FUNDAÇÃO GETULIO VARGAS
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KELLY GONÇALVES DOS SANTOS

DOES IT MATTER WHICH TOP INSTITUTION YOU CHOOSE? A CASE STUDY OF BRAZILIAN GRADUATE ADMISSIONS

São Paulo
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Campo de Conhecimento: Economia da Educação

Orientadora: Profa. Dra. Fernanda Gonçalves De La Fuente Estevan

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ABSTRACT

In this thesis, we investigate the effect of attending a selective master institution in Economics in terms of Ph.D. placement. To do that, we use data from the ANPEC exam, which master programs use to select their students. To address the potential selection bias and identify the causal effect, we adopt two empirical strategies. The first is the method proposed by Dale and Krueger (2002), and the second is the RDD framework. The Dale and Krueger (2002) approach matches students who applied to and were admitted by the same institutions. In the RDD framework, we exploit the admission discontinuity. Using the sample in which students passed in the four of the Top 4 institutions, i.e., in FGV-EESP, FGV-EPGE, IPE-USP, PUC-RIO, we compare within the selective institutions. The results suggest that only students at IPE-USP seem to enroll with a lower probability in a Ph.D. program in Brazil. Using the sample in which students passed in at least two of the Top 4 institutions, we compare within the selective institutions pairwise. In that case, the results suggest that FGV-EPGE seems to have an advantage over IPE-USP in terms of Ph.D. enrollments abroad. That advantage persists when we consider only high reputation Ph.D. programs. PUC-RIO has an advantage compared to IPE-USP only when we consider the most reputable Ph.D. programs, but does not seem to have an advantage when compared to FGV-EESP and FGV-EPGE. In addition, the estimates for ANPEC exam performance are significant. In particular, the students ranked until the 15th position seems to have higher chances of enrolling in a Ph.D. program. In the RDD framework, estimated coefficients are not significant when we compare Top 4 with non-Top 4 institutions. It seems that students that attend a more selective institution and were admitted in the margin enroll in a Ph.D. program with the same probability than a student that attends a less selective institution.

Key-words: Selective Institutions, Ph.D. Enrollments, Higher Education, Return of Education

JEL Codes: I23, I26

RESUMO

Nessa dissertação, investigamos o efeito de se cursar um instituto seletivo durante o mestrado em economia na probabilidade de se cursar doutorado. Para isso, utilizamos os dados do exame da ANPEC, que é utilizado pelos instituto para selecionar os alunos. Para abordar o potencial viés de seleção e identificar o efeito causal, adotamos dois métodos empíricos: o primeiro deles, é o método proposto por Dale e Krueger (2002) e o segundo é o método da regressão descontínua (RD). A abordagem de Dale e Krueger (2002) compara os estudantes que escolheram e que foram admitidos pelos mesmos institutos. No método da RD, exploramos a descontinuidade da admissão. Na comparação entre os institutos seletivos, comparamos alunos que passaram nos quatro dos *Top 4* institutos, ou seja, que passaram na FGV-EESP, FGV-EPGE, IPE-USP e PUC-RIO. Os resultados sugerem que apenas os alunos da IPE-USP parecem se matricular com menor frequência em um doutorado no Brasil. Na comparação dos institutos seletivos em pares, utilizamos a amostra de alunos que foram aprovados em pelo menos dois dos *Top 4* institutos. Nesse caso, os resultados sugerem que a FGV-EPGE parece ter vantagem sobre a IPE-USP em termos de matrículas no doutorado no exterior. Essa vantagem persiste quando consideramos apenas programas de doutorados de alta reputação. Além disso, a PUC-RIO parece ter vantagem em relação à IPE-USP somente quando consideramos os programas de doutorado de maior reputação. Porém, a PUC-RIO parece não ter vantagem quando a comparamos com a FGV-EESP e FGV-EPGE. Além disso, as estimativas em relação ao desempenho no exame da ANPEC são significativas. Em particular, os alunos classificados até a 15ª posição parecem ter maiores chances de fazerem doutorado. Em relação ao modelo de RD, os coeficientes estimados não são significativos quando comparamos as *Top 4* com os demais institutos não seletivos. O resultado sugere que os alunos que frequentam um instituto mais seletivo e que foram aprovados na margem fazem doutorado com a mesma probabilidade dos alunos que frequentam um instituto menos seletivo.

Palavras-Chave: Institutos Seletivos, Participação no Doutorado, Pós-graduação, Retorno da Educação

Códigos JEL: I23, I26

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1 Introduction

In recent times, the discussion about the impact of schooling on future outcomes became increasingly intense. The literature identifies a correlation between wages and college attendance. For example, Kane (1998) shows that applicants with higher college entrance exam scores tend to have 3 to 7% higher future salaries in the United States. An important question is whether these benefits are due to the quality of college attended or to individual preexisting characteristics.

The challenge of measuring the educational institution's influence on students' future outcomes is dealing with the problem of identification: students with larger unobserved skills are more likely to attend the best and most selective institutions. This occurs because the most selective institutions typically choose the students with better scores in the admission process, while the less selective ones admit students with lower scores. Therefore, we would not know if the student's professional success is due to their characteristics or due to the institution they have attended.

In this thesis, we investigate the effect of attending a selective master's program on future Ph.D. enrollment. To do that, we use data from the ANPEC exam, the Economics postgraduate admission exam.[1] In Brazil, the most selective institutions are FGV-EESP, FGV-EPGE, IPE-USP, PUC-RIO. These institutions are more restrictive and admit students with higher ANPEC scores.[2]

We contribute to the literature by estimating the causal effect of a selective master institution attendance on Ph.D. enrollment, an issue with no consensus in the literature.[3] Furthermore, the determinants of Ph.D. enrollment have not yet been widely explored.[4] Also, to our knowledge, this is the first study using the ANPEC data set. An indirect result of this study is the provision of an objective institution's ranking for applicants. One of the critical factors in the decision to invest in human capital is whether the institution influences the student's payoffs afterward. When making an educational enrollment choice,

[1] The ANPEC exam is organized by the National Association of Postgraduate Programs in Economics (ANPEC) to rank the students, and it is used for admission by graduate institutions. We provide more details on the ANPEC exam in Section 3.

[2] The ANPEC average classification of the last applicant admitted in FGV-EESP, FGV-EPGE, IPE-USP, PUC-RIO is respectively 67, 42, 48, and 27. In the other less selective institutions in our sample, the average of the classification of the last student admitted is 87.

[3] Behrman et al. (1996), Altonji and Dunn (1996), Brewer et al. (1999), and Black and Smith (2004) focus on the effect of the institutions quality on the student's outcomes. Hastings et al. (2013), Kirkeboen et al. (2016), and Arteaga (2018) conclude that the field of study degree is the principal determinant of student's outcomes. Finally, Dale and Krueger (2002), Hoekstra (2009), Clark (2010), Dobbie and Fryer (2014), and Dustan et al. (2015) examine the impacts of the selectivity of institutions on student's outcomes. We detail those studies and the results found by the literature in Section 2.

[4] Eide et al. (1998), Bedard and Herman (2008), and Johnson (2013) attempt to uncover the determinants of Ph.D. enrollment. We detail the estimates of Ph.D. enrollment determinants found by the literature in Section 2.

it is vital to know whether choosing a more selective institution generates better payoffs. Therefore, this thesis can be also used to guide the student's choice.

In the ANPEC admission process, students choose the institutions to which they want to apply, while institutions select the students they will admit. That process could lead to a selection bias problem that is approached in this thesis using two frameworks. The first is the methodology suggested by Dale and Krueger (2002), which deals with the student's application bias. This methodology matches students who applied to and were admitted by the same institutions. In particular, in this study, we use the student's preferences revealed in the ANPEC subscription and the admission results of the ANPEC exam to apply this matching method. The second methodology is the Regression Discontinuity Design (RDD). Using the ANPEC exam score, institutions rank the applicants and determine whether they are accepted. The admission is conditional on a minimum score achieved by the applicant in the exam. Using the discontinuity of approval to address the institutions' selection bias, we can compare students just above and below that threshold.

Overall, our findings in the RDD framework suggest that attending a selective institutions does not impact the Ph.D. enrollments for the last students admitted in selective institutions. In the joint comparison among the Top 4 institutions, the effect of each institution seems to be equivalent.[5] To measure that, we use the sample in which students passed in the four of the Top 4 institutions and listed all four institutions in their preference. Only students at FGV-EPGE seem to enroll with a significantly higher probability in a Ph.D. program in Brazil. In the pairwise comparison among the Top 4, the results suggest that there is a significant difference in Ph.D. placement when we compare some institutions pairs. The sample, in that case, is the students who listed and passed in at least two of the Top 4 institutions. It seems that the FGV-EPGE has an advantage in terms of Ph.D. placement in Brazil or abroad when compared to IPE-USP and PUC-RIO. FGV-EPGE's students have a probability 0.242 p.p higher to attend to a Ph.D. program in Brazil or abroad when compared to IPE-USP and 0.157 p.p higher when compared to PUC-RIO. When we consider only Ph.D. programs abroad, FGV-EPGE's students enroll in a Ph.D. program with a probability of 0.138 p.p. higher when compared to IPE-USP. In particular, PUC-RIO seem to have an advantage when we examine only the higher reputation Ph.D. programs and when we compare to IPE-USP. PUC-RIO's students have a probability of 0.126 p.p. higher to enroll in a top 10 Ph.D. program. These impacts represent 66 % of the average probability of top 10 Ph.D. enrollments. Moreover, PUC-RIO does not seem to have an advantage when compared to FGV-EESP and FGV-EPGE.

Finally, in most specifications of the two estimates comparing within the Top 4 institutions, the coefficient for ANPEC performance is significant. In particular, the

[5] We consider Top 4 programs the FGV-EESP, FGV-EPGE, PUC-RIO, and IPE-USP masters programs. In our sample, that are the most selective institutions.

students ranked until the 15th position seem to have higher chances of enrolling in a Ph.D. program.

The thesis is organized as follows. Section 2 presents the literature review. Section 3 presents the ANPEC exam characteristics. Section 4 describes the data used. Section 5 reports the empirical strategy. Section 6 presents the main results separately by comparison within Top 4 and between Top 4 and non-Top 4. Finally, Section 7 concludes.

2 Literature Review

Our paper relates to the literature that examines the effects of the educational institution's attendance in student's returns and the determinants of Ph.D. enrollment.

In general, theoretical works support the idea that the educational institution's attendance could impact student's outcomes, given that schools should improve students' human capital. The literature suggests that human capital obtained through years of education appears to have a positive effect on student earnings (Becker (1962), Mincer (1974)). However, a relevant issue is whether the features of the chosen school affect student's outcomes or whether the characteristics of the selected degree are the only factors that matter.

A strand of the literature argues that the attributes of school, the so-called school quality, like well-paid professors, the granting of Ph.D., and small enrollments affect the student's earning (Fox (1993), Loury and Garman (1995), Daniel et al. (1997)). A concern when measuring the effect of school quality on earnings is that the student who attends schools with higher quality may also have different potential earning than his counterfactuals who do not attend these schools. Brewer et al. (1999) indicates that the estimates that do not control for endowments and pre-college investments overestimate the positive effects of college on earnings. Even after controlling for selection effects, the college or high school quality seems to have a significant positive impact on wages (Behrman et al. (1996), Altonji and Dunn (1996)). Using matching methods with covariates that affect college quality choice and labor market outcomes, Black and Smith (2004) estimates the effects of attending a high-quality college. The authors conclude that attendance in the college of a fourth quantile of the quality distribution increases future wages.

However, other papers conclude that the institution's quality or characteristics have a relatively small effect if compared with the field of study effect. Using administrative data for Norway's postsecondary education system, Kirkeboen et al. (2016) shows that the labor market payoffs differ according to the fields of study chosen by the student, and the effect on earnings from attending a more selective institution tends to be relatively small. Arteaga (2018) exploits a reform at Universidad de Los Andes and concludes that the different sets of skills and knowledge acquired in each degree affect earnings. Using administrative and college admission data from Chile, Hastings et al. (2013) find that returns are heterogeneous concerning a degree, and they are significant and positive when they consider the highly selective degrees.

In addition to the measure of the impact associated with school quality and heterogeneous returns of degree, the literature also investigates the impact of selective schools on student's outcomes. For example, Dale and Krueger (2002) find that students who attended more selective colleges earned about the same as students who attended less selective schools. Hoekstra (2009) finds that attending the most selective colleges results in approximately 20% higher earnings for white men in the US. Dustan et al. (2015) uses a regression discontinuity design to estimate the effect of attendance in selective schools in Mexico City. They find that admission in a selective school raises the high school dropout rate by 9.4 percentage points and increases the math grades at the end of high school. Similarly, Dobbie and Fryer (2014) uses a discontinuity generated by an admission high school exam in New York City to estimate the impact of attending a selective school. The results suggest that the exam eligibility have no effects on college enrollment and longer-term postsecondary outcomes. Clark (2010) estimates the impact of attending a selective school using data from the UK. Comparing the students that attended a selective school with those that did not attend, the author shows that the effect of selective school is positive in terms of course-taking and university enrollment.

Through different empirical methods used, the results in the literature about the impact of selective institutions are not conclusive. Specifically, the impact of high school selectivity on college enrollment is a topic under study since the result is not a consensus. In addition, a possible schooling outcome may be related to the determinants of Ph.D. enrollment. There are a few studies that link enrollment in graduate programs with labor market conditions. For instance, Bedard and Herman (2008) conclude that labor market conditions do not affect graduate school enrollment while Johnson (2013) shows that enrollments respond to unemployment only for woman. In addition, some studies focus on the college quality effect on Ph.D. enrollments. Eide et al. (1998) find that the quality of college significantly increases the probability of attending a graduate school at a major research institution.

Thus, using the Ph.D. future enrollment as one of the possible effects of the selective school, the thesis tries to fill the literature gap measuring the impact of attending a selective master program in terms of Ph.D. placement.

3 The ANPEC Admission Exam

ANPEC exam is the centralized postgraduate admission exam in the field of Economics organized by the National Association of Postgraduate Programs in Economics (ANPEC). The ANPEC exam ranks the students, and the postgraduate institutions use the exam result as a criterion to fill its vacancies. During the ANPEC subscription, the students are required to provide personal data and to pay a fee. Also, the student needs to select preferred institutions from a list of postgraduate institutions in economics that use ANPEC as the entrance exam. The student's selection of preferred graduate institutions is unordered, and they have to choose up to six options.

The test is performed in a single stage, in which students take tests on six different undergraduate subjects: Microeconomics, Macroeconomics, Mathematics, Statistics, Brazilian Economy, and English. The exam is the same for all applicants, and it consists of multiple choice and open questions. ANPEC calculates the final score considering that an item answered incorrectly cancels the score obtained in an item responded correctly.

The ANPEC classification takes into account equal weighting for the five subjects scores excluding English. However, each institution can weigh each subject score in a particular way. After rating, each institution invites the best-ranked applicants to fill the vacancy in the master's degree, and, in some cases, the institution invites the admitted students to visit the campus. Institutions dispute those students with the best classifications.

The student who received the invitation can accept or decline the invitation. If the applicant was admitted to more than one institution, they would have a set of institutions from which to choose from. In summary, the choice of applicants involves two significant decisions. First, the applicant chooses a set of institutions that they will apply to. Second, after the result, the student decides which institution he will attend among those institutions that invited them, i.e., among the feasible institutions.

Since students have different preferences for institutions, the attendance choice is not random among feasible institutions. As the students' preferences are listed in the exam subscription, and the students' attendance decision is made after visiting the institutions, the student can be influenced by the visits. However, the students' preference is related to the student's decision among feasible institutions, which is important information about the attendance decision.

After the first round of invitation made by the institutions, students must select the institution they choose to attend to join the master's program. After this filling of vacancies, a new round of invitations is made to fill those remaining vacancies. That is, not all vacancies offered by the institutions are filled at the same time.

In the visiting process, applicants can coordinate the attendance decision. A concern for our strategy that uses preferences before student visits to campus is whether students coordinate attendance decisions. However, the pre-visit preferences are correlated with the attendance decision, which reduces the concern with the coordination problem during visits.

4 Data and Descriptive Statistics

In this thesis, we use the ANPEC data set, Sucupira's thesis catalog, and RAIS.[6] In addition, we extract data from student's online curricula using LinkedIn, Lattes Curriculum and personal applicants websites.[7] These data sets allow us to analyze whether ANPEC's applicant enrollment in a given master's institution has an impact on their subsequent Ph.D. placement.

The main data set is provided by ANPEC. It contains the individual performance of ANPEC's applicants from 2001 until 2017. In particular, the data set includes scores and placement according to ANPEC and each institution's ranking criteria. The data also hold background information for each applicant like nationality, gender, race, age, marital status, undergraduate degree, and information declared in the application form of how many times the student took the exam before and in which year the applicant finished undergraduate studies.

Importantly, the data include the applicant's preference for institutions that they want to attend for a master's program, with the exception of years 2002-2003. The student is required to select up to six preferred institutions from a list of postgraduate institutions in the ANPEC subscription without ordering them.

The ANPEC's data set contains the institution which the applicant attended only for 2009-2017, but not for 2001-2008. To obtain the 2001-2008 data, we linked the exam records by the applicant's names to the economics thesis catalog 2001-2017 - Sucupira data set - to identify where the student attended the master's program. All individuals who obtained a master's or Ph.D. in Brazil during 2001-2017 are in the Sucupira's database. That data set includes the title of the thesis, the name of the author, the year of the thesis presentation, and the master's degree institution. With that information, we obtained the

[6] Sucupira's thesis catalog is a catalog of thesis developed by *CAPES* (*Coordenação de Aperfeiçoamento de Pessoal de Nível Superior*), the Brazilian federal government agency under the Ministry of Education, responsible for undergraduate and postgraduate institutions in Brazil. *RAIS* (*Relação Anual de Informações Sociais*) is a matched employee-employer data set containing all formal workers in Brazil. Sucupira's thesis catalog data can be accessed in CAPES (2019).

[7] Lattes Curriculum is the national register of the academic activity of students and researchers in Brazil developed by CNPq (*Conselho Nacional de Desenvolvimento Científico e Tecnológico*). The data are available in CNPq (2019).

master's degree institution for the 2001-2008 ANPEC cohorts that concluded a master's program. We then searched online master program attendance for those who did not conclude a master program, which corresponds to 17.36% of the sample. As a master's program in Brazil lasts on average 2 years, and the students without attendance in our sample took the ANPEC exam in 2001-2008, these cases typically correspond to dropouts, students who decided not to pursue an M.A. or to students who enroll in a Ph.D. in the same institution without completing the master program. For those, we obtain the placement after the subscription on the ANPEC exam by their Lattes CVs or LinkedIn. Combining all these data sources, we find information for 97.58% of the sample.

Using the Sucupira's data set, we also identify those applicants who did a Ph.D. in Brazil in any field of study between 2001-2017 after taking the ANPEC exam. For those who did not present a Ph.D. thesis in economics in Brazil, we obtain the Ph.D. placement after master's degree enrollment. For applicants who attended the master program at PUC-RIO and FGV-EESP, we use the public placements list published by these institutions. For applicants who attended other institutions, we consult their Lattes CVs, LinkedIn, and personal websites. Finally, for those we do not identify attendance in a Ph.D. program, we searched for their job market placement. To do that, we use the RAIS data set, which registers every formal worker in Brazil. The RAIS database includes the name of the employee, the name of the employer, employee's date of birth, and admission date in that job. We merge the 2001-2017 ANPEC information with the 2002-2017 RAIS data using the applicant's name for all and age when available using exact and probabilistic matching. We double-check the applicant's online curriculum (Lattes and LinkedIn) to confirm the match or select the correct one in case of several matches. We only consider employment contracts signed after the year of the ANPEC exam subscription. For those with Ph.D. attendance in Brazil and an employment contract in Brazil, we discard the job market data and consider only the Ph.D. enrollment, since this information is more meaningful for our analysis.[8] We do not find any information for 10.94% of our sample.

We can speculate on the observations of applicants that were not found. In principle, some of these applicants could be enrolled in a Ph.D. program in Brazil. To be out of our sample, the student did not present a thesis in Brazil in the year under analysis or did not update their Curriculum Lattes. As the Ph.D. program in Brazil often lasts four years, the thesis catalog years used would be enough to identify the majority of students who attended the Ph.D. programs in our sample. Also, it is common that the institutions encourage Ph.D. students in Brazil to update their Curriculum Lattes. Therefore, we believe that the majority of students who enrolled in a Ph.D. program in Brazil have been identified in our sample. Another portion of these applicants may have joined a Ph.D.

8 In our sample, students who attended a Ph.D. program abroad did not present employment contracts in Brazil.

program abroad. It is common that students who enrolled in a Ph.D. program abroad have personal websites and update the Curriculum Lattes. So, we also believe that the majority of students who attended a Ph.D. program abroad have been identified in our sample. Finally, we hypothesize that the majority of students who are not included in our sample works without a formal labor contract in Brazil. A non-formal contract can typically be established in consultancies and research organizations.

As our analysis focuses on the most selective institutions, we keep only the ANPEC applicants who rank in the first 250 classifications, representing 24.49% of the total ANPEC applicants. We make some restrictions on our population of interest. First, we discard the years 2002 and 2003, since we do not have the applicant's preference for institutions. We use the ANPEC data set from 2001, and 2004 until 2015. When the applicant took the exam more than once, we considered only the most recent application (approximately 11.44% of applicants in our sample take the exam more than once). Our final sample that excludes those that we do not find any information contains 1,804 observations for the years 2001 and 2004-2015.

Our data allow us to observe the institution the applicant attended, but we do not have in the data set the institutions that admitted the applicant, i.e., where they could have enrolled. The information of where the student was approved is essential for us to implement the method proposed by Dale and Krueger (2002) and the RDD framework. Therefore, we infer in which institutions applicants passed. In a nutshell, if the student was the last that attended an institution, then we consider that all applicants above him were admitted to that same institution.

We illustrate how we infer admission to institutions other than the one the applicant attended in Table 1. Suppose that the last student that enrolls in institution 1 was the student ranked 56.[9] Above this student, we assume that all individuals were admitted to institution 1. We also assume that all students ranked below the last student who enrolled in institution 1 were not admitted to institution 1. Using this method, we construct a dummy variable that is equal to 1 if the applicant was admitted to institution 1 and 0 otherwise.

When inferring admission, we also discard outlier applicants who attended the institution but were more than 20 places away from the nearest above-ranked applicant to infer admission.[10] About 5.39% of applicants in our sample are outliers.

[9] Each institution sorts students according to their classification. When the institution did not present its ranking in the data set, we consult the public documentation of the ANPEC exam to set the subjects' weights for each institution. institutions UERJ, UFJF, UFRGS, UFSCAR, UFU, ESALQ, UNICAMP, and UEM did not present their classification in at least one year of the exam. To calculate the classification for those institutions, we consult the ANPEC exam regulation available in: http://www.anpec.org.br/novosite/br/exame.

[10] These outliers may exist because some institutions may select applicants taking into account other factors in addition to the ANPEC score, as a letter of recommendation or research experience. In that

Table 1 – Illustration of Admission Inference Method

Ranking in institution 1	Attendance	Admitted to institution 1
55	institution 2	1
56	institution 1	1
57	institution 2	0
58	institution 3	0
59	institution 2	0

Our method fails if the student that attended a given institution is not necessarily the last to be accepted by that institution. Indeed if the applicant did not attend an institution, then we do not know if he was not admitted or simply opted for another institution. To check the effectiveness of our admission inference method, we compare our inference with the actual classification. Following our request, FGV-EESP and IPE-USP provided us the ranking of successful applicants for some years. The information allows us to compare the last positions of the accepted applicants with the last position of our inferences. Although the years 2016-2018 are not in our final sample, we can verify that for FGV-EESP, the actual ranking position of the last admitted was close to our inferred classification. For 2016 and 2018, we fail to detect five and two students who were admitted, respectively. The inference for the last students accepted in IPE-USP was also close enough: two students in 2013, one in 2014, and six in 2015 students were considered not accepted by IPE-USP in our method when in fact, they were accepted. Thus, our admission inference method seems to be a reasonable estimate of the actual admission decisions.

Table 2 shows the descriptive statistics of our final sample. Most of our sample consists of men, white, and single students. The mean age is approximately 24 years. A total of 14.2% took the exam more than one year after completing the bachelor's degree. The mean of the ANPEC exam score is 39.8. Approximately 53.5% of the applicant enrolled in a Ph.D. program after masters. When we consider only the Ph.D. programs abroad, that proportion drops to 14.7%. We use the Shangai rankings of Ph.D. programs in Economics to group the Ph.D. programs into the top 10 and top 20. Only 7.8% and 5.5% of the applicants enroll in a top 20 and a top 10 Ph.D. programs abroad, respectively.

Figure 1 shows the ANPEC score and ANPEC ranking mean by college city that applicants attended during undergraduate degree.[11] There is a divergence of students score and ranking across cities: the students with the highest scores come from cities *São Paulo* and *Rio de Janeiro*, where the Top 4 are located. That fact is evidence that there is a polarization of skill across cities. Additionally, these cities also concentrate the top-ranked

case, the student approved only for these purposes would be in a ranking detached from the majority of students approved for the program by the exam score.

[11] We use the eight cities with the most significant number of applicants in our sample. These cities are: *São Paulo, Rio De Janeiro, Brasilia, Belo Horizonte, Campinas, Porto Alegre, Recife, Niterói.*. ANPEC score and ANPEC ranking weigh the five main tests with the same weight (20% each subject).

Table 2 – Descriptive Statistics

	Mean	Std. Dev.
Male	0.762	
Single	0.800	
White	0.759	
Age	23.7	3.3
Took the exam more than one year after graduate	0.142	
Enrolled in Ph.D.	0.535	
Enrolled in Ph.D. abroad	0.147	
Enrolled in top 20 Ph.D.	0.078	
Enrolled in top 10 Ph.D.	0.055	
Application score	39.8	9.9
Observations	1,804	

Notes: The table reports the descriptive statistics of our sample. We consider only the most recent ANPEC subscription and the applicants ranking in the first 250 positions. The years of our sample are 2001 and 2004-2015.

students in ANPEC exam (see Figure 2). Despite the difference in score, the majority of applicants in these cities are men with an average age of 23 years (see Figure 3). The table with means and standard deviations of the score in the Microeconomics, Macroeconomics, Statistics, Mathematics, and Brazilian Economy tests, and the characteristics of students are in Appendix 2.

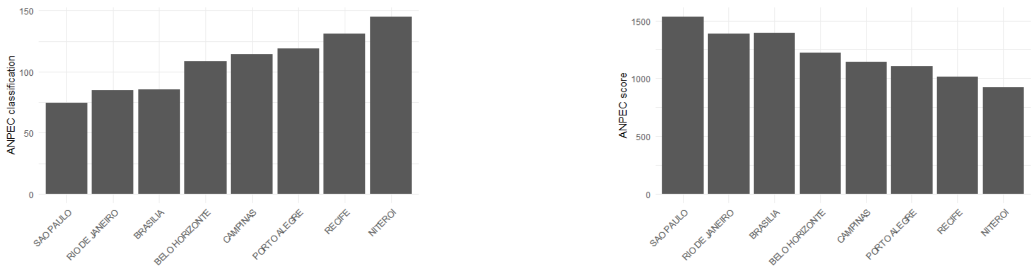
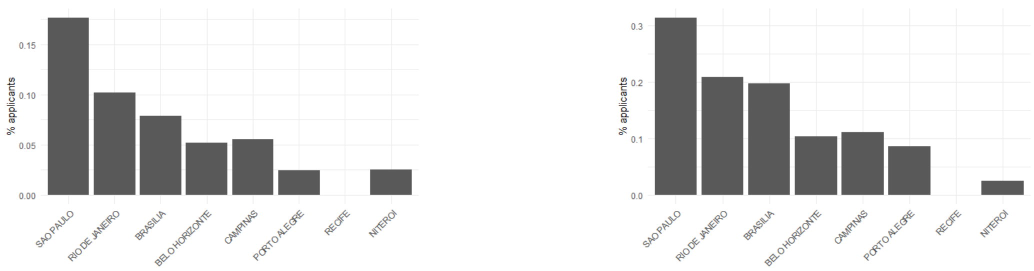


Figure 1 – ANPEC score and classification across cities



(a) % of applicants in the first 15 positions

(b) % of applicants in the first 30 positions

Figure 2 – % of applicants in the first ANPEC positions across cities

Figure 4 shows that some cities stand out when allocating undergraduate students to Ph.D. programs in Brazil or abroad, such as *Belo Horizonte*, *Porto Alegre* and *Recife*.

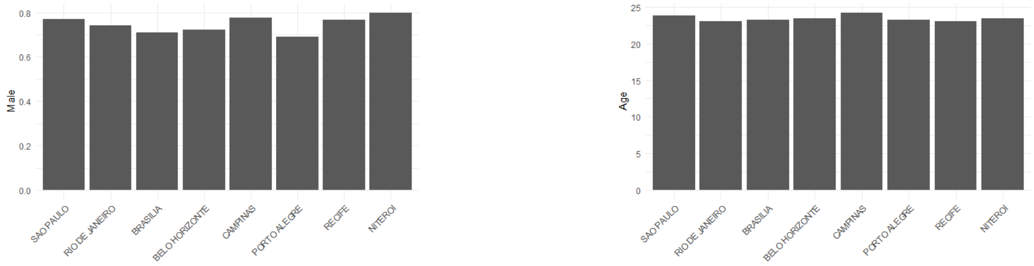


Figure 3 – % of male applicants and mean age across cities

However, *São Paulo* and *Rio de Janeiro* concentrate students that enroll in a Ph.D. program abroad, mainly when we consider Top 20 and Top 10 programs.

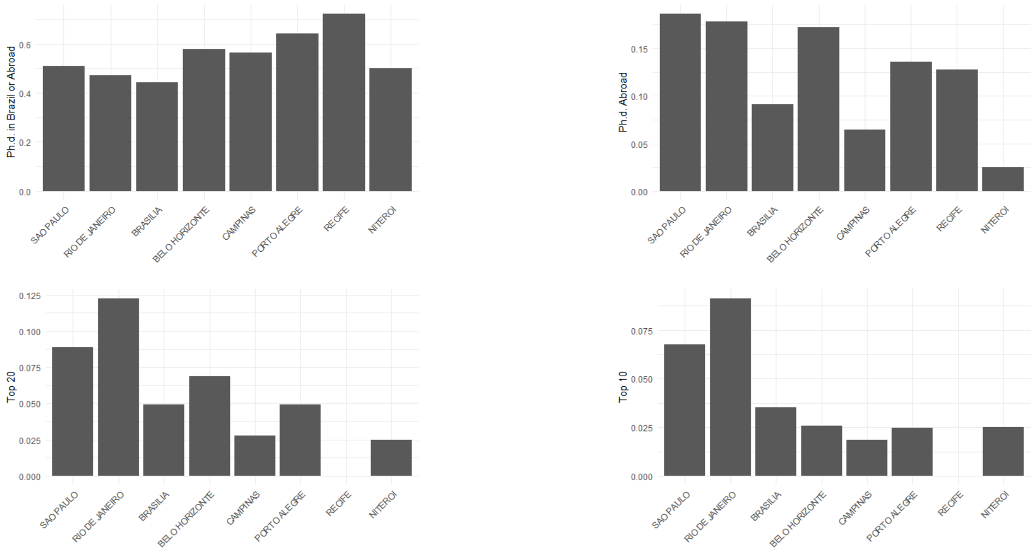


Figure 4 – % of applicants that attended Ph.D. programs across cities

Figure 5 shows the ANPEC score and ANPEC ranking mean by the institution that applicants attended during masters. The applicants with the highest score and lowest classifications tend to enroll in the PUC-RIO. The opposite occurs with FGV-EESP. Additionally, PUC-RIO concentrates the applicants with the best ANPEC ranking, attracting, on average, 70% of applicants classified up to position 30 (see Figure 6).

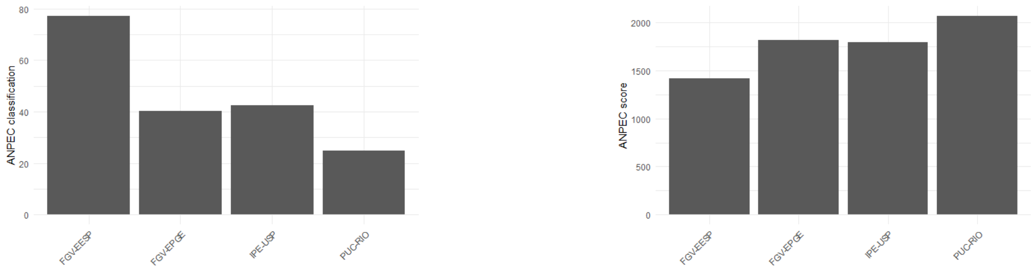
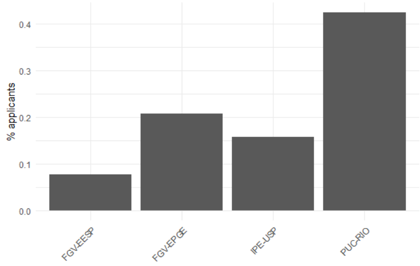
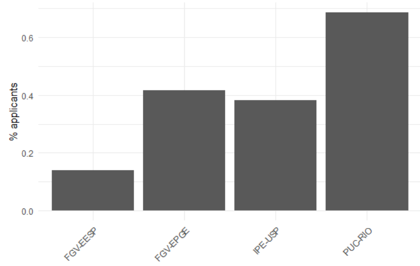


Figure 5 – ANPEC score and classification across institutions



(a) % of applicants in the first 15 positions



(b) % of applicants in the first 30 positions

Figure 6 – % of applicants in the first ANPEC positions across institutions

Figure 7 shows the proportion of students that attended a Ph.D. program by the M.A. institutions. Graphically, when considering a Ph. D. in Brazil or abroad, FGV-EPGE seems to have a small advantage in allocating its students in Ph.D. programs. However, when we consider programs abroad, we see a more significant proportion of students from PUC-RIO and FGV-EPGE who enroll in a Ph. D. abroad. The differences between these institutions with FGV-EESP and FGV-EPGE strengthen when considering the Ph.D. programs of higher reputation. Since PUC-RIO and FGV-EPGE concentrate students with the best ratings, we cannot interpret the differences between the Ph.D. placement of students as an institution effect. Our analysis tries precisely to deal with the selection problem in the admission process to measure the institution's impact on the Ph.D. placements.

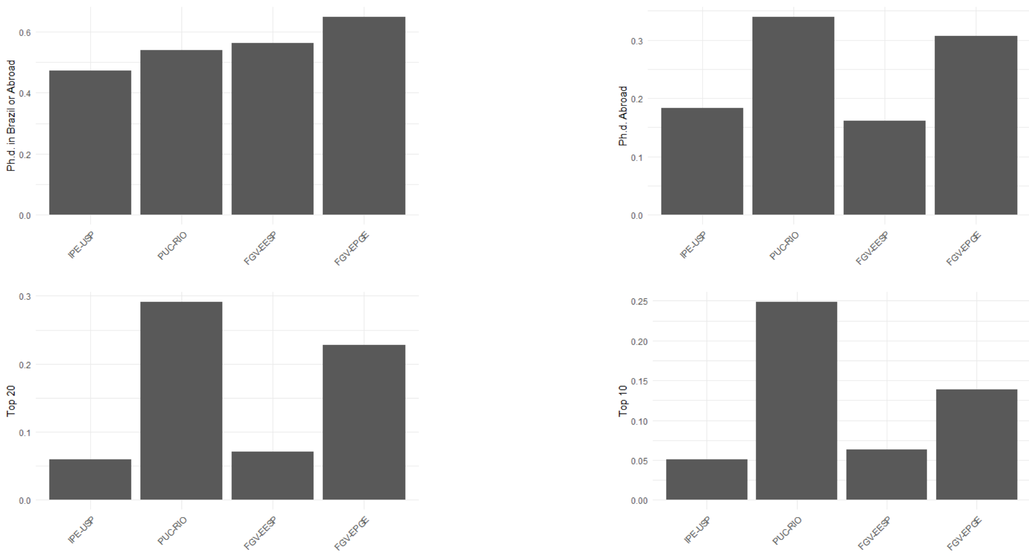
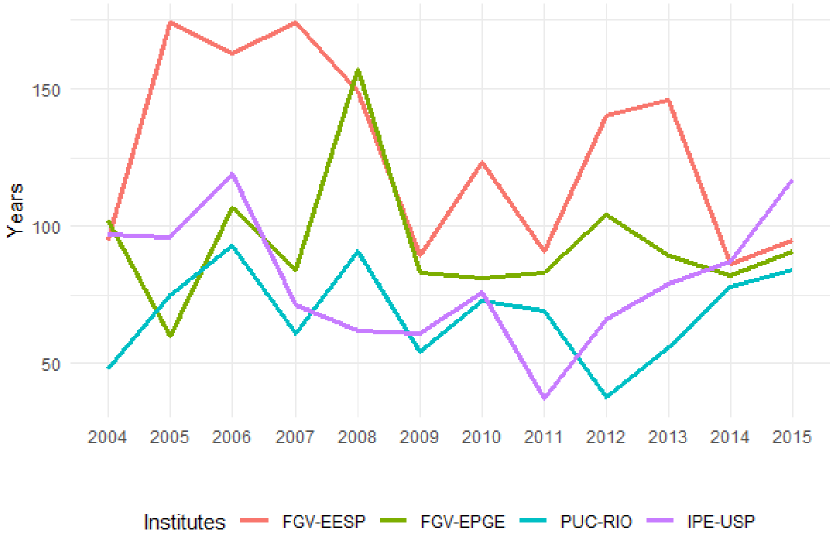


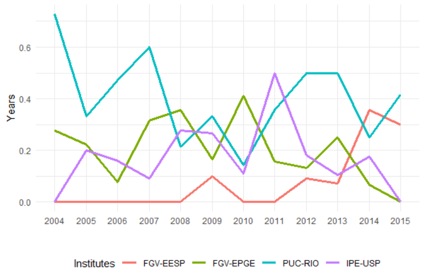
Figure 7 – % of applicants that attended Ph.D. programs across institutions

Figure 8 displays some information about the students admitted in the Top 4 institutions per year. Figure 8a shows the ANPEC classification of the last student admitted to each of the Top 4 institutions. We see that FGV-EESP is the institution that admitted the student with the highest classification in most years of the sample, while

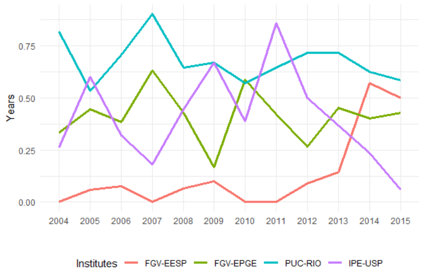
PUC-RIO and IPE-USP admit the lowest classification. In recent years, this pattern has tended to change: the last student admitted to IPE-USP ranks in a higher position, while FGV-EPGE, FGV-EESP, and PUC-RIO tend to admit students in the lowest positions. Figure 8b shows the percentage of students admitted to each of the Top 4 institutions who rank up to 15th ANPEC position. In the first years of the sample, we see that PUC-RIO concentrated the students who had the best fifteen placements. FGV-EESP did not concentrate many students in the first positions. More recently, the proportion is balanced, and we see that FGV-EESP and PUC-RIO concentrate similar amounts of students in the first positions. Figure 8c shows the percentage of students admitted to each of the Top 4 institutions who rank up to 30th ANPEC position. In that case, the pattern remains similar to Figure 8b: FGV-EPGE, IPE-USP, and PUC-RIO compete for students with the best 30 ratings. Therefore, PUC-RIO continues to concentrate on students in the first 30 placements in recent years.



(a) ANPEC classification of the last applicant that attended the M.A. institution across institutions



(b) % of applicants in the first 15 positions



(c) % of applicants in the first 30 positions

Figure 8 – ANPEC score across Top 4 institutions and by year

5 Empirical strategy

In our main analysis, we want to estimate the payoff of attending a selective institution in terms of their Ph.D. placement among students who enroll in a master's program. First, we compare the Top 4 programs with each other and then the Top 4 with non-Top 4 institutions.[12] We consider a Ph.D. placement only when students enroll in a Ph.D. program in a department of Economics or Finance.

If we were to compare simply the Ph.D. placements of different master programs, we would incur in, at least, two potential selection problems. The first is the institution selection bias that occurs since institutions choose the students. If the institution chooses a student using an admission process, it is selecting students with different unobserved abilities. Then, the most skilled students are likely to be admitted to more competitive and selective institutions. The second problem is the student selection bias that occurs when the students choose institutions to which they want to attend. Students that attend more selective institutions, when compared to students that attend less selective institutions, have different unobserved abilities. These abilities can be associated with the analyzed potential outcome, which is the Ph.D. enrollment. Thus, comparing the placement of students who have attended institutions with varying selectivity can lead us to erroneous conclusions.

To address these potential selection problems, we adopt two frameworks. The first methodology is the empirical strategy proposed by Dale and Krueger (2002), which matches students who applied to and were admitted by the same institutions. That match deals with the application selection problem. When students choose the institutions they want to attend, they reveal a preference for more selective or less selective institutions. This preference would correlate with the student's unobservable characteristics that relate to the potential outcome. Then, when we match the students with the same preference and compare among that group, we can at least partially address the student application bias problem. Moreover, students admitted by the same sets of institutions experience a similar decision-making process. Therefore, when we match the students with the same admission set of institutions and compare them, we address the institution selection bias. We denote that method as the matching framework, and detail it in Section 5.1. For those analyses, we use the sample of students that were accepted by and apply to at least two of the most selective institutions, the Top 4.

[12] We consider Top 4 programs the FGV-EESP, FGV-EPGE, PUC-RIO, and IPE-USP masters programs. We also compare Top 3 and non-Top 3 institutions alternatively. We exclude IPE-USP from the second definition because this institution admits applicants who are ranked in relatively lower positions among the Top 4, recently. Our sample of non-Top 4 institutions contains: PUC-SP, UCB, UEM, UERJ, UFBA, UFC, UFES, UFF, UFJF, UFMG, UFPB, UFPE, UFPR, UFRGS, UFRJ, UFSC, UFSCAR, UFU, UNB, UNESP, UNICAMP, USP-RP, IBMEC, and ESALQ.

The second methodology is the Regression Discontinuity Design (RDD) framework that focuses on the acceptance or rejection of the students by a small margin in a Top 4 versus a non-Top 4 institution. In this case, we are analyzing locally around the admission cutoffs. The RDD framework also aims to evaluate the effect of student's attendance in a more selective versus a less selective institution in terms of Ph.D. placement. Each institution, using the ANPEC exam score, determines which will be the cutoff score of its admitted students. Since we do not have the exact invitations received by students, we use our admission inference to determine the cutoffs. The students just below the (inferred) cutoff are those who did not pass in the most selective institutions. Those students just above the cutoff are those who passed in the most selective institutions. Therefore, using the admission discontinuity, we compare the Ph.D. enrollment of students around the (inferred) cutoff ranking. We detail that framework in Section 5.2.

Using those two frameworks, we attempt to measure the M.A. institution effect on student's Ph.D. placement. Note that we use different samples in each analysis. While the sample of the method proposed by Dale and Krueger (2002) uses students admitted to at least two Top 4, the RDD uses students only around the admission cutoff.

5.1 Matching framework

This section presents the identification strategy proposed by Dale and Krueger (2002) to estimate the causal impact of selective institutions attendance on Ph.D. enrollments. We investigate the relations within the Top 4 institutions when we estimate the regression within groups of students who received the same admissions decision. That is, we compare students with the same set of approvals and preferred institutions. When we compare the four of Top 4 institutions, we match applicants who stated preferences for the four institutions. When comparing institutions in pairs, we match applicants who chose the two Top 4 institutions analyzed as preference.

While the method addresses the student's application problem, it does not solve the student selection problem. Students still choose among the feasible alternatives. For example, if the student was admitted in the four institutions, then he must choose among these alternatives. If one of these institutions has a greater reputation for enrolling its students in Ph.D. programs, then students with a greater willingness to attend a Ph.D. program would likely choose that institution. We consider that for the Ph.D. in Brazil, all institutions among the Top 4 have the same reputation. Considering only Ph.D. abroad, PUC-RIO seems to have a reputation for having an advantage in enrolling its students in Ph.D. programs. Then, when we compare PUC-RIO with other institutions, we are estimating the upper-bound effect of obtaining a master degree at PUC-RIO.

On the ANPEC subscription, the students list the preferred institutions through an options system. We need to ensure that students use the system of ANPEC options when they are applying to reveal their preferences regarding the institutions. About 79% of the people in our sample selected the attended institution among their listed options in the ANPEC subscription. If we consider only the Top 4 institutions, that number increases to 98% of the applicants in the sample. Therefore, we suppose that it is reasonable to assume that applicants use the options system. It is also pertinent to highlight that the applicants have only six possibilities to choose favorite colleges, i.e., applicants pick a limited number of institutions as preferred. This limit is important because if applicants could choose an infinite number of options, those choices would hardly be informative.

Denote the outcome by Y_i, a dummy variable equal to one if the applicant i attended a Ph.D. in Economics or Finance after the master's degree.[13] To allow for distinct levels of Ph.D. reputation, we consider the following distinctions: Ph.D. in Brazil or abroad, Ph.D. abroad, Ph.D. in a top 20 program, and Ph.D. in a top 10 program.[14] We regress the outcome on binary variables of assignment, D_i^j, which is one if student i attended institution j. We control for applicant's performance in the ANPEC exam (i.e., general score or ranking), S_i, for a binary variable equal to one if the student moved to another city between undergraduate and master,X_i, and dummies of year, A_t. In addition to the linear control of the ANPEC ranking, we also run the regression using ranking ranges (ranges from 1 to 60 position and 60 forward). The main regression equation is given as follows:

$$Y_i = \sum_{j}^{3} \beta_j D_i^j + \beta_4 S_i + \gamma X_i + \sum_t \delta_t A_t + \epsilon_i \tag{1}$$

where ϵ_i is the error term. In all estimates, we cluster standard errors by years. The parameters of interest are β_1, β_2 and β_3. Each of these β_j parameters represents the effect of attending the j institution. In this regression, we can test if the institution's effect is equal among the four institutions through a F-test. The sample, in this case, is the students who passed in the four of Top 4 institutions and listed all four institutions in their preference.

To compare the Top 4 institutions with each other, we measure the difference in the student's Ph.D. placement between pairs of institutions. We compare two institutions $j \times k$ within groups of matched students using:

$$Y_i = \alpha + \beta_1 D_i^j + \beta_2 S_i + \gamma X_i + \sum_t \delta_t A_t + \epsilon_i \tag{2}$$

[13] We consider attendance instead of Ph.D. conclusion since we want to measure the institution's capacity to place its students into a Ph.D. program.

[14] We classify the Ph.D. programs as top 20 or top 10 according to the 2019 Shanghai Global Ranking of Academic Subjects (see Appendix A).

where ϵ_i is the error term. In all estimates, we cluster standard errors by years. The parameter of interest is β_1. If $\beta_1 > 0$, institution j has an advantage in enrolling its students in a Ph.D. program as compared to the institution k. The sample, in that case, is the students who listed and passed in at least two of Top 4 institutions.

To verify the appropriateness of the Dale and Krueger (2002) method, we estimated the equation (2) without matching the students by the admission decision. We show the results in Appendix 3. The results suggest that not controlling for preferences makes PUC-RIO's estimators significant and positive; that is, the PUC-RIO's students enroll more frequently in Ph.D. programs. The preference for PUC-RIO may be correlated with students' willingness to attend a Ph.D. program. Then, controlling these preferences would be helping us to deal with the student selection.

5.2 RDD framework

This section discusses the identification strategy of the RDD framework used to estimate the causal local effect of selective institutions attendance in Ph.D. enrollments. First, we present the baseline model. Second, we show the validity of the RDD in our setting.

5.2.1 Baseline RDD Model

Our second estimation approach exploits the regression discontinuity design to compare the Top 4 and non-Top 4 institutions. We also examine the Top 3 institutions (FGV-EESP, FGV-EPGE, and PUC-RIO) with the non-Top 3 institutions, by excluding IPE-USP. We use the admission discontinuity as the cutoff. If the student reached a lower ranking in the ANPEC exam than the cutoff ranking for each of the institution's classifications, we assume they were approved by the institution.

As already seen in Section 4, the cutoff that we infer is very close to the original cutoff in the years for which we have such information. Small differences arise since we consider that some accepted students below the inferred cutoff were not accepted. Given that this misconception does not represent a large part of the sample, we believe this has little impact on our estimates. The outliers that we discard when conducting our process of inferring invitations are the observations that are below the cutoff but have passed in the institution. Since there are students below the institution's cutoff that attend that institution (outliers) and students above the cutoff that do not attend that institution, we use the fuzzy RDD.[15] Our estimation approach exploits the fact that applicants with

[15] Outliers represent 5.39% of our sample. We detail how we define outliers in Section 4.

exam scores above the cutoff are more likely to receive an offer and attend a more selective institution. We estimate the local average treatment effect (LATE) to obtain the causal interpretation.

We consider that the applicant attended the Top 4 if he attended to at least one of the Top 4 institutions. As before, the outcome Y_i is equal to 1 if the student enrolls in a Ph.D. program in Brazil or abroad after attending a master's. D_i^j is a binary variable that is one if student i attended one of the institutions of the group j. In particular, the group of institutions j is the Top 4 institutions or Top 3 institutions. c is the cutoff, i.e., the maximum ANPEC ranking to be admitted to the institutions' group j.[16] X_i is the ANPEC ranking of student i, and Z_i^j is a dummy variable equals to one if student i was admitted in the institutions' group j. We use the same method to define the variables for the Top 3 institutions.

We estimate the regression:

$$Y_i = \alpha_1 + \beta_j D_i^j + \gamma_r^j (X_i - c) Z_i^j + \gamma_l^j (X_i - c)(1 - Z_i^j) + \epsilon_i \tag{3}$$

and

$$D_i^j = \alpha_2 + \rho Z_i^j + \lambda_r^j (X_i - c) Z_i^j + \lambda_l^j (X_i - c)(1 - Z_i^j) + u_i \tag{4}$$

where ϵ_i and u_i are the error terms. Regression (3) is the second-stage equation, and (4) is the first stage equation. We estimate the first stage equation and present the result in Appendix 6. The main assumption is that the assignment to the institution in the master is not correlated with the error term. The parameter of interest is β_j. If $\beta_j > 0$, group of institutions j has an advantage of enrolling its students in a Ph.D. program.

We use the methodology suggested by Calonico et al. (2014) to calculate the CER-optimal bandwidth, which is, according to the authors, a more appropriate bandwidth to a small sample. For all estimates, we use triangular kernel weights. Appendix 4 provides the empirical results using the MSE-optimal bandwidth. Appendix 5 provides the robustness results to RD specification using the CER-optimal bandwidth. In that Appendix, we also do the robustness checks varying the bandwidth. [17]

5.2.2 RDD validity

Our RDD estimation uses the admission discontinuity as the cutoff. We explore that discontinuity to estimate the effect of being approved in a selective institution in the Ph.D. placement. However, first, we must verify the necessary conditions to implement the RDD framework.

[16] The ANPEC ranking weights the five main subjects score equally; that is, each test receives a weighting of 20%.

[17] We also estimates using the bandwidths 0.25, 0.125 and 0.07.

A potential threat to our design would occur if applicants could manipulate their score to sort themselves above the admission cutoff in the desired institution. The manipulation hypothesis is unlikely since the individual classification depends on the performance of other students, and students do not know what the exact cutoff will be. Thus, if students are unable to manipulate the assignment variable precisely, the variation in attendance to a given institution around the admission cutoff is as good as random.

We test the validity of our randomization by checking the predetermined covariate balance test. Predetermined covariates are the variables determined before the attendance in masters. In Table 3 and 4, we do the balance test using the variables of student characteristics that we have available in the our data set. We use the method proposed by Cattaneo et al. (2019), where all predetermined covariates should be analyzed in the same way as the outcome of interest. Therefore for each covariate, we do a RD estimation and calculate the CER-optimal bandwidth using each covariate as the outcome. The test shows that there are no discontinuities in the covariate variable. The covariates are similar in the groups above and below the cutoff in the two comparisons of interest. In addition, we conduct a placebo test and conclude that there were no discontinuities when we chose a random cutoff (see Appendix 4).

Table 3 – Balance check of covariate variables - Top 4 x non-Top 4

Variable	CER-Bandwidth	RD estimator	p-value	Observations
Male	0.258	-0.293	0.609	410
Single	0.250	-0.465	0.144	410
White	0.207	0.367	0.648	305
Took the exam before	0.255	0.394	0.364	410
Took the exam more than 1 year after graduate	0.259	-0.150	0.803	240
Age	0.199	-0.516	0.811	240

Notes: The first column reports the CER-bandwidth calculated for each covariate. The second column shows the RD estimator from estimation using each covariate as an outcome. The third column shows the p-values. If the RD estimator is not significant, then the sample is balanced for that covariate. *Significant at 10%; **Significant at 5%; ***Significant at 1%

Table 4 – Balance check of covariate variables - Top 3 x non-Top 3

Variable	CER-Bandwidth	RD estimator	p-value	Observations
Male	0.196	0.433	0.381	492
Single	0.262	-0.111	0.575	492
White	0.179	0.337	0.406	337
Took the exam before	0.299	-0.253	0.392	492
Took the exam more than 1 year after graduate	0.311	0.175	0.786	246
Age	0.232	1.162	0.689	246

Notes: The first column reports the CER-bandwidth calculated for each covariate. The second column shows the RD estimator from estimation using each covariate as an outcome. The third column shows the p-values. If the RD estimator is not significant, then the sample is balanced for that covariate. *Significant at 10%; **Significant at 5%; ***Significant at 1%

6 Main Results

In this section, we first document the comparison among the Top 4 institutions in terms of Ph.D. placement using the matching framework. Second, we examine the comparison between Top 4 and non-Top 4 institutions using the RDD framework.

6.1 Comparisons Within Top 4

This subsection presents the results when we compare it within selective institutions. To do that, first, we regress the equation (1) to compare the placement within the Top 4 institutions. In that case, we use the sample in which students passed in the four of Top 4 institutions and listed all four institutions in their preference list. We show the results in Tables 5, 6, 7 and 8. In all tables, we vary the exam performance control in the regression using the following variables: Normalised ANPEC score, ANPEC ranking, and range of ANPEC ranking. In all estimates, the ANPEC performance is significant. When we adopt the range of ANPEC ranking, the effect is more pronounced for the first ranking positions (i.e., 1-15, or 1-30, depending on the specification).

We first examine the Ph.D. attendance, considering Ph.D. in Brazil or abroad. Table 5 presents the results. Only IPE-USP's estimator is significant in the four columns. The probability that an IPE-USP student attends a Ph.D. program in Brazil or abroad is about 0.264 percentage point lower than students that attend FGV-EESP (see column (4)). The low significance of the other estimates can be a result of low power since the variance of the estimator is high. Indeed, our sample is quite small, as we only have 234 observations of students who opted for and were admitted by all Top 4 institutions. In column (1), in the regression without controls, for dummies FGV-EPGE and PUC-RIO, the standard error represents respectively 1.66 and 0.60 of the coefficient estimates. The F-test results suggest that the institution effect on Ph.D. placement is different for the four institutions.

We now examine the attendance in a Ph.D. program abroad. We present the results in Table 6. First, the four institutions' parameters seem to be equal, even when we add the controls for ANPEC score or ranking (see F-test). The IPE-USP coefficient becomes insignificant when we consider Ph.D. abroad as the outcome. Therefore, the significance of the coefficient estimated at Table 5 seems mainly due to the Ph.D. enrollments in Brazil. Second, the estimators of ANPEC performance are consistently significant. Students who rank 1-15 have a 88.7% higher probability of enrolling in a Ph.D. abroad (see column (4)). Finally, in this table, the magnitude of the coefficients is much lower, reducing the concern that the absence of statistical power is due to number of observations.

Table 5 – Probability of attending a Ph.D. program in Brazil or abroad, Top 4 institutions

	(1)	(2)	(3)	(4)
FGV-EPGE	0.053	0.090	0.082	0.068
	(0.110)	(0.103)	(0.106)	(0.113)
PUC-RIO	-0.208	-0.202*	-0.195	-0.205
	(0.119)	(0.109)	(0.110)	(0.123)
IPE-USP	-0.243*	-0.264*	-0.263*	-0.264*
	(0.130)	(0.125)	(0.122)	(0.127)
Normalised ANPEC score		0.295***		
		(0.067)		
ANPEC ranking			-0.004**	
			(0.002)	
Range of ANPEC ranking				
0 to 15				0.330***
				(0.099)
16 to 30				0.095
				(0.117)
31 to 45				0.219*
				(0.110)
46 to 60				0.108
				(0.099)
F-test	0.002	0.001	0.002	0.001
Dependent variable (mean)	0.556	0.556	0.556	0.556
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	234	234	234	234

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Ph.D program, zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. F-test is testing if the parameters of institution's attendance are equal. Robust standard errors are shown in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%.

Table 6 – Probability of attending a Ph.D. abroad, Top 4 institutions

	(1)	(2)	(3)	(4)
FGV-EPGE	0.044	0.091	0.079	0.089
	(0.086)	(0.087)	(0.093)	(0.086)
PUC-RIO	0.024	0.031	0.040	0.039
	(0.100)	(0.104)	(0.105)	(0.093)
IPE-USP	-0.049	-0.075	-0.074	-0.066
	(0.105)	(0.114)	(0.113)	(0.110)
Normalised ANPEC score		0.374***		
		(0.074)		
ANPEC ranking			-0.006**	
			(0.002)	
Range of ANPEC ranking				
0 to 15				0.385***
				(0.109)
16 to 30				0.153**
				(0.050)
31 to 45				0.086
				(0.125)
46 to 60				0.146
				(0.132)
F-test	0.604	0.332	0.378	0.434
Dependent variable (mean)	0.312	0.312	0.312	0.312
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	234	234	234	234

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Ph.D program abroad, zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. F-test is testing if the parameters of institution's attendance are equal. Robust standard errors are shown in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%.

Considering that institutions do not differ in terms of Ph.D. abroad enrollments, it would be relevant to check whether some institution stands out when considering programs with higher reputation. We analyze the attendance in the top 20 and top 10 Ph.D. abroad programs. We show the results in Tables 7 and 8. We notice that the institution effect on enrollments in the top 20 and top 10 Ph.D. programs abroad is still equivalent among Top 4 institutions (see F-test).

Table 7 – Probability of attending a top 20 Ph.D. abroad, Top 4 institutions

	(1)	(2)	(3)	(4)
FGV-EPGE	0.046	0.090	0.078	0.085
	(0.067)	(0.069)	(0.074)	(0.071)
PUC-RIO	0.023	0.029	0.038	0.036
	(0.076)	(0.087)	(0.084)	(0.087)
IPE-USP	-0.051	-0.076	-0.074	-0.068
	(0.087)	(0.097)	(0.092)	(0.091)
Normalised ANPEC score		0.351***		
		(0.069)		
ANPEC ranking			-0.005**	
			(0.002)	
Range of ANPEC ranking				
0 to 15				0.307***
				(0.087)
16 to 30				0.115***
				(0.036)
31 to 45				0.049
				(0.094)
46 to 60				0.068
				(0.085)
F-test	0.411	0.233	0.200	0.279
Dependent variable (mean)	0.235	0.235	0.235	0.235
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	234	234	234	234

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Top 20 Ph.D program, zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. F-test is testing if the parameters of institution's attendance are equal. Robust standard errors are shown in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%.

Table 8 – Probability of attending a top 10 Ph.D. abroad, Top 4 institutions

	(1)	(2)	(3)	(4)
FGV-EPGE	-0.011	0.031	0.020	0.025
	(0.077)	(0.084)	(0.086)	(0.084)
PUC-RIO	-0.007	-0.001	0.007	0.006
	(0.093)	(0.102)	(0.101)	(0.102)
IPE-USP	-0.073	-0.096	-0.094	-0.085
	(0.097)	(0.112)	(0.108)	(0.103)
Normalised ANPEC score		0.326***		
		(0.060)		
ANPEC ranking			-0.005***	
			(0.001)	
Range of ANPEC ranking				
0 to 15				0.289***
				(0.060)
16 to 30				0.129***
				(0.038)
31 to 45				0.059
				(0.036)
46 to 60				0.127*
				(0.070)
F-test	0.286	0.201	0.161	0.260
Dependent variable (mean)	0.192	0.192	0.192	0.192
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	234	234	234	234

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Top 10 Ph.D program, zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. F-test is testing if the parameters of institution's attendance are equal. Robust standard errors are shown in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%.

In summary, the results suggest that each institution's effect seems to be equivalent in terms of Ph.D. placement. Only IPE-USP's students seem to enroll with a lower probability in a Ph.D. program in Brazil. If we consider that PUC-RIO has a reputation of enrolling more students in Ph.D. programs abroad, we can imagine that the ANPEC applicants most interested in attending a Ph.D. program abroad will attend, with a higher probability, PUC-RIO. If that were the case, we would be estimating the upper-bound effect of the PUC-RIO. Therefore, the non-significance of the estimates for PUC-RIO suggests that this institution does not seem to have an advantage in enrolling its students in Ph.D. programs abroad.

In contrast, the estimates for ANPEC performance are significant in most specifications. As expected, the results show that applicants with higher exam scores and lower classification are more likely to enroll in a Ph.D. program. In particular, the students ranked until the 15th classification seems to have higher chances of enrolling in a Ph.D. program.

We now compare the Ph.D. placement within the Top 4 institutions using equation (2). We show the results in Tables 9, 10, 11 and 12. The sample, in that case, is the students who listed and passed in at least two of Top 4 institutions. As we defined four top institutions, we need six pairs to compare them two-by-two, and the results are shown in columns (1) to (6). As before, we also control for exam performance and present the result in four panels.

In Table 9, we report the estimates using the Ph.D. enrollments in Brazil or abroad as the outcome. The results show a consistently significant estimate for FGV-EPGE compared to PUC-RIO and IPE-USP students, representing an advantage of FGV-EPGE students in terms of Ph.D. enrollments in Brazil or abroad. According to Panel D, FGV-EPGE's students attend a Ph.D. program with a probability of 0.242 p.p. higher when we control for the range of ANPEC ranking. Attending FGV-EPGE instead of IPE-USP makes the probability of attending a Ph.D. program increase by 41 %. In comparison with PUC-RIO, FGV-EPGE's students attend a Ph.D. program with a probability 0.157 p.p. higher, which correspond to an increase of 26 %. As before, notice that we also have few observations in the pairwise comparison sample. In principle, we cannot distinguish low power from low institution effect on Ph.D. placement. However, the effect of FGV-EPGE institution, when compared to IPE-USP and PUC-RIO, is significant in all estimations.

Table 10 shows the pairwise comparisons between Top 4 institutions for the outcome Ph.D. abroad. FGV-EPGE stands out when allocating its students in Ph.D. programs abroad when compared with IPE-USP. According to panel D, FGV-EPGE's student has a probability of enrolling at a Ph.D. abroad 0.138 p.p. higher than an IPE-USP's student. Once more, there is no significant effect of attending PUC-RIO relative to the other Top 4 institutions.

Comparing the Ph.D. programs abroad with higher reputation, the estimates of

Table 9 – Probability of attending a Ph.D. program in Brazil or abroad, Top 4 institutions - Pairwise Comparisons

	(1) FGV-EESP x FGV-EPGE	(2) FGV-EESP x PUC-RIO	(3) FGV-EESP x IPE-USP	(4) FGV-EPGE x PUC-RIO	(5) FGV-EPGE x IPE-USP	(6) PUC-RIO x IPE-USP
Panel A: Without Control						
FGV-EESP	-0.129	0.250*	0.091			
	(0.111)	(0.131)	(0.102)			
FGV-EPGE				0.119*	0.244***	
				(0.061)	(0.067)	
PUC-RIO						0.037
						(0.104)
Dependent variable (mean)	0.657	0.508	0.484	0.610	0.597	0.521
Number of observations	169	118	219	300	258	211
Panel B: Control Score						
FGV-EESP	-0.110	0.182	0.123			
	(0.103)	(0.137)	(0.102)			
FGV-EPGE				0.185***	0.262***	
				(0.056)	(0.066)	
PUC-RIO						0.058
						(0.103)
Normalised ANPEC score	0.159*	0.477***	0.139	0.236***	0.173**	0.295***
	(0.073)	(0.112)	(0.137)	(0.061)	(0.069)	(0.073)
Dependent variable (mean)	0.657	0.508	0.484	0.610	0.597	0.521
Number of observations	169	118	219	272	241	195
Panel C: Control Ranking						
FGV-EESP	-0.106	0.169	0.126			
	(0.104)	(0.150)	(0.101)			
FGV-EPGE				0.161**	0.256***	
				(0.056)	(0.064)	
PUC-RIO						0.070
						(0.096)
ANPEC ranking	-0.002*	-0.009***	-0.002	-0.005***	-0.002	-0.007***
	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
Dependent variable (mean)	0.657	0.508	0.484	0.610	0.597	0.521
Number of observations	169	118	219	300	258	211
Panel D: Control Range of Ranking						
FGV-EESP	-0.117	0.149	0.123			
	(0.107)	(0.147)	(0.103)			
FGV-EPGE				0.157**	0.242***	
				(0.056)	(0.066)	
PUC-RIO						0.076
						(0.100)
Range of ANPEC ranking						
0 to 15	0.221**	0.580***	0.129	0.406***	0.202*	0.597***
	(0.080)	(0.124)	(0.160)	(0.092)	(0.106)	(0.103)
16 to 30	-0.029	0.435***	-0.023	0.280***	0.019	0.474***
	(0.114)	(0.104)	(0.118)	(0.082)	(0.110)	(0.114)
31 to 45	0.091	0.376**	0.141	0.276***	0.057	0.536***
	(0.129)	(0.168)	(0.117)	(0.067)	(0.098)	(0.119)
46 to 60	0.049	0.035	-0.089	0.314***	0.105	0.399**
	(0.129)	(0.122)	(0.081)	(0.081)	(0.095)	(0.153)
Dependent variable (mean)	0.657	0.508	0.484	0.610	0.597	0.521
Number of observations	169	118	219	300	258	211
Year fixed effects	Yes	Yes	0.055	Yes	Yes	Yes

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Ph.D program, zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

FGV-EPGE and PUC-RIO are significant when compared with IPE-USP (see columns (5) and (6) of Table 11). According to Panel D, FGV-EPGE's students place in a top 20 Ph.D. program with a probability 0.153 p.p. higher comparing to IPE-USP. At the same time,

Table 10 – Probability of attending a Ph.D. abroad, Top 4 institutions - Pairwise Comparisons

	(1) FGV-EESP x FGV-EPGE	(2) FGV-EESP x PUC-RIO	(3) FGV-EESP x IPE-USP	(4) FGV-EPGE x PUC-RIO	(5) FGV-EPGE x IPE-USP	(6) PUC-RIO x IPE-USP
Panel A: Without Control						
FGV-EESP	-0.147	0.015	-0.049			
	(0.082)	(0.125)	(0.077)			
FGV-EPGE				-0.033	0.135*	
				(0.052)	(0.070)	
PUC-RIO						0.052
						(0.087)
Dependent variable (mean)	0.302	0.339	0.196	0.340	0.306	0.313
Number of observations	169	118	219	300	258	211
Panel B: Control Score						
FGV-EESP	-0.113	-0.066	0.001			
	(0.068)	(0.121)	(0.067)			
FGV-EPGE				0.009	0.131	
				(0.055)	(0.077)	
PUC-RIO						0.060
						(0.094)
Normalised ANPEC score	0.281***	0.566***	0.215*	0.335***	0.292***	0.282***
	(0.060)	(0.099)	(0.108)	(0.063)	(0.073)	(0.080)
Dependent variable (mean)	0.302	0.339	0.196	0.340	0.306	0.313
Number of observations	169	118	219	272	241	195
Panel C: Control Ranking						
FGV-EESP	-0.115	-0.071	-0.009			
	(0.070)	(0.134)	(0.070)			
FGV-EPGE				0.013	0.153*	
				(0.054)	(0.073)	
PUC-RIO						0.078
						(0.087)
ANPEC ranking	-0.003**	-0.010***	-0.002	-0.005***	-0.003**	-0.005**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Dependent variable (mean)	0.302	0.339	0.196	0.340	0.306	0.313
Number of observations	169	118	219	300	258	211
Panel D: Control Range of Ranking						
FGV-EESP	-0.149*	-0.099	-0.025			
	(0.077)	(0.109)	(0.077)			
FGV-EPGE				0.029	0.138*	
				(0.056)	(0.077)	
PUC-RIO						0.064
						(0.092)
Range of ANPEC ranking						
0 to 15	0.418***	0.678***	0.167	0.415***	0.319***	0.350***
	(0.096)	(0.096)	(0.119)	(0.061)	(0.103)	(0.090)
16 to 30	0.029	0.368***	0.000	0.223***	0.033	0.173
	(0.119)	(0.083)	(0.090)	(0.055)	(0.080)	(0.119)
31 to 45	-0.031	0.194	0.029	0.052	-0.067	0.186
	(0.147)	(0.153)	(0.117)	(0.071)	(0.088)	(0.126)
46 to 60	0.104	0.162	-0.045	0.253**	0.143	0.182
	(0.173)	(0.106)	(0.087)	(0.095)	(0.097)	(0.149)
Dependent variable (mean)	0.302	0.339	0.196	0.340	0.306	0.313
Number of observations	169	118	219	300	258	211
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Ph.D program abroad., zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

PUC-RIO has an advantage of approximately 0.158 p.p. (see panel D). The comparison between FGV-EESP and FGV-EPGE shows that the probability that FGV-EPGE students enroll in a top 20 Ph.D. program is 0.138 p.p. higher. Table 12 present the results when we examine the attendance in a top 10 Ph.D. program abroad. The pairwise comparisons reveal that PUC-RIO seem to have an advantage when allocating its students in a top 10 Ph.D. program, as compared to IPE-USP. PUC-RIO maintains an advantage of about 0.126 p.p. in placing its students at a top 10 Ph.D. program abroad to IPE-USP (see column (6) of panel D).

The results suggest that PUC-RIO does not seem to have an advantage of enrolling its students in a top Ph.D. abroad when compared to FGV-EPGE and FGV-EESP. In contrast, we find a significant (upper-bound) effect for PUC-RIO when compared to IPE-USP. If PUC-RIO attracts students with a higher propensity to attend to a Ph.D. top 10 or top 20 programs abroad, the effect of attending PUC-RIO could be less than the effects estimated (0.158 p.p. and 0.126 p.p. when we consider top 20 and top 10 programs, respectively).

In summary, the pairwise comparison suggests that FGV-EPGE seems to have an advantage over IPE-USP in terms of Ph.D. enrollments abroad, also in Ph.D. programs with a higher reputation. Moreover, PUC-RIO does not have an advantage when compared to FGV-EESP and FGV-EPGE, even when we consider the most reputable Ph.D. programs abroad. However, PUC-RIO seems to have an advantage when compared to IPE-USP.

We conduct the multiple testing hypothesis (MHT) in Appendix 7. The conclusion is similar. We also present the results considering only the recent years (2009-2015) and the results using an alternative ranking in Appendix 8. In that case, the conclusion is also similar.

6.2 Comparisons between Top 4 and non-Top 4

In this section, we present the results for the comparison between the Top 4 with non-Top 4 institutions using the RDD framework. As described in Section 5, we set the RDD cutoff as the ANPEC inferred classification. That inference determines if the student was admitted to the master's program for each institution. We estimate equation 3 using probability of attendance in a Ph.D. and Ph.D. programs abroad as the outcomes. As a result, we estimate the effect of attending a selective institution considering small changes in admission cutoffs in terms of the Ph.D. placement.

Figures 9 and 10 illustrate the probability that students attend a Ph.D. program comparing the most selective institutions to the relatively less selective institutions.[18] We compare attendance in Ph.D. programs and Ph.D. programs abroad of students just below and just above the cutoff. In Figure 9, we compare the students that passed at least in

[18] We centralized the cutoff in zero and divided by 100. The variation in the student's classification around the cutoff is on the x-axis.

Table 11 – Probability of attending a top 20 Ph.D. abroad, Top 4 institutions - Pairwise Comparisons

	(1) FGV-EESP x FGV-EPGE	(2) FGV-EESP x PUC-RIO	(3) FGV-EESP x IPE-USP	(4) FGV-EPGE x PUC-RIO	(5) FGV-EPGE x IPE-USP	(6) PUC-RIO x IPE-USP
Panel A: Without Control						
FGV-EESP	-0.141	-0.039	0.012			
	(0.093)	(0.098)	(0.067)			
FGV-EPGE				-0.043	0.141*	
				(0.056)	(0.065)	
PUC-RIO						0.145**
						(0.066)
Dependent variable (mean)	0.201	0.271	0.096	0.280	0.194	0.232
Number of observations	169	118	219	300	258	211
Panel B: Control Score						
FGV-EESP	-0.108	-0.116	0.068			
	(0.067)	(0.113)	(0.049)			
FGV-EPGE				-0.002	0.151*	
				(0.061)	(0.074)	
PUC-RIO						0.163**
						(0.067)
Normalised ANPEC score	0.275**	0.534***	0.241**	0.307***	0.273***	0.276***
	(0.099)	(0.077)	(0.086)	(0.062)	(0.049)	(0.074)
Dependent variable (mean)	0.201	0.271	0.096	0.280	0.194	0.232
Number of observations	169	118	219	272	241	195
Panel C: Control Ranking						
FGV-EESP	-0.108	-0.119	0.063			
	(0.071)	(0.120)	(0.053)			
FGV-EPGE				-0.000	0.162**	
				(0.058)	(0.070)	
PUC-RIO						0.170**
						(0.065)
ANPEC ranking	-0.003**	-0.009***	-0.003**	-0.005***	-0.004***	-0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Dependent variable (mean)	0.201	0.271	0.096	0.280	0.194	0.232
Number of observations	169	118	219	300	258	211
Panel D: Control Range of Ranking						
FGV-EESP	-0.138*	-0.141	0.051			
	(0.068)	(0.121)	(0.061)			
FGV-EPGE				0.018	0.153*	
				(0.057)	(0.072)	
PUC-RIO						0.158*
						(0.073)
Range of ANPEC ranking						
0 to 15	0.405***	0.589***	0.202**	0.375***	0.331***	0.319***
	(0.124)	(0.073)	(0.084)	(0.052)	(0.066)	(0.089)
16 to 30	0.088	0.372***	0.069	0.166***	0.105	0.153
	(0.070)	(0.088)	(0.050)	(0.052)	(0.069)	(0.122)
31 to 45	0.025	0.210	0.055	0.020	-0.022	0.163
	(0.091)	(0.131)	(0.056)	(0.065)	(0.057)	(0.100)
46 to 60	0.185	0.138	-0.018	0.179**	0.142	0.139
	(0.131)	(0.101)	(0.042)	(0.079)	(0.087)	(0.127)
Dependent variable (mean)	0.201	0.271	0.096	0.280	0.194	0.232
Number of observations	169	118	219	300	258	211
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Top 20 Ph.D program , zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

one Top 4 institution with those who passed only in a non-Top 4 institution. In Figure 10, we make a similar comparison but using the Top 3 institutions.[19] Graphically, it appears

[19] We consider only the institutions FGV-EESP, FGV-EPGE, and PUC-RIO in the Top 3 definition.

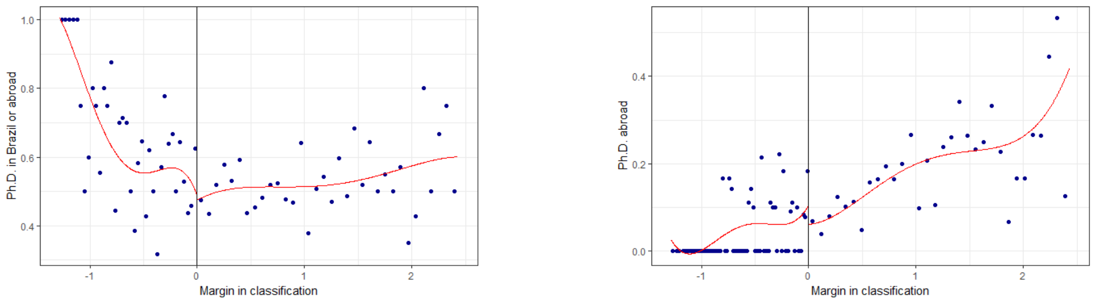
Table 12 – Probability of attending a top 10 Ph.D. abroad, Top 4 institutions - Pairwise Comparisons

	(1) FGV-EESP x FGV-EPGE	(2) FGV-EESP x PUC-RIO	(3) FGV-EESP x IPE-USP	(4) FGV-EPGE x PUC-RIO	(5) FGV-EPGE x IPE-USP	(6) PUC-RIO x IPE-USP
Panel A: Without Control						
FGV-EESP	-0.071	-0.023	0.033			
	(0.076)	(0.091)	(0.068)			
FGV-EPGE				-0.093	0.088	
				(0.061)	(0.057)	
PUC-RIO						0.122**
						(0.056)
Dependent variable (mean)	0.148	0.237	0.082	0.210	0.143	0.190
Number of observations	169	118	219	300	258	211
Panel B: Control Score						
FGV-EESP	-0.035	-0.092	0.074			
	(0.048)	(0.099)	(0.058)			
FGV-EPGE				-0.059	0.103	
				(0.064)	(0.065)	
PUC-RIO						0.145**
						(0.057)
Normalised ANPEC score	0.290**	0.483***	0.178**	0.322***	0.256***	0.248**
	(0.100)	(0.074)	(0.076)	(0.061)	(0.045)	(0.083)
Dependent variable (mean)	0.148	0.237	0.082	0.210	0.143	0.190
Number of observations	169	118	219	272	241	195
Panel C: Control Ranking						
FGV-EESP	-0.032	-0.093	0.070			
	(0.050)	(0.103)	(0.063)			
FGV-EPGE				-0.056	0.108	
				(0.062)	(0.062)	
PUC-RIO						0.141**
						(0.055)
ANPEC ranking	-0.003**	-0.008***	-0.002*	-0.004***	-0.004***	-0.004*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Dependent variable (mean)	0.148	0.237	0.082	0.210	0.143	0.190
Number of observations	169	118	219	300	258	211
Panel D: Control Range of Placement						
FGV-EESP	-0.065	-0.114	0.064			
	(0.056)	(0.110)	(0.067)			
FGV-EPGE				-0.044	0.099	
				(0.061)	(0.064)	
PUC-RIO						0.126**
						(0.057)
Range of ANPEC Placement						
0 to 15	0.392***	0.513***	0.136*	0.298***	0.280***	0.217**
	(0.116)	(0.082)	(0.064)	(0.057)	(0.054)	(0.076)
16 to 30	0.130	0.320***	0.072	0.127*	0.114	0.077
	(0.105)	(0.073)	(0.054)	(0.061)	(0.074)	(0.098)
31 to 45	0.032	0.143	0.055	0.017	0.010	0.094
	(0.043)	(0.100)	(0.052)	(0.037)	(0.052)	(0.068)
46 to 60	0.191	0.131	-0.018	0.141	0.163*	0.100
	(0.122)	(0.081)	(0.041)	(0.089)	(0.088)	(0.117)
Dependent variable (mean)	0.148	0.237	0.082	0.210	0.143	0.190
Number of observations	169	118	219	300	258	211
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Top 10 Ph.D program, zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

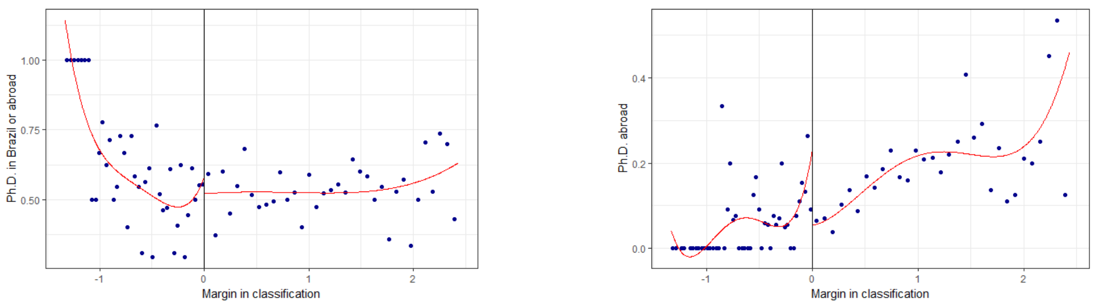
that there is no discontinuity in the probability of attending Ph.D. programs around the cutoff when comparing Top 4 with non-Top 4. But, when comparing Top 3 with non-Top 3, it seems that there is a discontinuity in the probability of attending Ph.D. programs abroad. Just above the cutoff, the probability of attending a Ph.D. program increases when a student's classification decreases.

The probability of enrolling in a Ph.D. program in Brazil or abroad is decreasing below the admission rating. Those students who have barely passed the Top 4 are less likely to attend a Ph.D. program than students who have barely passed the Top 4. When we consider only Ph.D. programs abroad, the probability becomes increasing, which means that a higher classification correlates with a higher chance of attending a Ph.D. abroad. This probability drops at the cutoff, suggesting that students very close to the cutoff who passed the Top 4 have a lower chance of attending a Ph.D. abroad. It seems that the students with the lowest ANPEC score that pass the Top 4 face higher competition when applying for the Ph.D. abroad, while students that did not pass the Top 4 face less competition.



(a) Ph.D. in Brazil or abroad (b) Ph.D. abroad

Figure 9 – Outcomes around admission cutoffs - Top 4 × non-Top 4



(a) Ph.D. in Brazil or abroad (b) Ph.D. abroad

Figure 10 – Outcomes around admission cutoffs - Top 3 × non-Top 3

Table 13 shows the RDD estimates from comparison Top 4 institutions with non-Top 4 institutions. The results suggest that attending one of the Top 4 institutions does not imply that the student has a higher chance of enrolling in a Ph.D. program or a Ph.D. program abroad more than an applicant attends one of the non-Top 4 institutions. Similarly, attending one of the Top 3 institutions does not imply that the student attends a Ph.D. program or a Ph.D. program abroad with a higher probability than an applicant attends one of the non-Top 3 institutions in Ph.D. (see Table 14).

Table 13 – Estimates of the effect of attending a Top 4 institution in Ph.D. enrollments

	Ph.D.	Ph.D. abroad
Top 4	-0.556	-0.446
	(0.810)	(0.480)
Sample Size	289	305

Notes: The first column reports the results using the dependent variable as a binary variable equal to one if the applicant attended to Ph.D. in Brazil or abroad, zero otherwise. The second column reports the results using the dependent variable is a binary variable equal to one if the applicant attended to Ph.D. abroad, zero otherwise. Top 4 is a dummy equal 1 if applicant passed to FGV-EESP, FGV-EPGE, PUC-RIO, IPE-USP for master's degree. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%

Table 14 – Estimates of the effect of attending a Top 3 institution in Ph.D. enrollments

	Ph.D.	Ph.D. abroad
Top 3	-0.234	-0.570
	(0.501)	(0.360)
Sample Size	340	261

Notes: The first column reports the results using the dependent variable as a binary variable equal to one if the applicant attended to Ph.D. in Brazil or abroad, zero otherwise. The second column reports the results using the dependent variable is a binary variable equal to one if the applicant attended to Ph.D. abroad, zero otherwise. Top 3 is a dummy equal 1 if applicant passed to FGV-EESP, FGV-EPGE, PUC-RIO for master's degree. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%

The result shows that the local effect of the attendance in a selective institution is insignificant in terms of Ph.D. enrollments. Even when we consider the most selective institutions, excluding IPE-USP, attendance does not affect Ph.D. attendance. Even if they are not significant, the coefficients are large and negative. Students with the lowest ANPEC score and highest classification seems to have a lower probability of enrolling in a Ph.D. program when attending the more selective institutions in master. We can imagine that students on the margin of admission, when attending more selective institutions, face higher competition when applying to a Ph.D. program while attending less selective institutions, they would face less competition.

7 Conclusion

In this thesis, we investigate the Ph.D. placement comparing students that attend a more selective institution during the master's degree with those that attend a less selective institution. To measure the institution's effect on Ph.D. placement, we have to approach the problem associated with the selection bias. The selection occurs when institutions choose the applicants accepted in their selection process and when the student decides to which institution he will apply. First, we use the methodology suggested by Dale and Krueger (2002) that matches students who applied to and were accepted by the same institutions. We also use the Regression Discontinuity Designs (RDD) framework that focuses on the acceptance or rejection of the students by a small margin.

Overall, our findings suggest that the most selective institutions do not have an impact on students' Ph.D. placement when we compare students just below with those just above the classification cutoff. In addition, the estimated coefficients in that analysis, although not significant, are large and negative. We can imagine that students on the margin of admission, when attending more selective institutions, face higher competition when applying to a Ph.D. program while attending less selective institutions, they would face less competition. In the joint comparison, where we consider students who were admitted in four of the Top 4 institutions, each institution's effect seems equivalent. Only students at IPE-USP seem to enroll with a lower probability in a Ph.D. program in Brazil. For this sample, what stands out most seems to be the ANPEC performance. That result suggests that the ANPEC score can be signaling to the Ph.D. admission committees, or the ANPEC score correlates with student's unobserved skills that correlate with the Ph.D. enrollment. In the pairwise comparison, where we consider students who were admitted to at least two of the Top 4 institutions, FGV-EPGE seems to have an advantage over IPE-USP in terms of Ph.D. enrollments abroad, also in Ph.D. programs with higher reputation. PUC-RIO has an advantage over IPE-USP only when we consider the most reputable Ph.D. programs, but it does not seem to have an advantage when compared to FGV-EESP and FGV-EPGE.

Since the results of the literature about the impact of selective institutions are mixed, this thesis tries to fill the literature gap measuring the impact of attending a selective school in Ph.D. placement relating the studies of the effects of attending a selective school and the determinants of Ph.D. enrollment. Our results conclude that attending a selective institution when compared to less selective institutions has no effect on the Ph.D. enrollment, but the effect among the most selective schools could be significant in some cases.

The next steps to exploit this issue are the analysis of the effect of selective schools in academic productivity. The Ph.D. placement possibly has a relation with academic production in economics. Future studies can focus on the effect of the schools of selective institutions on academic production after completing the master's degree.

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1 Appendix - Shangai Ranking

In this appendix, we provide the Shanghai Ranking published by Shanghai Ranking Consultancy, an independent organization dedicating to research on higher education intelligence and consultation. We use this ranking to classify the programs that students in our sample enroll in. The classification used was that of 2019, and it is present in Table 15.

Table 15 – Shanghai Ranking

Shanghai Ranking	Institution
1	University of Chicago
2	Harvard University
3	University of California, Berkeley
4	Columbia University
5	Massachusetts institution of Technology (MIT)
6	Princeton University
7	London School of Economics and Political Science
8	Stanford University
9	New York University
10	Yale University
11	Northwestern University
12	University of Cambridge
13	University of Pennsylvania
14	University of Oxford
15	University of California, Los Angeles
16	University of California, San Diego
17	University College London
18	Duke University
19	University of Michigan-Ann Arbor
20	University of Maryland, College Park

2 Appendix - Descriptive Statistics

In this section, we present additional descriptive statistics of our sample. Table 16 presents the average score, the proportion of students that enrolled in a Ph.D. program, and demographic characteristics of the applicants depending on the city where they attended college. We found that the majority of applicants among the top 250 of ANPEC did their undergraduate studies in *São Paulo* and *Rio de Janeiro*. These two cities also concentrate the applicants with the highest scores and lowest classifications. The score in most subjects follows this pattern, while the city of *Campinas* has the students with the best grades in the Brazilian Economy exam. That pattern could be due to the presence of a local research center that weighs the Brazilian Economy score more. The proportion of students who attend a Ph.D. program is similar among cities, while it seems that students from *Rio de Janeiro* enroll in a Ph.D. program abroad with a higher probability.

Table 17 presents the average score, the proportion of students that enrolled in a Ph.D. program, and demographic characteristics of the applicants across the M.A. institutions. The number of applicants in the sample that attended IPE-USP is higher compared to the Top 4 and lower at FGV-SP. The average ANPEC classification of those that attended PUC -RIO is the lowest compared to the Top 4. PUC-RIO also has a higher proportion of its students enrolling in Ph.D. programs abroad. That advantage is more pronounced when we consider only the top 10 Ph.D. programs.

Table 18 presents the proportion of ANPEC applicants that stayed in the same city between college and M.A. Students from *Rio de Janeiro* and *Recife* migrate less after college, and most students from *Porto Alegre* migrate. The institutions located in *São Paulo* (FGV-EESP and IPE-USP) have a higher proportion of students that already lived in the city. In contrast, the *Rio de Janeiro* institutions (PUC-RIO and FGV-EPGE) have more migrant students.

Table 19 shows the mean and standard deviation of the ANPEC score per year of the sample. We see that the average is higher in some years, and the standard deviation is smaller, meaning that there are different levels of competition per year. Table 20 shows the class size by M.A. institution and year. On average, among the Top 4, FGV-EESP is the institution with the fewest students by class, and IPE-USP is the institution with the most students.

Table 16 – Descriptive Statistics across college institutions cities

Undergraduate institutions' city	ANPEC Ranking	ANPEC Score	Microeconomics	Macroeconomics	Statistics	Maths	Brazilian Economy	Observations
SAO PAULO	75 (59.11)	1535 (613.14)	7 (2.37)	7 (2.44)	7 (2.90)	7 (2.56)	6 (2.55)	430
RIO DE JANEIRO	85 (58.50)	1392 (539.37)	7 (2.45)	7 (2.27)	7 (2.82)	7 (2.71)	4 (2.64)	421
BRASILIA	86 (53.82)	1391 (538.80)	7 (2.30)	7 (2.13)	6 (2.85)	6 (2.23)	5 (2.22)	152
BELO HORIZONTE	108 (64.51)	1220 (532.57)	6 (2.53)	6 (2.37)	6 (2.57)	6 (2.43)	5 (2.19)	116
CAMPINAS	114 (57.79)	1145 (506.16)	6 (2.25)	6 (2.40)	4 (2.43)	5 (2.55)	7 (2.17)	108
PORTO ALEGRE	119 (61.15)	1104 (471.82)	6 (2.05)	6 (2.06)	5 (2.53)	6 (2.42)	4 (2.86)	81
RECIFE	131 (59.59)	1015 (405.13)	6 (1.94)	6 (2.00)	6 (2.46)	5 (2.39)	5 (2.68)	47
NITEROI	145 (53.36)	922 (409.12)	5 (2.38)	6 (1.99)	5 (2.94)	5 (2.42)	4 (2.55)	40

	Enrolled in Ph.D.	Enrolled in Ph.D. abroad	Enrolled in top 20 Ph.D.	Enrolled in top 10 Ph.D.
SAO PAULO	0.51	0.19	0.09	0.07
RIO DE JANEIRO	0.47	0.18	0.12	0.09
BRASILIA	0.45	0.09	0.05	0.03
BELO HORIZONTE	0.58	0.17	0.07	0.03
CAMPINAS	0.56	0.06	0.03	0.02
PORTO ALEGRE	0.64	0.14	0.05	0.02
RECIFE	0.72	0.13	0.00	0.00
NITEROI	0.50	0.03	0.03	0.03

	Male	Single	White	Age
SAO PAULO	0.77	0.82	0.81	23.82 (3.18)
RIO DE JANEIRO	0.74	0.78	0.75	23.15 (3.29)
BRASILIA	0.71	0.78	0.79	23.23 (3.22)
BELO HORIZONTE	0.72	0.77	0.77	23.45 (1.66)
CAMPINAS	0.78	0.82	0.73	24.26 (1.80)
PORTO ALEGRE	0.69	0.83	0.98	23.26 (2.60)
RECIFE	0.77	0.79	0.60	23.09 (1.82)
NITEROI	0.80	0.78	0.67	23.42 (1.98)

	% applicants from 0 to classification 15 by city					% applicants from 0 to classification 30 by city				
	ANPEC Ranking	FGV-EESP Ranking	FGV-EPGE Ranking	IPE-USP Ranking	PUC-RIO Ranking	ANPEC Ranking	FGV-EESP Ranking	FGV-EPGE Ranking	IPE-USP Ranking	PUC-RIO Ranking
SAO PAULO	0.18	0.15	0.13	0.16	0.13	0.31	0.29	0.26	0.30	0.26
RIO DE JANEIRO	0.10	0.13	0.15	0.14	0.16	0.21	0.24	0.27	0.24	0.27
BRASILIA	0.08	0.05	0.05	0.06	0.06	0.20	0.16	0.14	0.18	0.14
BELO HORIZONTE	0.05	0.05	0.07	0.05	0.06	0.10	0.09	0.14	0.11	0.13
CAMPINAS	0.06	0.04	0.05	0.06	0.04	0.11	0.11	0.08	0.09	0.08
PORTO ALEGRE	0.02	0.04	0.04	0.04	0.04	0.09	0.07	0.06	0.07	0.06
RECIFE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.02	0.09
NITEROI	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.03

Notes: The table reports the variables mean by the city applicant coursed undergraduate. We consider only the most recent ANPEC subscription and the applicants ranking in the first 250 positions. The years of our sample are 2001 and 2004-2015. Standard deviations are shown in parentheses.

Table 17 – Descriptive Statistics across M.A. institutions

M.A. institutions	ANPEC Ranking	ANPEC Score	Microeconomics	Macroeconomics	Statistics	Maths	Brazilian Economy	Observations
FGV-EESP	77 (40.57)	1416 (449.11)	7 (2.17)	8 (2.15)	7 (2.43)	7 (1.84)	5 (2.57)	142
FGV-EPGE	40 (27.70)	1814 (419.48)	9 (1.68)	9 (2.15)	8 (2.30)	9 (1.91)	4 (2.74)	202
PUC-RIO	25 (20.94)	2064 (460.64)	9 (1.80)	9 (1.84)	9 (2.19)	9 (1.79)	5 (2.91)	165
IPE-USP	42 (27.15)	1795 (383.81)	8 (1.95)	8 (2.04)	7 (2.34)	7 (2.09)	6 (2.36)	235

	Enrolled in Ph.D.	Enrolled in Ph.D. abroad	Enrolled in top 20 Ph.D.	Enrolled in top 10 Ph.D.
FGV-EESP	0.56	0.16	0.07	0.06
FGV-EPGE	0.65	0.31	0.23	0.14
PUC-RIO	0.54	0.34	0.29	0.25
IPE-USP	0.47	0.18	0.06	0.05

	Male	Single	White	Age
FGV-EESP	0.80	0.83	0.83	23.15 (2.10)
FGV-EPGE	0.84	0.81	0.81	22.36 (1.48)
PUC-RIO	0.78	0.82	0.77	22.42 (1.58)
IPE-USP	0.78	0.80	0.73	23.11 (2.37)

	% applicants from 0 to classification 15 by city					% applicants from 0 to classification 30 by city				
	ANPEC Ranking	FGV-EESP Ranking	FGV-EPGE Ranking	IPE-USP Ranking	PUC-RIO Ranking	ANPEC Ranking	FGV-EESP Ranking	FGV-EPGE Ranking	IPE-USP Ranking	PUC-RIO Ranking
FGV-EESP	0.08	0.07	0.06	0.08	0.06	0.14	0.15	0.15	0.15	0.15
FGV-EPGE	0.21	0.26	0.28	0.25	0.28	0.42	0.46	0.49	0.47	0.52
PUC-RIO	0.42	0.42	0.43	0.45	0.43	0.68	0.76	0.81	0.77	0.81
IPE-USP	0.16	0.11	0.11	0.12	0.11	0.38	0.31	0.26	0.34	0.24

Notes: The table reports the variables mean by the institution. We consider only the most recent ANPEC subscription and the applicants ranking in the first 250 positions. The years of our sample are 2001 and 2004-2015. Standard deviations are shown in parentheses.

Table 18 – Proportion of students that did not migrate across cities and M.A. institutions

	Stayed in the same city between undergraduate and graduate	Attended the master's degree at the same undergraduate institution	Observations
Undergraduate institutions' city			
SAO PAULO	0.57	0.26	430
RIO DE JANEIRO	0.74	0.34	421
BRASILIA	0.53	0.22	152
BELO HORIZONTE	0.36	0.21	116
CAMPINAS	0.47	0.27	108
PORTO ALEGRE	0.02	0.00	81
RECIFE	0.64	0.17	47
NITEROI	0.35	0.05	40
M.A. institutions			
FGV-EESP	0.60	0.09	142
FGV-EPGE	0.51	0.14	202
PUC-RIO	0.45	0.30	165
IPE-USP	0.61	0.46	235

Notes: The table reports the variables mean by the city and the institution. We consider only the most recent ANPEC subscription and the applicants ranking in the first 250 positions. The years of our sample are 2001 and 2004-2015. Standard deviations are shown in parentheses.

Table 19 – ANPEC Score statistics

Years	Mean	Standard deviation	Min	Max	p25	p50	p75	p90	p95	p99	Observations
2004	1.379,2	547,1	575,9	3082,2	933,3	1319,6	1689,0	2180,2	2395,2	2981,9	132
2005	1.374,2	564,0	472,1	2683,6	914,1	1358,4	1769,4	2166,5	2404,5	2607,8	127
2006	1.287,4	526,1	474,2	2808,2	855,5	1193,7	1683,3	2005,7	2192,2	2752,2	144
2007	1.156,1	554,1	304,6	2718,6	709,1	1043,0	1531,5	1923,6	2271,5	2600,3	129
2008	1.080,3	566,6	200,1	3149,7	682,6	1006,4	1387,6	1820,3	2127,2	2613,2	143
2009	1.181,7	656,6	180,1	3519,5	661,7	1039,8	1569,9	2089,4	2280,3	3133,4	146
2010	1.291,6	558,2	466,7	3046,0	792,1	1220,4	1613,1	2142,8	2334,8	2493,6	130
2011	1.331,4	595,5	503,7	2879,1	830,3	1247,0	1738,1	2171,1	2544,8	2849,7	155
2012	1.453,40	613,80	572,9	3050,2	934,2	1265,1	1912,6	2364,3	2635,4	2943,2	143
2013	1.390,74	552,61	447,6	2939,3	959,7	1292,9	1798,6	2134,3	2490,4	2781,2	139
2014	1.444,89	432,59	814,7	2734,1	1055,4	1428,8	1716,4	1980,3	2242,7	2706,1	128
2015	1.448,89	497,79	752,3	3269,8	1098,0	1369,0	1787,2	2143,9	2315,4	2733,4	127

Notes: The table reports the statistics for ANPEC Score by year. We consider only the most recent ANPEC subscription and the applicants ranking in the first 250 positions. The years of our sample are 2001 and 2004-2015.

Table 20 – Class size by M.A. institution and year

Class size	*FGV-EESP*	*FGV-EPGE*	*PUC-RIO*	*IPE-USP*
Years:				
2001	-	17	14	25
2004	9	18	11	19
2005	17	9	15	15
2006	13	13	17	25
2007	9	19	10	11
2008	15	14	14	18
2009	10	12	15	15
2010	7	17	7	18
2011	12	19	14	14
2012	11	15	14	22
2013	14	20	14	19
2014	14	15	8	17
2015	10	14	12	17
Mean	12	16	13	18

3 Appendix - Estimation without using the Dale and Krueger (2002) method

In this section, we present the result of the estimation of equation (1) if we do not use the method proposed by Dale and Krueger (2002), that is, without matching the students with the same admission decision. As already discussed in section 5, the students' comparison can lead us to wrong conclusions given the students' selection. Table 21 shows the results for Ph.D. in Brazil or abroad. FGV-EPGE seems to have an advantage in enrolling students in Ph.D. programs in Brazil or abroad compared to FGV-EESP and IPE-USP (see Panel D). That is a similar result that we obtained using Dale and Krueger (2002) method.

Table 22 shows the result for Ph.D. abroad. We continue to conclude that FGV-EPGE has an advantage over FGV-EESP (see Panel D). However, some estimators are significant now: PUC-RIO seems to have an advantage over FGV-EESP. PUC-RIO has no advantage when we match students who were admitted to the same institutions and preferred the same institutions. Therefore, part of the PUC-RIO's effect found in the Table 22 seems to be explained by the student's preference: those who prefer PUC-RIO must have a predisposition to enrolls in a Ph.D. program abroad.

Table 23 shows the results using only the top 20 Ph.D. programs. The conclusions are similar, but here the estimator of the FGV-EESP and PUC-RIO comparison is now significant (see Panel D). Table 24 considers only the top 10 programs. The positive effect of attending PUC-RIO when comparing with FGV-EESP and FGV-EPGE is now significant, which shows that preferences for PUC-RIO may be correlated with a predisposition to enroll in a top 10 Ph.D. program (see Panel D).

Table 21 – Probability of attending a Ph.D. program in Brazil or abroad, Top 4 institutions - Pairwise Comparisons using all sample

	(1) FGV-EESP x FGV-EPGE	(2) FGV-EESP x PUC-RIO	(3) FGV-EESP x IPE-USP	(4) FGV-EPGE x PUC-RIO	(5) FGV-EPGE x IPE-USP	(6) PUC-RIO x IPE-USP
Panel A: Without Control						
FGV-EESP	-0.127***	-0.011	0.051			
	(0.037)	(0.051)	(0.045)			
FGV-EPGE				0.018	0.086**	
				(0.050)	(0.038)	
PUC-RIO						0.042
						(0.039)
Dependent variable (mean)	0.535	0.535	0.535	0.535	0.535	0.535
Number of observations	1804	1804	1804	1804	1804	1804
Panel B: Control Score						
FGV-EESP	-0.131**	0.007	0.054			
	(0.042)	(0.054)	(0.050)			
FGV-EPGE				0.070	0.109**	
				(0.051)	(0.043)	
PUC-RIO						0.037
						(0.043)
Normalised ANPEC score	0.005	0.005	0.005	0.045**	0.045**	0.001
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.024)
Dependent variable (mean)	0.540	0.540	0.540	0.540	0.540	0.540
Number of observations	1643	1643	1643	1643	1643	1643
Panel C: Control Ranking						
FGV-EESP	-0.163***	-0.055	0.016			
	(0.037)	(0.042)	(0.041)			
FGV-EPGE				0.014	0.084**	0.022
				(0.044)	(0.036)	(0.039)
PUC-RIO						
ANPEC ranking	0.000**	0.000**	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dependent variable (mean)	0.535	0.535	0.535	0.535	0.535	0.535
Number of observations	1804	1804	1804	1804	1804	1804
Panel D: Control Range of Ranking						
FGV-EESP	-0.100**	0.047	0.073			
	(0.046)	(0.057)	(0.048)			
FGV-EPGE				0.094	0.116***	
				(0.053)	(0.038)	
PUC-RIO						0.022
						(0.000)
Range of ANPEC ranking						
0 to 15	0.135**	0.135**	0.135**	0.176***	0.176***	0.113***
	(0.047)	(0.047)	(0.047)	(0.042)	(0.042)	(0.036)
16 to 30	-0.007	-0.007	-0.007	0.032	0.032	-0.024
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.041)
31 to 45	0.051	0.051	0.051	0.087**	0.087**	0.036
	(0.035)	(0.035)	(0.035)	(0.030)	(0.030)	(0.040)
46 to 60	-0.045	-0.045	-0.045	-0.017	-0.017	-0.060
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.044)
Dependent variable (mean)	0.535	0.535	0.535	0.535	0.535	0.535
Number of observations	1804	1804	1804	1804	1804	1804
Year fixed effects	Yes	Yes	0.055	Yes	Yes	Yes

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Ph.D program, zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 22 – Probability of attending a Ph.D. abroad, Top 4 institutions - Pairwise Comparisons using all sample

	(1) FGV-EESP x FGV-EPGE	(2) FGV-EESP x PUC-RIO	(3) FGV-EESP x IPE-USP	(4) FGV-EPGE x PUC-RIO	(5) FGV-EPGE x IPE-USP	(6) PUC-RIO x IPE-USP
Panel A: Without Control						
FGV-EESP	-0.188***	-0.227***	-0.056			
	(0.038)	(0.031)	(0.039)			
FGV-EPGE				-0.179***	0.002	
				(0.029)	(0.039)	
PUC-RIO						0.001
						(0.040)
Dependent variable (mean)	0.147	0.147	0.147	0.147	0.147	0.147
Number of observations	1804	1804	1804	1804	1804	1804
Panel B: Control Score						
FGV-EESP	-0.063	-0.070	0.049			
	(0.036)	(0.046)	(0.038)			
FGV-EPGE				-0.030	0.086*	
				(0.048)	(0.043)	
PUC-RIO						0.086*
						(0.039)
Normalised ANPEC score	0.154***	0.154***	0.154***	0.176***	0.176***	0.179***
	(0.027)	(0.027)	(0.027)	(0.030)	(0.030)	(0.018)
Dependent variable (mean)	0.148	0.148	0.148	0.148	0.148	0.148
Number of observations	1643	1643	1643	1643	1643	1643
Panel C: Control Ranking						
FGV-EESP	-0.116**	-0.140***	0.012			
	(0.039)	(0.041)	(0.040)			
FGV-EPGE				-0.079*	0.074*	0.078*
				(0.038)	(0.040)	(0.039)
PUC-RIO						
ANPEC ranking	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dependent variable (mean)	0.147	0.147	0.147	0.147	0.147	0.147
Number of observations	1804	1804	1804	1804	1804	1804
Panel D: Control Range of Ranking						
FGV-EESP	-0.122**	-0.100**	-0.004			
	(0.040)	(0.039)	(0.042)			
FGV-EPGE				-0.037	0.056	
				(0.041)	(0.043)	
PUC-RIO						0.078
						(0.000)
Range of ANPEC ranking						
0 to 15	0.281***	0.281***	0.281***	0.331***	0.331***	0.331***
	(0.052)	(0.052)	(0.052)	(0.056)	(0.056)	(0.042)
16 to 30	0.056	0.056	0.056	0.103**	0.103**	0.095**
	(0.044)	(0.044)	(0.044)	(0.046)	(0.046)	(0.038)
31 to 45	0.013	0.013	0.013	0.058**	0.058**	0.044
	(0.033)	(0.033)	(0.033)	(0.026)	(0.026)	(0.029)
46 to 60	0.030	0.030	0.030	0.066*	0.066*	0.051
	(0.032)	(0.032)	(0.032)	(0.035)	(0.035)	(0.031)
Dependent variable (mean)	0.147	0.147	0.147	0.147	0.147	0.147
Number of observations	1804	1804	1804	1804	1804	1804
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Ph.D program abroad., zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 23 – Probability of attending a top 20 Ph.D. abroad, Top 4 institutions - Pairwise Comparisons using all sample

	(1) FGV-EESP x FGV-EPGE	(2) FGV-EESP x PUC-RIO	(3) FGV-EESP x IPE-USP	(4) FGV-EPGE x PUC-RIO	(5) FGV-EPGE x IPE-USP	(6) PUC-RIO x IPE-USP
Panel A: Without Control						
FGV-EESP	-0.185***	-0.252***	-0.011			
	(0.028)	(0.032)	(0.026)			
FGV-EPGE				-0.202***	0.049	
				(0.035)	(0.028)	
PUC-RIO						0.057**
						(0.024)
Dependent variable (mean)	0.078	0.078	0.078	0.078	0.078	0.078
Number of observations	1804	1804	1804	1804	1804	1804
Panel B: Control Score						
FGV-EESP	-0.085**	-0.125**	0.075**			
	(0.031)	(0.041)	(0.024)			
FGV-EPGE				-0.071	0.125***	
				(0.046)	(0.031)	
PUC-RIO						0.138***
						(0.020)
Normalised ANPEC score	0.129***	0.129***	0.129***	0.158***	0.158***	0.172***
	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)	(0.018)
Dependent variable (mean)	0.077	0.077	0.077	0.077	0.077	0.077
Number of observations	1643	1643	1643	1643	1643	1643
Panel C: Control Ranking						
FGV-EESP	-0.133***	-0.189***	0.038			
	(0.029)	(0.037)	(0.028)			
FGV-EPGE				-0.118**	0.109***	0.127***
				(0.041)	(0.031)	(0.021)
PUC-RIO						
ANPEC ranking	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dependent variable (mean)	0.078	0.078	0.078	0.078	0.078	0.078
Number of observations	1804	1804	1804	1804	1804	1804
Panel D: Control Range of Placement						
FGV-EESP	-0.113***	-0.119**	0.048			
	(0.027)	(0.039)	(0.029)			
FGV-EPGE				-0.058	0.107**	
				(0.044)	(0.035)	
PUC-RIO						0.127***
						(0.000)
Range of ANPEC Placement						
0 to 15	0.274***	0.274***	0.274***	0.320***	0.320***	0.333***
	(0.041)	(0.041)	(0.041)	(0.042)	(0.042)	(0.035)
16 to 30	0.088**	0.088**	0.088**	0.131***	0.131***	0.134***
	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)	(0.031)
31 to 45	0.023	0.023	0.023	0.064**	0.064**	0.060***
	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)	(0.018)
46 to 60	0.034	0.034	0.034	0.068**	0.068**	0.061***
	(0.022)	(0.022)	(0.022)	(0.026)	(0.026)	(0.020)
Dependent variable (mean)	0.078	0.078	0.078	0.078	0.078	0.078
Number of observations	1804	1804	1804	1804	1804	1804
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Top 20 Ph.D program, zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 24 – Probability of attending a top 10 Ph.D. abroad, Top 4 institutions - Pairwise Comparisons using all sample

	(1) FGV-EESP x FGV-EPGE	(2) FGV-EESP x PUC-RIO	(3) FGV-EESP x IPE-USP	(4) FGV-EPGE x PUC-RIO	(5) FGV-EPGE x IPE-USP	(6) PUC-RIO x IPE-USP
Panel A: Without Control						
FGV-EESP	-0.110***	-0.223***	-0.019			
	(0.023)	(0.033)	(0.026)			
FGV-EPGE				-0.197***	0.013	
				(0.036)	(0.026)	
PUC-RIO						0.039
						(0.022)
Dependent variable (mean)	0.055	0.055	0.055	0.055	0.055	0.055
Number of observations	1804	1804	1804	1804	1804	1804
Panel B: Control Score						
FGV-EESP	-0.025	-0.121***	0.056*			
	(0.025)	(0.039)	(0.028)			
FGV-EPGE				-0.105**	0.071**	
				(0.045)	(0.031)	
PUC-RIO						0.113***
						(0.023)
Normalised ANPEC score	0.114***	0.114***	0.114***	0.123***	0.123***	0.156***
	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.017)
Dependent variable (mean)	0.055	0.055	0.055	0.055	0.055	0.055
Number of observations	1643	1643	1643	1643	1643	1643
Panel C: Control Ranking						
FGV-EESP	-0.072**	-0.176***	0.018			
	(0.024)	(0.036)	(0.030)			
FGV-EPGE				-0.141***	0.052*	0.096***
				(0.040)	(0.029)	(0.022)
PUC-RIO						
ANPEC ranking	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dependent variable (mean)	0.055	0.055	0.055	0.055	0.055	0.055
Number of observations	1804	1804	1804	1804	1804	1804
Panel D: Control Range of Ranking						
FGV-EESP	-0.055**	-0.121***	0.027			
	(0.024)	(0.037)	(0.033)			
FGV-EPGE				-0.094**	0.052	
				(0.042)	(0.034)	
PUC-RIO						0.096**
						(0.000)
Range of ANPEC ranking						
0 to 15	0.211***	0.211***	0.211***	0.233***	0.233***	0.272***
	(0.031)	(0.031)	(0.031)	(0.033)	(0.033)	(0.032)
16 to 30	0.068*	0.068*	0.068*	0.089**	0.089**	0.116***
	(0.036)	(0.036)	(0.036)	(0.035)	(0.035)	(0.036)
31 to 45	0.010	0.010	0.010	0.030	0.030	0.048***
	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.015)
46 to 60	0.039	0.039	0.039	0.055*	0.055*	0.066**
	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)	(0.022)
Dependent variable (mean)	0.055	0.055	0.055	0.055	0.055	0.055
Number of observations	1804	1804	1804	1804	1804	1804
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Top 10 Ph.D program , zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

4 Appendix - RDD Bandwidth Robust Test

In this appendix, we show the robustness tests when we change the RD bandwidth. Table 25 shows the balance test for the MSE-Optimal bandwidth in the Top 4 with non-Top 4 comparison. Similarly, Table 26 shows the balance test for comparison Top 3 with non-Top 3. The results show that the covariates are balanced.

Table 25 – Balance check of covariate variables using MSE-Optimal bandwidth - Top 4 x non-Top 4

Variable	MSE-Bandwidth	RD estimator	p-value	Observations
Male	0.375	-0.354	0.548	469
Single	0.364	-0.328	0.284	454
White	0.290	-0.032	0.968	231
Took the exam before	0.371	0.350	0.403	469
Took the exam more than 1 year after graduate	0.425	-0.210	0.749	261
Age	0.283	-1.835	0.430	171

Notes. The first column reports the MSE-bandwidth calculated for each covariate. The second column shows the RD estimator from estimation using each covariate as an outcome. The third column shows the p-values. If the RD estimator is not significant, then the sample is balanced for that covariate. *Significant at 10%; **Significant at 5%; ***Significant at 1%

Table 26 – Balance check of covariate variables using MSE-Optimal bandwidth - Top 3 x non-Top 3

Variable	MSE-Bandwidth	RD estimator	p-value	Observations
Male	0.360	0.319	0.515	470
Single	0.394	-0.021	0.925	512
White	0.277	0.177	0.689	222
Took the exam before	0.435	-0.236	0.466	567
Took the exam more than 1 year after graduate	0.470	0.078	0.915	291
Age	0.322	-0.068	0.982	198

Notes. The first column reports the MSE-bandwidth calculated for each covariate. The second column shows the RD estimator from estimation using each covariate as an outcome. The third column shows the p-values. If the RD estimator is not significant, then the sample is balanced for that covariate. *Significant at 10%; **Significant at 5%; ***Significant at 1%

Table 27 shows the estimation for the MSE-Optimal bandwidth in the analysis of Top 4 comparison with non-Top 4. Similarly, Table 28 presents the results for comparison Top 3 with non-Top 3. In the two analyses, the results with the MSE-Optimal bandwidth are most similar to our principal results. In both cases, we conclude that attending a selective institution does not impact the Ph.D. enrollments in the margin of admission.

In Figure 11, we present a placebo test that verifies RDD estimators' density around zero for cutoffs randomly drawn. We do this test for comparison Top 4 and non-Top 4 and Top 3 and non-Top 3. We found in both that most estimators calculated are around zero, which means that there is no discontinuity around randomly chosen cutoffs.

Table 27 – Estimates of the effect of attending Top 4 institution in Ph.D. attendance - MSE-Optimal bandwidth

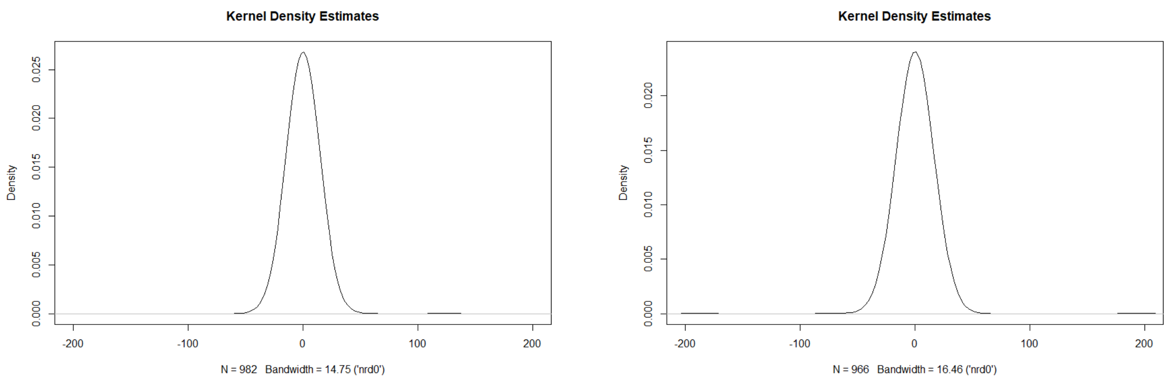
	Ph.D.	Ph.D. abroad
Top 4	-0.351	-0.352
	(0.778)	(0.437)
Sample Size	502	437

Notes: The first column reports the results using the dependent variable as a binary variable equal to one if the applicant attended to Ph.D. in Brazil or abroad, zero otherwise. The second column reports the results using the dependent variable is a binary variable equal to one if the applicant attended to Ph.D. Abroad, zero otherwise. Top 4 is a dummy equal 1 if applicant passed to FGV-EESP, FGV-EPGE, PUC-RIO, IPE-USP for master's degree. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%

Table 28 – Estimates of the effect of attending Top 3 institution in Ph.D. attendance - MSE-Optimal bandwidth

	Ph.D.	Ph.D. abroad
Top 3	-0.307	-0.583
	(0.518)	(0.376)
Sample Size	497	453

Notes: The first column reports the results using the dependent variable as a binary variable equal to one if the applicant attended to Ph.D. in Brazil or abroad, zero otherwise. The second column reports the results using the dependent variable is a binary variable equal to one if the applicant attended to Ph.D. Abroad, zero otherwise. Top 3 is a dummy equal 1 if applicant passed to FGV-EESP, FGV-EPGE, and PUC-RIO for master's degree. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%



(a) Top 4 x non-Top 4

(b) Top 3 x non-Top 3

Figure 11 – Placebo Test

5 Appendix - RDD Specification Test

In this appendix, we show the robustness tests when we change the RD specification. In that case, we estimate the equation (3) using the CER-bandwidth. Table 29 show the estimates when we compare Top 4 institutions with non-Top 4. We estimate three specifications for the outcomes Ph.D. in Brazil or abroad and Ph.D. abroad: kernel uniform, kernel Epanechnikoff, and control for fixed effect of year. Table 30 show the same result when we compare Top 3 institutions with non-Top 3. We conclude that attending a selective institution does not impact the Ph.D. enrollments in the margin of admission.

Table 29 – Estimates of the effect of attending Top 4 institution in Ph.D. attendance - Robustness to RD Specification

	Ph.D.	Ph.D. abroad
Top 4	-0.649	-0.405
	(0.884)	(0.477)
RD Kernel	Linear	Linear
Fixed Effect	No	No
Sample Size	261	203
Top 4	-0.592	-0.421
	(0.873)	(0.492)
RD Kernel	Epanechnikoff	Epanechnikoff
Fixed Effect	No	No
Sample Size	250	289
Top 4	-0.751	-0.476
	(0.876)	(0.517)
RD Kernel	Triangular	Triangular
Fixed Effect	Yes	Yes
Sample Size	276	289

Notes: The first column reports the results using the dependent variable as a binary variable equal to one if the applicant attended to Ph.D. in Brazil or abroad, zero otherwise. The second column reports the results using the dependent variable is a binary variable equal to one if the applicant attended to Ph.D. Abroad, zero otherwise. Top 4 is a dummy equal 1 if applicant passed to FGV-EESP, FGV-EPGE, PUC-RIO, IPE-USP for master's degree. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%

We also do robustness tests using predetermined bandwidths. The chosen bands are: 0.25, 0.125 and 0.07. We show the results in Table 31 and 32. We found that even if the sample is smaller when comparing the Top 4 with non-Top 4 institutions, the estimators remain insignificant, and the conclusion is the same. However, when comparing the Top 3 with non-Top 3 institutions using the 0.07 bandwidth, the estimator became positive and significant. The result means that attending one of the Top 3 institutions would make the probability of attending a Ph.D. program abroad higher.

Table 30 – Estimates of the effect of attending Top 3 institution in Ph.D. attendance - Robustness to RD Specification

	Ph.D.	Ph.D. abroad
Top 3	-0.450	-0.668
	(0.507)	(0.470)
RD Kernel	Linear	Linear
Fixed Effect	No	No
Sample Size	261	203
Top 3	-0.303	-0.609
	(0.521)	(0.405)
RD Kernel	Epanechnikoff	Epanechnikoff
Fixed Effect	No	No
Sample Size	299	237
Top 3	-0.238	-0.569
	(0.500)	(0.359)
RD Kernel	Triangular	Triangular
Fixed Effect	Yes	Yes
Sample Size	328	261

Notes: The first column reports the results using the dependent variable as a binary variable equal to one if the applicant attended to Ph.D. in Brazil or abroad, zero otherwise. The second column reports the results using the dependent variable is a binary variable equal to one if the applicant attended to Ph.D. Abroad, zero otherwise. Top 3 is a dummy equal 1 if applicant passed to FGV-EESP, FGV-EPGE, and PUC-RIO for master's degree. Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%

Table 31 – Top 4 x non-Top 4

	.25		0.125		0.07	
	Ph.D. in Brazil or abroad	Ph.D. abroad	Ph.D. in Brazil or abroad	Ph.D. abroad	Ph.D. in Brazil or abroad	Ph.D. abroad
Top 4	-0.943	-0.748	-1.279	-0.995	-0.753	-1.013
	1.111	0.741	1.167	0.910	1.474	1.282
Sample Size	305	305	157	157	89	89

*Significant at 10%; **Significant at 5%; ***Significant at 1%

Table 32 – Top 3 x non-Top 3

	.25		0.125		0.07	
	Ph.D. in Brazil or abroad	Ph.D. abroad	Ph.D. in Brazil or abroad	Ph.D. abroad	Ph.D. in Brazil or abroad	Ph.D. abroad
Top 3	-0.078	-0.329	-0.015	0.078	0.396	0.579*
	0.700	0.450	0.799	0.326	0.916	0.315
Sample Size	313	313	168	168	92	92

*Significant at 10%; **Significant at 5%; ***Significant at 1%

6 Appendix - RDD First Stage

In this section, we present the first-stage estimation for main RDD estimations. We estimate the regression (4) and show the results in Tables 33 and 34. As the first stage estimator is significant, we conclude that the instrument used in the RDD framework for comparison Top 4 versus non-Top 4 and Top 3 versus non-Top 3 is valid.

Table 33 – First-Stage - Comparison Top 4 × non-Top 4

First-Stage	Passed in a Top 4
Attend to a Top 4	0.357***
	(0.117)
Sample Size	331

Notes: Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%

Table 34 – First-Stage - Comparison Top 3 × non-Top 3

First-Stage	Passed in a Top 3
Attend to a Top 3	0.502***
	(0.117)
Sample Size	331

Notes: Robust standard errors are shown in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%

7 Appendix - Multiple Hypothesis Test

In this section, we show the results of the multiple hypothesis tests (MHT) conducted to test the results found in section 6 together. In Table 35, we present the result when we examine the estimator's significance concerning comparison pairwise within the outcomes. For the outcome Ph.D. abroad, the estimators of the comparisons FGV-EESP x FGV-EPGE and FGV-EPGE x IPE-USP are interpreted as significant, when the joint test points out that together they are not significant. For the outcome Ph.D. abroad, the estimators of the comparisons FGV-EPGE x IPE-USP and PUC-RIO x IPE-USP seems not to be jointly significant. We can conclude that FGV-EPGE may not have an advantage over FGV-EESP and IPE-USP when allocating its students in Ph.D. programs abroad. Moreover, FGV-EPGE and PUC-RIO may not have an advantage over IPE-USP when considering the top 10 Ph.D. programs.

Table 36 presents the result when we test the significance of estimator of comparison pairwise within the comparisons. When we compare FGV-EESP with FGV-EPGE, the estimator for Ph.D. abroad and Ph.D. in a top 20 program outcomes were considered significant when MHT suggests that they are not jointly significant. The same occurs in FGV-EPGE and IPE-USP comparison for Ph.D. in a top 10 program outcomes. Then, FGV-EPGE may not have an advantage over FGV-EESP when allocating its students in Ph.D. programs abroad and Top 20 Ph.D. programs. Moreover, PUC-RIO may not have an advantage over IPE-USP when considering Top 10 programs. Therefore, there is evidence that the effects of FGV-EPGE and FGV-EESP are equivalent, and the advantage of FGV-EPGE and PUC-RIO over IPE-USP remains only in terms of the top 20 programs.

Finally, the last multiple tests conducted relates to the joint comparison. Table 37 shows the results. The significance of the MHT estimators is equivalent to the estimator's significance, and therefore, the conclusion remains the same as that exposed in section 6.

Table 35 – Multiple test along comparison within outcomes - Pairwise Comparison

MHT along treatment within outcomes	Model p-value	Resample p-value	Romano-Wolf p-value
Panel A: Ph.D. in Brazil or abroad			
FGV-EESP x FGV-EPGE	0.1684	0.2574	0.5248
FGV-EESP x PUC-RIO	0.2898	0.297	0.6733
FGV-EESP x IPE-USP	0.1454	0.1683	0.5248
FGV-EPGE x PUC-RIO	0.0077	0.0198	0.0594
FGV-EPGE x IPE-USP	0.0004	0.0099	0.0198
PUC-RIO x IPE-USP	0.3485	0.5248	0.6733
Panel B: Ph.D. abroad			
FGV-EESP x FGV-EPGE	0.0489	0.0792	0.198
FGV-EESP x PUC-RIO	0.4563	0.3663	0.901
FGV-EESP x IPE-USP	0.7104	0.7624	0.9109
FGV-EPGE x PUC-RIO	0.6008	0.6238	0.9109
FGV-EPGE x IPE-USP	0.0243	0.1188	0.198
PUC-RIO x IPE-USP	0.3984	0.396	0.901
Panel C: Ph.D. in Top 10 programs			
FGV-EESP x FGV-EPGE	0.2676	0.2376	0.5545
FGV-EESP x PUC-RIO	0.3605	0.3168	0.5545
FGV-EESP x IPE-USP	0.1777	0.2178	0.4653
FGV-EPGE x PUC-RIO	0.3665	0.4158	0.5545
FGV-EPGE x IPE-USP	0.0363	0.0891	0.2475
PUC-RIO x IPE-USP	0.0473	0.0297	0.2475
Panel D: Ph.D. in Top 20 programs			
FGV-EESP x FGV-EPGE	0.0353	0.0693	0.1386
FGV-EESP x PUC-RIO	0.2741	0.1881	0.6436
FGV-EESP x IPE-USP	0.3106	0.3663	0.6436
FGV-EPGE x PUC-RIO	0.7341	0.802	0.802
FGV-EPGE x IPE-USP	0.0036	0.0396	0.0693
PUC-RIO x IPE-USP	0.0206	0.0198	0.099

Table 36 – Multiple test along outcomes within comparison - Pairwise Comparison

MHT along outcomes within treatment	Model p-value	Resample p-value	Romano-Wolf p-value
Panel A: Comparison FGV-EESP x FGV-EPGE			
Ph.D. in Brazil or abroad	0.1684	0.2871	0.3861
Ph.D. abroad	0.0489	0.0594	0.1584
Ph.D. in Top 10 programs	0.2676	0.2178	0.3861
Ph.D. in Top 20 programs	0.0353	0.0594	0.1188
Panel B: Comparison FGV-EESP x PUC-RIO			
Ph.D. in Brazil or abroad	0.2898	0.3069	0.505
Ph.D. abroad	0.4563	0.297	0.505
Ph.D. in Top 10 programs	0.3605	0.2772	0.505
Ph.D. in Top 20 programs	0.2741	0.2277	0.495
Panel C: Comparison FGV-EESP x IPE-USP			
Ph.D. in Brazil or abroad	0.1454	0.1287	0.4257
Ph.D. abroad	0.7104	0.7228	0.7228
Ph.D. in Top 10 programs	0.1777	0.3267	0.4257
Ph.D. in Top 20 programs	0.3106	0.396	0.5248
Panel D: Comparison FGV-EPGE x PUC-RIO			
Ph.D. in Brazil or abroad	0.0077	0.0198	0.0396
Ph.D. abroad	0.6008	0.5347	0.7327
Ph.D. in Top 20 programs	0.3665	0.4455	0.5842
Ph.D. in Top 10 programs	0.7341	0.8317	0.8317
Panel E: Comparison FGV-EPGE x IPE-USP			
Ph.D. in Brazil or abroad	0.0004	0.0099	0.0396
Ph.D. abroad	0.0243	0.1287	0.1782
Ph.D. in Top 10 programs	0.0363	0.1485	0.1782
Ph.D. in Top 20 programs	0.0036	0.0396	0.1089
Panel F: Comparison FGV-EPGE x IPE-USP			
Ph.D. in Brazil or abroad	0.3485	0.505	0.6337
Ph.D. abroad	0.3984	0.4752	0.6337
Ph.D. in Top 10 programs	0.0473	0.0792	0.2574
Ph.D. in Top 20 programs	0.0206	0.0396	0.1782

Table 37 – Multiple test along outcomes within comparison - Joint Comparison

MHT along outcomes within treatment	Model p-value	Resample p-value	Romano-Wolf p-value
Panel A: Estimator FGV-EPGE			
Ph.D. in Brazil or abroad	0.5942	0.5644	0.7525
Ph.D. abroad	0.4499	0.2673	0.6832
Ph.D. in Top 10 programs	0.8058	0.7327	0.7525
Ph.D. in Top 20 programs	0.4379	0.2178	0.6832
Panel B: Estimator PUC-RIO			
Ph.D. in Brazil or abroad	0.1066	0.1089	0.2376
Ph.D. abroad	0.7365	0.6733	0.9604
Ph.D. in Top 10 programs	0.9516	0.9901	0.9901
Ph.D. in Top 20 programs	0.7386	0.6832	0.9604
Panel C: Estimator IPE-USP			
Ph.D. in Brazil or abroad	0.0523	0.0297	0.0891
Ph.D. abroad	0.5935	0.604	0.6238
Ph.D. in Top 10 programs	0.4319	0.4059	0.5842
Ph.D. in Top 20 programs	0.5573	0.4158	0.6238

8 Appendix - Estimations for recent years and an alternative ranking

In this section, we graphically display the pairwise comparison results by estimating the equation 2 and using the method proposed by Dale and Krueger (2002). First, we plot the main result estimated in section 6. Second, we present the results using only the recent years. In this case, we consider recent years the years 2009 to 2015. Third, we present the results using a ranking alternative to Shanghai Ranking to ranks Ph.D. programs. Here, we use the U.S. News ranks graduate programs in social sciences and the humanities to rank the Ph.D. programs into top 10 and top 20 definitions.[20] In the two complementary estimates (see Figures 13 and 14), we find similar results to the main estimate (see Figure 12).

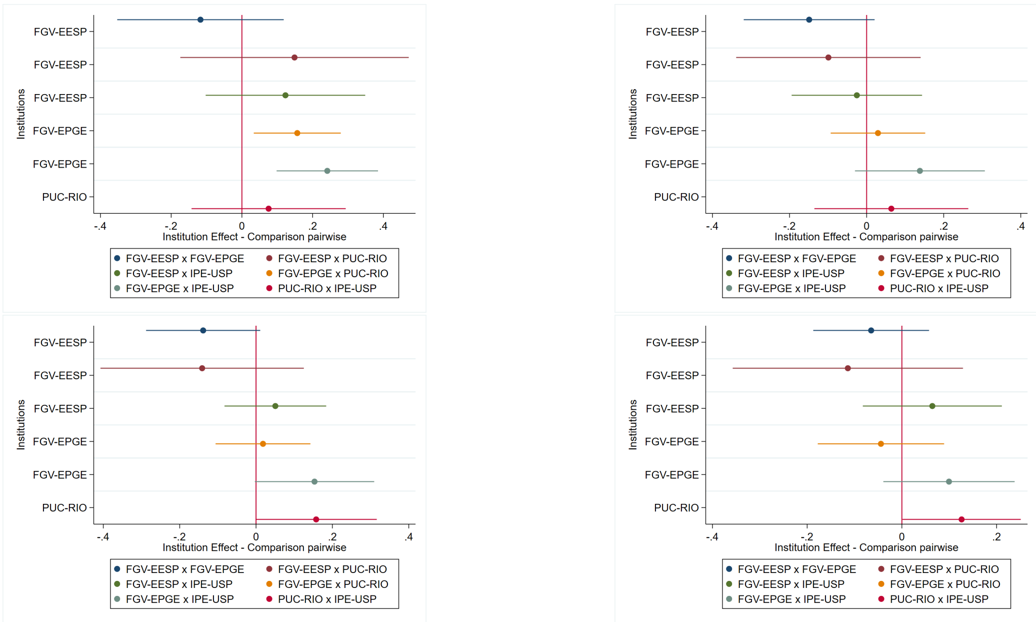


Figure 12 – Principal pairwise comparison results

[20] Available in: https://www.usnews.com/best-graduate-schools/top-humanities-schools/economics-rankings

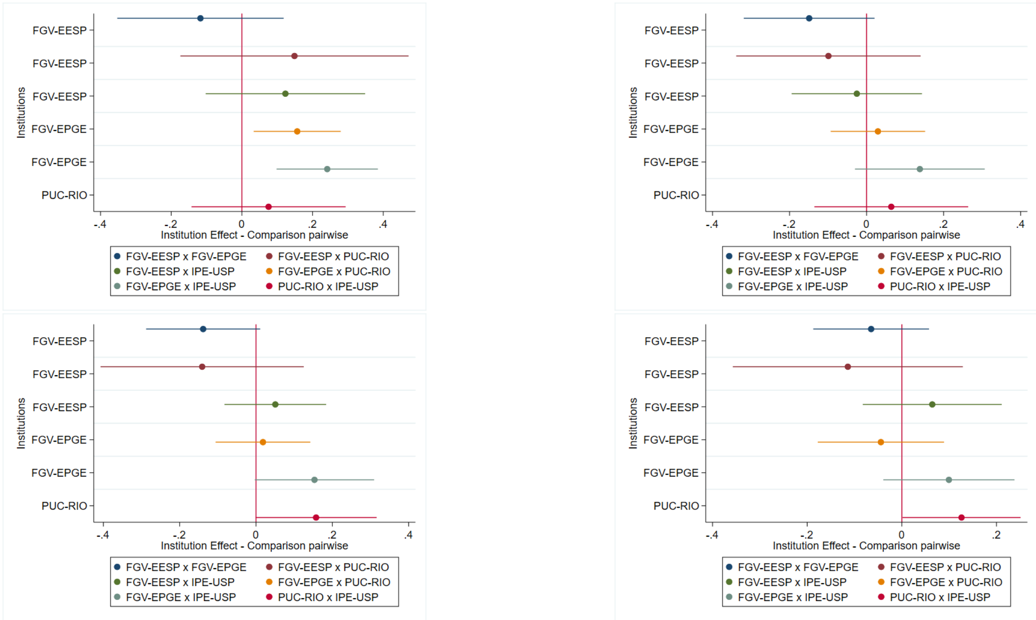


Figure 13 – Pairwise comparison results for recent years (2009-2015)

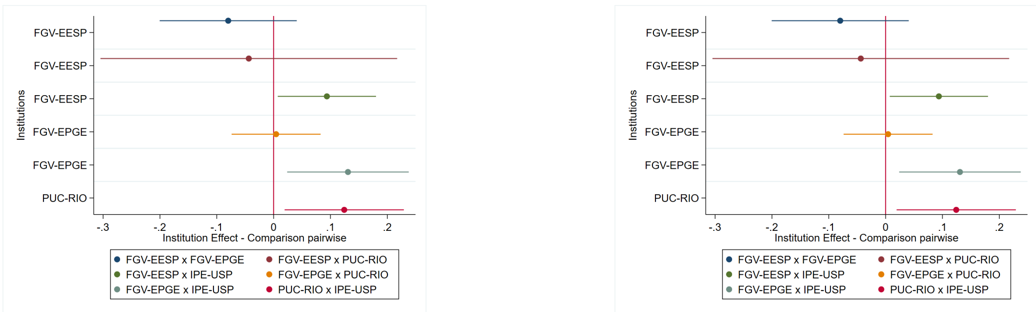


Figure 14 – Pairwise comparison results using an alternative ranking (U.S. News ranks graduate programs)

9 Appendix - Peer Effects

In this section, we briefly discuss the possible existence of peer effects on the outcomes of students who attend the same institution. If peer influences are a major factor in generating the Ph.D. enrollments, then the institution effect is not so influential.

If a student's classmates have higher abilities related to the Ph.D. enrollment decision, the student could learn from them. This spillover can influence the student's outcome at a given institution. Several papers use the random allocation roommate to measure peer effects.[21] The results from these papers are mixed. Additionally, other studies adopt different identification strategies. Lavy and Schlosser (2011) uses the cohort variation within the school and finds that the gender peer effect impacts the boys' and girls' cognitive outcomes. Using a student integration program, Angrist and Lang (2004) concludes that

[21] Examples of these studies are: Sacerdote (2001), Carrell et al. (2008), and, Lyle (2007).

there are peer gains in student grades. A concern in our study will be to know if peer effects cause part of the measured effect.

The linear-in-means model is the most commonly estimated in the peer effects literature.[22] We adopt this model in our context, and we define as follows:

$$Y_i = \beta_0 + \beta_1 S_i + \delta \bar{S}_i^{jt} + \gamma X_i + \epsilon_i \tag{5}$$

where Y_i, a dummy variable equal to one if the applicant i attended a Ph.D. in Economics or Finance after the master's degree. We consider the following distinctions: Ph.D. in Brazil or abroad, Ph.D. abroad, Ph.D. in a top 20 program, and Ph.D. in a top 10 program. We regress the outcome on the ANPEC score, S_i, and on the ANPEC exam mean of each institution j in a given year t, $\bar{S^j}_{it}$. We control for a binary variable equal to one if the student moved to another city between undergraduate and master,X_i. ϵ_i is the error term. In all estimates, we cluster standard errors by years.

Using equation (5), we can test if the estimator for institutions' ANPEC score means is significant. If the institution's average score is not significant, it means that the average score does not affect the outcome which is evidence that the peer effect is not significant.

Table 38 shows the estimation of equation (5) results for the four institutions across Top 4. We see that most of the ANPEC score coefficients are significant, while the coefficient for the average ANPEC score by institution and year is not significant or significant and negative. This suggests that peer effects do not have a large impact on Ph.D. enrollment.

[22] Sacerdote (2011).

Table 38 – Estimation of the linear-in-means model to measure the peer effects

	FGV-EESP	FGV-EPGE	PUC-RIO	IPE-USP
	(1)	*(2)*	*(3)*	*(4)*
Panel A: Ph.D. in Brazil or abroad				
ANPEC Score	0.232	0.155**	0.337***	0.109
	(0.137)	(0.058)	(0.077)	(0.126)
ANPEC Score Mean	-0.139	-0.451*	0.116	-0.363*
	(0.242)	(0.230)	(0.243)	(0.167)
Panel B: Ph.D. abroad				
ANPEC Score	0.267*	0.351***	0.355***	0.211*
	(0.130)	(0.091)	(0.078)	(0.117)
ANPEC Score Mean	-0.052	-0.762*	-0.093	-0.223
	(0.117)	(0.350)	(0.160)	(0.171)
Panel C: Top 20 Ph.D. program				
ANPEC Score	0.224*	0.308***	0.362***	0.185**
	(0.115)	(0.074)	(0.080)	(0.062)
ANPEC Score Mean	-0.017	-0.712**	-0.187*	-0.180*
	(0.086)	(0.296)	(0.087)	(0.099)
Panel D: Top 10 Ph.D. program				
ANPEC Score	0.175*	0.325***	0.344***	0.130*
	(0.094)	(0.065)	(0.081)	(0.063)
ANPEC Score Mean	-0.009	-0.673**	-0.164	-0.084
	(0.062)	(0.287)	(0.126)	(0.068)
Number of observations	141	185	151	210

Notes. The dependent variable is a binary variable equal to one if the applicant attended a Ph.D program/Ph.D. program abroad/Top 20 Ph.D. program/Top 10 Ph.D. program, zero otherwise. FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP are dummy equal 1 if applicant attended, a master program at FGV-EESP, FGV-EPGE, PUC-RIO and IPE-USP, respectively. We control for a binary variable equal to one if the student moved to another city between graduation and master and dummy of year. Robust standard errors are shown in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%.