurate estimates for the ranking effect. Another concern is that the lower tail represents a specific set of programs. Table A2 of the Appendix highlights all the programs that fell into this tail at least once, ensuring that the results are not driven by specific fields.

Figure 4 About Here

According to Carrell, Sacerdote and West (2013) and Booij, Leuven and Oosterbeek (2017), peer heterogeneity could also influence our results. Unlike the difference in median quality, the difference in peer variability is close to zero for most of our sample. But given the deviations from zero, shown at the bottom of Figure 4, we also include differences in class heterogeneity in our model to examine the sensitivity of the ranking effect.

To estimate accurate ranking effects, the ranking discontinuity must be strong also in cases in which the class difference is close to zero. Table 3 shows how the ranking discontinuity changes as a function of the difference in the median peer's score and the difference in peer heterogeneity. Regardless of how different the classes are, the ranking discontinuity is always significant and between 12 pctl and 55 pctl. Although the ranking gap does not change much with the difference in heterogeneity, it increases drastically with the difference in peer quality. Hence, if all effects are monotonic, the non-marginal ranking effect must increase along with the non-marginal peer effect.

Table 3 About Here

6.2 Academic Outcomes

6.2.1 Major Switching, Graduation and Dropout

Being the last student in the best class may have pros and cons, as stated in Proposition 1. To weight these pros and cons, we first present the net effect of going to the first class on the probability of graduation and on the decision to switch majors.

Table 4 About Here

The findings presented in Table 4 suggest that being at the bottom of the first class, rather than at the top of the second class, has almost no effect on females. For males, going to the first class increases their probability of trying another *vestibular* by 6.8 p.p. and switching majors by 6.5 p.p. Despite the difference in peer quality, going to the bottom of the first class makes male students more likely to give up their original major choice. This result is robust to the bandwidth choice, as shown in Figure A1 of the Appendix.

The next step is to verify how the net effect changes as a function of the difference in peer quality. Figure 5 presents the estimated relationship using the difference in class median scores. We also define the class difference using other percentiles and find similar patterns (see Figure A2 of the Appendix). If the peer difference is zero, both males and females at the bottom of the first class are less likely to graduate on time. This effect, however, diminishes with the difference in peer quality. Since the ranking discontinuity also increases with the difference (see Table 3), this pattern suggests that the peer quality offsets the ranking effect after a certain level. For men, this level is between 0.4 and 0.7 s.d., which implies that the ranking effect is predominant for at least 50% of the students close to the cutoff. For women, the ranking effect on graduation is predominant at least until 0.2 s.d., which represents almost 20% of the students close to the cutoff. This difference between males and females explains why the net effect of the first class is shown higher for men in Table 4.

Figure 5 About Here

The lower, but increasing graduation rate in the first class is followed by a higher, but decreasing chance of trying another *vestibular*. For males, we also observe a similar pattern in major switching. For females, in contrast, the effect on major switching is flat and insignificant for all levels of peer quality. This result suggests that the pure ranking effect makes graduation in the first class harder for both genders. But while males respond to the difficulty by starting a new program, females are less able to do likewise. In fact, Table 2 shows that women already enroll in less competitive programs, so they do not have as many remaining options as men. Despite the difficulty, neither gender is found to drop out of college because of the class assignment.

Given the way in which ranking effect and peer effect are confounded, we try to isolate the former by centering our estimates on program cohorts whose classes are very similar. Table 5 shows the marginal ranking effect, estimated for classes in which the peer difference is close to to zero. We find that a 10 pctl drop in a student's rank increases the probability of trying another *vestibular* by 3.6 p.p. for males and 1.9 p.p. for females. But for men alone this effect is followed by an actual change in majors (of the same magnitude). The drop in ranking also reduces the chance of graduation by 9.3 p.p. for men and 5.6 p.p. for women.

TABLE 5 ABOUT HERE

In Table 5, we also let the marginal ranking effect change conditionally on the difference in class heterogeneity. Although the ranking effect is even stronger with a greater deviation among students, our findings remain the same whenever there is no difference between classes. Figure A3 of the Appendix confirms that the findings are robust to the bandwidth choice for the entrance score and for the difference in peer quality.

6.2.2 Academic Performance and Engagement

So far, our findings suggest that the pure ranking effect makes graduation in a timely manner more unlikely for students at the bottom of the first class. We now verify whether those effects are related to grades and attendance in class.

Table 6 shows that the class assignment has no significant effect on the number of courses that a student enrolls and on the attendance to the first midterm. That is, there is no clear evidence that students immediately respond to the class assignment and ranking by taking fewer courses or not showing up. The first midterm, however, seems to be the starting point for the ranking effect. Both men and women have a worse grade if they are at the bottom of the first class. For a 10 pctl drop in rank, their midterm grade declines by around 0.09 s.d. For women in particular, this effect is very close to the one on the final grade in the first semester. These students also have a higher number of absences in class, but we do not know if these absences occur before or after the midterm.

Table 6 About Here

In addition to estimating the average effect on grades, we also estimate quantile regression discontinuity models, as proposed by Frandsen, Frölich and Melly (2012). For practical purposes, we estimate the net effect of the first class, instead of the ranking effect. These estimates, presented in Figure 6, reveal that the first class negatively affects the whole distribution of grades, from top to bottom. For women, however, the effect on lower grades is higher. That is, a lower rank (and better peers) make the grades of underperforming women even lower, increasing their chances of failing the course.

Figure 6 About Here

The effect found on grades in the first semester seems to persist throughout the program. Figure 7 presents the estimated ranking effect on GPA, failure rate, and the number of enrolled courses from the first to the eighth semester. We count the semesters starting at students' first enrollment at the university and do not reset the variables in cases where they start a new program. After the first semester, for example, the GPA could be a combination of grades in two or more programs.

Despite the slight decline of the ranking effect in the third semester, we find that students with lower initial rank continue to have lower GPA and higher failure rates in the following semesters.[20] The magnitudes for men and women are very similar, but estimates from the female sample are more accurate, which makes them significant. The higher chance of switching majors may also explain the declining and insignificant effect for men in later semesters. By moving to another program, students can improve their GPA.

Figure 7 About Here

Unlike the effect on grades, the effect on the number of courses is negligible; we do not find significant evidence that lower-ranked students take fewer courses. We also find that the ranking effect on the dropout rate (failure by attendance) is small and only significant for women in some semesters. Unfortunately, we cannot observe students' effort or test whether perceived rank has a direct effect on it. As far as it goes, our results indicate that it is harder for the student at the bottom of the first class to get passing grades, making the study program more difficult.[21] The ranking effect is even more damaging to underperforming women, widening the gap between the low ranked and the top ranked. Figure A5 of the Appendix shows that these findings are robust to the bandwidth choice for the entrance score and for the difference in peer quality.

6.3 Earnings and Occupation

For the cohorts that are observed from zero to five years after the expected graduation, we estimate the net effect of the first class and the ranking effect on employment, earnings and occupation. The further in the future, the higher the number of former UFPE students found in the labor market, which makes our estimates less biased and more accurate. On the other hand, only the older cohorts have reached those further years, which reduces our

[20] Andre and Carvalho (2016) estimate the discontinuity in GPA between classes in another university in Brazil and find similar results.

[21] The ranking effect on grades does not change much as the difference in peer quality increases (see Figure A4 of the Appendix).

sample and makes our estimates more time-specific.

Figure 8 presents the net effect of the first class in those years,[22] while Figure 9 presents the relationship between ranking effect and peer quality. First, we find that men are about 11 p.p. less likely to be employed one and three years after their expected graduation if they attend the first class. Likewise, women in the first class are 11 p.p. less likely to be employed in year two. These differences are in part related to the fact that first-class students graduate later. In year five, however, the difference is very close to zero.

Figure 8 About Here

If employed, men in the first class also earn 66% less than those in the second class two years after the expected graduation and 45% less a year later. This net effect is largely explained by the rank discontinuity. If the difference in peer quality is zero, a 10 pctl drop in rank decreases by 20% the earnings in year two. In Figure 9, we observe that this ranking effect stays intact regardless of the gap in peer quality. Even though the effect on earnings is high and not moderated by peer quality, it is not persistent and disappears in year four.

Figure 9 About Here

The quantile estimates in Figure 10 indicate that the effect of the first class on earnings is higher at the lower end of the distribution. The quantile effects below the median are significant not only for men, but also for women two years after the expected graduation. Therefore, being assigned to the first class is particularly detrimental to the less productive workers, at least in the beginning of their careers.

Figure 10 About Here

In spite of the transient effect on earnings, the first class also affects males' occupation. Figure 8 shows that five years after expected graduation the first class reduces by 27 p.p. their chance of being a public servant. In addition to a wage premium, government jobs in Brazil

[22]For short programs, which last three to four years, year one means six to eight semesters after the classes started. For long programs, which last five years or more, year one means ten semesters later.

are considered safer and offer better retirement plans, particularly to high-skilled workers (Belluzzo, Anuatti-Neto and Pazello, 2005; Braga, Firpo and Gonzaga, 2009). Given the limited number of positions, the selection process is very competitive and based on specific exams applied by each governmental entity. As a result, some of the best college graduates end up having a public career.

For both men and women, attending the first class also affects the likelihood of being a manager. However, the effect on men is merely temporary. Because of their class, top-ranked males reach a management position earlier than the others. But this does not mean that the others will never reach such a position. The effect on women, on the other hand, increases over time. In year five, women in the first class are 13 p.p. less likely to be a manager than similar women in the second class. According to Coelho, Fernandes and Foguel (2014), women find it harder, unless they outperform their male colleagues, to get promotion in Brazilian firms. The glass ceiling imposed on women's ascent may explain this long-term effect.

The probabilities of men being public servants and women being managers are much affected by their rank. Being 10 pctl higher in the class order increases by 8.2 p.p. the chance of men's working in the public service and by 4.6 p.p. the chance of women's having a management position in year five. Even so, Figure 9 shows that these effects decline as a function of peer quality. The ranking effects are almost fully cancelled out in cohorts where the difference in peer quality is higher than 0.6 s.d. Nonetheless, this great difference between classes is found in less than 10% of the program cohorts.

In addition to the influence on grades, time to graduation and career changes, the class ranking affects earnings and occupation in different ways. By changing the time of their graduation, the ranking temporally affects students' employment and men's earnings and promotion. These effects tend to disappear in the long run as bottom-ranked students catch up with highly ranked students. However, the rank seems to permanently affect the probability of crucial events, such as men's getting a government job and women's being promoted to manager. Figure A6 of the Appendix shows that these findings are robust to the bandwidth choice for the entrance score and for the difference in peer quality.

6.4 Heterogeneity in the Ranking Effect

To better understand the mechanism behind the ranking effect, we verify whether it is related to the type of program and students' characteristics. For the type of program, we split the sample into harder and easier curriculum, based on a program's average failure rate, into higher and lower shares of male students, and into harder and easier admission, based on a program's median round 1 score. For each gender and categorization, we make a median split so that the subsamples within males and females are of the same size. For the type of student, we separate the sample based on parents' education and reason for choosing the program. Parents' education can be either 'both parents have a college degree' or 'neither parent has a college degree,' while the reason for choosing the program can be either 'market opportunities and career prestige' or 'other motive,' which includes self-fulfillment, the program's prestige, low competition, and parents' choice. Tables 7 and 8 present the estimated ranking effect for each group. Since sample sizes are smaller, estimates are much less accurate.

Results for the type of program in Table 7 suggest that the ranking effects on academic performance and on the decision to change majors are not necessarily related. Poorly ranked men are more likely to switch programs if the original curriculum is easier and the share of female classmates is higher. However, their absolute performance is more sensitive to class ranking in programs with a harder curriculum and the presence of more males. For bottom-ranked women, the pattern is similar, except that they only try to change programs but do not go through with it. Therefore, the willingness to change careers is not necessarily driven by the absolute performance of poorly ranked students, but by how they see themselves in comparison to their classmates. For males, in particular, this feeling is much stronger in programs where women outnumber them.

<u>Table 7 About Here</u>

If either the risk of failing or the share of men is higher, ranking matters not only for males' academic performance but also for their long-term outcomes in the job market. This finding is consistent with Proposition 2, which states that a lower rank has a negative effect on effort particularly in competitive environments. We also observe that these effects are higher in programs to which admission is easier, so that the overall quality of students is lower. This finding may be related to the fact that ranking has a higher effect on less productive workers, as shown in Figure 10. For women, we find that the easier the admission, the higher the effect on academic performance. However, the long-term effect on their likelihood of being a manager is felt particularly by the best college candidates, which is consistent with the glass-ceiling hypothesis.

As regards individual characteristics, in Table 8, almost all the estimated effects are higher among those whose parents do not have a college degree and who choose their major for reasons other than market opportunities and prestige. The difference in those groups suggests that prior information plays a critical role in explaining the ranking effect, as stated in Proposition 3. If students are either better informed by their parents about their college experience or have a strong conviction about their career investment, they are less susceptible to their perceived rank. Otherwise, the class order will affect their academic performance, long-term occupation, and willingness to change careers. The only exception is the effect on management position for men, which is higher among those driven by market opportunities.

<u>Table 8 About Here</u>

These findings broadly suggest the following. First, the willingness to change careers is not necessarily related to academic performance. Second, academic performance is more affected among less knowledgeable students in adverse conditions. Third, males' earnings and occupation are also more affected in these circumstances, whereas women's future promotion is particularly affected in highly competitive programs. Finally, misinformation makes poorly ranked students invest less in their initial career choice.

6.5 Additional Tests

6.5.1 Balance at the Cutoff

In addition to McCrary's test for class manipulation, shown in Figure 3, we also verify whether students' characteristics are similar around the cutoff. The concern is that our findings may be driven by characteristics that remain unbalanced in the RD design. Table 9 presents RD estimates for all the characteristics that we can observe. These estimates confirm that with regard to these characteristics the students are not significantly different.

TABLE 9 ABOUT HERE

Likewise, we test for the balance in instructor characteristics. As already mentioned, required courses are taught every semester and their instructor rarely changes. As a result, no significant difference is found in terms of observed characteristics and predicted quality.

6.5.2 The Effect of a Delayed Start

The class assignment is also responsible for a five-month delayed start for students in the second class, which could explain our findings. In our design, the estimated ranking effect is for students who want to join the first class and the identification is possible because some of them are not able to. Hence, we ask what if first-class students had to delay their start, but without changing their rank or peer quality.

To answer this question, we exploit a strike in 2005 that caught all prospective students by surprise. This strike started after the 2006 cohort had applied to UFPE — so they could not have changed their preferred class — and delayed their initial courses by five months. By comparing the last student in the first class in 2006 and in cohorts that were not affected by strikes,[23] we mimic the effect of a delayed start in our design. In practice, we estimate the relationship between each outcome and the entrance score on the right side of the cutoff for the two types of cohort. Then we compare the predicted values for the last student in the first class. Table 10 presents our estimates.

TABLE 10 ABOUT HERE

These estimates show that the strike reduced the grades of male students and made them more likely to try another *vestibular* and drop out of the institution. For females, all differences are small and not significant, except for the number of courses taken in the first semester. Overall, these findings indicate that the enforced delay had, if anything, a negative effect on a student's commitment to the program, which is the opposite of the ranking effect that we find above. In fact, the effect of ranking on academic performance and dropout may be underestimated due to the enforced delay in our design.

7 Conclusion

Joining a better group of aspirants is not necessarily a better option for entering a chosen career. In a setting that we control for institutional aspects, such as teaching quality and reputation, we find that college students are less willing to change their major and more likely to graduate early if they are the best in the worse class. If the same students were in a better class, their lower rank would increase their desire to start a new program, delaying their graduation. A lower rank is also found to reduce future earnings, particularly among the less productive workers, and reduce the chance of getting a prime occupation.

This disruptive effect can be mitigated if the difference in peer quality between classes is high enough. For men, however, the ranking effect is so strong that going to the worst class is for most of them a better option. For women, on the other hand, the ranking effect

[23] Namely, 2008 for 2+ year outcomes, plus 2009 and 2010 for 1-year outcomes and 2004, 2005 and 2011 for 1-semester outcomes.

is predominant only in some programs, where the difference between classes is small. On average, the small ranking effect on women's graduation is cancelled out by the peer effect.

In addition to institutional excellence and peer quality, the difference between the two groups, programs, or schools should also take perceived rank into account. The simple feeling of being at the bottom may undermine the benefit of joining more selective programs, which could in turn explain the dissenting findings in the literature.[24] Despite the distinct learning environment, top peers make bottom-ranked students underestimate their abilities and future returns in the chosen career. The discouragement in pursuing this career is not necessarily related to the risk of academic failure, but it is associated with parents' education and individual motivation. Students who are either better informed by their parents or who have a strong conviction about the value of their choice are less sensitive to the ranking effect.

It is worth remembering that these conclusions are drawn from a specific setting. UFPE is a public university that does not charge tuition fees. The only cost of changing programs is the delayed entry in the job market. If the cost of education were higher, the ranking effect on major switching and delay in graduation might not be as pronounced.

References

Abdulkadiroğlu, Atila, Joshua Angrist, and Parag Pathak (2014). "The elite illusion: Achievement effects at Boston and New York exam schools," *Econometrica*, 82(1): 137–196.

Almås, Ingvild, Alexander W Cappelen, Kjell G Salvanes, Erik Ø Sørensen, and Bertil Tungodden (2016). "What explains the gender gap in college track dropout? Experimental and administrative evidence," *American Economic Review*, 106(5): 296–302.

Andre, Diego de Maria and Jose Raimundo Carvalho (2016). "Peer Effects and Academic Performance in Higher Education - A Regression Discontinuity Design Approach," Working Paper, Universidade Federal do Ceará.

[24] See, for instance, Dale and Krueger (2002); Hoekstra (2009); Abdulkadiroğlu, Angrist and Pathak (2014); Dobbie and Fryer Jr (2014); Zimmerman (2014); Dobbie and Fryer Jr (2014); Kirkeboen, Leuven and Mogstad (2016).

Arcidiacono, Peter, V Joseph Hotz, and Songman Kang (2012). "Modeling college major choices using elicited measures of expectations and counterfactuals," *Journal of Econometrics*, 166(1): 3–16.

Arcidiacono, Peter and Michael Lovenheim (2016). "Affirmative Action and the Quality-Fit Trade-Off," *Journal of Economic Literature*, 54(1): 3–51.

Arcidiacono, Peter, Michael Lovenheim, and Maria Zhu (2015). "Affirmative Action in Undergraduate Education," *Annual Review of Economics*, 7(1): 487–518.

Azoulay, Pierre, Joshua S Graff Zivin, and Jialan Wang (2010). "Superstar extinction," *Quarterly Journal of Economics*, 125(2): 549–589.

Babcock, Linda, Maria P Recalde, Lise Vesterlund, and Laurie Weingart (2017). "Gender differences in accepting and receiving requests for tasks with low promotability," *American Economic Review*, 107(3): 714–747.

Bedard, Kelly and Elizabeth Dhuey (2006). "The persistence of early childhood maturity: international evidence of long-run age effects," *Quarterly Journal of Economics*, 121(4): 1437–1472.

Bedard, Kelly and Elizabeth Dhuey (2012). "School entry policies and skill accumulation across directly and indirectly affected individuals," *Journal of Human Resources*, 47(3): 643–683.

Belluzzo, Walter, Francisco Anuatti-Neto, and Elaine T. Pazello (2005). "Distribuição de salários e o diferencial público-privado no Brasil," *Revista Brasileira de Economia*, 59(4): 511–533.

Berkowitz, Daniel and Mark Hoekstra (2011). "Does high school quality matter? Evidence from admissions data," *Economics of Education Review*, 30(2): 280–288.

Bertrand, Marianne and Kevin F Hallock (2001). "The gender gap in top corporate jobs," *ILR Review*, 55(1): 3–21.

Bettinger, Eric P, Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu (2012). "The role of application assistance and information in college decisions: Results from the H&R Block FAFSA experiment," *Quarterly Journal of Economics*, 127(3): 1205–1242.

Black, Sandra E, Paul J Devereux, and Kjell G Salvanes (2011). "Too young to leave the nest? The effects of school starting age," *Review of Economics and Statistics*, 93(2): 455–467.

Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes (2013). "Under Pressure? The Effect of Peers on Outcomes of Young Adults," *Journal of Labor Economics*, 31(1): 119–153.

Bond, Timothy, George Bulman, Xiaoxiao Li, and Jonathan Smith (2017). "Updating human capital decisions: Evidence from SAT score shocks and college applications," *Journal of Labor Economics*, forthcoming.

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.

Bottan, Nicolas L. and Ricardo Perez-Truglia (2017). "Choosing Your Pond: Location Choices and Relative Income," working paper, UCLA.

Braga, Breno, Sergio Firpo, and Gustavo Gonzaga (2009). "Escolaridade e diferencial de rendimentos entre o setor privado e o setor público no Brasil," *Pesquisa e Planejamento Economico*, 39(3): 431–464.

Breen, Richard and Cecilia García-Peñalosa (2002). "Bayesian Learning and Gender Segregation," *Journal of Labor Economics*, 20(4): 899–922.

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

Busso, Matias, Taryn Dinkelman, A. Claudia Martinez, and Dario Romero (2017). "The effects of financial aid and returns information in selective and less selective schools: Experimental evidence from Chile," *Labour Economics*, 45 79–91.

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

Canaan, Serena and Pierre Mouganie (2018). "Returns to Education Quality for Low-Skilled Students: Evidence from a Discontinuity," *Journal of Labor Economics*, forthcoming.

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.

Carrell, Scott E, Bruce I Sacerdote, and James E West (2013). "From natural variation to optimal policy? The importance of endogenous peer group formation," *Econometrica*, 81(3): 855–882.

Cattaneo, Matias D., Michael Jansson, and Xinwei Ma (2017). "Simple Local Polynomial Density Estimators," working paper, University of Michigan.

Cicala, Steve, Roland G Fryer, and Jörg L Spenkuch (2016). "Comparative advantage in social interactions," *Journal of the European Economic Association*, forthcoming.

Coelho, Danilo, Marcelo Fernandes, and Miguel N. Foguel (2014). "Foreign Capital and Gender Differences in Promotions: Evidence from Large Brazilian Manufacturing Firms," *Economía*, 14(2): 55–84.

Cornelissen, Thomas, Christian Dustmann, and Uta Schönberg (2017). "Peer Effects in the Workplace," *American Economic Review*, 107(2): 425–456.

Dale, Stacy Berg and Alan B. Krueger (2002). "Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables," *Quarterly Journal of Economics*, 117(4): 1491–1527.

Daly, Michael, Christopher Boyce, and Alex Wood (2015). "A Social Rank Explanation of How Money Influences Health," *Health Psychology*, 34(3): 222–230.

Dhuey, Elizabeth and Stephen Lipscomb (2008). "What makes a leader? Relative age and high school leadership," *Economics of Education Review*, 27(9): 173–183.

Dobbie, Will and Roland G Fryer Jr (2014). "The impact of attending a school with high-achieving peers: Evidence from the New York City exam schools," *American Economic Journal: Applied Economics*, 6(3): 58–75.

Elder, Todd E and Darren H Lubotsky (2009). "Kindergarten entrance age and children's achievement: impacts of state policies, family background, and peers," *Journal of Human Resources*, 44(3): 641–683.

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.

Fabregas, Raissa (2017). "A Better School but a Worse Position? The Effects of Marginal Middle School Admissions in Mexico City," working paper, Harvard University.

Falk, Armin and Andrea Ichino (2006). "Clean Evidence on Peer Effects," *Journal of Labor Economics*, 24(1): 39–57.

Feld, Jan and Ulf Zölitz (2017). "Understanding peer effects: on the nature, estimation, and channels of peer effects," *Journal of Labor Economics*, 35(2): 387–428.

Frandsen, Brigham R, Markus Frölich, and Blaise Melly (2012). "Quantile treatment effects in the regression discontinuity design," *Journal of Econometrics*, 168(2): 382–395.

Fredriksson, Peter and Bjorn Öckert (2014). "Life-cycle effects of age at school start," *Economic Journal*, 124(579): 977–1004.

French, Robert and Philip Oreopoulus (2017). "Behavioral barriers transitioning to college," *Labour Economics*, 47(4): 48–63.

Goodman, Joshua, Michael Hurwitz, and Jonathan Smith (2017). "Access to 4-Year Public Colleges and Degree Completion," *Journal of Labor Economics*, 35(3): 829–867.

Hastings, Justine, Christopher A. Neilson, and Seth D. Zimmerman (2015). "The Effects of Earnings Disclosure on College Enrollment Decisions," Working Paper 21300, National Bureau of Economic Research.

Hastings, Justine S, Christopher A Neilson, Anely Ramirez, and Seth D Zimmerman (2016). "(Un)informed college and major choice: Evidence from linked survey and administrative data," *Economics of Education Review*, 51 136–151.

Hastings, Justine S., Christopher A. Neilson, and Seth D. Zimmerman (2013). "Are Some Degrees Worth More than Others? Evidence from college admission cutoffs in Chile," Working Paper 19241, National Bureau of Economic Research.

Heinesen, Eskil (2018). "Admission to higher education programmes and student educational outcomes and earnings–Evidence from Denmark," *Economics of Education Review*, 63 1–19.

Herbst, Daniel and Alexandre Mas (2015). "Peer effects on worker output in the laboratory generalize to the field," *Science*, 350(6260): 545–549.

Hoekstra, Mark (2009). "The effect of attending the flagship state university on earnings: A discontinuity-based approach," *Review of Economics and Statistics*, 91(4): 717–724.

Hoekstra, Mark, Pierre Mouganie, and Yaojing Wang (2018). "Peer Quality and the Academic Benefits to Attending Better Schools," *Journal of Labor Economics*, forthcoming.

Hoxby, Caroline M. and Sarah Turner (2015). "What High-Achieving Low-Income Students Know about College," *American Economic Review*, 105(5): 514–17.

Imberman, Scott A, Adriana D Kugler, and Bruce I Sacerdote (2012). "Katrina's children: Evidence on the structure of peer effects from hurricane evacuees," *American Economic Review*, 102(5): 2048–2082.

Jackson, C Kirabo and Elias Bruegmann (2009). "Teaching students and teaching each other: The importance of peer learning for teachers," *American Economic Journal: Applied Economics*, 1(4): 85–108.

Jensen, Robert (2010). "The (perceived) returns to education and the demand for schooling," *Quarterly Journal of Economics*, 125(2): 515–548.

Kirkeboen, Lars J., Edwin Leuven, and Magne Mogstad (2016). "Field of Study, Earnings, and Self-Selection," *Quarterly Journal of Economics*, 131(3): 1057–1111.

Kling, Jeffrey R, Sendhil Mullainathan, Eldar Shafir, Lee C Vermeulen, and Marian V Wrobel (2012). "Comparison friction: Experimental evidence from Medicare drug plans," *Quarterly Journal of Economics*, 127(1): 199–235.

Kramarz, Francis and Oskar Nordström Skans (2014). "When strong ties are strong: Networks and youth labour market entry," *Review of Economic Studies*, 81(3): 1164–1200.

Laschever, Ron (2012). "The doughboys network: Social interactions and the employment of World War I veterans," working paper, University of Illinois.

Lavy, Victor, M. Daniele Paserman, and Analia Schlosser (2012). "Inside the Black Box of Ability Peer Effects: Evidence from Variation in Low Achievers in the Classroom," *Economic Journal*, 122(559): 208–237.

Lavy, Victor, Olmo Silva, and Felix Weinhardt (2012). "The Good, The Bad and The Average: Evidence on Ability Peer Effects in Schools," *Journal of Labor Economics*, 30(2): 367–414.

Marsh, Herbert W (1987). "The big-fish-little-pond effect on academic self-concept," *Journal of Educational Psychology*, 79(3): 280–295.

Marsh, Herbert W (1991). "Failure of high-ability high schools to deliver academic benefits commensurate with their students' ability levels," *American Educational Research Journal*, 28(2): 445–480.

Marsh, Herbert W and Kit-Tai Hau (2003). "Big-Fish-Little-Pond effect on academic self-concept: A cross-cultural (26-country) test of the negative effects of academically selective schools," *American Psychologist*, 58(5): 364–376.

Marsh, Herbert W, Olaf Köller, and Jürgen Baumert (2001). "Reunification of East and West German school systems: Longitudinal multilevel modeling study of the big-fish-little-pond effect on academic self-concept," *American Educational Research Journal*, 38(2): 321–350.

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.

McEwan, Patrick J and Joseph S Shapiro (2008). "The benefits of delayed primary school enrollment: discontinuity estimates using exact birth dates," *Journal of Human Resources*, 43(1): 1–29.

Murphy, Richard and Felix Weinhardt (2016). "Top of the class: The importance of ordinal rank," working paper, University of Texas at Austin.

Nguyen, Trang (2008). "Information, role models and perceived returns to education: Experimental evidence from Madagascar," working paper, MIT.

Ockert, Bjorn (2010). "What's the value of an acceptance letter? Using admissions data to estimate the return to college," *Economics of Education Review*, 29(4): 504–516.

Perez-Truglia, Ricardo (2016). "The Effects of Income Transparency on Well-Being: Evidence from a Natural Experiment," working paper, UCLA.

Sacerdote, Bruce (2001). "Peer effects with random assignment: Results for Dartmouth roommates," *Quarterly Journal of Economics*, 116(2): 681–704.

Shue, Kelly (2013). "Executive Networks and Firm Policies: Evidence from the Random Assignment of MBA Peers," *Review of Financial Studies*, 26(6): 1401–1442.

Stinebrickner, Ralph and Todd R. Stinebrickner (2014). "A Major in Science? Initial Beliefs and Final Outcomes for College Major and Dropout," *Review of Economic Studies*, 81(1): 426–472.

Stinebrickner, Todd and Ralph Stinebrickner (2012). "Learning about Academic Ability and the College Dropout Decision," *Journal of Labor Economics*, 30(4): 707–748.

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

Waldinger, Fabian (2011). "Peer effects in science: Evidence from the dismissal of scientists in Nazi Germany," *Review of Economic Studies*, 79(2): 838–861.

Wiswall, Matthew and Basit Zafar (2015). "Determinants of college major choice: Identification using an information experiment," *Review of Economic Studies*, 82(2): 791–824.

Wood, Alex M., Christopher J. Boyce, Simon C. Moore, and Gordon D.A. Brown (2012). "An evolutionary based social rank explanation of why low income predicts mental distress: A 17 year cohort study of 30,000 people," *Journal of Affective Disorders*, 136(3): 882–888.

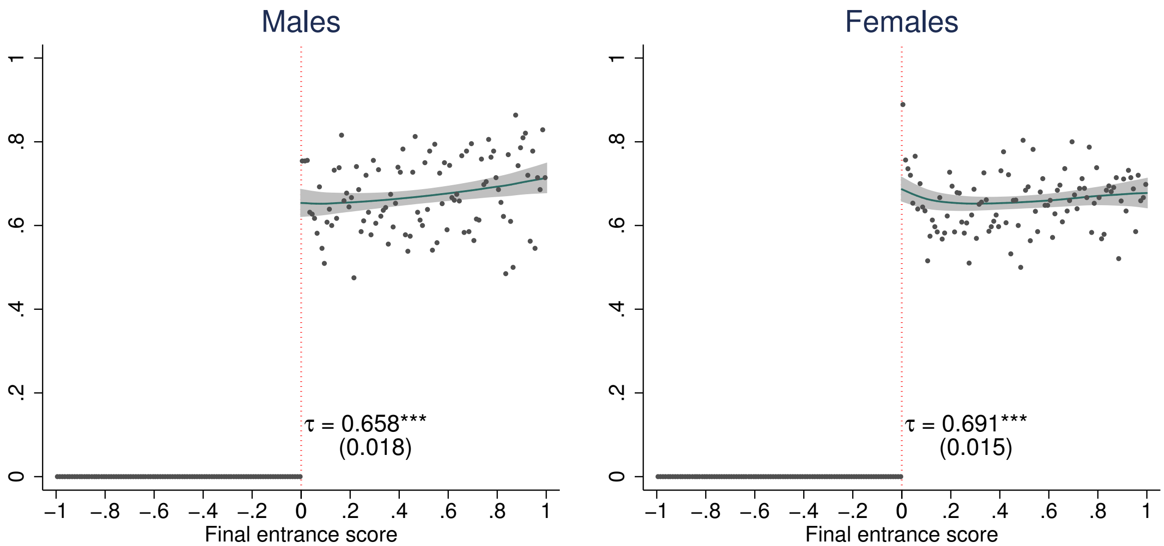
Zafar, Basit (2011). "How Do College Students Form Expectations?," *Journal of Labor Economics*, 29(2): 301–348.

Zeidner, Moshe and Esther Jane Schleyer (1999). "The big-fish-little-pond effect for academic self-concept, test anxiety, and school grades in gifted children," *Contemporary Educational Psychology*, 24(4): 305–329.

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. (2014). "The Returns to College Admission for Academically Marginal Students," *Journal of Labor Economics*, 32(4): 711–754.

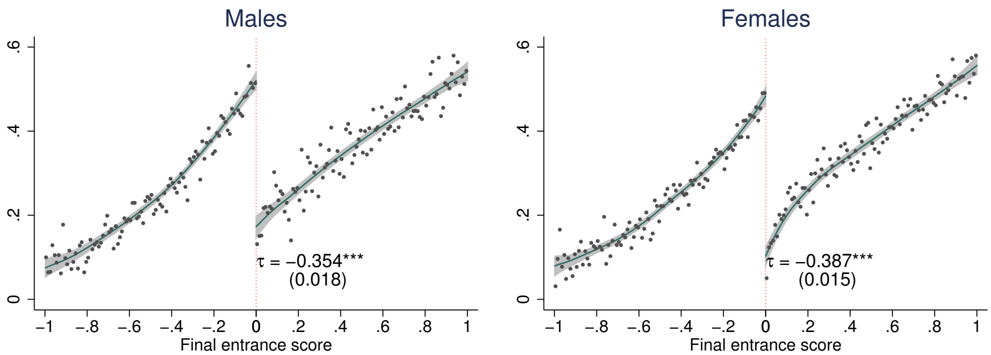
Figure 1: Relationship between Final Entrance Score and Class Assignment



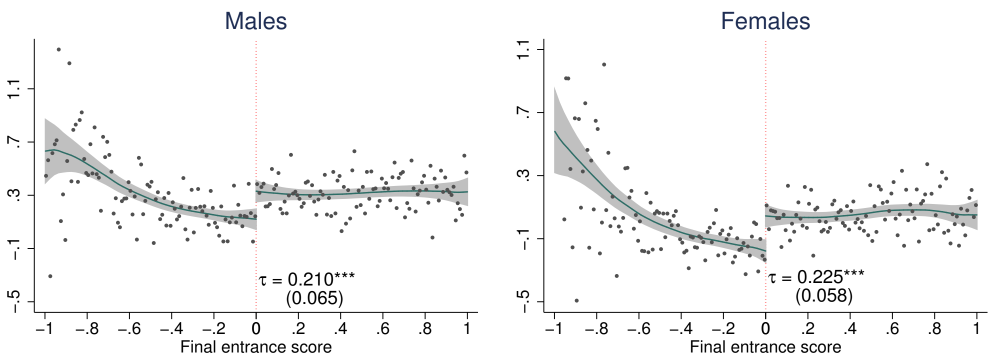
Final entrance score is standardized by program and year using the first-class cutoff and the standard deviation of admitted candidates' scores. Sample restriction is described in Section 4.1. Class assignment is 1 if candidate goes to the first class and 0 otherwise. It is estimated using triangular kernel with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). τ is the regression discontinuity estimate, with robust standard errors in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Figure 2: Relationship Between Final Entrance Score and Treatments

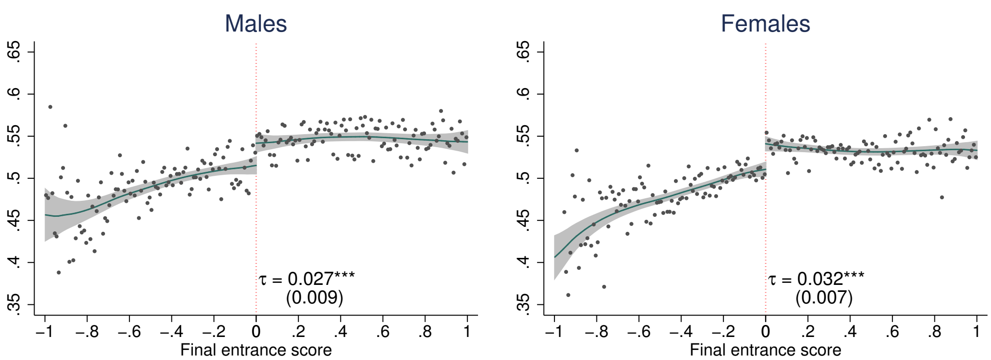
(a) Student's Rank



(b) Peer Quality

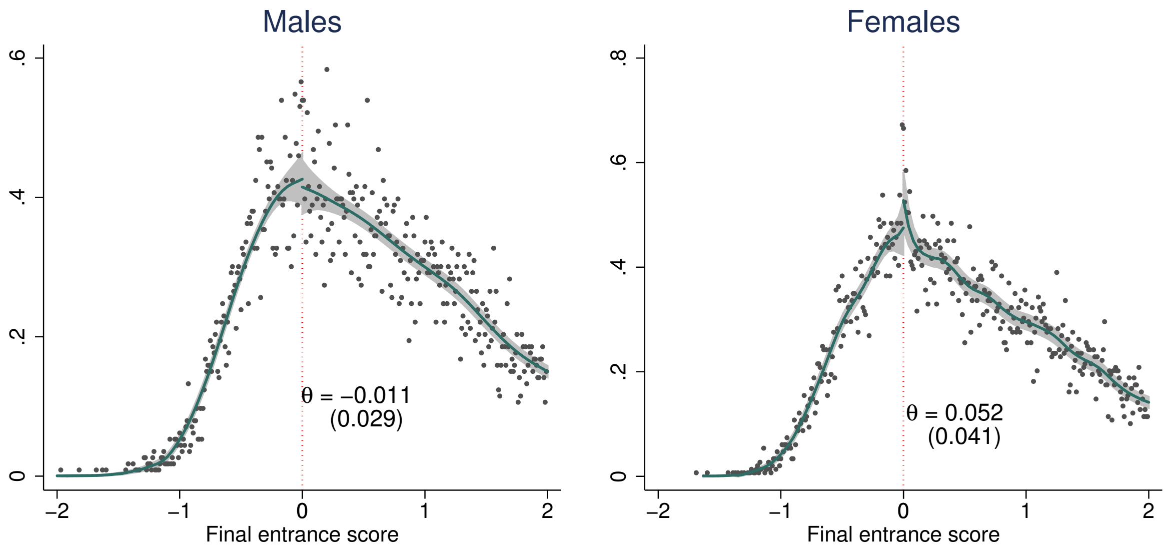


(c) Peer Heterogeneity



Final entrance score is standardized by program and year using the first-class cutoff and the standard deviation of admitted candidates' scores. A student's rank is defined by the within-class percentile of their final entrance score. Peer quality is measured by their median classmate's round 1 score and peer heterogeneity is measured by the within-class standard deviation of round 1 scores. The sample comprises candidates admitted for the first time, who are 21 years or less. Functions are estimated using triangular kernel with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). τ is the regression discontinuity estimate, with robust standard errors in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

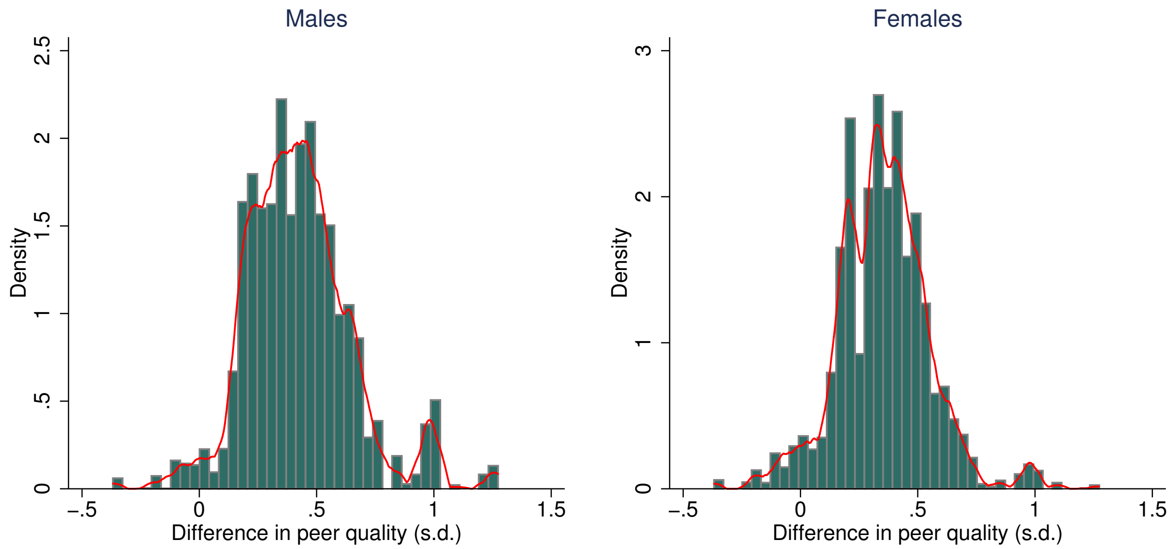
Figure 3: Density of Final Entrance Score and McCrary Test



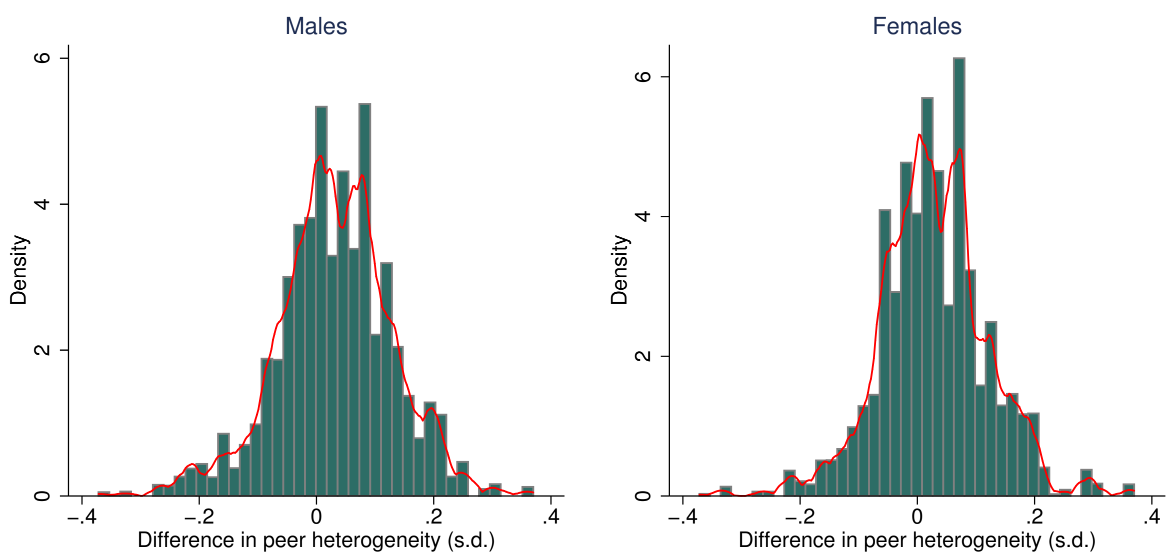
Final entrance score is standardized by program and year using the first-class cutoff and the standard deviation of admitted candidates' scores. The sample comprises candidates admitted for the first time, who are 21 years or less. θ is the Cattaneo, Jansson and Ma's (2017) estimator for density discontinuity, with robust standard error in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. Grey dots are bins of 0.02 s.d.

Figure 4: Distribution of Differences in Peer Quality and Heterogeneity

(a) Peer Quality

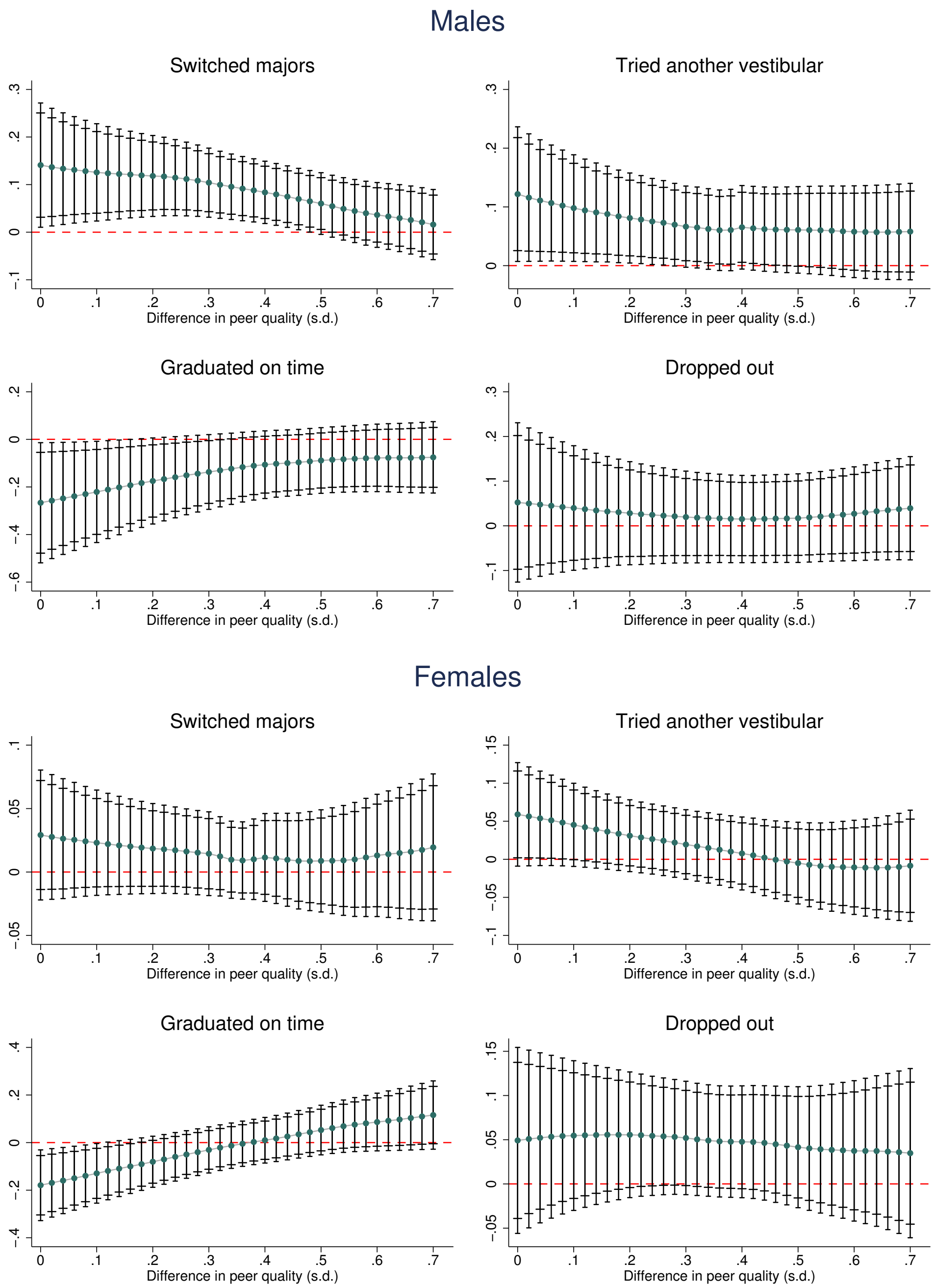


(b) Peer Heterogeneity



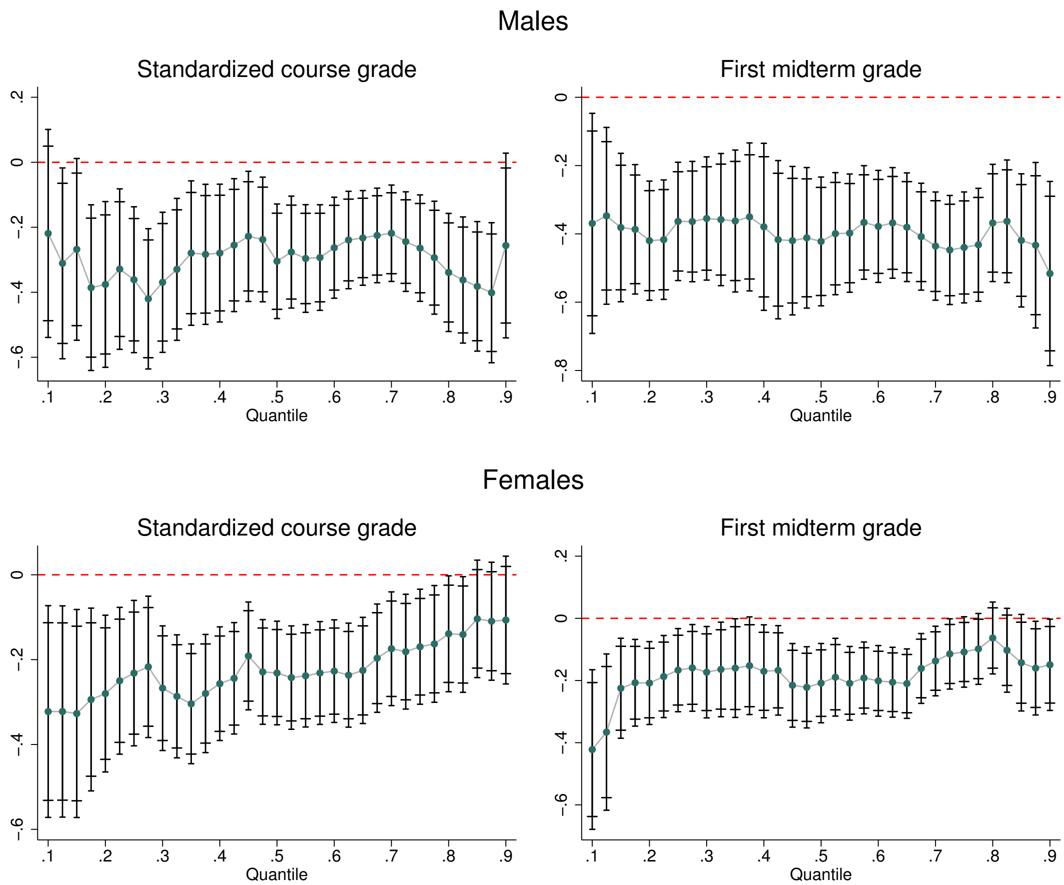
This figure presents the histograms for differences in peer quality and heterogeneity between classes in the same program in the same year. Peer quality is measured by a student's median classmate's round 1 score and peer heterogeneity is measured by the within-class standard deviation of round 1 scores.

Figure 5: Net Effect of First Class by Difference in Peer Quality



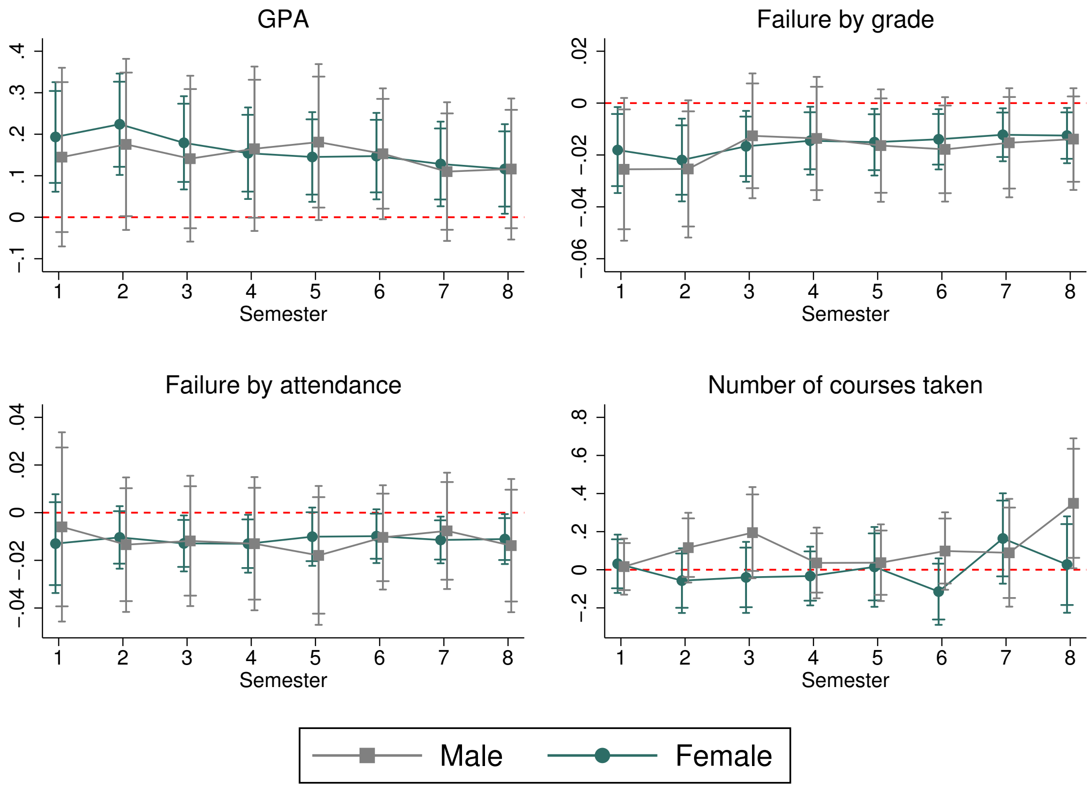
This figure presents the fuzzy regression discontinuity (FRD) estimates of the first-class effect as a function of differences in the median peer's round 1 score (peer quality). The vertical bars represent the robust confidence interval at the 90% and 95% levels. The sample comprises candidates admitted for the first time, who are 21 years or less. FRDs and their relationships with peer quality are estimated using triangular kernels. The bandwidth for difference in peer quality is 0.9 s.d. and the bandwidth for entrance score is selected by using Calonico, Cattaneo and Titiunik's (2014) procedure.

Figure 6: Quantile Effect of First Class on Grades in the 1st Semester



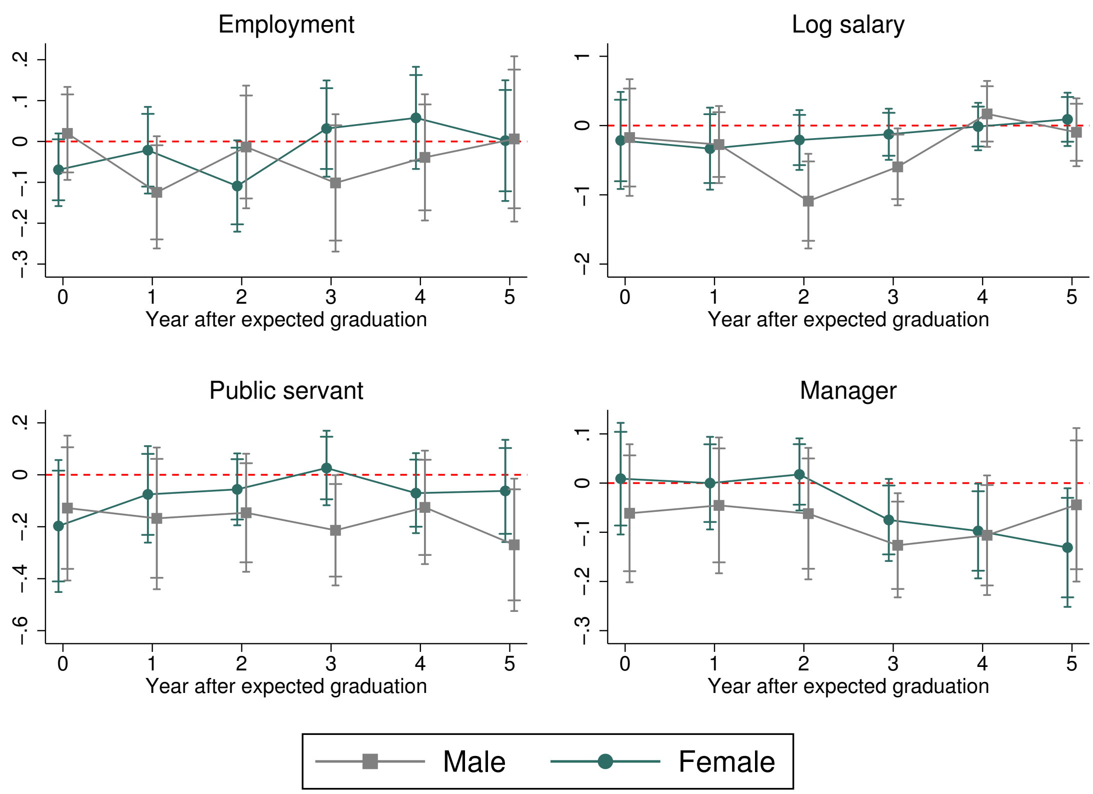
This figure presents the fuzzy regression discontinuity (FRD) estimates for the first-class effect at different quantiles. The vertical bars represent the confidence interval at the 90% and 95% levels. The sample comprises candidates admitted for the first time, who are 21 years or less. FRDs are estimated using a procedure proposed by Frandsen, Frölich and Melly (2012). Bandwidths are selected by using Calonico, Cattaneo and Titiunik's (2014) procedure for the average effect.

Figure 7: Ranking Effects on Academic Performance per Semester



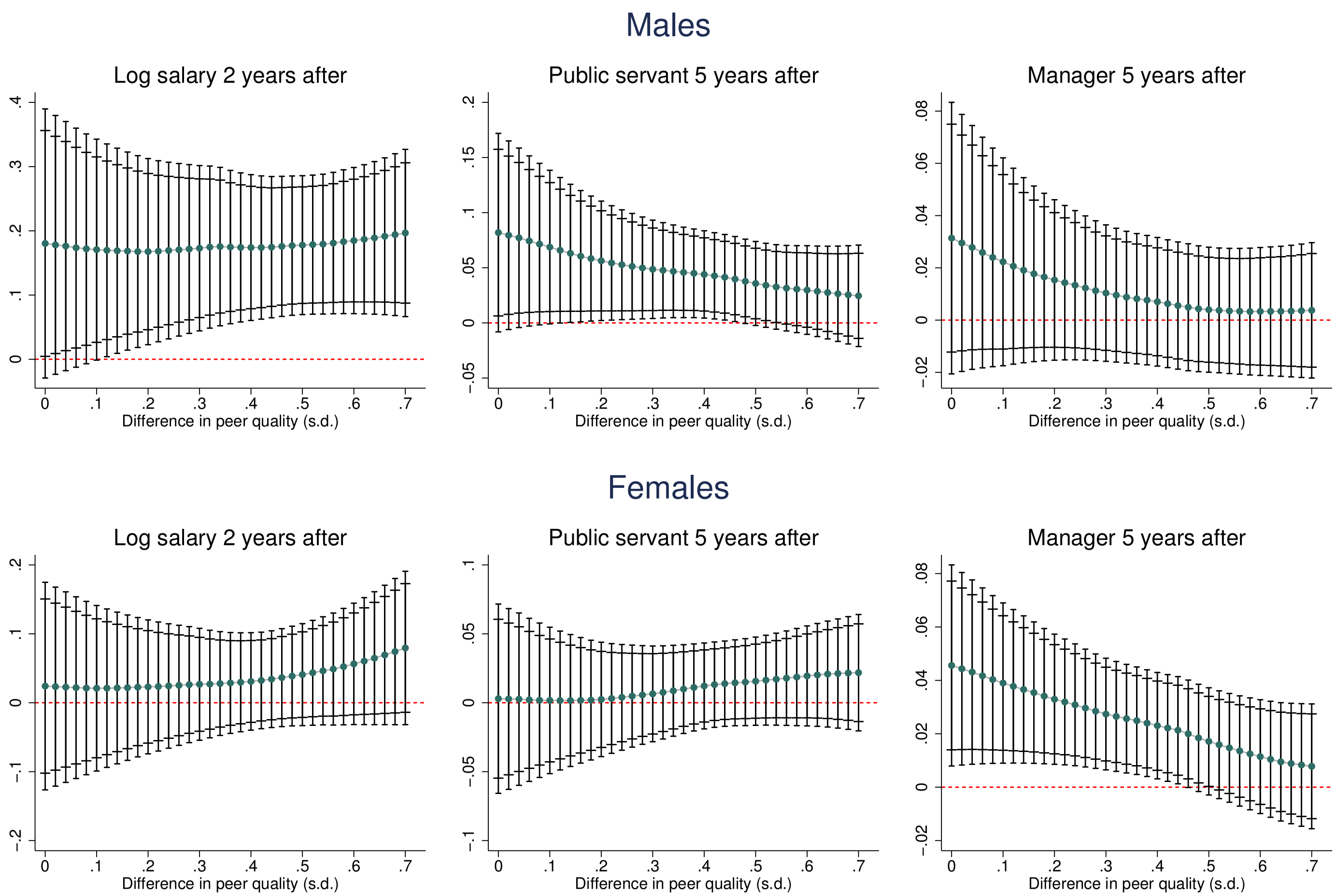
This figure presents the fuzzy regression discontinuity (FRD) estimates of the ranking effect on academic performance up to each semester. The ranking effect derives from the discontinuity between classes in which the difference in median score is zero. The vertical bars represent the robust confidence interval at the 90% and 95% levels. The sample comprises candidates admitted for the first time, who are 21 years or less. FRDs and their relationships with peer quality are estimated using triangular kernels. The bandwidth for difference in peer quality is 0.9 s.d. and the bandwidth for entrance score is selected by using Calonico, Cattaneo and Titiunik's (2014) procedure.

Figure 8: Net Effect of First Class on Labor Market Outcomes



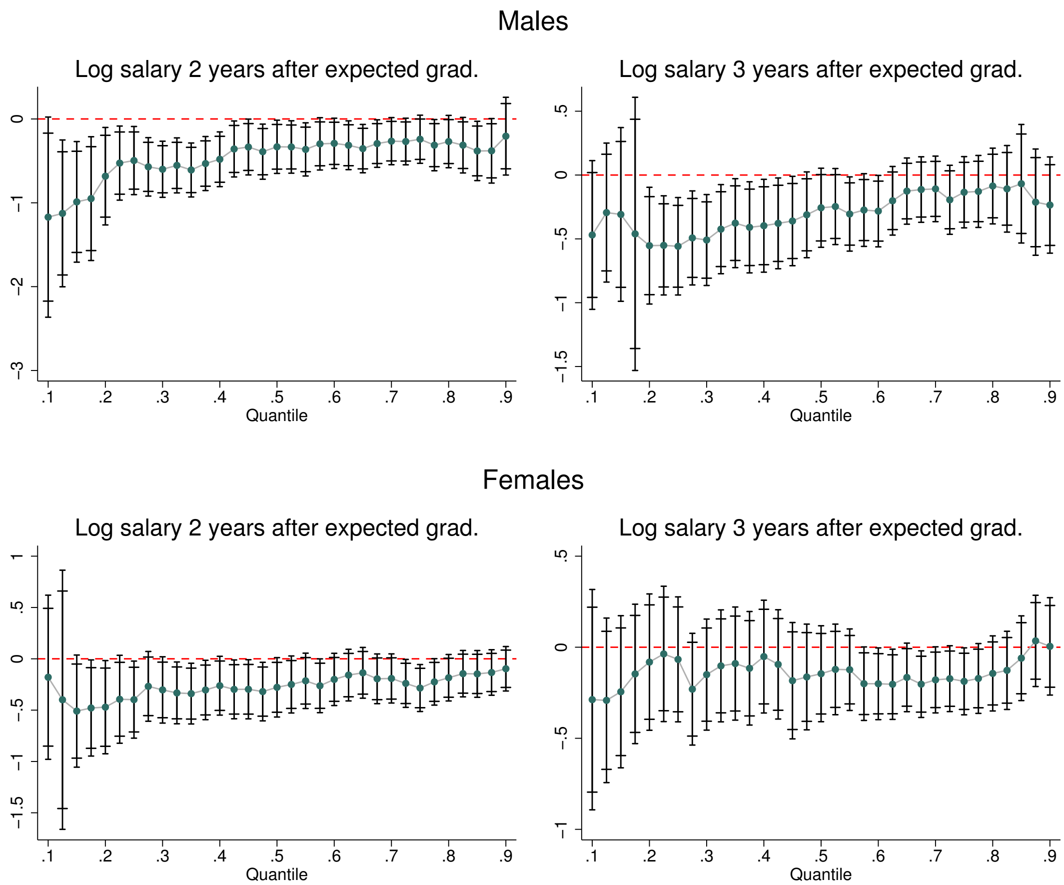
This figure presents the fuzzy regression discontinuity (FRD) estimates of the first-class effect on employment, earnings and occupation for each year after the expected graduation in the initial program. The vertical bars represent robust confidence interval at the 90% and 95% levels. The sample comprises candidates admitted for the first time, who are 21 years or less. FRDs are estimated using triangular kernels and the bandwidths are selected by using Calonico, Cattaneo and Titiunik's (2014) procedure.

Figure 9: Ranking Effect on Labor Outcomes by Difference in Peer Quality



This figure presents the fuzzy regression discontinuity (FRD) estimates of the net ranking effect on labor outcomes as a function of differences in the median peer's round 1 score (peer quality). The vertical bars represent the confidence interval at the 90% and 95% levels. The sample comprises candidates admitted for the first time, who are 21 years or less. FDRs and their relationship with peer quality are estimated using triangular kernels. The bandwidth for difference in peer quality is 0.9 s.d. and the bandwidth for entrance score is selected by using Calonico, Cattaneo and Titiunik's (2014) procedure.

Figure 10: Quantile Effect of First Class on Earnings



This figure presents the fuzzy regression discontinuity (FRD) estimates for the first-class effect at different quantiles. The vertical bars represent the confidence interval at the 90% and 95% levels. The sample includes candidates admitted for the first time, who are 21 years or less. FRDs are estimated using the procedure proposed by Frandsen, Frölich and Melly (2012). Bandwidths are selected by using Calonico, Cattaneo and Titiunik's (2014) procedure for the average effect.

Table 1: Sample Size in Employment Data

Years after expected graduation	Males			Females		
	All	Employed	Rate	All	Employed	Rate
0	8,904	2,066	0.232	11,338	2,166	0.191
1	7,790	2,620	0.336	9,699	3,348	0.345
2	6,543	3,214	0.491	8,049	4,157	0.516
3	5,575	3,248	0.583	6,586	4,020	0.610
4	4,770	3,103	0.651	5,627	3,760	0.668
5	3,642	2,556	0.702	4,291	3,045	0.710

Table 2: Descriptive Statistics

	Males				**Females**			
	1st class		2nd class		1st class		2nd class	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Final entrance score	1.216	0.913	0.273	0.957	1.164	0.917	0.301	0.943
Round 1 score	0.532	0.989	0.179	0.963	0.203	0.986	-0.139	0.983
Class rank	0.473	0.278	0.480	0.287	0.462	0.282	0.469	0.284
Switched programs	0.086	0.280	0.068	0.252	0.046	0.210	0.037	0.188
Tried another vestibular	0.136	0.343	0.114	0.318	0.092	0.289	0.072	0.258
Graduated on time	0.483	0.500	0.432	0.495	0.665	0.472	0.644	0.479
Dropped out*	0.239	0.427	0.260	0.439	0.147	0.354	0.154	0.361
Number of courses taken**	5.399	1.114	5.444	1.239	5.840	1.511	5.755	1.572
Missed first midterm	0.061	0.209	0.075	0.231	0.038	0.171	0.049	0.193
First midterm grade	-0.161	0.713	-0.161	0.726	-0.041	0.634	-0.041	0.660
Number of absences**	1.263	4.184	1.325	3.928	0.970	3.245	1.199	3.887
Standardized course grade***	-0.171	0.695	-0.198	0.684	-0.019	0.616	-0.019	0.619
GPA***	7.184	1.426	6.983	1.457	7.707	1.063	7.614	1.088
Failure by grade***	0.094	0.165	0.119	0.189	0.049	0.116	0.057	0.124
Failure by attendance***	0.101	0.239	0.096	0.216	0.046	0.167	0.043	0.147
3 years after expected graduation								
Employed	0.573	0.495	0.593	0.491	0.607	0.489	0.614	0.487
Log salary	10.250	1.277	10.211	1.033	9.953	1.149	9.905	0.992
Public servant	0.401	0.477	0.417	0.477	0.386	0.473	0.347	0.459
Manager	0.101	0.295	0.089	0.275	0.075	0.256	0.079	0.254
Covariates								
Age	18.98	1.056	19.07	1.034	19.04	1.051	19.08	1.059
White	0.612	0.487	0.569	0.495	0.579	0.494	0.548	0.498
Living in Pernambuco	0.873	0.332	0.877	0.329	0.886	0.317	0.891	0.311
From public high school	0.217	0.412	0.237	0.425	0.248	0.432	0.287	0.452
Employed at application	0.094	0.292	0.114	0.318	0.073	0.260	0.087	0.282
Number of vestibular tries	1.711	0.803	1.724	0.788	1.805	0.831	1.816	0.830
Both parents with college degree	0.321	0.467	0.284	0.451	0.258	0.438	0.202	0.402
Neither parent with college degree	0.414	0.493	0.462	0.499	0.505	0.500	0.569	0.495
Reason for choosing the program								
Opportunities and prestige	0.252	0.434	0.274	0.446	0.225	0.418	0.251	0.434
Self-fulfillment	0.532	0.499	0.529	0.499	0.596	0.491	0.569	0.495
Other motives	0.216	0.412	0.197	0.398	0.178	0.383	0.180	0.384
Instructor characteristics								
Female instructors	0.369	0.241	0.361	0.244	0.492	0.231	0.485	0.245
40+ year-old instructors	0.602	0.266	0.584	0.268	0.673	0.266	0.666	0.257
Assistant professors	0.451	0.264	0.467	0.248	0.506	0.258	0.502	0.235
Associate or full professors	0.356	0.280	0.338	0.272	0.331	0.277	0.324	0.268
Instructor quality								
Dropout rate	-0.043	0.027	-0.043	0.024	-0.033	0.019	-0.035	0.019
Failure rate	-0.018	0.022	-0.018	0.023	-0.010	0.015	-0.011	0.017
Number of observations	5,686		5,624		7,254		7,620	

*Only for students who are at least two years at UFPE. **In the first semester. ***In the first year, sample does not include those who drop out before the third semester. The sample comprises candidates admitted for the first time, who are 21 years or less.

Table 3: Ranking Discontinuities by Difference in Peer Quality and Heterogeneity

		Difference in peer quality (s.d.)									
		Males					Females				
		Δ=0	Δ=.175	Δ=.350	Δ=.525	Δ=.700	Δ=0	Δ=.175	Δ=.350	Δ=.525	Δ=.700
Difference in peer heterogeneity (s.d.)	Δ=-.20	-0.154***	-0.244***	-0.326***	-0.412***	-0.469***	-0.237***	-0.324***	-0.390***	-0.455***	-0.510***
		(0.031)	(0.028)	(0.028)	(0.029)	(0.032)	(0.025)	(0.026)	(0.027)	(0.030)	(0.034)
	Δ=-.10	-0.172***	-0.259***	-0.336***	-0.417***	-0.476***	-0.230***	-0.318***	-0.386***	-0.463***	-0.522***
		(0.026)	(0.023)	(0.022)	(0.023)	(0.025)	(0.020)	(0.019)	(0.019)	(0.022)	(0.027)
	Δ=0	-0.179***	-0.265***	-0.340***	-0.416***	-0.474***	-0.230***	-0.321***	-0.401***	-0.476***	-0.538***
		(0.026)	(0.022)	(0.019)	(0.020)	(0.022)	(0.018)	(0.016)	(0.015)	(0.018)	(0.024)
	Δ=.10	-0.157***	-0.248***	-0.330***	-0.405***	-0.467***	-0.214***	-0.313***	-0.404***	-0.477***	-0.545***
		(0.028)	(0.023)	(0.021)	(0.021)	(0.023)	(0.022)	(0.018)	(0.017)	(0.018)	(0.025)
	Δ=.20	-0.118***	-0.209***	-0.293***	-0.370***	-0.435***	-0.187***	-0.288***	-0.385***	-0.468***	-0.537***
		(0.036)	(0.031)	(0.028)	(0.027)	(0.030)	(0.029)	(0.026)	(0.024)	(0.025)	(0.030)

This table presents the discontinuity in student's rank as a function of differences (Δ) in peer quality and heterogeneity between classes in the same program in the same year. Students' rank is defined by the within-class percentile of their final entrance score. Peer quality is measured by their median classmate's round 1 score and peer heterogeneity is measured by the within-class standard deviation of round 1 scores. The sample comprises candidates admitted for the first time, who are 21 years or less. Functions are estimated using triangular kernel with the bandwidth selection procedure adapted from Calonico, Cattaneo and Titiunik (2014). Robust standard errors are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4: Net Effect of First Class on Major Switching and Graduation

	Males		**Females**	
	Reduced form	Net effect	Reduced form	Net effect
Switched programs	0.044**	0.065**	0.014	0.019
	(0.021)	(0.031)	(0.012)	(0.017)
Tried another vestibular	0.045**	0.068**	0.020	0.027
	(0.023)	(0.034)	(0.017)	(0.024)
Graduated on time	-0.070	-0.098	-0.015	-0.019
	(0.048)	(0.069)	(0.037)	(0.049)
Dropped out	0.023	0.034	0.040*	0.053
	(0.032)	(0.048)	(0.024)	(0.033)

This table presents the estimated regression discontinuity (RD) at the first class cutoff (reduced form) and fuzzy RD estimates of the first-class effect (net effect). The sample comprises candidates admitted for the first time, who are 21 years or less. RDs are estimated using triangular kernels. The bandwidth for entrance score is selected by using Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5: Ranking Effect on Major Switching and Graduation

	Marginal Ranking Effect					
		By difference in peer heterogeneity (s.d.)				
	Average	Δ=-.20	Δ=-.10	Δ=0	Δ=.10	Δ=.20
	Males					
Switched Programs	-0.046**	-0.040	-0.032	-0.039*	-0.069**	-0.126*
	(0.023)	(0.036)	(0.023)	(0.021)	(0.033)	(0.070)
Tried another vestibular	-0.036*	-0.025	-0.031	-0.037*	-0.043*	-0.075
	(0.019)	(0.040)	(0.025)	(0.019)	(0.024)	(0.051)
Graduated on time	0.093**	0.131	0.099*	0.102**	0.127**	0.180**
	(0.045)	(0.080)	(0.056)	(0.047)	(0.053)	(0.085)
Dropped out	-0.014	-0.033	-0.020	-0.015	-0.007	0.008
	(0.029)	(0.054)	(0.033)	(0.028)	(0.038)	(0.067)
	Females					
Switched Programs	-0.009	-0.011	-0.006	-0.007	-0.012	-0.016
	(0.009)	(0.016)	(0.011)	(0.008)	(0.010)	(0.015)
Tried another vestibular	-0.019*	-0.026	-0.017	-0.015	-0.024	-0.036
	(0.012)	(0.020)	(0.013)	(0.011)	(0.015)	(0.024)
Graduated on time	0.056**	0.052	0.046*	0.057**	0.065**	0.076*
	(0.024)	(0.036)	(0.026)	(0.023)	(0.030)	(0.043)
Dropped out	-0.016	-0.038	-0.025	-0.015	-0.002	0.012
	(0.018)	(0.028)	(0.019)	(0.018)	(0.023)	(0.035)

This table presents the fuzzy regression discontinuity (FRD) estimates of the average ranking effect in the first column and the ranking effect conditional on differences in peer heterogeneity between the classes (Δ) in the remaining columns. The ranking effect is estimated for cohorts in which the difference between median scores is zero. Peer heterogeneity is measured by the within-class standard deviation of round 1 scores. The sample comprises candidates admitted for the first time, who are 21 years or less. FRDs and their relationships with peer quality and peer heterogeneity are estimated using triangular kernels. The bandwidth for peer quality is 0.9 s.d. and for peer heterogeneity is 0.4 s.d. The bandwidth for entrance score is selected by using Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 6: Net Effect of First Class and Ranking Effect on Performance in the 1st Semester

	Males			**Females**		
	Reduced form	Net effect	Ranking effect	Reduced form	Net effect	Ranking effect
Number of courses taken	-0.108	-0.159	0.016	-0.039	-0.053	0.031
	(0.089)	(0.134)	(0.075)	(0.102)	(0.143)	(0.078)
Missed first midterm	0.019	0.029	-0.012	0.020*	0.029*	-0.005
	(0.019)	(0.029)	(0.017)	(0.012)	(0.017)	(0.009)
First midterm grade	-0.282***	-0.427***	0.094*	-0.162***	-0.220***	0.087***
	(0.060)	(0.093)	(0.055)	(0.044)	(0.062)	(0.031)
Number of absences	0.741**	1.096**	-0.391	0.551**	0.730**	-0.300
	(0.359)	(0.537)	(0.261)	(0.271)	(0.370)	(0.200)
Standardized course grade	-0.182***	-0.272***	0.044	-0.183***	-0.241***	0.081**
	(0.060)	(0.090)	(0.052)	(0.048)	(0.065)	(0.037)
GPA	-0.265**	-0.394**	0.145	-0.285***	-0.371***	0.193***
	(0.130)	(0.195)	(0.110)	(0.089)	(0.118)	(0.067)
Failure rate	0.059**	0.086**	-0.030	0.066***	0.086***	-0.026**
	(0.027)	(0.040)	(0.024)	(0.018)	(0.024)	(0.013)

This table presents the estimated regression discontinuity (RD) at the first class cutoff (reduced form) and fuzzy RD estimates of the first-class effect (net effect) and the ranking effect. The ranking effect derives from the discontinuity between the classes in which the difference in median score is zero. The sample comprises candidates admitted for the first time, who are 21 years or less. RDs and their relationships with peer quality are estimated using triangular kernels. The bandwidth for difference in peer quality is 0.9 s.d. (for the ranking effect) and the bandwidth for entrance score is selected by using Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7: Heterogeneity in the Ranking Effect by Type of Program

	Males						Females					
	Difficulty of the curriculum		Share of males		Competition for admission		Difficulty of the curriculum		Share of males		Competition for admission	
	Easy	Hard	Low	High	Low	High	Easy	Hard	Low	High	Low	High
Academic outcomes												
Switched programs	-0.049**	-0.015	-0.048**	-0.022	-0.024	-0.027**	-0.004	-0.014	-0.015	-0.000	-0.009	0.000
	(0.020)	(0.018)	(0.022)	(0.020)	(0.028)	(0.013)	(0.007)	(0.015)	(0.011)	(0.010)	(0.013)	(0.008)
Tried another vestibular	-0.034	-0.020	-0.044**	-0.004	-0.041	-0.016	-0.021*	-0.013	-0.015	-0.013	-0.022	-0.003
	(0.023)	(0.021)	(0.022)	(0.022)	(0.042)	(0.014)	(0.011)	(0.018)	(0.016)	(0.012)	(0.017)	(0.011)
Graduated on time	0.157***	0.033	0.045	0.059*	0.043	0.036*	0.039	0.051	0.079*	0.035	0.055	0.031
	(0.058)	(0.032)	(0.047)	(0.035)	(0.112)	(0.020)	(0.026)	(0.048)	(0.041)	(0.026)	(0.046)	(0.021)
First midterm grade	0.044	0.071	0.042	0.058	0.121	0.021	0.009	0.138***	0.054	0.077**	0.072*	0.060*
	(0.064)	(0.052)	(0.063)	(0.057)	(0.110)	(0.033)	(0.031)	(0.049)	(0.048)	(0.033)	(0.041)	(0.035)
GPA year 1	0.090	0.172	0.060	0.110	0.138	0.085	0.044	0.351***	0.117	0.253***	0.227***	0.158***
	(0.085)	(0.114)	(0.093)	(0.122)	(0.164)	(0.073)	(0.052)	(0.096)	(0.084)	(0.069)	(0.084)	(0.060)
Failure rate year 1	-0.028*	-0.051**	-0.012	-0.040*	-0.038	-0.022	-0.005	-0.053***	-0.019	-0.029***	-0.046***	-0.010
	(0.016)	(0.023)	(0.019)	(0.023)	(0.034)	(0.013)	(0.008)	(0.017)	(0.014)	(0.011)	(0.016)	(0.010)
Labor market outcomes												
Employed 2 years after	0.013	0.001	-0.012	0.013	0.009	-0.003	0.025*	0.011	0.033**	0.003	0.025	0.016
	(0.019)	(0.016)	(0.019)	(0.015)	(0.021)	(0.016)	(0.013)	(0.019)	(0.015)	(0.014)	(0.017)	(0.012)
Log salary 2 years after	0.180*	0.283**	0.174*	0.179**	0.217***	0.130*	0.017	0.054	0.019	0.055	0.038	0.029
	(0.096)	(0.118)	(0.089)	(0.073)	(0.078)	(0.072)	(0.041)	(0.075)	(0.056)	(0.046)	(0.056)	(0.054)
Log salary 3 years after	0.025	0.211**	-0.004	0.177**	0.109	0.068	0.007	-0.009	-0.002	0.052	0.065	-0.018
	(0.065)	(0.083)	(0.049)	(0.073)	(0.071)	(0.054)	(0.044)	(0.061)	(0.047)	(0.049)	(0.044)	(0.049)
Public servant 3 years after	0.023	0.036	0.008	0.067**	0.068**	0.014	0.007	-0.036	0.017	-0.021	0.001	-0.010
	(0.026)	(0.023)	(0.023)	(0.027)	(0.033)	(0.017)	(0.017)	(0.028)	(0.020)	(0.018)	(0.023)	(0.016)
Public servant 5 years after	0.057	0.019	0.019	0.047*	0.066**	0.017	-0.005	0.006	-0.014	0.028	0.015	0.003
	(0.038)	(0.027)	(0.027)	(0.025)	(0.033)	(0.023)	(0.021)	(0.035)	(0.029)	(0.020)	(0.031)	(0.020)
Manager 3 years after	0.021	0.021**	0.016	0.023**	0.026**	0.014	0.012	0.029	0.006	0.021*	0.013	0.012
	(0.018)	(0.011)	(0.013)	(0.010)	(0.012)	(0.011)	(0.008)	(0.018)	(0.009)	(0.012)	(0.011)	(0.009)
Manager 5 years after	0.022	-0.000	0.000	0.011	0.013	0.000	0.027*	0.018	0.020*	0.023	0.005	0.032**
	(0.026)	(0.016)	(0.015)	(0.017)	(0.018)	(0.015)	(0.015)	(0.019)	(0.012)	(0.015)	(0.014)	(0.013)

This table presents the fuzzy regression discontinuity (FRD) estimates of the ranking effect by type of program. The ranking effect derives from the discontinuity between classes in which the difference in median score is zero. 'Difficulty of the curriculum' is defined on the basis of the expected failure rate. 'Competition for admission' is defined on the basis of the program's median round 1 score. For both males and females, the sample of programs is split at the overall median. The sample includes candidates admitted for the first time, who are 21 years or less. FRDs and their relationships with peer quality are estimated using triangular kernels. The bandwidth for difference in peer quality is 0.9 s.d. and the bandwidth for entrance score is selected by using Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8: Heterogeneity in the Ranking Effect by Individual Characteristics

	Males				Females			
	Parents with college degree		Career motivation		Parents with college degree		Career motivation	
	Both	Neither	Market	Other	Both	Neither	Market	Other
Academic outcomes								
Switched programs	0.023	-0.043	-0.010	-0.069**	0.006	-0.002	-0.009	-0.003
	(0.023)	(0.028)	(0.021)	(0.030)	(0.012)	(0.012)	(0.022)	(0.008)
Tried another vestibular	-0.033	-0.018	-0.014	-0.027	0.001	-0.014	-0.008	-0.012
	(0.041)	(0.028)	(0.024)	(0.026)	(0.020)	(0.015)	(0.032)	(0.011)
Graduated on time	-0.039	0.074	0.065	0.034	0.054	0.060	0.050	0.054**
	(0.050)	(0.065)	(0.077)	(0.036)	(0.039)	(0.039)	(0.158)	(0.023)
First midterm grade	-0.011	0.124	0.002	0.080	0.079*	0.083**	0.209**	0.047*
	(0.086)	(0.104)	(0.071)	(0.061)	(0.044)	(0.041)	(0.103)	(0.027)
GPA year 1	0.192	0.098	0.192	0.103	0.135*	0.268***	0.289*	0.214***
	(0.193)	(0.168)	(0.140)	(0.103)	(0.079)	(0.084)	(0.164)	(0.057)
Failure rate year 1	-0.025	-0.055*	-0.029	-0.035*	-0.021	-0.038***	-0.053*	-0.026***
	(0.027)	(0.031)	(0.024)	(0.019)	(0.014)	(0.014)	(0.029)	(0.009)
Labor market outcomes								
Employed 2 years after	-0.005	0.007	-0.022	0.012	-0.008	0.034**	0.027	0.012
	(0.022)	(0.021)	(0.027)	(0.015)	(0.019)	(0.015)	(0.027)	(0.012)
Log salary 2 years after	0.189	0.118	0.045	0.288***	0.013	0.108*	0.145	0.022
	(0.129)	(0.083)	(0.089)	(0.088)	(0.058)	(0.059)	(0.091)	(0.044)
Log salary 3 years after	0.038	0.086	-0.071	0.152**	-0.002	0.043	0.031	0.003
	(0.075)	(0.093)	(0.073)	(0.060)	(0.057)	(0.040)	(0.100)	(0.038)
Public servant 3 years after	0.044	0.088**	0.020	0.034*	-0.030	0.008	-0.006	-0.003
	(0.029)	(0.035)	(0.034)	(0.019)	(0.023)	(0.020)	(0.034)	(0.015)
Public servant 5 years after	0.021	0.082**	0.013	0.045**	0.008	0.012	-0.015	0.017
	(0.034)	(0.035)	(0.045)	(0.022)	(0.021)	(0.026)	(0.043)	(0.017)
Manager 3 years after	0.015	0.016*	0.055**	0.009	0.006	0.019**	0.011	0.018**
	(0.017)	(0.009)	(0.022)	(0.006)	(0.014)	(0.009)	(0.012)	(0.008)
Manager 5 years after	-0.021	0.009	0.025	-0.004	0.015	0.021	0.020	0.022*
	(0.020)	(0.016)	(0.027)	(0.012)	(0.017)	(0.013)	(0.017)	(0.012)

This table presents the fuzzy regression discontinuity (FRD) estimates of the ranking effect by students characteristics. The ranking effect derives from the discontinuity between classes in which the difference in median score is zero. 'Career motivation' is split between market opportunities and prestige ('market') and other motives ('other'). The sample comprises candidates admitted for the first time, who are 21 years or less. FRDs and their relationships with peer quality are estimated using triangular kernels. The bandwidth for difference in peer quality is 0.9 s.d. and the bandwidth for entrance score is selected by using Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 9: Balance of Covariates at the Cutoff

	Males		Females	
	Estimate	p-value	Estimate	p-value
Age	0.044	0.563	0.063	0.335
	(0.077)		(0.066)	
White	0.055	0.250	-0.047	0.256
	(0.048)		(0.042)	
Living in Pernambuco	0.017	0.482	-0.010	0.641
	(0.024)		(0.021)	
From public high school	0.009	0.783	-0.024	0.452
	(0.031)		(0.032)	
Employed at application	-0.019	0.431	0.010	0.616
	(0.025)		(0.021)	
Number of vestibular tries	0.009	0.878	0.010	0.855
	(0.057)		(0.056)	
Both parents with college degree	-0.045	0.229	-0.016	0.566
	(0.038)		(0.028)	
Neither parent with college degree	0.021	0.594	0.016	0.640
	(0.039)		(0.034)	
Reason for choosing the program				
Opportunities and prestige	0.018	0.586	0.038	0.220
	(0.033)		(0.031)	
Self-fulfillment	-0.023	0.550	-0.014	0.682
	(0.039)		(0.035)	
Other motives	0.003	0.922	-0.017	0.485
	(0.031)		(0.025)	
Instructor characteristics				
Female instructors	0.003	0.865	0.006	0.719
	(0.020)		(0.016)	
40+ year-old instructors	0.027	0.214	0.007	0.694
	(0.022)		(0.017)	
Assistant professors	-0.007	0.742	0.009	0.552
	(0.021)		(0.016)	
Associate or full professors	-0.013	0.571	0.022	0.225
	(0.023)		(0.018)	
Instructor quality				
Dropout rate	0.001	0.604	0.001	0.316
	(0.002)		(0.001)	
Failure rate	0.002	0.415	-0.000	0.734
	(0.002)		(0.001)	

This table presents the regression discontinuity (RD) estimates for all covariates observed at the application and the characteristics of instructors in the first semester. The sample comprises candidates admitted for the first time, who are 21 years or less. RDs are estimated using triangular kernel with the bandwidth selection procedure proposed by Calonico, Cattaneo and Titiunik (2014). Robust standard errors are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 10: Effect of Delayed Start Using Strikes

	Males		**Females**	
	All students	Sample	All students	Sample
Switched programs$^+$	-0.004	-0.003	-0.008	-0.005
	(0.004)	(0.007)	(0.006)	(0.005)
Tried another vestibular$^+$	0.027	0.071*	-0.003	0.000
	(0.025)	(0.042)	(0.019)	(0.023)
Graduated on time$^+$	0.032	0.007	0.042	-0.010
	(0.083)	(0.102)	(0.068)	(0.078)
Dropped out$^+$	0.109*	0.195***	-0.030	-0.012
	(0.058)	(0.074)	(0.038)	(0.049)
Number of courses taken semester 1	0.189	-0.179	-0.415***	-0.527***
	(0.138)	(0.163)	(0.135)	(0.166)
Missed first midterm	-0.029	0.010	0.017	0.013
	(0.032)	(0.041)	(0.031)	(0.032)
First midterm grade	-0.095	-0.306**	-0.031	0.027
	(0.092)	(0.125)	(0.082)	(0.095)
Number of absences semester 1	1.743	2.439*	1.351	1.313
	(1.106)	(1.377)	(0.847)	(0.935)
GPA semester 1	0.108	-0.229	0.078	0.060
	(0.195)	(0.265)	(0.143)	(0.161)
GPA year 1	-0.045	-0.294	0.112	0.072
	(0.172)	(0.250)	(0.125)	(0.150)
Failure rate semester 1	-0.012	0.070	-0.026	-0.012
	(0.043)	(0.053)	(0.033)	(0.034)
Failure rate year 1	0.043	0.105**	-0.017	-0.002
	(0.039)	(0.050)	(0.027)	(0.031)

This table presents the difference in academic outcomes between the last student in first classes who faced an unexpected delay in the first semester of 2006 and the last student in first classes who faced no delay. The expected outcome for the last student is estimated using a local linear regression with the bandwidth selected using Calonico, Cattaneo and Titiunik's (2014) procedure. 2004, 2005, 2008, 2009, 2010 and 2011 are the years in which the first class did not experience delays (strikes) in the first semester. Due to later strikes, we exclude 2004, 2005 and 2011 for one-year outcomes, and also 2009 and 2010 for 2+ year outcomes ($^+$). 'All students' represents all freshmen with no sample restriction, while 'sample' represents the candidates admitted for the first time, who are 21 years or less, and enrolled on a program with two classes. Robust standard errors are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix

A Proofs of Section 2

A.1 Proof of Proposition 1

From value function (2), given the initial choice for program k, the probability of switching programs is given by:

$$\begin{aligned}\Pr(S) &= \Pr\left\{\theta V_i^{k'} \geq \theta v_i^k + \theta w^k \hat{p}_i^k\left[h_i^k\left(e_i^k, s_{-i(c)}\right)\right] - \gamma e_i^k\right\} \qquad \text{(A.1)}\\ &= \Pr\left\{v_i^k \leq V_i^{k'} + \gamma e_i^k/\theta - w^k \hat{p}_i^k\left[h_i^k\left(e_i^k, s_{-i(c)}\right)\right]\right\}\\ &\propto \gamma e_i^k/\theta - w^k \hat{p}_i\left[h_i^k\left(e_i^k, s_{-i(c)}\right), s_{-i(c)}\right], \qquad \text{(A.2)}\end{aligned}$$

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

$$w^k \frac{\partial \hat{p}_i}{\partial h}\left[h_i^k\left(e_i^k, s_{-i(c)}\right), s_{-i(c)}\right] \frac{\partial h_i^k}{\partial e}\left(e_i^k, s_{-i(c)}\right) - \frac{\gamma}{\theta} = 0. \qquad \text{(A.3)}$$

Then differentiating (A.2) with respect to $s_{-i(c)}$ and with condition (A.3), we have:

$$\frac{\partial \Pr(S)}{\partial s_{-i(c)}} \propto -\frac{\partial \hat{p}_i}{\partial s_{-i(c)}}\left[h_i^k\left(e_i^k\right), s_{-i(c)}\right] - \frac{\partial \hat{p}_i}{\partial h}\left[h_i^k\left(e_i^k, s_{-i(c)}\right), s_{-i(c)}\right] \frac{\partial h_i^k}{\partial s_{-i(c)}}\left(e_i^k, s_{-i(c)}\right). \qquad \text{(A.4)}$$

From Definition 3, $\partial \hat{p}_i / \partial s_{-i(c)}$ is a ranking effect and the first term on the RHS of (A.4) 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 (A.4) 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 programs.

The probability of dropping out of college, $\Pr(D)$, is also proportional to (A.2), so the same result applies to $\partial \Pr(D) / \partial s_{-i(c)}$. ■

A.2 Proof of Proposition 2

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

$$\partial_{ee}\hat{V}_i^k = \frac{\partial^2 \hat{p}_i}{\partial h^2}\left[h_i^k\left(e_i^k\right)\right] \cdot \left[\frac{\partial h_i^k}{\partial e}\left(e_i^k, s_{-i(c)}\right)\right]^2 + \frac{\partial \hat{p}_i}{\partial h}\left[h_i^k\left(e_i^k\right)\right] \cdot \frac{\partial^2 h_i^k}{\partial e^2}\left(e_i^k, s_{-i(c)}\right) < 0. \quad \text{(A.5)}$$

By differentiating (A.3) with respect to $s_{-i(c)}$, we have:

$$\begin{aligned}\frac{\partial e_i^k}{\partial s_{-i(c)}} &= \left(-\partial_{ee}\hat{V}_i^k\right)^{-1}\left[\frac{\partial h_i^k}{\partial e}\frac{\partial^2 \hat{p}_i}{\partial h \partial s_{-i(c)}} + \frac{\partial h_i^k}{\partial e}\frac{\partial^2 \hat{p}_i}{\partial h^2}\frac{\partial h_i^k}{\partial s_{-i(c)}} + \frac{\partial \hat{p}_i}{\partial h}\frac{\partial^2 h_i^k}{\partial e \partial s_{-i(c)}}\right] \\ &\propto \frac{\partial h_i^k}{\partial e}\frac{\partial^2 \hat{p}_i}{\partial h \partial s_{-i(c)}} + \frac{\partial h_i^k}{\partial e}\frac{\partial^2 \hat{p}_i}{\partial h^2}\frac{\partial h_i^k}{\partial s_{-i(c)}} + \frac{\partial \hat{p}_i}{\partial h}\frac{\partial^2 h_i^k}{\partial e \partial s_{-i(c)}}. \qquad \text{(A.6)}\end{aligned}$$

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 (A.6) 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 (A.6) 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.

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

$$\begin{aligned}\frac{\partial E\left(w_i^k\right)}{\partial s_{-i(c)}}\left(e_i^k, s_{-i(c)}\right) &= w^k\frac{\partial p}{\partial h}\left(\frac{\partial h_i^k}{\partial e}\frac{\partial e_i^k}{\partial s_{-i(c)}} + \frac{\partial h_i^k}{\partial s_{-i(c)}}\right) \\ &\propto \left(\frac{\partial h_i^k}{\partial e}\right)^2\frac{\partial^2 \hat{p}_i}{\partial h \partial s_{-i(c)}} - \frac{\partial^2 h_i^k}{\partial e^2}\frac{\partial \hat{p}_i}{\partial h}\frac{\partial h_i^k}{\partial s_{-i(c)}} + \frac{\partial h_i^k}{\partial e}\frac{\partial \hat{p}_i}{\partial h}\frac{\partial^2 h_i^k}{\partial e \partial s_{-i(c)}} \qquad \text{(A.7)}\end{aligned}$$

The second and third terms on the RHS of (A.7), 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. ■

A.3 Proof of Proposition 3

Note that

$$\frac{\partial \hat{p}_i}{\partial s_{-i(c)}} = \frac{\partial \hat{p}_i}{\partial \hat{F}_i^{k-1}} \frac{\partial \hat{F}_i^{k-1}}{\partial s_{-i(c)}},$$

and the relationship between $\hat{F}_i^{k-1}$ and $s_{-i(c)}$ depends on I_i, so that:

$$\left(\frac{\partial \hat{F}_i^{k-1}}{\partial s_{-i(c)}}\right)^{-1} \cdot \frac{\partial}{\partial I_i}\left(\frac{\partial \hat{F}_i^{k-1}}{\partial s_{-i(c)}}\right) \leq 0.$$

That is, the larger the information set I_i, the lower the adjustment in $\hat{F}_i^{k-1}$ given $s_{-i(c)}$.

Therefore, the relative adjustment in $\hat{p}_i$ given $s_{-i(c)}$ is:

$$\begin{aligned}
\left(\frac{\partial \hat{p}_i}{\partial s_{-i(c)}}\right)^{-1} \cdot \frac{\partial}{\partial I_i}\left(\frac{\partial \hat{p}_i}{\partial s_{-i(c)}}\right) &= \left(\frac{\partial \hat{p}_i}{\partial \hat{F}_i^{k-1}} \frac{\partial \hat{F}_i^{k-1}}{\partial s_{-i(c)}}\right)^{-1} \cdot \frac{\partial \hat{p}_i}{\partial \hat{F}_i^{k-1}} \frac{\partial}{\partial I_i}\left(\frac{\partial \hat{F}_i^{k-1}}{\partial s_{-i(c)}}\right) \\
&= \left(\frac{\partial \hat{F}_i^{k-1}}{\partial s_{-i(c)}}\right)^{-1} \cdot \frac{\partial}{\partial I_i}\left(\frac{\partial \hat{F}_i^{k-1}}{\partial s_{-i(c)}}\right) \leq 0.
\end{aligned}$$

Similarly,

$$\begin{aligned}
\left(\frac{\partial^2 \hat{p}_i}{\partial h \partial s_{-i(c)}}\right)^{-1} \cdot \frac{\partial}{\partial I_i}\left(\frac{\partial^2 \hat{p}_i}{\partial h \partial s_{-i(c)}}\right) &= \left(\frac{\partial^2 \hat{p}_i}{\partial h \partial \hat{F}_i^{k-1}} \frac{\partial \hat{F}_i^{k-1}}{\partial s_{-i(c)}}\right)^{-1} \cdot \frac{\partial^2 \hat{p}_i}{\partial h \partial \hat{F}_i^{k-1}} \frac{\partial}{\partial I_i}\left(\frac{\partial \hat{F}_i^{k-1}}{\partial s_{-i(c)}}\right) \\
&= \left(\frac{\partial \hat{F}_i^{k-1}}{\partial s_{-i(c)}}\right)^{-1} \cdot \frac{\partial}{\partial I_i}\left(\frac{\partial \hat{F}_i^{k-1}}{\partial s_{-i(c)}}\right) \leq 0.
\end{aligned}$$

Function $h_i^k(.)$ does not depend on $\hat{F}_i^{k-1}$, but it depends directly on $s_{-i(c)}$. ■

B Instructor Quality

Let y_{isp} be the performance of student i in course s, taught by instructor p. Let N_s be the set of students who took course s. The first step is to subtract the average outcome per course from the student's observed performance:

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

The second step is to calculate the student fixed-effect by averaging $\hat{y}_{ip}(s)$ per student:

$$\hat{\mu}_i = \frac{\sum_s 1(i \in N_s) \cdot \hat{y}_{ip}(s)}{\sum_s 1(i \in N_s)}. \tag{B.2}$$

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

$$\hat{\gamma}_p = \frac{\sum_s \sum_i 1(i \in N_{s,p}) \cdot \left[\hat{y}_{ip}(s) - \hat{\mu}_i\right]}{\sum_s \sum_i 1(i \in N_{s,p})}. \tag{B.3}$$

C Estimation Procedure

Set $Y = [y_1 \ \dots \ y_n]'$, $C = \left[\mathbf{1}(c_1 = 1) \ \dots \ \mathbf{1}(c_n = 1)\right]'$, $R = [r_1 \ \dots \ r_n]'$, 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.

To estimate the standard fuzzy RD, we first apply the following locally weighted regression (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, equation (5), is:

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

and the estimator for the net (naive) ranking effect, equation (6), is

$$\frac{\widehat{\Delta y}}{\widehat{\Delta r}} = \frac{\hat{\mu}_+^y - \hat{\mu}_-^y - \hat{B}^y\,(b, b^*)}{\hat{\mu}_+^r - \hat{\mu}_-^r - \hat{B}^r\,(b, b^*)}, \tag{C.2}$$

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 for estimators (C.1) and (C.2).

To estimate the RD conditional on Δq, first we set $XQ = \left[(1, x_1 - \underline{x}, \Delta q_1) \ldots (1, x_n - \underline{x}, \Delta q_n)\right]'$ and $V_-^u = \operatorname{diag}\left(\mathbf{1}(x_1 < \underline{x})\, k_1 h_1^u, \ldots, \mathbf{1}(x_n < \underline{x})\, k_n h_n^u\right)$ and $V_+^u = \operatorname{diag}\left(\mathbf{1}(x_1 \geq \underline{x})\, k_1 h_1^u, \ldots, \mathbf{1}(x_n \geq \underline{x})\, k_n h_n^u\right)$, where $h_i^u = \max\left[0, \left(1 - |\Delta q_i - u| / d\right)\right]$ 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 the marginal ranking effect, equation (7), is:

$$\frac{\widehat{\Delta y}(\Delta q = 0)}{\widehat{\Delta r}(\Delta q = 0)} = \frac{\hat{\eta}_+^y(0) - \hat{\eta}_-^y(0) - \hat{B}^y(0, b, b^*)}{\hat{\eta}_+^r(0) - \hat{\eta}_-^r(0) - \hat{B}^r(0, b, b^*)}, \tag{C.3}$$

and the estimator for Δy as a function of Δq is:

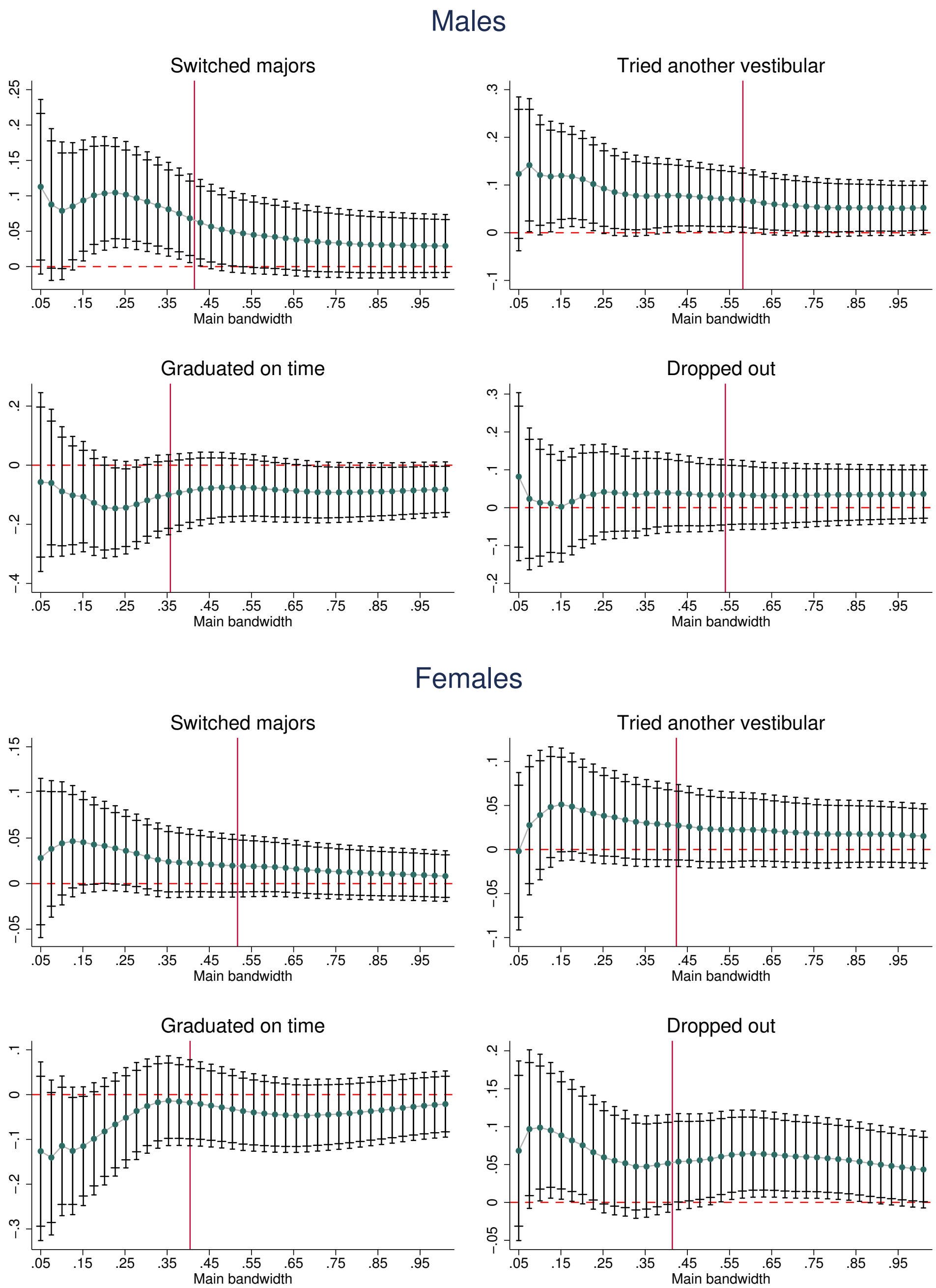
$$\widehat{\Delta y}(\Delta q = u) = \frac{\hat{\eta}_+^y(u) - \hat{\eta}_-^y(u) - \hat{B}^y(u, b, b^*)}{\hat{\eta}_+^c(u) - \hat{\eta}_-^c(u) - \hat{B}^c(u, b, b^*)}. \tag{C.4}$$

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

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

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

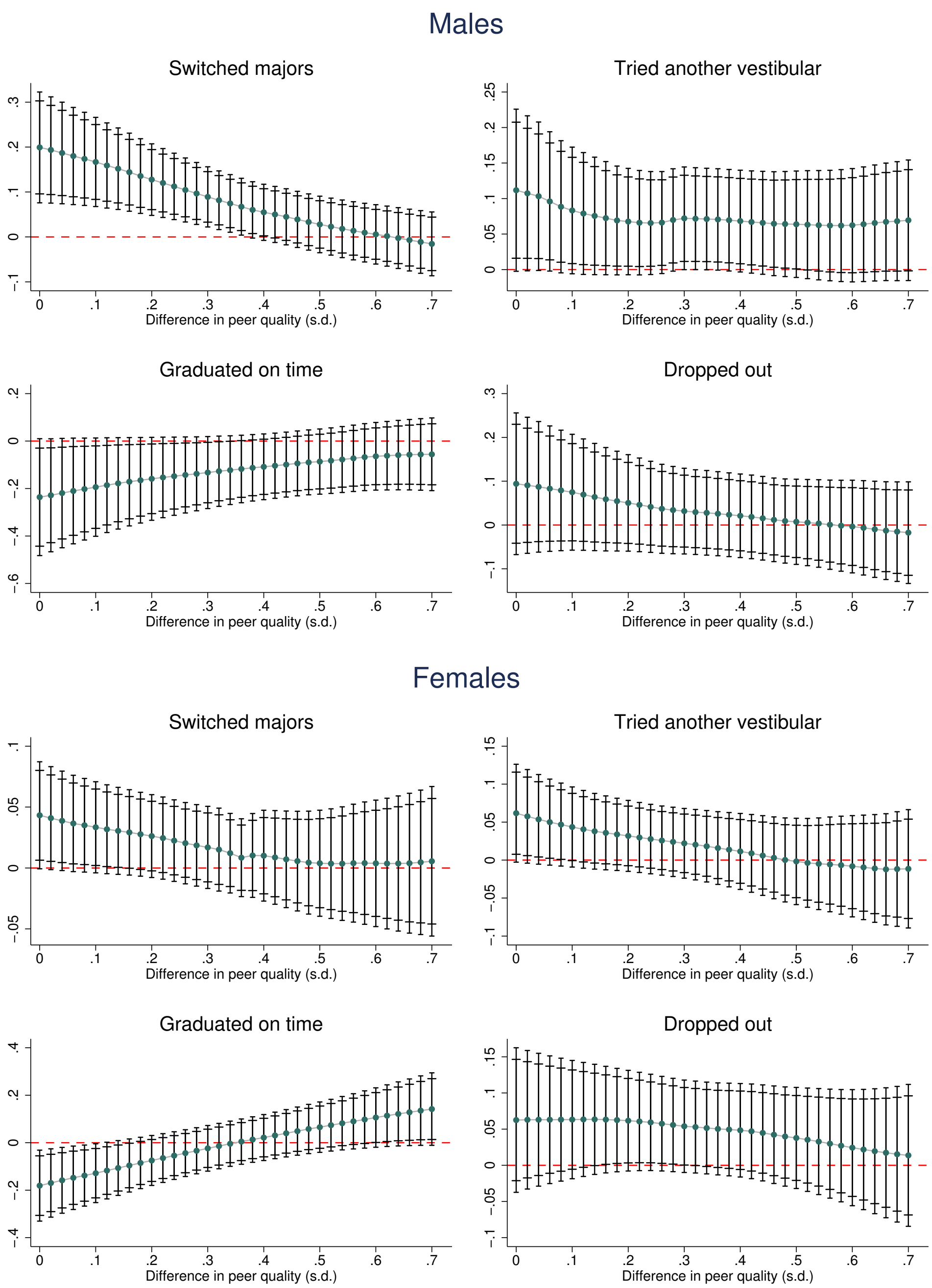
Figure A1: Net Effect of First Class Using Different Bandwidths



This figure presents estimates of the first-class effect using different bandwidths. The vertical bars represent the robust confidence interval at the 90% and 95% levels. The sample comprises candidates admitted for the first time, who are 21 years or less. Functions are estimated using triangular kernel. The vertical line indicates the main bandwidth obtained with the procedure proposed by Calonico, Cattaneo and Titiunik (2014).

Figure A2: Net Effect of First Class by Difference in Other Percentiles of Peer Scores

(a) Difference in the 20th percentile



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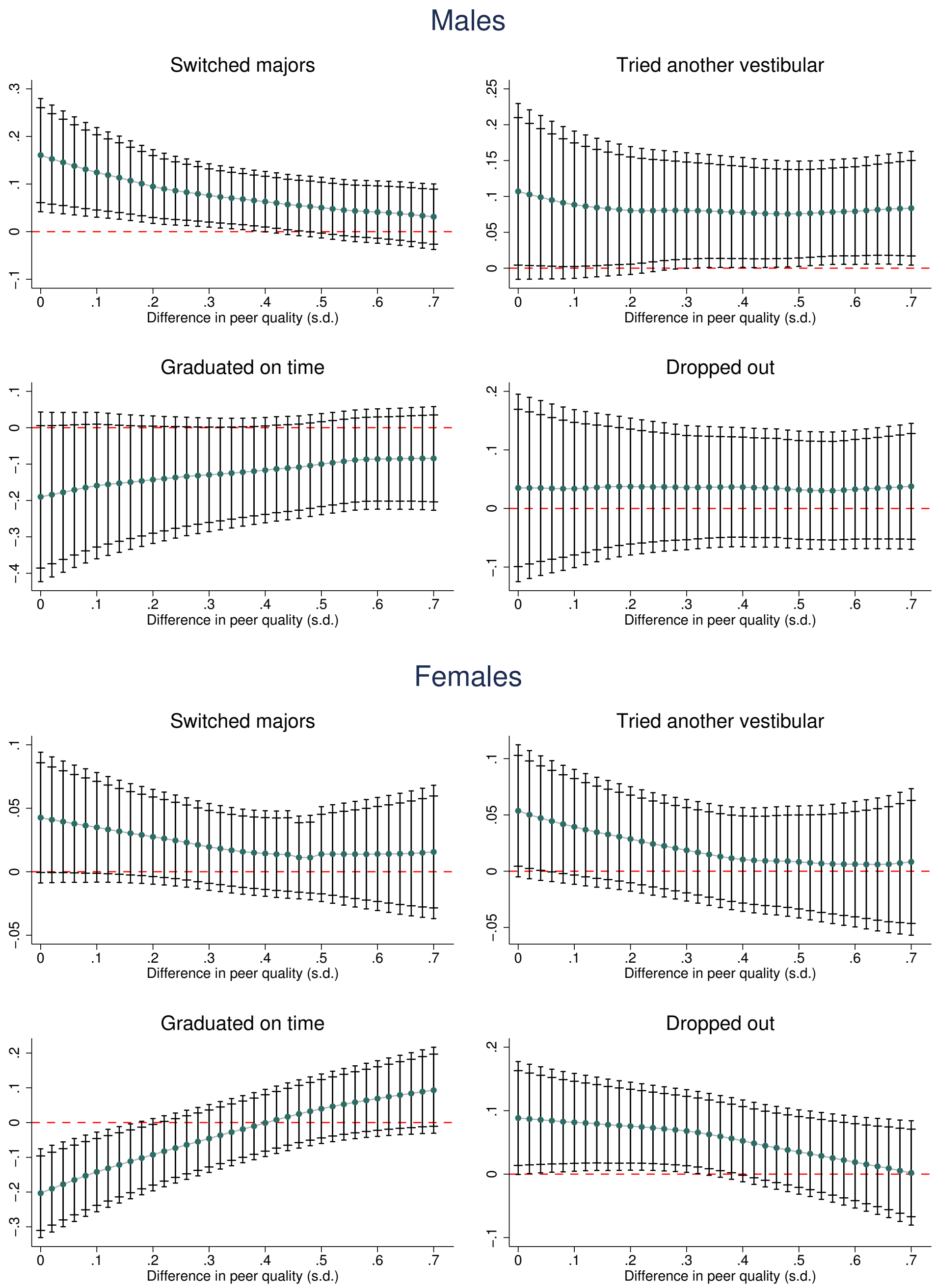
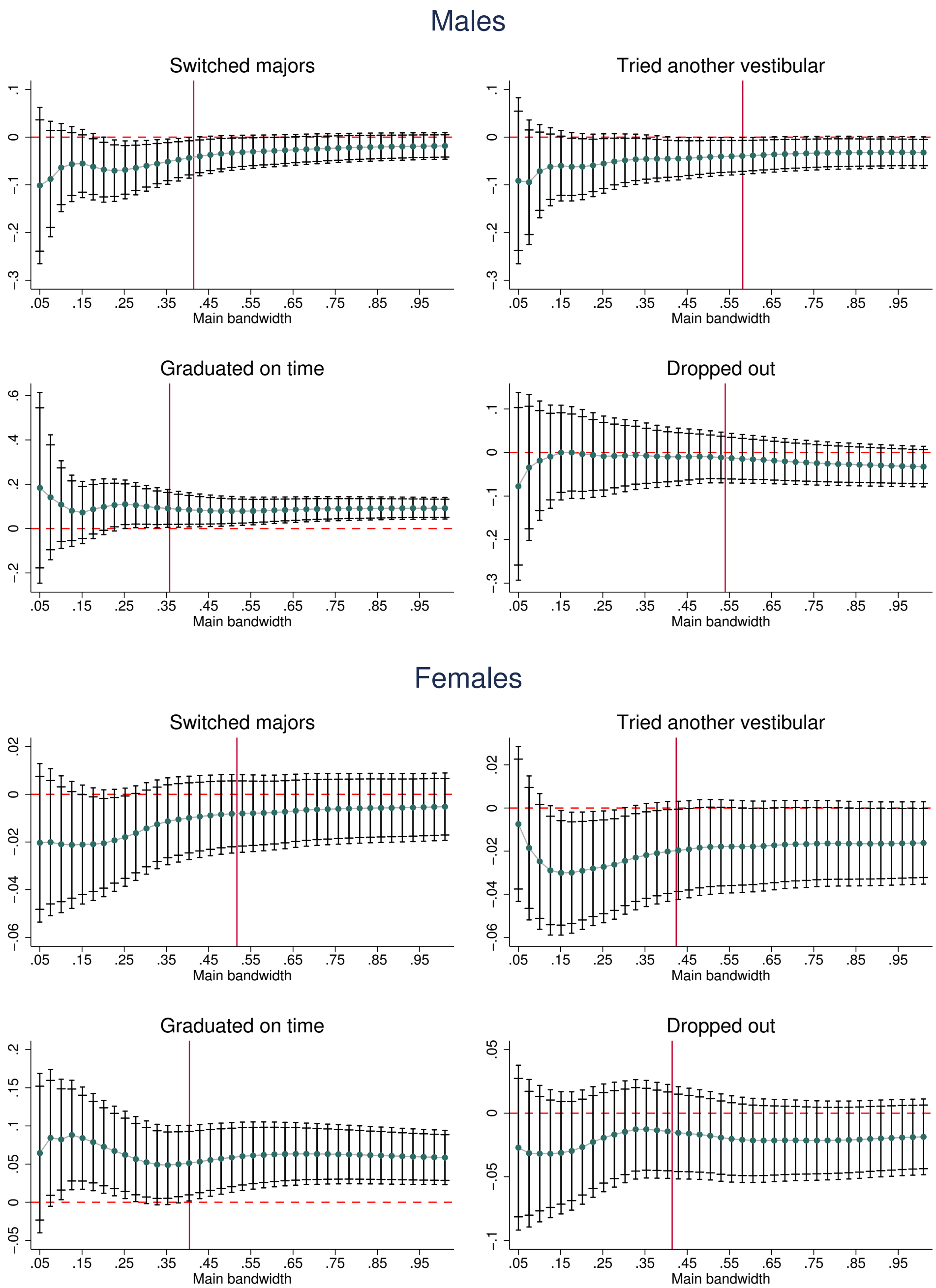
(b) Difference in the 80th percentile



This figure presents the fuzzy regression discontinuity (FRD) estimates of the first-class effect as a function of differences in the 20th percentile (panel a) and 80th percentile of round 1 scores (panel b). The vertical bars represent robust confidence interval at the 90% and 95% levels. The sample comprises candidates admitted for the first time, who are 21 years or less. FRDs and their relationships with peer quality are estimated using triangular kernels. The bandwidth for difference in peer quality is 0.9 s.d. and the bandwidth for entrance score is selected by using Calonico, Cattaneo and Titiunik's (2014) procedure.

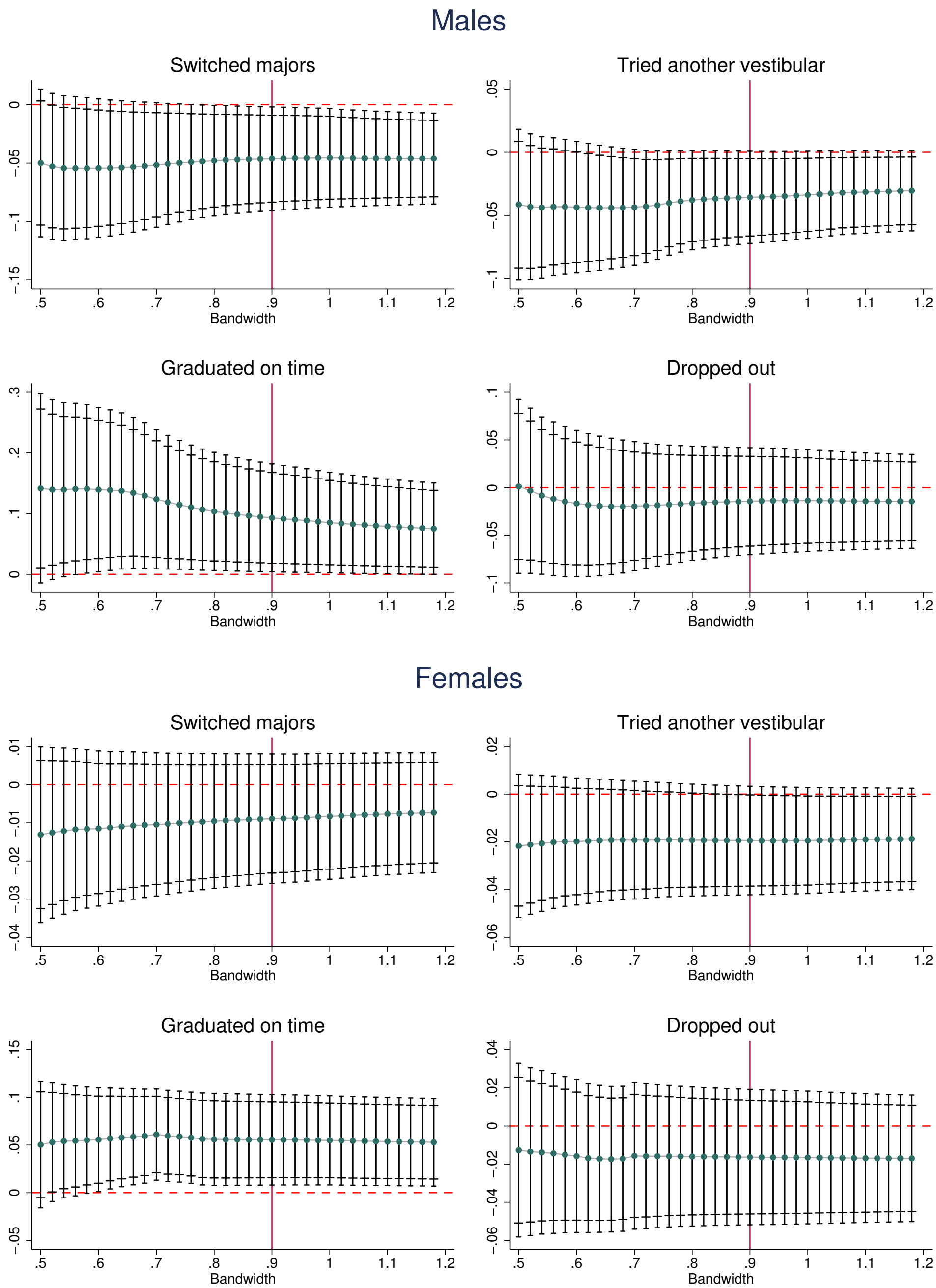
Figure A3: Ranking Effect on Major Switching and Graduation Using Different Bandwidths

(a) Bandwidths for entrance score



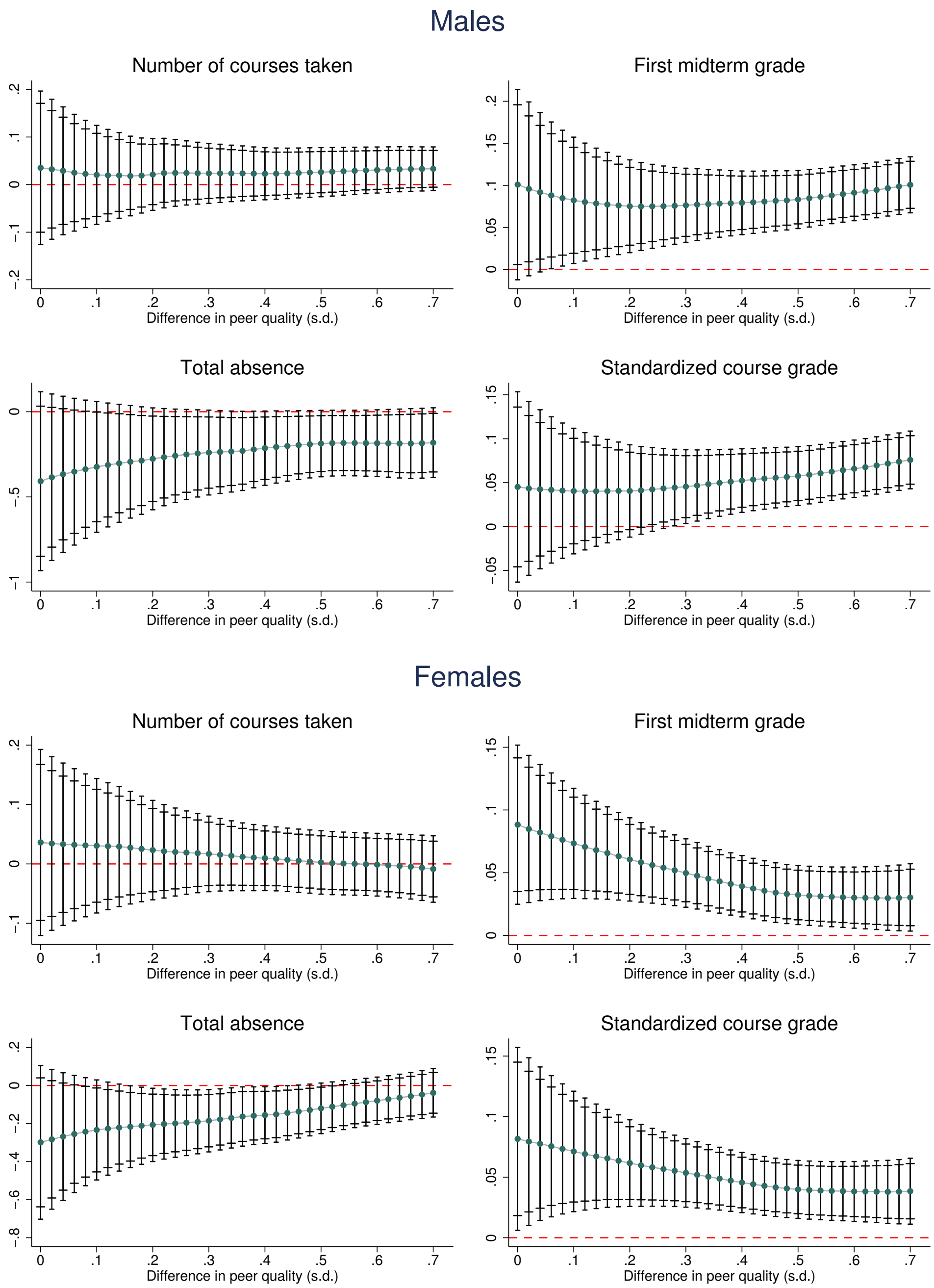
(continuing)

(b) Bandwidths for difference in peer quality



This figure presents the fuzzy regression discontinuity (FRD) estimates of the ranking effect using different bandwidths for the entrance score (panel a) and difference in peer quality (panel b). The vertical bars represent robust confidence interval at the 90% and 95% levels. The sample comprises candidates admitted for the first time, who are 21 years or less. FRDs and their relationships with peer quality are estimated using triangular kernels. In panel (a), the vertical line indicates the main bandwidth obtained with the procedure proposed by Calonico, Cattaneo and Titiunik (2014). In panel (b), the vertical line indicates the bandwidth used in the main findings.

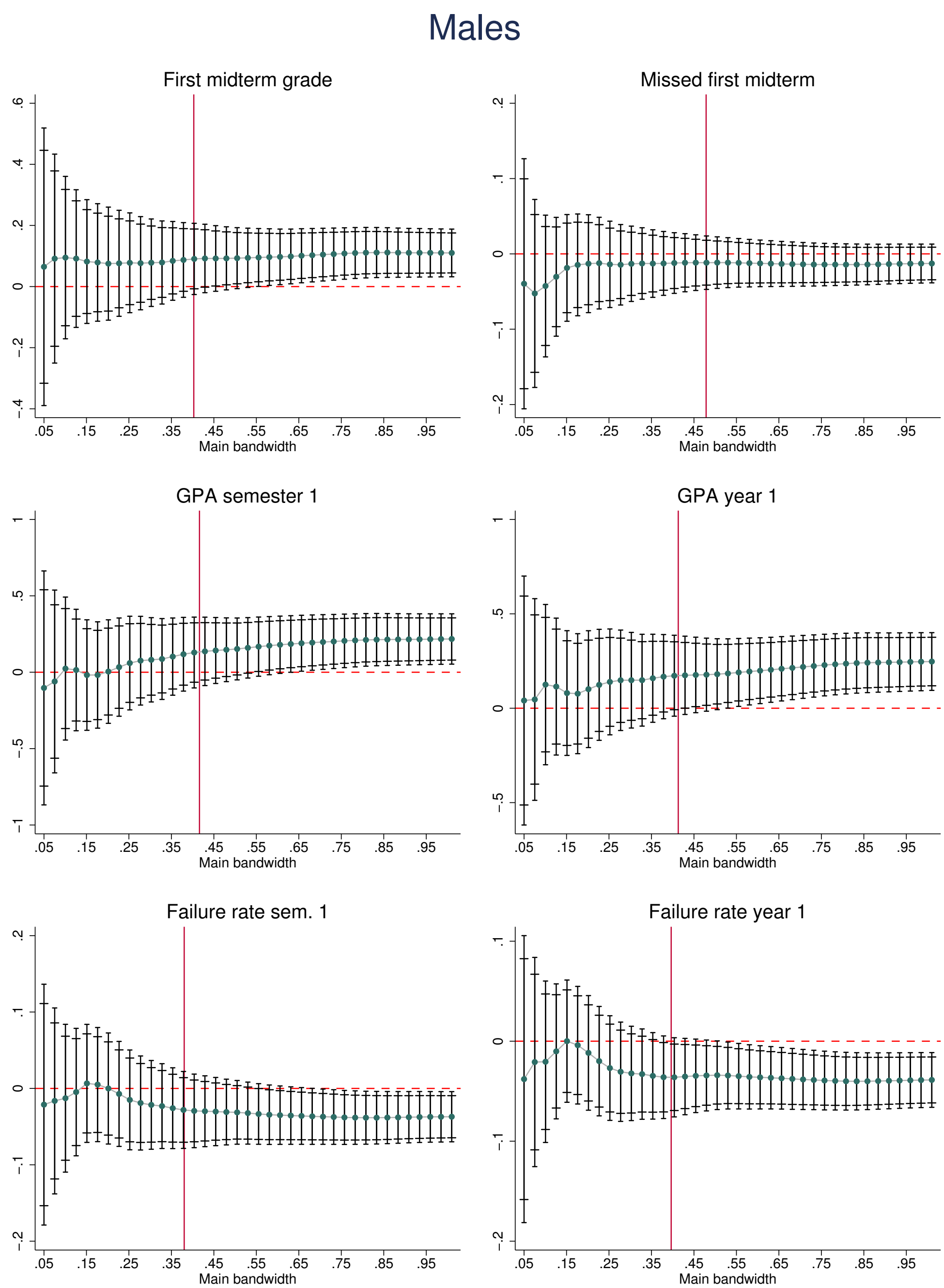
Figure A4: Ranking Effect on Performance in the 1st Semester by Difference in Peer Quality



This figure presents the fuzzy regression discontinuity (FRD) estimates of the net ranking effect as a function of differences in the median peer's round 1 score (peer quality). The vertical bars represent the robust confidence interval at the 90% and 95% levels. The sample comprises candidates admitted for the first time, who are 21 years or less. FDRs and their relationships with peer quality are estimated using triangular kernels. The bandwidth for difference in peer quality is 0.9 s.d. and the bandwidth for entrance score is selected by using Calonico, Cattaneo and Titiunik's (2014) procedure.

Figure A5: Ranking Effect on Academic Performance Using Different Bandwidths

(a) Bandwidths for entrance score



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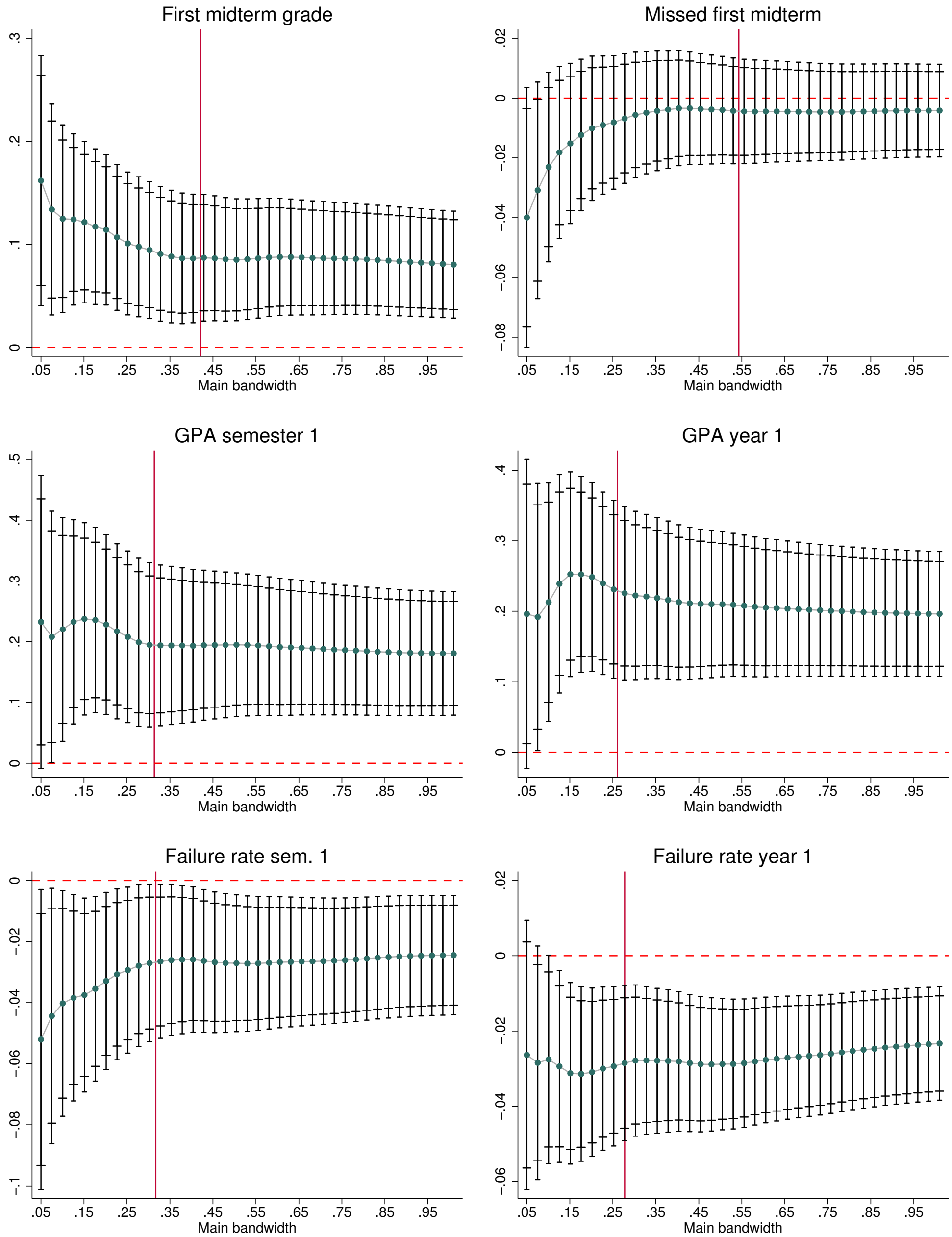
Females



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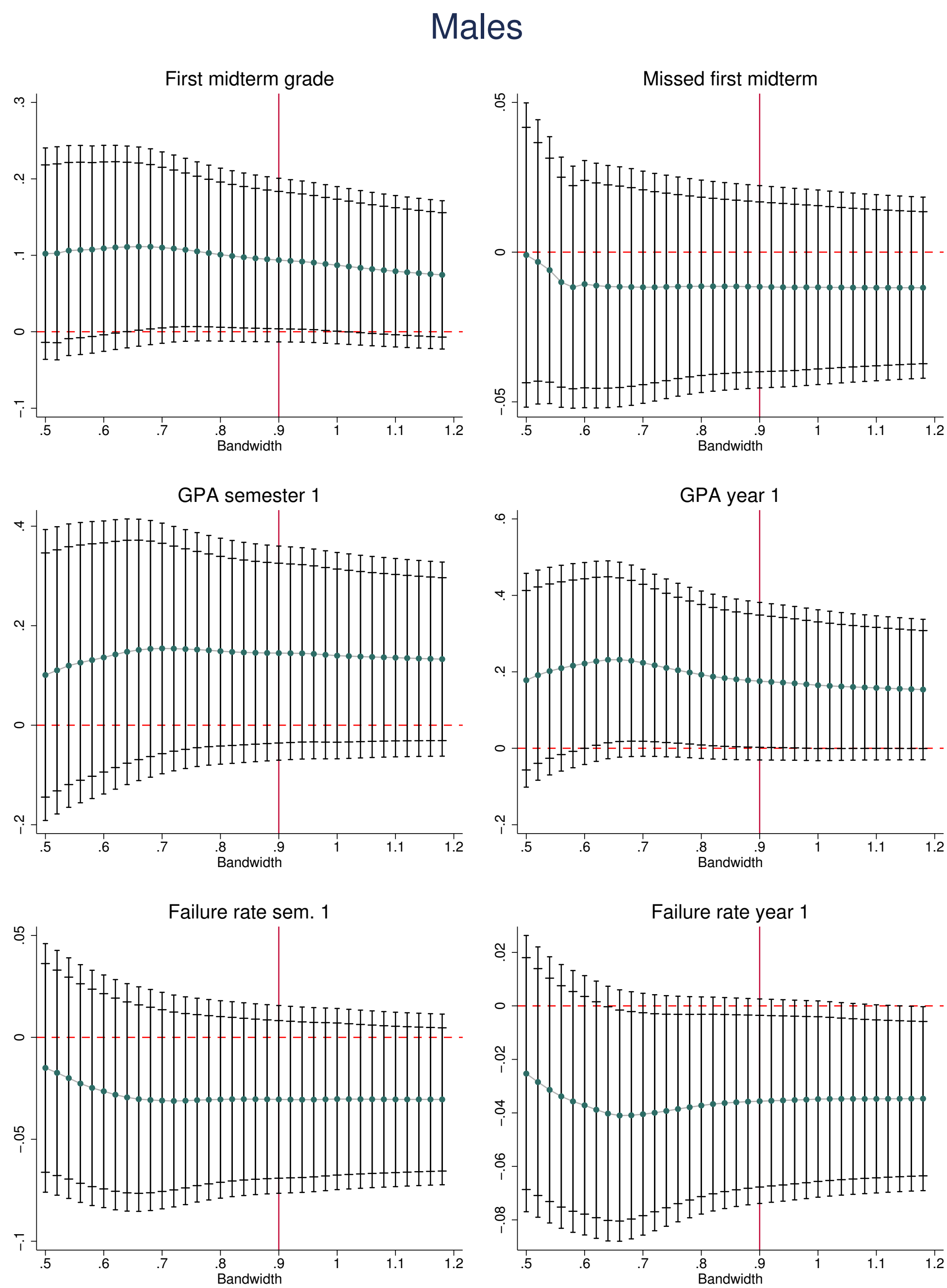
(b) Bandwidths for difference in peer quality



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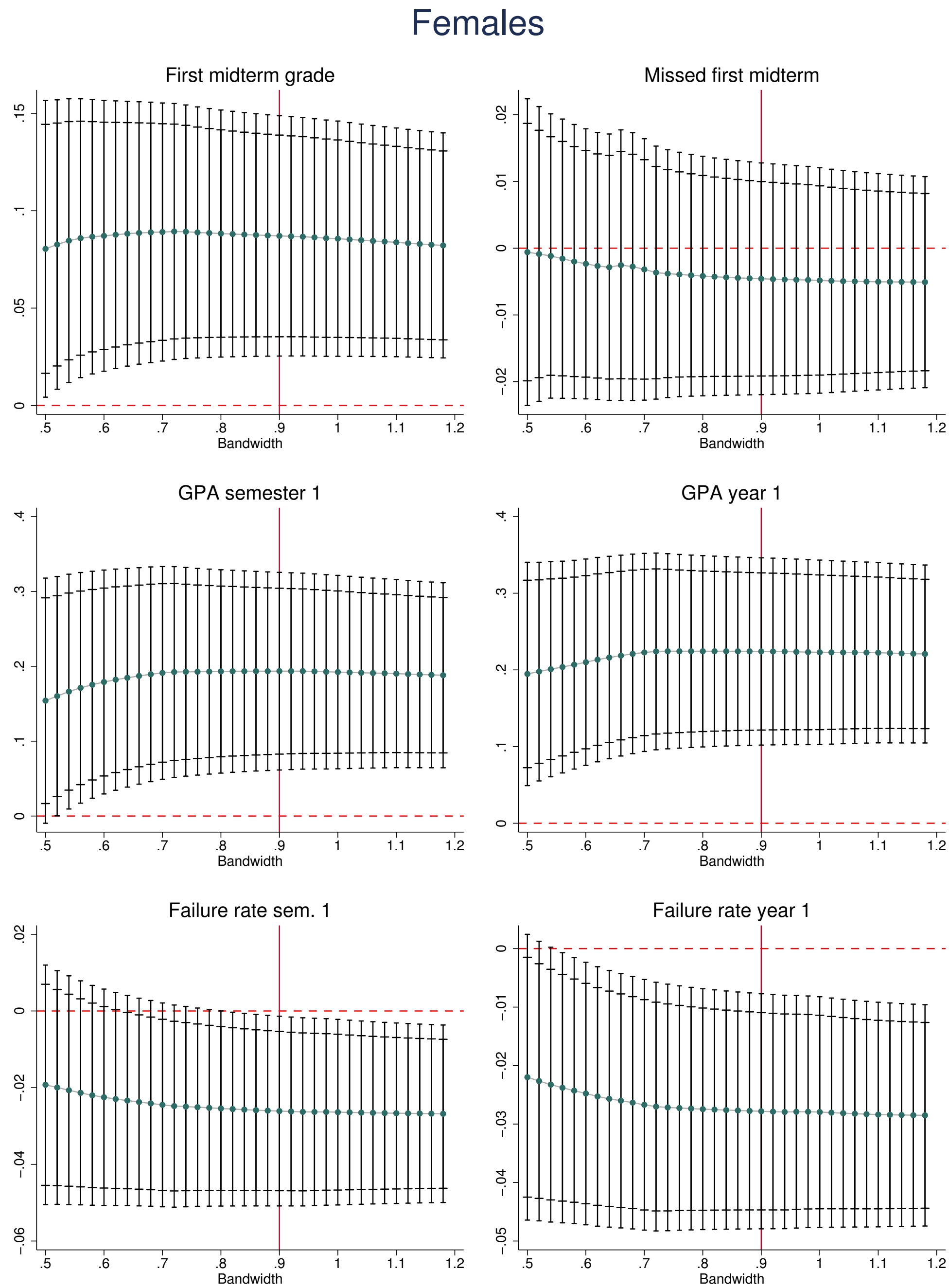
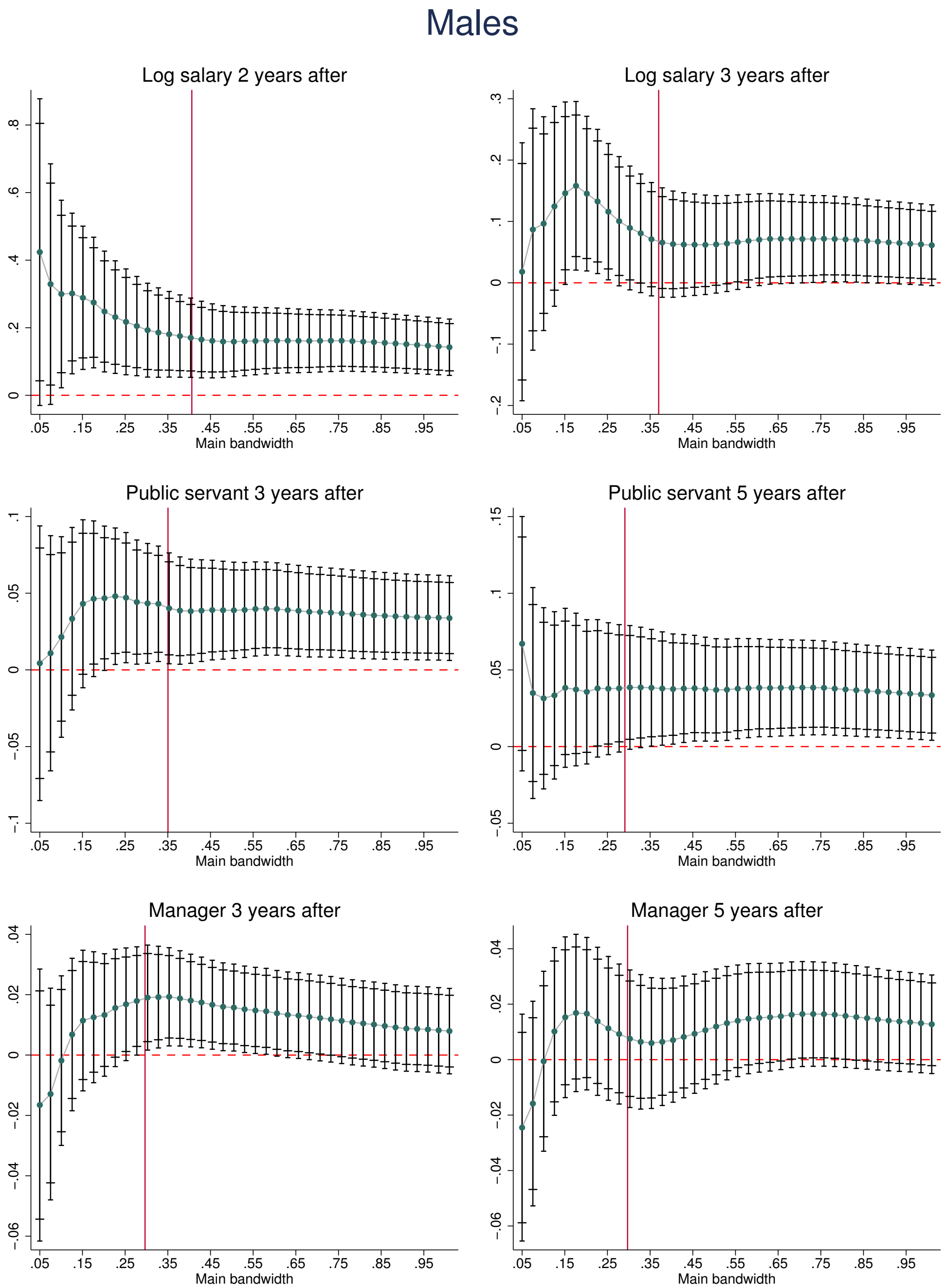


This figure presents the fuzzy regression discontinuity (FRD) estimates of the ranking effect using different bandwidths for the entrance score (panel a) and the difference in peer quality (panel b). The vertical bars represent the robust confidence interval at the 90% and 95% levels. The sample comprises candidates admitted for the first time, who are 21 years or less. FRDs and their relationships with peer quality are estimated using triangular kernels. In panel (a), the vertical line indicates the main bandwidth obtained with the procedure proposed by Calonico, Cattaneo and Titiunik (2014). In panel (b), the vertical line indicates the bandwidth used in the main findings.

Figure A6: Ranking Effect on Labor Market Outcomes Using Different Bandwidths

(a) Bandwidths for entrance score



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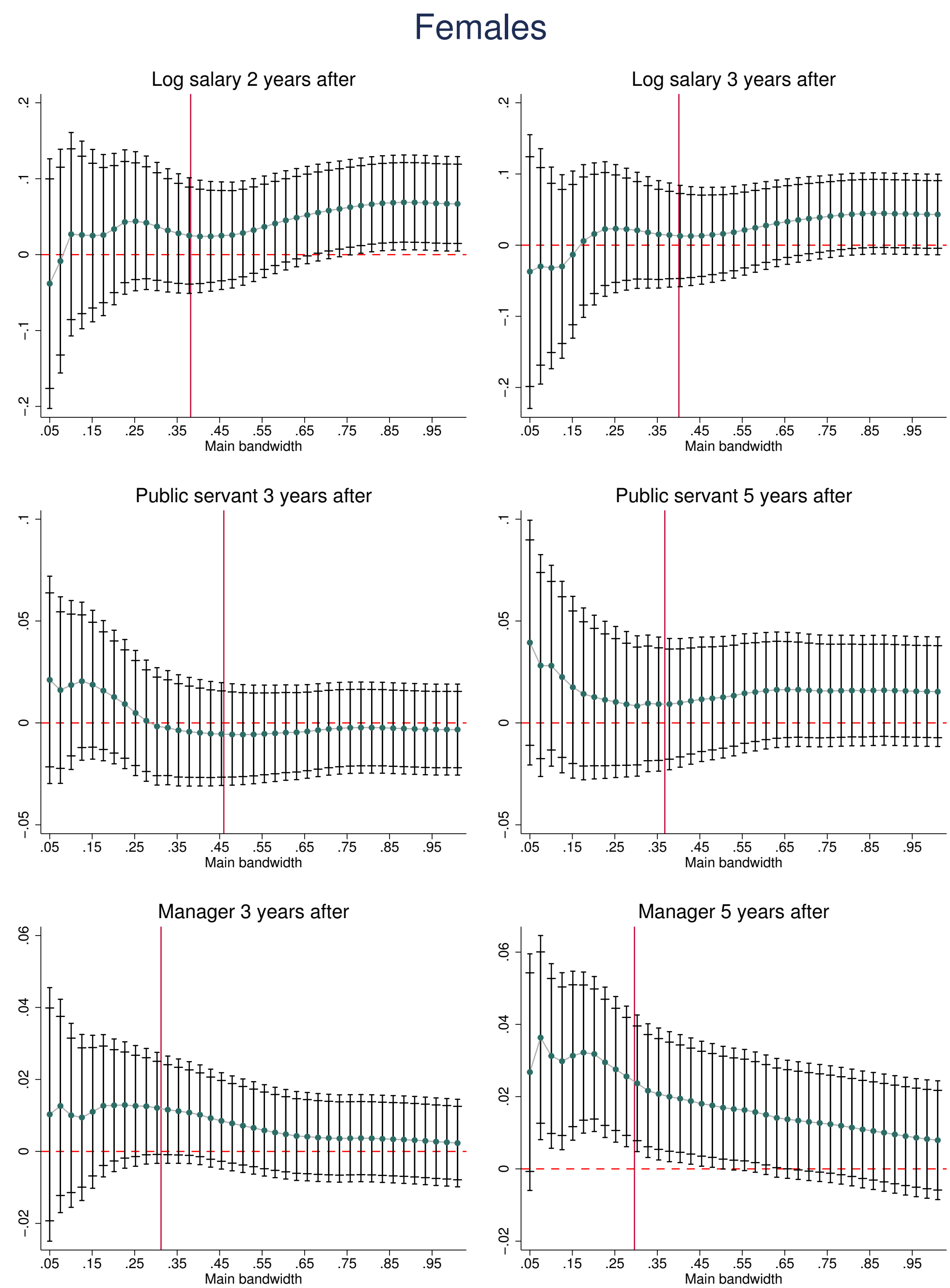
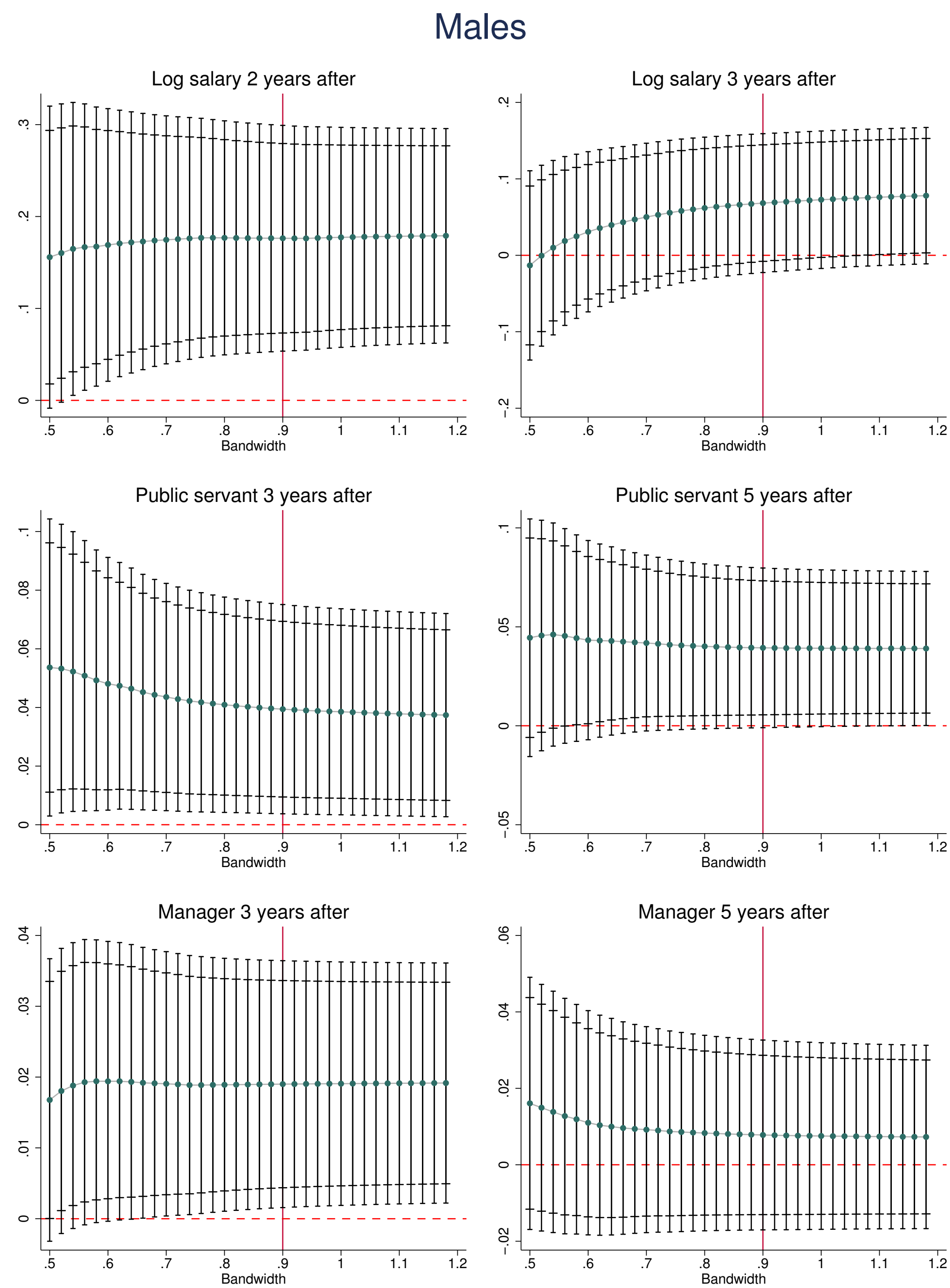

Females
Log salary 2 years after
Log salary 3 years after
Public servant 3 years after
Public servant 5 years after
Manager 3 years after
Manager 5 years after
Main bandwidth

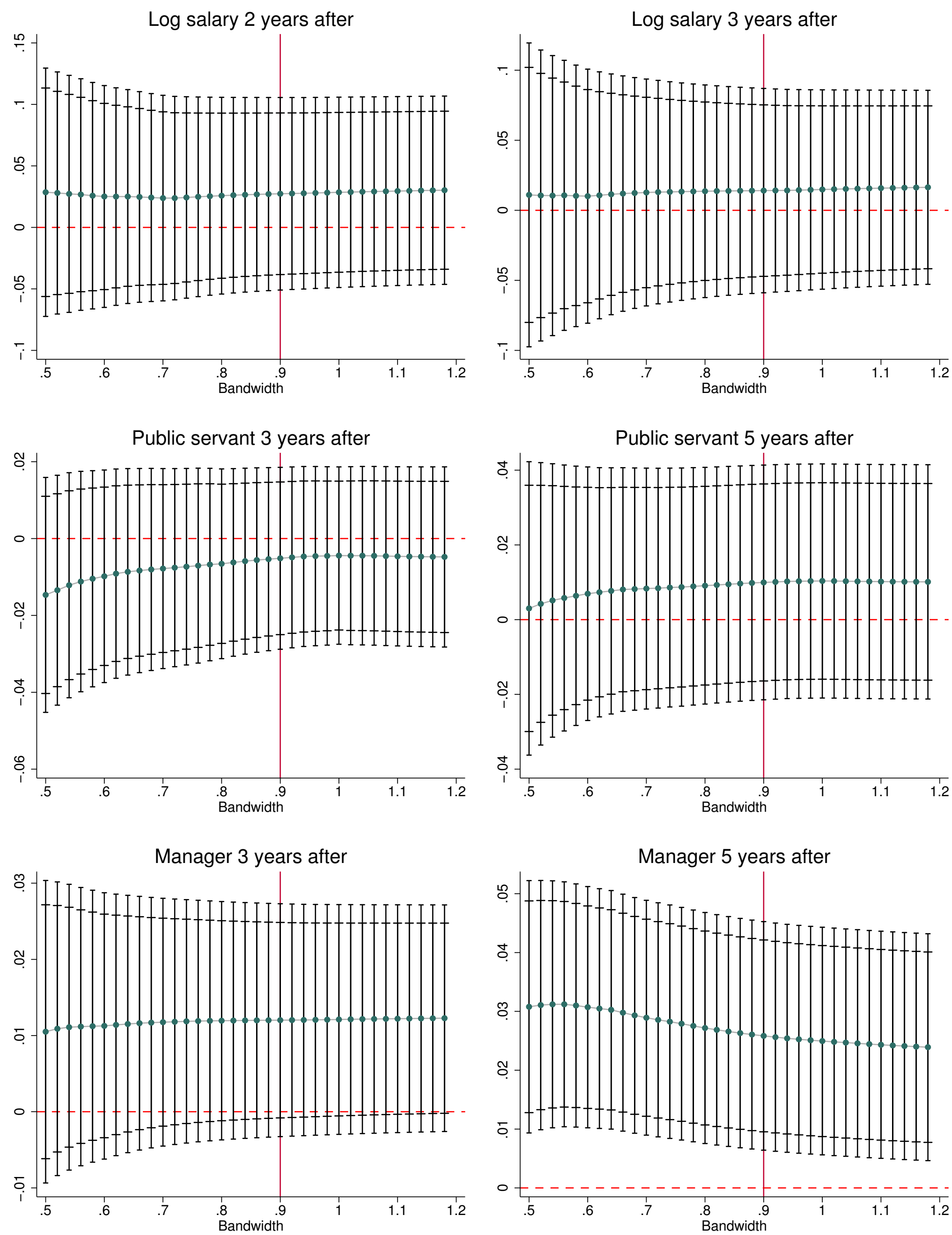
(continuing)

(b) Bandwidths for difference in peer quality



(continuing)

Females



This figure presents the fuzzy regression discontinuity (FRD) estimates of the ranking effect using different bandwidths for the entrance score (panel a) and the difference in peer quality (panel b). The vertical bars represent the robust confidence interval at the 90% and 95% levels. The sample comprises candidates admitted for the first time, who are 21 years or less. FRDs and their relationships with peer quality are estimated using triangular kernels. In panel (a), the vertical line indicates the main bandwidth obtained with the procedure proposed by Calonico, Cattaneo and Titiunik (2014). In panel (b), the vertical line indicates the bandwidth used in the main findings.

Table A1: All Regular Undergraduate Programs Offered by UFPE

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)		Theatre	
Language Education (English)		Tourism Management	✓
Language Education (Spanish)	✓	Visual Arts	
Law	✓		

*Material Engineering and Public Health are not included in the sample due to the small number of freshmen; Physical Activity and Physical Education are not included because their ranking is not determined by cognitive skills only. CAA and CAV are campi located in other cities.

Table A2: All Sampled Classes by Undergraduate Program and Year

Program	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Accounting*	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Architecture	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Audiovisual Communication								✓	✓	✓	✓
Biology*	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓
Biology (CAV)*						✗	✓	✓	✓	✓	✓
Biology - Medical Sciences	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓
Biology Education*	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓
Biomedicine	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Business Administration*	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Business Administration (CAA)					✓	✓	✓	✓	✓	✓	✓
Cartographic Engineering	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
Chemical Engineering	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
Chemistry Education (CAA)*					✗	✗	✗	✗	✗	✓	✓
Civil Engineering	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓
Civil Engineering (CAA)					✓	✗	✗	✓	✓	✓	✓
Computational Engineering	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Computational Science	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dental Medicine*	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Design	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓
Design (CAA)					✓	✓	✓	✓	✓	✓	✓
Economics (CAA)*					✓	✓	✓	✓	✓	✓	✓
Electrical Engineering	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗
Electronics Engineering	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗
Engineering							✓	✓	✗	✗	✓
Geology	✗	✗	✗	✓	✓	✗	✗	✓	✓	✓	✓
History*	✓	✓	✓	✓	✓	✗	✓	✓	✓	✗	✗
History Education	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
Information Management*								✗	✓	✓	✗
Information Systems										✓	✓
Language Education (Spanish)									✗	✗	✓
Law	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Linguistics and Literature	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗
Mathematics Education (CAA)					✗	✗	✗	✗	✗	✓	✓
Mechanical Engineering	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓
Medicine	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mining Engineering	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	✓
Music Education	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nursing*	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓
Nursing (CAV)*						✓	✓	✓	✓	✓	✗
Nutrition*	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nutrition (CAV)*						✓	✓	✓	✓	✓	✓
Occupational Therapy*	✗	✓	✓	✗	✓	✗	✓	✗	✓	✓	✓
Pedagogy	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pedagogy (CAA)*					✓	✗	✗	✗	✓	✓	✓
Pharmacy	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Physics Education (CAA)					✗	✗	✗	✗	✗	✓	✓
Physiotherapy*	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Production Engineering (CAA)*										✓	✓
Psychology*	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Secretarial Science*	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sign Language Education	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓
Social Service	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Tourism Management*	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

*Programs that fall within a small bandwidth (0.1 s.d.) in the difference in peer quality at least once. ✗ means that the number of freshmen in either class is less than 15, so the cohort is not in the sample; while ✓ means that the cohort is in the sample. An empty cell means that the program was not available at the time.