

With honors. University Honors Programs and Graduates' Careers*

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Abstract

Quality in tertiary education pays off. In countries with competitive tertiary education, elite flagship institutions attract high-achieving students. Not all bright students, however, access elite institutions. Can honors programs be an alternative way to nurture talent? This paper studies the causal impact of attending an honors program offered to high achieving students at a non-selective university in a context with non-competitive tertiary institutions. We exploit plausibly exogenous variation in the program's admission procedure, which leads to a strong discontinuity in the probability of admission and enrollment. We show the program works as both a recruitment device, increasing the probability of enrolling at the parent university, as well as a commitment device, reducing late graduation rates for admitted students. Moreover, enrolment into the program leads to a sizeable improvement in academic achievement (+0.53 GPA points on a scale of 30) and shapes future labour market prospects towards post graduate studies (+18 pp). Prospects are confirmed by an increase (+37 pp) in the proportion of graduates enrolled in PhD programs one year after graduation. We find that, while honors students from different backgrounds have different starting points in terms of academic achievements and prospects, they tend to converge by the end of the program. According to our findings, honors programs can be an effective tool to improve educational attainment and foster further human capital accumulation in talented students, mainly through an increase in transitions towards PhD programs.

JEL Classification: I21, I23, I26

Keywords: economics of education, excellence, university honors programs, tertiary education, regression discontinuity design

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1 Introduction

Quality in tertiary education pays off (Anelli (2020), Hoekstra (2009), Oreopoulos and Petronijevic (2013), Dale and Krueger (2002)). Acquiring elite university education is however costly, so that financially constrained students might fail to enroll in or graduate from quality institutions (Alon (2007)). Similarly, information costs play a role in the under-enrollment of students (Jensen (2010), Goodman (2016)). Geographic and cultural distance can also hinder access to elite schools for otherwise qualified students. This might explain why several tertiary institutions developed honors programs as an alternative way to promote talent within their student bodies. Honors programs offer bright students enrolled in non-competitive institutions the opportunity to broaden their education and skills on top of their regular degrees, while also acting as a signalling device.

Can honors programs be a viable way to promoting talent within a non-competitive tertiary education system? This paper first investigates the impact of being accepted, and then of enrolling, in an honors program on academic choices, achievements and labour market outcomes by exploiting plausibly exogenous variation along the main admission score. The paper provides evidence that having been offered a place at SSST, the honors program offered to outstanding university students in Turin, Italy, increases the probability of enrolling at the University of Turin and reduces late graduation rates. It then shows that program enrolment strongly improves academic achievement and shapes attitudes about future careers. Our results indicate that honors program graduates shift their labour market prospects at graduation towards PhD programs, a perspective which is then confirmed by actual enrollment in graduate programs one year after graduation.

Scuola di Studi Superiori “Ferdinando Rossi” (SSST) is an honors program designed for high-achieving students enrolled at the University of Torino. Students admitted to SSST are offered additional tailored academic activities on top of their regular degree programs. The honors program is built around the idea of multidisciplinary, with honors classes aimed at offering complementary education beyond the student’s main field of study, ie the traditional degree course she is enrolled in. Program participants also benefit from close interaction with faculty and with a community of highly-motivated and talented peers by living together in dedicated accommodation provided free of charge. They also enjoy a tuition fee waiver and a scholarship. SSST belongs to the set of 22 *Scuole Superiori Universitarie*, a range of similar honors institutions set up across Italy, as we show in Figure A.3 in the Appendix.

The selection process into the honors program represents a unique setting to empirically identify the effects of interest. This is due to the nature of the admission process, which ranks candidates based on an essay-type written test. Scores range from 1 to 10, with most applicants being awarded an integer grade in the period under analysis. In this setting, candidates are invited to pick three out of six essay questions and develop an argument, making it extremely difficult for a candidate to manipulate her score towards the cutoff. Importantly, the grading process is completely blind, with examiners learning candidates’

names and profiles only after grades have been assigned. While the admission process involves a second round of selection, through an interview, as we show below in Section 2.3, most of the screening takes place at the written test.

Our identification strategy leverages a natural experiment which is the product of combining a coarse grading scheme, an essay-based test and the specificities of the admission cutoff. The admission cutoff is positioned in a portion of the ability distribution which, we argue, makes it difficult for the selection committee to separate candidates based on their underlying ability. We use a regression discontinuity design in a local randomization framework to accommodate the discrete nature of our running variable (Cattaneo et al. (2015), Cattaneo et al. (2017)). The analysis is hence built on the assumption that, in a window around the selection cutoff, candidates are selected as if they were randomly assigned. We provide abundant evidence of it throughout the paper. We also develop an intuitive conceptual framework formalizing this requirement and provide additional evidence to corroborate it. Finally, we show how our main result on academic achievement is robust to several robustness checks and to relaxing our identifying assumptions (Conley et al., 2012).

We combine unique administrative data with census surveys. We start from administrative data retrieved from the selection process into the honors program and enrolment registers at the University of Turin. From the honors program we retrieve the list of applicants, their application package and the selection logs. We combine the data with information on the housing market from the Italian Revenues Agency, where we observe average property sale prices relative to the applicant's neighbourhood. We augment the data with administrative records obtained from enrolment registers at the University of Turin, identifying whether candidates enroll in the university, whether they drop out or move to a different institution before graduating. Next, we retrieve census survey data collected for all university graduates. This survey is a graduation requirement for all students and collates data on parental and socio-economic background characteristics, academic experience and prospects for the future. Students are also surveyed one year after graduation and asked about their labour market or further training experience.

This paper first shows, using administrative enrolment data, that receiving an admission offer from the honors program leads to an increase in the probability of enrolling in Turin (+8 pp). Honors programs can thus act as a recruitment device, helping the University of Turin recruit a desirable portion of the student population, which is likely to benefit the local academic community through peer effects. Moreover, the set of incentives available to honors students operates as a commitment device. Indeed, we find an increase in the proportion of graduates who complete their programs on time (+24 pp). We then turn to graduate census survey data, which implies conditioning on having graduated from the University of Turin, and show that having enrolled in the honors program leads to strong improvements in academic achievement, with a remarkable rise in GPA (+0.53 points on a scale of 30), university exit grade (+1.56 on a scale of 110) and in the proportion of

students graduating *cum laude*¹ (+17 pp).

Moreover, our results also show that enrollment in the honors program shapes prospects on labour market transitions. When asked about future careers, graduates who attended the honors program are less likely to be considering an immediate entry into the labour force (-21 pp), a result closely matched by the increase in interest towards PhD programs (+18 pp)². Honors graduates also show a reduction in the minimum salary to start a full time activity (-212 euros), a result we discuss in Section 5.2. Finally, our estimates on career outcomes, measured one year after leaving university, confirm prospects stated at graduation: we report evidence of a marked decrease of senior graduates in the labour force (-41 pp) mirrored by a strong rise in the proportion enrolled in a PhD (+37 pp).

We explore the presence of heterogeneous treatment effects by socio-economic background and find that, while honors students from different backgrounds have different starting points, they tend to converge by the end of the program. Indeed, the effects on academic achievement are driven by honors students from a privileged background, as students from a lower social class in our estimation sample tend to do well regardless of admission into the honors program. On the other hand, honors students from lower socio-economic status drive the results on labour market indicators, such as intention to enter the labour market at graduation and reservation wage, possibly in favour of pursuing graduate education. In this sense, one could regard the honors program as broadening the perspective on the future of bright students from modest backgrounds.

This paper relates to studies across several strands of the literature. We contribute to the recently growing literature investigating returns to quality in higher education. Previous studies have analyzed academic and labour market returns of having graduated from flagship or elite institutions through discontinuities generated in the admission procedure. Hoekstra (2009) for instance shows how marginally admitted students in an elite US institution enjoy a 20% earning wage premium. Similar findings are echoed by Anelli (2020), looking at a private elite institution in Italy and finding a 52% increase in graduates' income, and by Jia and Li (2021) for China. Saavedra (2008) shows how marginally admitted candidates to a flagship institution in Colombia gained better skills, having performed better in a university exit test, are more likely to be employed and earn more, with stronger effect for graduates from a low socio-economic background. Barrera-Orsorio and Bayona-Rodríguez (2019) build on this analysis and, while reporting a positive impact on graduates' employment and salaries, find no evidence of an effect for exit exams, consistent with the idea that salary premia are likely to derive from signalling. We complement this literature by looking at the so-far neglected role of honors programs offered by non-competitive institutions to promote and foster talented students. We argue that

¹Graduating *cum laude* should not be confused with graduating from the honors program. Being enrolled in an honors program is not a prerequisite to receive a *cum laude* degree: any university student meeting the merit-based requirements could obtain a degree *cum laude*

²The question on future PhD participation is only asked to senior graduates who completed either a master degree or an equivalent single cycle degree

these programs are easier and cheaper to set up, as they can be offered by pooling together the necessary resources across the departments of each university, and work as an effective tool to improve academic achievement and foster aspirations to undertake postgraduate education.

Our setting speaks also to papers looking at merit based aid to attract and retain an high achieving segment of the student population (Chakrabarti and Roy, 2013). Similarly, magnet scholarships are commonly deployed strategies across selective colleges in the US and are aimed at fostering enrolment rates of academically-talented students. Previous research (Cohodes and Goodman, 2014) has shown how even relatively small merit-based scholarships can play a role in swinging candidates to offering colleges, with an ultimate effect on graduation rates. Some of these policies, because of their need blind nature, are most likely to play an effect for students from budget constrained backgrounds. Firoozi (2022), for instance, exploits random assignment by a US institution offering a scholarship worth 3,000 dollars together with the promise of on campus housing, making it relatively similar to the merit-based aid component of the honors program we study. His estimates report a marked increase in enrolment rate of 16.6 percentage points for students from disadvantaged socio-economic backgrounds, relative to a control mean of 21.3%. Our results complement existing papers by analysing a setting with non-competitive institutions and showing how universities can attract talent by setting up programs for outstanding students.

Our study is also related to the literature investigating the impact of being exposed to better quality peers. Several papers have documented an improvement in education attainment driven by interacting with higher quality peers during tertiary education (Carrieri et al. (2015), Canaan and Mouganie (2018)). In our setting, marginally admitted students not only take honor classes with higher quality peers but they also live together and interact with them on a daily basis. In that sense our effects are a combination of being exposed to both higher academic quality, in the form of honors classes and close interaction with faculty, and higher average peer ability. Moreover, our program is also likely to play a positive and indirect effect to regular students enrolled at the University of Turin by helping the university expand its base of high-achieving students.

Finally, to the best of our knowledge, this is the first paper providing causal evidence of the impact of attending an honors programs on graduates' academic achievements and subsequent labour market choices after completing university. Our findings are particularly relevant to many policymakers across the world as similar programs are becoming more and more widespread in Italy and across Europe while being already common in the US. To the best of our knowledge, current evidence on honors programs, focused on the US, does not pay particular attention on the choice of the control group and on making causal statements (Kool et al. (2016), Cosgrove (2004)). The sole exception would be the contemporaneous work of Pugatch and Thompson (2022) who study academic achievement for students attending an honors program offered by a nonselective public institution in the US and show how participation into their honors program improves course grades. Our results go

beyond those in Pugatch and Thompson (2022) as we observe enrollment outcomes at the University of Turin, academic performance and labour market prospects at graduation, in addition to labour market choices one year after leaving university.

The remainder of this paper is organized as follows. Section 2 introduces the *Scuola di Studi Superiori “Ferdinando Rossi”* and illustrates its admission process. Section 3 exhibits the data we collected and Section 4 outlines the identification strategy. Section 5 presents the main results, Section 6 discusses robustness checks while Section 7 concludes.

2 Institutional setting

Scuola di Studi Superiori “Ferdinando Rossi” is an honors program designed for high-achieving students of the University of Torino (UniTO or parent university). UniTO is one of the oldest, most prestigious and largest Italian academic institutions, having been founded in 1404 and having welcomed 14,505 new students in the 2020/2021 academic year alone ³. According to the well-known QS ranking, UniTO is also among the top 500 universities worldwide and scores number 13 in Italy ⁴. This paper first investigates the impact of being accepted, and then of enrolling, at *Scuola di Studi Superiori “Ferdinando Rossi”* on graduates’ academic choices, achievement, perspective on their future careers as they conclude their degrees and labour market outcomes one year after graduation. We discuss in more detail the Italian university system in Subsection 2.1, the nature of the honors program in Subsection 2.2 and conclude this section by illustrating the selection process to the program in Subsection 2.3.

2.1 University education in Italy

This subsection summarizes the key features of the Italian university system. As of 2022 Italy is home to 97 institutions, most of them public (67) and a smaller group offering private tertiary education (19) or private online teaching only (11)⁵.

Since the introduction of the Bologna process in 1999, higher education in Italy is based on a three layer system. All high school graduates are eligible to apply for either a 3-year bachelor degree, which then leads to admission to a 2-year master program, or a single cycle program, equivalent to a master degree, lasting usually five years. The choice usually depends on the subject of study, with most fields offering only 3+2 schemes and single cycle programs being available only for a selected group of subjects, including law and medicine. Across all programs, normal degree completion time is equivalent to the nominal program duration plus an additional six months period, which can be used to write and defend

³Ministry of University and Research (2021)

⁴University of Turin (2021)

⁵Most of the student population, totalling about 1,793,210 individuals, is enrolled in public universities (%86.09) compared to students enrolled in private institutions (%13.91)

a degree thesis, a compulsory requirement for all graduates. Both 3+2 and single cycle degrees can lead to PhD programs, lasting either three or four years, depending on subject and university offering.

An important feature of the Italian university system is the large proportion of bachelor graduates who progress to master degrees. In 2022, about 68.8% of all bachelor graduates were enrolled in a master degree. This result is likely due to the relatively low tuition fees charged by Italian public institutions⁶ and the non-competitive nature of higher education.

Despite a long tradition in higher education⁷, Italian institutions generally lag behind in international ranking with no single public institution in the top 125 QS ranking in 2022. The relative weak performance of the Italian university system is likely to derive from the absence of flagship institutions within the public system and the wide admission policies pursued by Italian universities. Both features of Italian universities give rise to a system with non-competitive tertiary institutions. Some universities across the country have addressed the promotion of talent and excellence in higher education by setting up a *Scuola Superiore Universitaria*, a dedicated honors program devoted to their most talented students.

2.2 The honors program

Scuola di Studi Superiori “Ferdinando Rossi” (henceforth, SSST or honors program) selects high-achieving students at the onset of their degree program at the University of Turin. Students are offered an array of tailored academic activities, on top of their regular degree programs. Moreover, they benefit from a closer relationship with faculty and interact with a community of highly-motivated peers, living together in dedicated accommodation provided free of charge. They also enjoy a tuition fee waiver and a scholarship.

Founded in 2009, this honors program admits students across all disciplines and degrees offered by the University of Turin. Admitted students are expected to take 3 additional honors courses per year, for a total of 15 credits⁸, to be selected from the array of courses offered by SSST. Honors courses are designed with a strong multidisciplinary component and meant to provide students with an education stretching outside their main field of studies (see Appendix A.2 for an example). Furthermore, students are expected, in both their programs at UniTO and at SSST, to maintain a GPA of at least 27/30, to pass all exams on time and to defend an honors thesis as they graduate⁹. Honors students therefore attend two kinds of classes: classes required towards their degrees, along with

⁶The average fees paid in the academic year 2020/2021 was 1,440 euros across all degree programs offered by public institutions

⁷The University of Bologna being the first university ever set up in 1088

⁸The European Credit Transfer and Accumulation System (ECTS) is a common framework employed by institutions across the European Higher Education Area to ensure transparency and comparability of degree programs across countries. A full academic year is made of 60 ECTS credits.

⁹This is an additional requirement compared to mandatory thesis requested to all students to complete any degree program at the parent university

peers enrolled in the same program at UniTO, and honors courses together with honors peers, irrespective of their degree program at the parent university¹⁰.

Scuola di Studi Superiori “Ferdinando Rossi” selects students as they enter their bachelor (first year students) or their master (fourth year students)¹¹ degree (see Figure 1). Every academic year, up to 30 first year students and around 10 fourth year students are selected¹². First year students are generally enrolled in the honors program for five years, i.e. the usual duration of tertiary education (bachelor and master) in the country. The program lasts two years, as their master’s degrees, for fourth year students. Finally, first year students are allowed an early exit only if they wish to enroll in another university for their master degrees. This subset of students will be enrolled in the program for three years instead of five. Students who fail to comply with any honors program requirements or drop out at any time before the end of the program will not be able to graduate from *Scuola di Studi Superiori “Ferdinando Rossi”*.

Several universities in the country offer their own honors programs¹³. While the specifics of the honors curriculum inevitably vary with each institution, honors programs are fairly similar in terms of requirements, admission procedures and overall academic offering, making SSST comparable to the wider set of similar programs across the country.

2.3 The selection process

The selection process at *Scuola di Studi Superiori “Ferdinando Rossi”* targets students as they start their undergraduate or master degree. In order to apply for the honors program, perspective students submit an application package consisting of two reference letters, a motivation letter and proof of identity. Perspective students under 21 years of age, not already enrolled in university and who obtained at least 80/100 in their high-school final exam can apply as first year students. On average, a little over 30% of all high school graduates in Italy would meet these requirements. Individuals under 24 years of age wishing to apply at the master level would need to show proof of having completed a bachelor degree with a final grade of at least 99/110, a GPA of at least 27/30 and having passed all exams but one with at least 24/30.

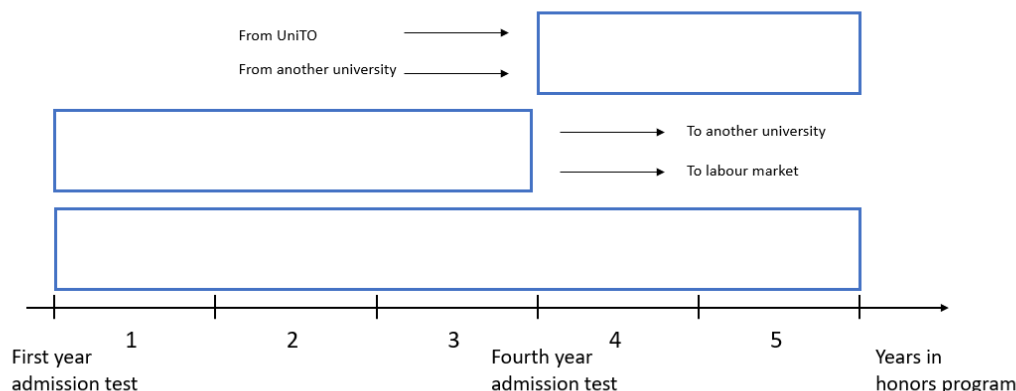
¹⁰Honors courses are not open to students not enrolled in the honors program

¹¹Students enrolled in five-year (or longer) programs, such as law or medicine, can participate in the selection process both as first year and fourth year students.

¹²Available slots for fourth year students were highly volatile in the period under study: 15 in 2012, 16 in 2013, 7 in 2014 and 6 in 2015. Starting from 2016 admission has been limited to first year students only.

¹³The generic name in the Italian university system is *Scuole Superiori Universitarie* (SSU). The system distinguishes between 7 older institutions, which are recognized (independent) by the Ministry of Education and granted autonomous university status, and over 15 unrecognized SSUs (spinoffs of a parent university) as shown in Figure A.3 in the Appendix. The former, including *Scuola Normale Superiore* and *Scuola Superiore Sant’Anna*, are research centres offering programs focusing on vertical PhD-level training and research skills. The latter are younger programs, direct offshoot of parent universities, offering a complementary training at the undergraduate and master level and focusing on interdisciplinarity.

Figure 1: Admission



Notes The figure shows how different paths in *Scuola di Studi Superiori “Ferdinando Rossi”* can look like. From the bottom, students can enter as they begin their first year in university and stay in the honors program for five years, until they graduate from their master or five-year degree. Students entering as first year students can also exit the program after three years, as they finish their bachelor, provided they either enroll in a different university for their master degree or leave tertiary education. Finally, until 2015 students could also enter as fourth year students coming either from UniTO or from other universities.

The actual admission process consists of a written test and an interview. During the written test, applicants are asked to write three short essays on relevant topical issues. Applicants are free to choose 3 out of the 6 proposed essays, which are similar in spirit to high school final exam essays. A different set of essays is presented to first year and fourth year applicants. Essay topics are quite general and cross-cutting, ranging from biology, physics or climate change, to philosophy, law or literary subjects. The aim is to give applicants the opportunity to showcase their reasoning, knowledge and ability to bridge different fields of study, irrespective of previous specific education received. The written test is taken in the morning of test day and lasts for two hours. We report the 2020-2021 admission essay set in Appendix A.1 for reference. A selection committee recruited from the honors program faculty then grades each applicant’s written performance on a scale from 1 to 10. It is important to note that, during this phase, essays are submitted anonymously and that the selection committee only accesses perspective students’ application packages at a later stage. Applicants who scored at least 7 in the written test can then proceed to the interview.

Interviews take place the following day, to ease travelling arrangements for candidates coming from afar. This leaves the selection committee with only a few hours to grade in the afternoon of test day, on average, one hundred essays. The limited time available also

increases the probability of adding a random component to the written test score. The interview step aims at assessing the candidate's cultural profile and motivation, with the aid of the application package. Applicants scoring at least 7 in the interview, also graded from 1 to 10, are deemed eligible for the honors program. In practice, students are ranked based on the sum of the two scores, with the top 30 (or 10, for fourth year students) applicants being offered a spot in the honors program¹⁴.

The selection process gives rise to a multi-score regression discontinuity design (RDD), with candidates having to pass a written test first to gain admission to the interview phase. Starting from 617 candidates who took the written test during the period 2012 - 2017, there are 271 candidates who were awarded at least a 7 and have hence been admitted to the interview. Most of them (194) were then offered a place at SSST¹⁵. Figure A.1 in the Appendix details the possible outcomes of the admission process. On average, each year, out of the 123 first year candidates sitting through the written test, 43 advance to the interview phase and 39 are admitted into the honors program.

These figures confirm insights we gathered during an in-depth interview with a senior SSST faculty member, who stated that the purpose of the oral interview is to ensure that eligible candidates can thrive in the challenging environment of the honors program. This feature of the selection process, coupled with the blind nature of grading in the written exam, leads us to choose the score of the written exam as our running variable and on its admission cutoff as the main discontinuity in the analysis. The grading scheme of the written test, ranging from 1 to 10, shapes the discrete nature of the running variable. As shown in the density plot in Figure 2, the running variable takes values from 4 to 10, with clear mass points at 5, 6, 7 and 8. These mass points have important implications in the analysis of the RDD, as we discuss in Section 4 in more detail.

Finally, the fuzzy nature of the design comes from both the presence of the interview and the observation that not all students who are admitted in the honors program end up enrolling in it. As we show in Figure A.1 in the Appendix, students who successfully pass the written examination then need to go through an interview before being offered a place at the SSST and some of those who are admitted might then fail to enroll. Figure 3 visualizes the discontinuity in the probability of being admitted at SSST and in the probability of enrolling.

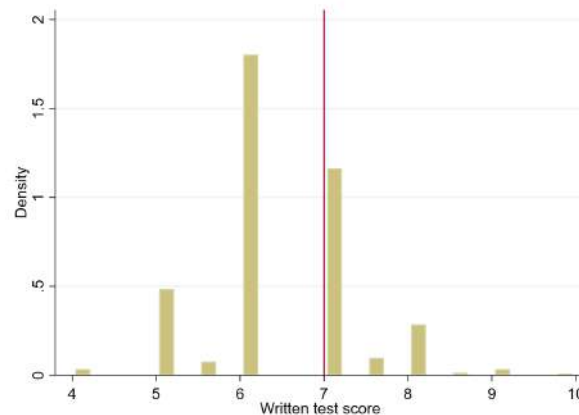
3 Data

We start our data collection by acquiring administrative data from the admission committee of the honors program and enrolment data from the University of Turin. We collect

¹⁴The offer is conditional on applicants being admitted and enrolling into one of the parent university regular degree programs.

¹⁵All candidates who passed the interview were offered a place at SSST as the number of eligible candidates has always been below the number of available places.

Figure 2: Density of the running variable



Notes The figure shows the density plot for the written test scores over the years 2012 - 2017. Non integer scores such as 7.5 were used in early years and then discontinued. Data refer to all applicants who showed up for the written test.

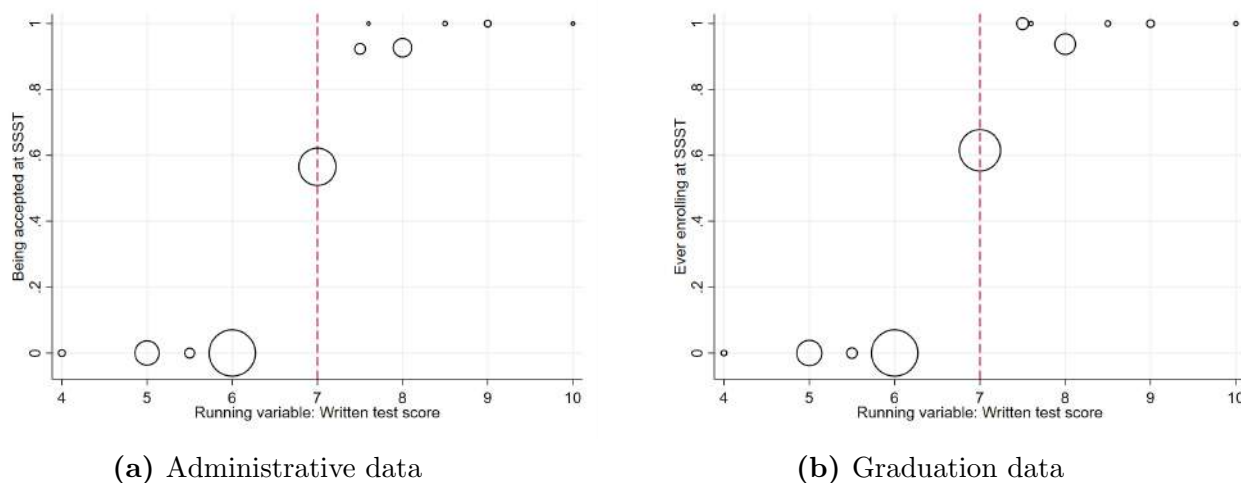
administrative information on the admission process into the honors program by retrieving the list of applicants, together with the application package they submitted at the time of application, and official minutes detailing the selection process. We restrict the dataset to candidates who showed up the day of the written test and took the exam by means of presence sign-up sheets included in the minutes. We obtain written test and interview scores from the transcript of each year's selection process¹⁶ and some background characteristics for all applicants including gender, high school type and final grade and the date they filed their application to the program. The application package includes a motivation letter, two reference letters and proof of identity, from which we retrieve information on area of residence. We augment the data with the administrative records obtained from the University of Turin identifying whether candidates enroll in Turin and whether they dropped out of university or moved to a different institution before graduating.

We geo-code data on area of residence whenever the information is present in the application package. We then merge this information with data on the housing market from *Osservatorio del Mercato Immobiliare* (OMI), the housing statistics body of the Italian Revenues Agency. OMI provides biannual data on property prices, at a fine neighbourhood level within each city, across different building categories. We are hence able to impute the average sell price of residential properties in the neighbourhood where the applicant lived around the time of the application¹⁷ and use it as an additional proxy for graduates'

¹⁶The score obtained during the interview is only available for graduates who were admitted to this second step of the selection process

¹⁷If OMI data was not available for any application year, we imputed average sell data relative to the closest semester in a range of three years around the application year.

Figure 3: First stage: Discontinuities in being accepted and enrolling at SSST



Notes Figures visualize the discontinuities along the running variable used in the first stage. Panel a reports the probability of being accepted (Panel a) using administrative data. Panel b plots the probability of enrolling using AlmaLaura data. Cutoff in both figures is at the threshold of 7. Each circle's radius is proportional to the number of candidates awarded each grade in the written test.

socio-economic background. We report summary statistics for this dataset in Table A.1 in the Appendix. Given that data on house prices is manually coded and only available for a subset of applicants, we include it in our balance tests as an additional proxy for socio-economic status, but do not include it in our preferred specification to avoid reducing our sample size. However, we show that our main result on academic achievement is robust to the inclusion of house value in Table A.11 in the Appendix.

We then merge, as a separate dataset, our administrative data with microdata from AlmaLaurea. AlmaLaurea is a consortium covering the majority of Italian universities with the aim of monitoring the performance of university studies and easing the transition into the labour market. Given that AlmaLaurea microdata is only collected for university graduates, while using this dataset we condition on having graduated from UniTO. All graduates are required, before proceeding to graduation, to complete a graduate profile survey (*Profilo dei Laureati*) making the data close to a census of university graduates. A subsequent survey (*Condizione Occupazionale dei Laureati*) tracks former students at one, three and five years after completing earning their degrees¹⁸.

The graduation survey provides a rich snapshot of graduates' background characteristics, including a detailed set of socio-economic variables recording graduates' high school history, parental occupation and study titles, for which we report summary statistics in

¹⁸Students who only complete a bachelor program are only surveyed one year after graduation, possibly reflecting the large proportion of students who progress to master degrees.

Table A.2 in the Appendix. The survey also include several items aimed at measuring how graduates fared during their time at university. The mandatory nature of the profile questionnaire, part of graduation requirements, ensures very high response rates¹⁹.

Data on the labour market is retrieved by surveying graduates one, three and five years after graduation²⁰. The surveys track graduates in their first jobs out of university and collect information about any additional education or training experience they have completed or are still pursuing at the time of the survey. The survey on employment condition maps further learning and training activities, the characteristics of jobs for those employed and data on employment search for those looking for a job.

We restrict our sample to admission years between 2012 and 2017. This is to avoid using data from the program's early cohorts, 2009 to 2011, where, due to a break in the admission procedure connected to a change in the program's selection committee, our identifying assumptions are unlikely to hold. Data for more recent cohorts (from 2018 onwards) are not available yet, given the usual university career lasts five years and data for each graduating cohort is released in the summer after graduation. We remove from all samples students who enrolled but dropped out at any time from the program, this is to avoid contaminating any treatment effects with a small partially treated group²¹. Nevertheless, our results remain qualitatively similar when we include drop outs in the treatment group as we show in Tables A.5 - 8 in the Appendix.

4 Identification strategy

This paper aims at identifying the impact of first being accepted, and then of enrolling, at *Scuola di Studi Superiori "Ferdinando Rossi"* on students' academic choices, achievements and subsequent labour market outcomes upon graduation. We exploit variation arising from the honors program admission process in a regression discontinuity design and provide empirical evidence to support the required exogeneity claims. We argue that the admission cutoff lies in a subset of the applicants' ability distribution where the selection committee is unable to perfectly discriminate between candidates, given the coarse grading scheme, the large volume of essays to grade and the limited time available²². This feature creates a natural experiment we aim to exploit for our identification strategy.

The most frequent framework to analyse an RDD is based on the assumption of continu-

¹⁹The response rate for graduates of the University of Turin for the period under study, from 2014 until 2020, was consistently well above 90% across all cohorts

²⁰The labour market survey also features relatively high response rates. One year after leaving university response rates for UniTO graduates, for the period from 2014 until 2020, have consistently been above 65% and only dipped below 70% for 2020 graduates

²¹As an example, 8 out of the 38 students who were admitted to SSST in the academic year 2012 eventually dropped out

²²As discussed in Section 2.3, interviews take place the morning after the written exam. This leaves the selection committee with roughly a few hours to grade, on average, a little over one hundred essays.

ity of the conditional expectation of the potential outcomes (see Lee and Lemieux (2010) and Cattaneo et al. (2019)). Studies relying on this framework typically employ either parametric (global and flexible) or non parametric local methods to approximate conditional expectation functions for estimation and inference. Because of the discrete nature of the running variable, taking on only a few mass points as shown in Figure 2, however, we cannot rely on conventional parametric estimation or non-parametric smoothing techniques that apply the continuity framework to the RDD.

Our identification strategy, instead, relies on a newly formalized local randomization framework (Cattaneo et al. (2015), Cattaneo et al. (2017)). This framework assumes the existence of a window, around the threshold, where assignment to treatment was allocated as if in a randomized experiment.

This framework relies on two assumptions. The first requirement is the strongest and translates in the distribution of the score to be same for all units inside the window, unrelated to individual potential outcomes, implying that the score needs to be “as good as randomly” assigned in the window. In our setting, this amounts to the selection committee randomizing 6 and 7 scores with some unobserved probability. This would be violated if the selection committee could accurately separate candidates on the basis of any unobserved ability component.

The second assumption refers to the relationship between potential outcomes and the running variable inside the window. It requires both that potential outcomes of units inside the window are not affected by scores of units outside the window and that, for units in the window, potential outcomes depend on the score only through the treatment indicator but not on the specific value of the score. This second requirement can be interpreted as an exclusion restriction following which there is no relationship between the potential outcome and score apart from treatment kicking in for some units in the window. In our setting, this translates in there being no direct effect of the written test score on future achievement. The assumption would be violated if a high score had a (dis)encouragement effect on candidates. While this assumption can be relaxed, as discussed by Cattaneo et al. (2017), by assuming a model for the relationship between the running variable and the potential outcomes, this is something that we cannot apply in our setting because of the discrete nature of the running variable, with only a few mass points. In our smallest window, as discussed below, we focus on observations with only one value of the running variable for each side of the cutoff, making it impossible to estimate any relationship between the score and the potential outcomes, but provide extensive evidence towards the randomization assumption.

We now rationalize both requirements above by postulating that the honors program selection committee aims at discriminating candidates in terms of their underlying ability. We assume that there are four types of candidates, who can be placed into groups according to their latent ability level: $t = Low, Mid - Low, Mid - High, High$. We also assume that the selection committee attempts to discriminate candidates types through the written test, where we observe four mass points in the data at 5, 6, 7 and 8 respectively. We denote

by c the profiling of candidates by the selection committee. Our maintained assumption, throughout this paper, is that the committee can easily discriminate candidates at the tail of the ability distribution $t = Low, High$ but fails to do so for candidates at the mid values of the distribution $t = Mid - Low, Mid - High$.

$$\begin{aligned} Pr(c = Mid-Low|t = Mid-Low) &= Pr(c = Mid-Low|t = Mid-High) \\ Pr(c = Mid-High|t = Mid-Low) &= Pr(c = Mid-High|t = Mid-High) \end{aligned} \quad (1)$$

We also note that both requirements above, necessary for the local randomization framework, are much stronger than the continuity assumption which is invoked in the continuity framework. They can be justified by providing context specific evidence or by regarding them as a reasonable approximation around the cutoff. In the continuity framework one has to assume that the potential outcomes would have evolved smoothly at the threshold. In the local randomization framework above, instead, the required conditions imply that potential outcomes are essentially flat within the window (i.e., there exists no relationship between the running variable and the potential outcomes)²³.

The first step towards the implementation of the analysis is to choose a window around the cutoff where the local randomization assumptions are likely to hold. We start our investigation by setting our window to be the smallest possible around the threshold of 7. We therefore compare individuals awarded a 6 and individuals awarded a 7 in the written test. We will show that the randomization requirements are likely to be met for units within this window by presenting a battery of balance tests on a rich set of pre-determined observable characteristics. We will then go back to the assignment conceptual framework outlined above, which can explain why the randomization requirement is likely to hold for units in the window, and provide suggestive evidence to support its validity. Finally, we also show that our main result on academic achievement is robust to plausible violations of the exclusion restriction following a procedure developed by Conley et al. (2012).

Having selected a window where the randomization assumptions, or at least a good approximation of them, are likely to hold, the analysis can proceed as in a randomized experiment. We can hence compare differences in outcomes between individuals on either sides of the cutoff within the window and interpret them as causal estimates. In practice we start by estimating a simple OLS regression of the outcome of interest on a dummy capturing whether an individual falls below or above the cutoff for admission into SSST, only for the subset of individuals within the window²⁴. We then augment the model to include a set of pre-determined characteristics \mathbf{X}_{it} and admission year fixed effects (FE) γ_k :

$$Y_{ikt} = \delta_0 + \delta_1 \text{cutoff}_{ik} + \mathbf{X}'_{ikt} \phi + \gamma_k + \epsilon_{ikt} \quad (2)$$

²³See Cattaneo et al. (2017) for a comparison between the two approaches.

²⁴In our AlmaLaurea sample, where we condition on having graduated from UniTO, we extend all specifications by also controlling for type of degree and fields of study

where Y_{ikt} indicates the outcome variable of interest for individual i applying to the honors program in academic year k and graduating from university in calendar year t , cutoff_{ik} is an indicator variable for students passing the written test, \mathbf{X}_{ikt} is a vector of individual and academic controls²⁵, γ_k is a set of SSST admission year FE and ϵ_{ikt} is the error term. If the identifying assumptions above hold, we do not expect the results to change sharply when adding controls. The choice of control variables included in \mathbf{X}_{ikt} changes according to the data we observe in our administrative dataset and in the matched graduate AlmaLaurea dataset. In the administrative dataset we control for gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates' geographical area of residence and a proxy for candidates' motivation (time from SSST call release and submitting an application to the honors program). The graduate AlmaLaurea dataset allows us to extend the model to family background variables (socio-economic status based on parental occupation and parental highest educational attainment).

Even though passing the written test does not always translate into admission into SSST, most of the selection is carried out during this step, as discussed in Section 2.3. Hence, we can still interpret the results of model (2) as being very close to the effect of being admitted to the honors program (intention to treat, ITT). The fact that some students then either fail the interview, drop out or refuse to enroll gives rise to one-sided non-compliance and produces the fuzzy nature of the RDD²⁶. We can hence obtain the effect of enrolling into the honors program by rescaling the ITT by the proportion of compliers in the sample in a 2SLS framework by running:

$$\text{Graduated}_{ikt} = \alpha_0 + \alpha_1 \text{cutoff}_{ik} + \mathbf{X}'_{ikt} \theta + \gamma_k + \eta_{ikt} \quad (3)$$

$$Y_{ikt} = \delta_0 + \delta_1 \widehat{\text{graduated}}_{it} + \mathbf{X}'_{ikt} \rho + \gamma_k + \xi_{ikt} \quad (4)$$

Importantly, because we only have one sided non-compliance, there are no always takers (i.e. defined as students who failed the written test but still enrolled into the honors program) and we can hence interpret our LATE as the Average Treatment effect on the Treated (ATT) (Angrist and Pischke, 2008). Lastly, given that the more stringent local randomization assumptions are likely to apply for a small number of units in our sample, we turn to randomization inference (Fisherian inference) to draw claims over statistical precision for our reduced form regression (see model (2))²⁷. As pointed out by Cattaneo et al. (2017), randomization inference in this setting is derived by the random distribution of treatment assignment within the window and allows for inference that is exact in finite

²⁵Individual controls are observed at the application year k , while controls measuring academic characteristics are observed at graduation in t .

²⁶See Cattaneo et al. (2015) for a technical discussion on how to extend the assumptions above to the case of a fuzzy RDD

²⁷We also report asymptotic p-values for all our main results.

sample, overcoming concerns over settings with few observations and unreliable asymptotic approximation.

5 Empirical analysis

In this section we first present and discuss empirical evidence to validate our identifying assumptions to then detail our results across outcomes.

5.1 Validity checks

We begin assessing the validity of our identification strategy by inspecting the balance in predetermined characteristics across units, inside the window and on both sides of the cutoff in Figure 4²⁸. We start with the sample of all applicants to the honors program where we observe gender, high school characteristics and final grade, residence and days to apply to the program, in panel 4a. We supplement this set of characteristics with average value of real estate property in the neighbourhood where each applicant lived and the results from an application of text analysis techniques to the cover letter candidates submit when applying to the program²⁹. We conduct the same balance tests for predetermined characteristics from the graduate dataset, panel 4b, and extend them to socio-economic status and parental educational attainment. We leverage this richer set of variables available to show that marginal honors students are very similar also when it comes to socio-economic background, measured from parental education and social class³⁰. Indeed, while the graduate dataset used in panel 4b allows us to assess balance over a richer set of predetermined characteristics, it effectively conditions on graduating from UniTO. This allows us to show that our sample is balanced both when we focus on characteristics that we observe for all applicants to the honors program (panel 4a) and also when we focus on the subset of students who graduated from the parent university³¹ (panel 4b). We verify this is due to the fact that the marginal applicants which we lose when switching from the administrative data to the graduate dataset are balanced, an empirical fact we show in Figure A.12 in the Appendix.

Table 2 and Table 3 report in more detail means and balance tests for units inside our chosen window, for both datasets, with p-values for testing the hypothesis of equal means.

²⁸We run balance tests by regressing each predetermined characteristics on a dummy for having crossed the cutoff only for units in the window.

²⁹Balance tests for covariates derived from text analysis techniques are available in Figure A.6 in the Appendix. From these letters we extract text length, proportions of nouns, verbs and adjectives over the number of all lemmas (meaningful base form of a word) used in the letter

³⁰Information on social class is computed by AlmaLaurea based on a reclassification of parental occupation

³¹This excludes for example students who dropped out, transferred or students who were admitted to the program but ended up not enrolling in either the honors program nor the parent university.

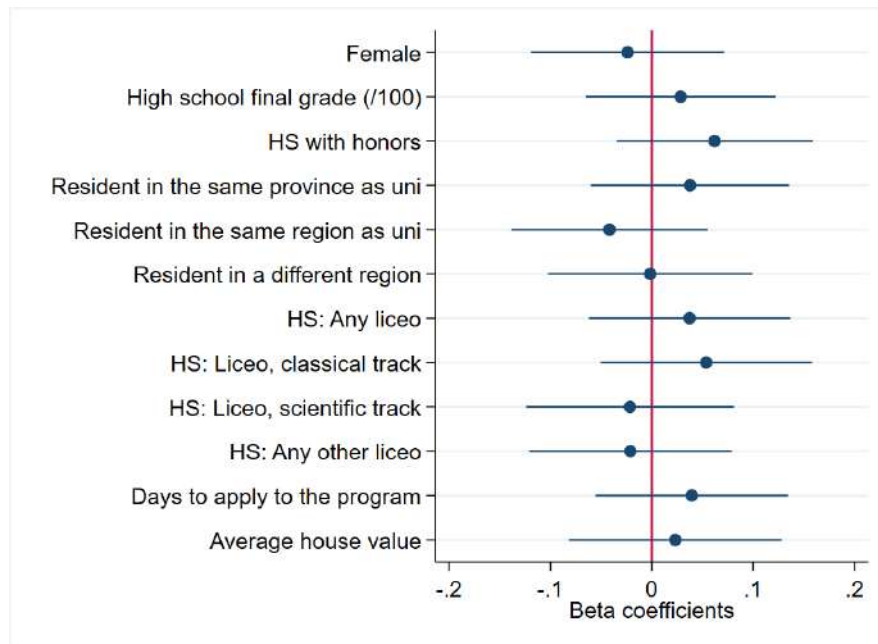
We report exact p-values, computed through permutation tests to overcome concerns over the modest sample sizes. Overall, all individual characteristics, but graduates' mother college attainment and our proxy for motivation, in Tables 2 to 3 are very similar across marginal candidates leading to the rejection of the null hypothesis at conventional levels of statistical significance. We do not find the imbalances in mothers' college attainment and our proxy for motivation particularly worrying as students awarded a 7 are more likely to come from families with less educated mothers and took longer to apply, contrary to expectations about the written test score being connected with underlying components of ability.

We further check whether predetermined covariates³² can jointly explain selection into treatment using the richer graduate dataset. We start by predicting the score using all variables we control for in equation (2) for all students in the window. We then test whether the average predicted test scores are different for marginally admitted and excluded students. The last row of Table 3 shows how students who barely scraped through the written test have a similar predicted score to those who just failed (6.46 vs 6.44), the p-value associated to the null of no difference is 0.26.

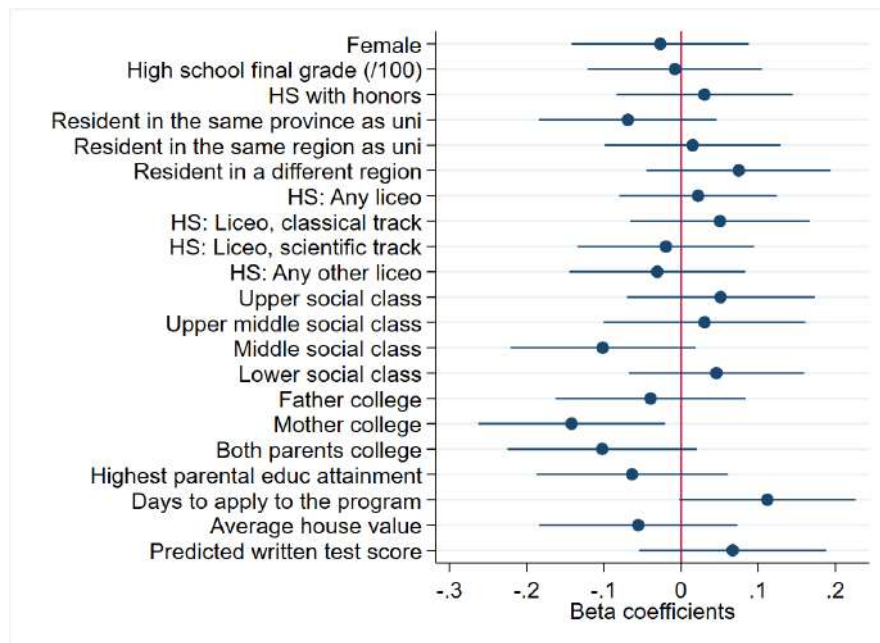
An additional check towards the validity of our identification comes from inspecting the relationship between observables characteristics and the running variable along the full support of the running. For our balance tests to be meaningful, we expect students within the window to be balanced while candidates at the tail of the distribution of the running variable are not. Figure A.4 and Figure A.5 in the Appendix show our findings for both the sample of all candidates and for those we observe in AlmaLaurea. We plot the distribution of predetermined characteristics over our running variable, the written test score. We report at the bottom of each plot the result of a test comparing the average value of the observable for candidates at different masspoints of the running variable together with exact p-values computed through permutation tests. Overall, our results provide evidence of clear imbalances as we compare our marginal candidates with those who lie outside the window. We are particularly reassured by the relatively large jump in the average high school grade between candidates awarded a 5 and those awarded a 6, hinting at the fact that the selection committee can partially capture some component of ability, as measured by the high school final exam. We also find noteworthy the overall relationship between having attended Liceo, classical high school track and the running variable. Figure A.4h in the Appendix clearly shows how larger values of the running variables are correlated with a higher proportion of candidates coming from this particular high school track, yet revealing a striking evidence of balance for those within the window. We find this relationship particularly relevant given the argumentative nature of the written test, which is likely to pick up on a set of writing and argumentative skills that are most commonly developed at that school type. We also note how there is no relationship in these graphs where we expect none, as in the case of gender, with the proportion stable across the support of the

³²See note in Table 3 for details

Figure 4: Balance tests



(a) Administrative data



(b) Graduation data

Notes Figures show beta coefficients from regression models where we regress each background characteristic on a dummy for having crossed the admission cutoff. Panel A refers to all applicants to the honors program from administrative data. Panel B looks at candidates which graduated from UniTO using data from the AlmaLaurea sample. Candidates' social class is a derived measure from parental occupation and educational attainment.

running variable.

We conduct an additional check based on the choice of essay questions candidates selected for their written exams. Overall, the results suggest that applicants in the window do not strongly differ in terms of chosen questions. The full details of this analysis can be found in Appendix A.3.

We provide further evidence corroborating our setup by analysing the results from an application of text analysis techniques to the cover letters submitted by candidates. These letters are part of the application package but are only read by the selection committee after grading the written test. We start by computing the length of each letter, by counting over tokens, to then perform basic pre-processing steps through which we remove stop words and apply a lemmatization algorithm³³. We then count the number of words and compute proportions for the number of adjectives, adverbs, nouns and verbs used in each letter over the number of lemmas. We provide evidence showing how these additional proxies for written ability are balanced for individuals within our chosen window (see Figure A.6) while there is evidence of imbalance along the written test score (see Figure A.7). We further explore the content available in the letters by first computing the Term Frequency - Inverse Document Frequency (TF-IDF) to rank the most relevant words candidates use in their letters. TF-IDF builds on word counts approaches by giving less weights to frequent terms that appear across many document, helping to find terms that are frequent in a few documents but not in others. TF-IDF will scale down very frequent words appearing across all documents because their associated IDF will be low, while words that only appear very infrequently will have a low TF-IDF because their TF will be low (Gentzkow et al., 2019). Table A.4 in the Appendix presents the top 10 words by the four mass points of the running variable. Comparing words for candidates inside the window reveals a striking similarity, with 9 out of 10 of their top words in common. The same analysis for candidates outside the window shows that they also share 5 of their top 10 words. We also note, and feel reassured by, the presence of words for “philosophy” and “classic” only for candidates awarded an 8, mirroring the larger proportion of candidates awarded this particular value of the running variable who attended classical high school (see Figure A.4h in the Appendix).

Through the application of text analysis techniques to cover letters, we showed that there are no apparent differences in writing styles between applicants in the window. Still, the identification assumption at the base of our identification strategy would be violated if the selection committee were able to reliably infer ability from candidates’ essay content, during the written test. To rule out this possibility, we arranged for 6 local economics professors to blindly regrade a random sample of 20 applicants’ written test performance³⁴, 10 of which to be considered as falling within the window (ie, scoring 6 or 7) and 10 outside

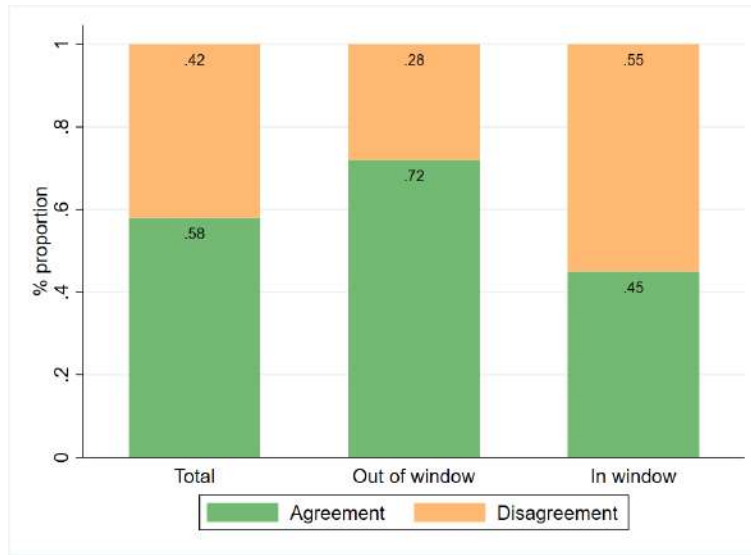
³³Tokens are defined as single terms in a document while lemmas refer to the base form of words commonly found in dictionaries, see Hovy (2020) for a discussion.

³⁴Applicants were sampled from the same admission year, 2013, to ensure comparability in essay questions

of the window (ie, scoring less than 6 or more than 7). Regraders were provided with extensive information on how to grade students' performance so as to recreate as much as possible the original setting in which essays are graded by the selection committee, including timing, grading scale and preferred applicant profile. We then used grades awarded by regraders to compute agreement scores: for each student, we would consider the regrader agreeing with the original selection committee if both recommended admission (non admission) in the honors program, disagreeing if only one party recommended admission. Figure 5 summarizes the results. The overall agreement rate between the original selection committee and blind regraders is 58%. This metric rises to 72% if we only consider out-of-window applicants, while it drops to 45% for in-window applicants. Results are in line with our conceptual framework: written exam scores are quite subjective and, while each examiner grades applicants' performance based on their definition of ability, results point to such a definition being volatile. Consistently with our take, parties tend to agree more when grading students outside of the window, ie at the tails of the applicants' ability distribution. At the same time, the agreement rate drops for students within the window, where we argue students are actually remarkably similar and in a portion of the ability distribution which makes it difficult to discriminate between them. For applicants within the window, if a barely passing or barely failing grade was awarded through a process which was as good as random, a regrader would hardly replicate it, which would explain the low agreement rate.

We then go back to the conceptual framework in Section 4 and check whether the explanatory power of the written test score, a proxy for ability as measured by the selection committee, in explaining college GPA, a post-determined ability proxy, is different for individuals inside the window compared to those outside. Based on the assumption that the selection committee can easily discriminate between high and low ability candidates but fails to successfully separate mid-high and mid-low type candidates, we would expect the written test score to perform very well in explaining the dependent for units outside the window but to fare poorly for units inside the window. Table 1 confirms our predictions: the regression of college GPA on written test score presents a much larger R^2 for students outside the window compared to those inside (24.14% vs 4.47%). Importantly, this relationship between GPA and a predetermined proxy for ability is unique to the written test score as measured by the selection committee. Indeed, the same does not happen when we regress college GPA on high school final grade, a more granular predetermined proxy for ability the selection committee does not observe during the written test, the jump in explanatory power for both units outside and within the window is much smaller (9.87% vs 5.69%).

Figure 5: Agreement rates based on regrading



Notes The figure shows the agreement rate between grades awarded by the original selection committee and grades awarded by blind regraders for a random sample of 20 applicants from the same admission year, 10 of which to be considered as falling within the window (ie, scoring 6 or 7) and 10 outside of the window (ie, scoring less than 6 or more than 7). We would consider the regrader agreeing (green) with the original selection committee if both recommended admission (non admission) in the honors program, disagreeing (orange) if only one party recommended admission. We plot the agreement rate between the original selection committee and regraders on the overall random sample (left), and then on applicants outside of the window (centre) and in the window (right).

Table 1: Adjusted R^2 when college GPA is the dependent variable

Sample	Control variables	
	High school final score	Admission test score
Full support	7.70	11.55
In window	5.69	4.47
Outside the window	9.87	24.14

Notes: Adjusted R^2 associated with a regression of college GPA on a constant and either high-school final grade (first column) or test score obtained in the written part of the admission process into the honors program (second column). In window sample includes students scoring between 6 and 7 in the written part of the admission process, outside the window sample includes students who scored less than 6 or more than 7. Full support includes all students who took the written test.

We conclude this section by inspecting the distribution of the running variable using the sample of all applicants to the honors program. Figure 2 shows how the density of the running is mostly concentrated for candidates in the window, with more candidates being awarded a 6 instead of a 7. While discontinuities in the density function of the running variable are commonly regarded as evidence of sorting around the cutoff, we consider this not probable in our setting for the following reasons. First, the subjective nature of the

Table 2: Balance tests: honors program applicants

Variable	In window		Score = 6		Score = 7		Difference	Exact
	N	Mean	N	Mean	N	Mean	in means	p-value
Female	428	0.53	260	0.54	168	0.52	-0.02	0.72
High school final grade (/100)	428	94.84	260	94.69	168	95.08	0.39	0.56
HS with honors	428	0.12	260	0.11	168	0.15	0.041	0.26
Resident in same province as uni	408	0.54	248	0.52	160	0.56	0.04	0.55
Resident in same region as uni	408	0.25	248	0.26	160	0.23	-0.04	0.49
Resident in a different region	408	0.21	248	0.21	160	0.21	-0.01	1.00
HS: Any liceo	362	0.88	217	0.87	145	0.90	0.02	0.62
HS: Liceo, classical track	362	0.46	217	0.44	145	0.50	0.05	0.37
HS: Liceo, scientific track	362	0.39	217	0.40	145	0.38	-0.02	0.71
Days to apply to the program	428	39.79	260	39.25	168	40.63	1.38	0.39
Average house value	363	1621.81	221	1609.17	142	1641.50	32.33	0.63

Note: The table shows the average and number of observations for a set of predetermined variables from the applicants dataset. The first two columns refer to the sample of applicants scoring between 6 and 7 (extremes included) in the written test, columns 3 and 4 to the subset of applicants scoring 6 while columns 5 and 6 to applicants scoring 7. Column 7 reports differences in means, for each variable, between applicants scoring 6 and applicants scoring 7. The last column reports exact (Fisherian) p-values for the difference in means. The class of *Resident in* variables refer to where the applicant resided as she was applying to the program: in the province of Turin, in other cities in the same region other than Turin, or outside the region. The dummy *HS: Liceo* indicates whether the applicant graduated from *Liceo* high schools, i.e. high schools meant to prepare students for university. *HS: Liceo, classical track*, *HS: Liceo, scientific track* and *HS: Any other Liceo* show which *Liceo* applicants attended, provided they graduated from a *Liceo* high school. *Days to apply* is the differences in days between when the call was released and the day the applicant submitted her application package. *Average house price* is the average sell price of residential estate in the neighbourhood where the applicant resided at the time of application.

test, as discussed in Section 2.3, makes it very difficult for candidates to effectively prepare. Second, the completely blind nature of the grading scheme poses an additional challenge for individual sorting. Third, given that entrance to the honors program carries clear monetary benefits for students, any sorting from candidates would have produced a larger mass point on 7, the contrary of what we observe in the data.

Table 3: Balance tests: Honors program students who graduated from host university

Variable	In window		Score = 6		Score = 7		Difference	Exact
	N	Mean	N	Mean	N	Mean	in means	p-value
Female	294	0.56	164	0.57	130	0.55	-0.03	0.76
High school final grade (/100)	294	94.99	164	95.04	130	94.93	-0.11	0.86
HS with honors	294	0.11	164	0.10	130	0.12	0.02	0.76
Resident in same province as uni	294	0.59	164	0.62	130	0.55	-0.07	0.30
Resident in same region as uni	294	0.23	164	0.23	130	0.24	0.01	0.87
Resident in a different region	294	0.18	164	0.15	130	0.21	0.06	0.30
HS: Any liceo	294	0.96	164	0.95	130	0.96	0.01	0.93
HS: Liceo, classical track	294	0.45	164	0.43	130	0.48	0.05	0.48
HS: Liceo, scientific track	294	0.39	164	0.40	130	0.38	-0.02	0.80
HS: Any other liceo	294	0.12	164	0.13	130	0.11	-0.02	0.74
Upper social class	267	0.38	154	0.36	113	0.41	0.05	0.51
Upper middle social class	267	0.16	154	0.16	113	0.18	0.02	0.80
Middle social class	267	0.37	154	0.41	113	0.31	-0.10	0.15
Lower social class	267	0.09	154	0.08	113	0.11	0.03	0.54
Father college	264	0.43	153	0.44	111	0.41	-0.04	0.63
Mother college	266	0.47	154	0.53	112	0.38	-0.14	0.03
Both parents college	264	0.29	153	0.33	111	0.23	-0.09	0.11
Highest parental educ attainment	266	4.61	154	4.65	112	4.56	-0.09	0.34
Days to apply to the program	294	41.48	164	39.73	130	43.68	3.95	0.05
Average house value	250	1647.08	138	1681.94	112	1604.13	-77.81	0.42
Predicted written test score	266	6.44	154	6.43	112	6.46	0.03	0.26

Note: The table shows the average and number of observations for a set of predetermined variables from the university graduate dataset. The first two columns refer to the sample of applicants scoring between 6 and 7 (extremes included) in the written test, columns 3 and 4 to the subset of applicants scoring 6 while columns 5 and 6 to applicants scoring 7. Column 7 reports differences in means, for each variable, between applicants scoring 6 and applicants scoring 7. The last column reports exact (Fisherian) p-values for the difference in means. The class of *Resident in* variables refer to where the applicant resided as she was applying to the program: in the province of Turin, in other cities in the same region other than Turin, or outside the region. The dummy *HS: Liceo* indicates whether the applicant graduated from *Liceo* high schools, i.e. high schools meant to prepare students for university. *HS: Liceo, classical track*, *HS: Liceo, scientific track* and *HS: Any other Liceo* show which *Liceo* applicants attended, provided they graduated from a *Liceo* high school. Highest parental educational attainment refers to the highest reported educational attainment between applicants' parents. It ranges from 1 to 5 (no title, elementary school, middle school, at least some high school, finished high-school, college). Socioeconomic status classification is based on parental occupation. *Days to apply* is the differences in days between when the call was released and the day the applicant submitted her application package. *Average house price* is the average sell price of residential estate in the neighbourhood where the applicant resided at the time of application. *Predicted written score* is the estimated outcome based on predetermined characteristics (gender, HS final grade, graduated HS with honors, geographical residence, HS: Liceo, parental education and socioeconomic status).

5.2 Results

We start this section by presenting results for enrolment and graduation outcomes at the University of Turin. We then condition on graduating from UniTO to progressively zoom in on outcomes connected to honours students' experience at university, academic achievement, prospects upon graduation and labour market outcomes one year after completing their degrees. Across Tables 4 - 10 Panel A reports LATE estimates, Panel B displays ITT results while Panel C shows the first stage. In all tables, odd columns report results for specification without controls while even columns add both individual controls and admission year FE. Throughout all outcomes the F-stat is very large mirroring the visual discontinuity in the probabilities of being accepted and enrolling in the program as shown in Figure 3. We also apply a procedure developed by Oster (2019) to quantify the selection on unobservables, based on the observables, that would be needed to drive to zero our results. We include an estimation of Oster's δ alongside our ITT results in Panel B and provide a discussion in Section 6.

We find that being offered a place in the honors program increases the probability of enrolling at Turin by 8 percentage points, in Table 4 column 2. This suggests the program acts as a recruitment device for a desirable portion of the student body, consistent with the literature on the role of magnet scholarships. We also find, in column 4, that students offered a spot in the honors program are 7 percentage points less likely to drop out from university³⁵, bringing the average drop out rate to virtually zero. Students are also 24 percentage points more likely to graduate on time. Indeed, the Italian university system places little disincentives to late graduations, so it is not uncommon for students to take some extra time to write their final thesis or complete their exam load. These two results point to the honors program acting as a commitment device, reducing the proportion of students who drop out and speeding up graduates' careers path at university.

We now turn to our AlmaLaurea dataset, where we explicitly condition on having graduated from the University of Turin. Table 5 explores graduates' experience at university, looking at outcomes for renting and living close to campus, working while at university and overall satisfaction with faculty members and fellow students. These outcomes are connected by design to being enrolled in SSST as honor students are offered complementary and communal accommodation close to campus, and enjoy a tuition fee waiver coupled with a scholarship to ease financial constraints. We are hence further reassured of the validity of our identification strategy to find an increase (+23 pp) in the proportion of graduates living within one hour from campus during lectures and a subsequent decrease in the proportion of students renting a place to attend university (-26 pp). We also find evidence that graduates enrolled in the honors program are less likely to work while attending university (-24 pp), a finding speaking to both the value of financial support provided in easing financial constraints and to the additional academic commitment related to being an honors student. We also find a small and positive, but statistically insignificant, rise

³⁵This figure also includes transfers to other institutions

in the proportion of honor graduates who are very happy of their relationship with the university faculty (+9 pp) and fellow classmates (+5 pp). Table 6 turns to the effect of honors program enrolment on academic achievement. Our estimates show that enrolling in the honors program leads to a strong increase in college GPA (+0.53 on a scale of 30), final graduation mark (+1.56 on a scale of 110) and in the probability of graduating *cum laude* (+17 pp). Table 6 also presents evidence of the effect of enrolling in the honors program on the average time to graduate. Our overall estimates point towards a small and imprecisely estimated reduction of around 0.14 years in time needed to complete one's program, consistent with the increase in probability of graduating on time presented in Table 4. These results are probably connected to the academic requirement honor students face as they need to maintain a high GPA (higher than 27/30) and be on time with their exams during their time at SSST or drop out if they fail to do so. Moreover, in the Italian university system GPAs are computed out of 30, with 18 being the minimum score to pass each exam. Final graduation mark strongly depends on GPA during university, with degrees being awarded out of 110 points and distinctions available for the best students³⁶. Additional points are then awarded during thesis defence, which is a mandatory requirement for all graduates, and to a lesser extent following additional rules which vary across departments. Finally, *cum laude* degrees are awarded to students by the graduating commission based on factors including, but not limited to, GPA and quality of the final thesis. These institutional rules explain why results on final graduation marks are closely connected to results on college GPA.

We next show results for labour market intentions reported by students at the very end of their fifth year of university³⁷ in Table 7. We start by showing how enrolment in the honors program leads to a reduction of 21 percentage points in the probability of reporting the intention to enter the labour market³⁸. This result is closely matched by the increase in interest towards PhD programs, +18 percentage points, describing students' intention to delay their entry into the labour market in favour of post-graduate education. Consistently, when asked to report the minimum compensation they would accept for a full time activity, what we refer to as their reservation wage, honors students report a value 212.27 euros lower than the control group. When compared to the control mean, honors students about to graduate seem to be willing to earn around 1,100 euros, an amount remarkably similar to the average monthly stipend awarded to PhD students in Italy in the period under study (MIUR, 2018). We corroborate this insight by reporting, in Table A.10 in the Appendix, how the reduction in reservation wage is entirely driven by the group of honors students who are planning to start a PhD after graduation. We then show that the honors program enlarges mobility horizons, with an increase of +11 percentage points

³⁶Graduation marks are derived by first rescaling GPAs to a 110 basis

³⁷Equivalent to completing an undergraduate degree and a master's degree. Enrolling in a master is a fairly common choice after a three-year undergraduate degree.

³⁸We defined willingness to enter the labour market as being willing to either look for a job, accept a job offer if received or continue a job had prior to graduation.

in willingness to work abroad, an effect entirely driven by mobility within Europe. Finally, focusing on students about to graduate from their undergraduate degree, we find that enrollment in the honors program leads to a positive yet insignificant increase in students' intention towards enrolling in a master degree.

Next, we turn to labour market outcomes where we assess in Table 8 whether intentions towards the future as stated right before exiting university are matched by actions registered one year after. We find evidence that enrolment in the honors program reduces by 41 percentage points the proportion of senior graduates in the labour force one year after graduation. This result is again closely matched by the striking increase, of almost the same magnitude, in the probability of being enrolled in a PhD program, +37 percentage points. Notably, the related mean for marginally untreated students (0.22) is quite high per se, reflecting the selected nature of this sample. At the same time, we again find a small and statistically insignificant increase in the probability of pursuing a master degree for junior graduates, a result possibly due to the already large proportion for the control group. These results suggest that the effects found in intentions at graduation time map in realized outcomes one year after degree completion.

Finally, we investigate heterogeneous effects across socio-economic backgrounds in Table 9 and Table 10. We show that both lower and upper class students, based on parental occupation and education, benefit from the honors program, albeit across different dimensions. This differential effect leads to the two groups converging towards the same means, rather than growing apart. In particular, we find that upper class students entirely drive the positive effects found on GPA (+0.66 on a scale of 30), final grade (+1.83 on a scale of 110) and on the probability of graduating *cum laude* (+0.25). Interestingly, despite not showing significant changes due to the honors program, lower class students display an higher untreated mean than upper class students. The opposite is true when we look at labour market intentions right before graduation. Here, results are driven by lower class students, with a decrease in the reported intention to enter the labour market (-42 pp) and in the monthly amount sufficient to accept a full-time activity (-290 euros). As for the academic outcomes, the untreated lower class students display higher intentions towards the labour market, while reservation wages are slightly higher for upper class students. The results of our heterogeneity analysis point towards a differential effect of the honors program depending on the students' socio-economic status: upper class students catch up in academics, while lower class students possibly adjust their expectations for the future and end up matching those of their upper class peers.

To address concerns over omitted variable bias, we apply, across all ITT results from equation 2, a procedure developed by Oster (2019) to quantify selection on unobservables. This procedure builds on the assumption that selection on observable characteristics can be informative of selection on unobservables³⁹. Oster's δ measures the relative degree of

³⁹The procedure also requires an assumption about R^2 max defined as the value of the R^2 we would achieve in a regression that also includes the relevant unobservable variables. Throughout this analysis we follow Oster (2019) in setting R^2 max equal to 1.3 times R^2 obtained from the regression with observable

selection on unobservables, based on selection on observables, that would be needed to drive to zero our estimates. We follow Oster (2019) in interpreting values of δ greater than 1 as robust. As we show in Panel B across Tables 4 to 10 all our estimated δ are above one in absolute value⁴⁰. Reassuringly, the estimated δ is large (3.15) when we regress our ex post measure of ability (GPA) on having been awarded a 7 instead of a 6. This implies an unrealistically large correlation between unobservables and our instrument of about 3 times compared to the correlation between our already rich set of controls and the instrument.

controls. We also show in Figure A.11 in the Appendix that our estimated deltas do not depend on the chosen value of R^2 max and remain robust even for implausibly larger values of this statistics

⁴⁰Negative values of deltas can be interpreted as a sign that unobservables need to have a correlation of opposite sign with our instrument than what happens for observables to drive our ITT to zero

Table 4: Enrolment, graduation and drop out outcomes

	Enroll in UniTO		Graduate on time		Drop out	
<i>Panel A: LATE</i>						
Admitted at SSST	0.04	0.08	0.26	0.24	-0.07	-0.07
P-value	0.34	0.04	0	0	0.04	0.04
Exact p-value	0.49	0.04	0	0	0.1	0.07
Mean - score 6	0.93	0.93	0.77	0.78	0.07	0.07
<i>Panel B: ITT</i>						
Score > cut - off	0.02	0.05	0.15	0.14	-0.04	-0.04
P-value	0.34	0.04	0	0	0.04	0.05
Exact p-value	0.49	0.04	0	0	0.1	0.07
Oster's delta		-11.40		26.81		10.95
<i>Panel C: FS</i>						
<i>Dependent: Pr(Admitted at SSST)</i>						
Score > cut - off	0.57	0.59	0.58	0.59	0.58	0.59
P-value	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0
F-stat	217.61	213.65	168.67	152.93	220.98	211.76
Controls	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes
N score 6	260	217	168	137	242	201
N score 7	168	145	122	105	160	140

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using administrative data for applicants to the program. Dependent variable for “graduate on time” is a dummy equal to 1 if students complete their degree program within nominal degree length plus an additional six months, “drop out” include both students who leave the university system and students transferred to another institution. “graduate on time” only defined for candidates who enrolled at UniTO and have exceeded completion time to graduate. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates’ geographical area of residence, a proxy for candidates’ motivation (time from SSST call release and submitting an application to the honors program) and admission year FE. We report Oster’s δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2017 and candidates within the chosen window (6 vs 7). SSST drop outs excluded from the sample. Endogenous variable: Admitted at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

Table 5: Graduates' experience at university

	Lived close to Uni		Working		Renting		Happy with faculty		Happy with students	
<i>Panel A: LATE</i>										
Enrolled at SSST	0.23	0.23	-0.24	-0.24	-0.15	-0.26	0.12	0.09	0.04	0.05
P-value	0.01	0.01	0	0	0.1	0	0.17	0.31	0.66	0.59
Exact p-value	0.01	0.02	0	0	0.1	0	0.17	0.37	0.72	0.62
Mean - score 6	0.65	0.65	0.28	0.29	0.39	0.39	0.19	0.19	0.44	0.44
<i>Panel B: ITT</i>										
Score > cut - off	0.14	0.14	-0.15	-0.15	-0.1	-0.16	0.07	0.05	0.03	0.03
P-value	0.01	0.01	0	0	0.11	0	0.18	0.34	0.67	0.62
Exact p-value	0.01	0.02	0	0	0.1	0	0.17	0.37	0.72	0.62
Oster's delta		14.48		-171.92		-9.48		3.61		1.95
<i>Panel C: FS</i>										
<i>Dependent: Pr(Enrolling at SSST)</i>										
Score > cut - off	0.63	0.62	0.63	0.62	0.62	0.62	0.63	0.62	0.63	0.62
P-value	0	0	0	0	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0	0	0	0	0
F-stat	191.68	188.21	191.68	188.21	188.19	188.21	191.68	188.21	191.68	188.21
Degree characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N score 6	155	154	155	154	155	154	155	154	155	154
N score 7	114	112	114	112	113	112	114	112	114	112

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using AlmaLaurea graduate survey data. Odd columns include controls for degree characteristics: type of degree and field of studies. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates' geographical area of residence, a proxy for candidates' motivation (time from SSST call release and submitting an application to the honors program), family background variables (socio economic status based on parental occupation and parental highest educational attainment) and admission year FE. We report Oster's δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2017 and candidates within the chosen window (6 vs 7). SSST drop outs excluded from the sample. Endogenous variable: Enrolled at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

Table 6: Academic outcomes

	GPA		Final grade		Graduating <i>cum laude</i>		Time to graduate	
<i>Panel A: LATE</i>								
Enrolled at SSST	0.52	0.53	1.83	1.56	0.19	0.17	-0.17	-0.14
P-value	0.01	0	0	0	0.02	0.03	0.09	0.16
Exact p-value	0.01	0	0	0.01	0.02	0.03	0.08	0.17
Mean - score 6	28.27	28.27	107.65	107.73	0.59	0.59	3.34	3.32
<i>Panel B: ITT</i>								
Score > cut - off	0.31	0.33	1.09	0.97	0.12	0.11	-0.1	-0.09
P-value	0.01	0	0	0.01	0.02	0.04	0.1	0.19
Exact p-value	0.01	0	0	0.01	0.02	0.03	0.08	0.17
Oster's delta		3.15		4.03		3.95		1.71
<i>Panel C: FS</i>								
<i>Dependent: Pr(Enrolling at SSST)</i>								
Score > cut - off	0.6	0.62	0.6	0.62	0.6	0.62	0.6	0.62
P-value	0	0	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0	0	0
F-stat	196.46	188.21	196.46	188.21	196.46	188.21	196.46	188.21
Degree characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes	No	Yes
N score 6	164	154	164	154	164	154	164	154
N score 7	130	112	130	112	130	112	130	112

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using AlmaLaurea graduate survey data for UniTO graduates. Dependent variable for “GPA” is measured out of 30 points, “Final grade” is measured out of 110 points, “Graduating *cum Laude*” is a dummy equal to one for graduates receiving a *Laude* in their degree and “Time to graduate” measures time to degree in years. Odd columns include controls for degree characteristics: type of degree and field of studies. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates’ geographical area of residence, a proxy for candidates’ motivation (time from SSST call release and submitting an application to the honors program), family background variables (socio economic status based on parental occupation and parental highest educational attainment) and admission year FE. We report Oster’s δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2017 and candidates within the chosen window (6 vs 7). SSST drop outs excluded from the sample. Endogenous variable: Enrolled at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

Table 7: Prospects at graduation

	Into LF		Reservation wage		PhD		Work abroad		Further studies	
<i>Panel A: LATE</i>										
Enrolled at SSST	-0.2	-0.21	-208.58	-212.27	0.11	0.18	0.11	0.11	0.09	0.1
P-value	0.03	0.02	0.01	0.01	0.3	0.1	0.11	0.09	0.18	0.12
Exact p-value	0.03	0.03	0.01	0.01	0.29	0.12	0.15	0.16	0.2	0.15
Mean - score 6	0.67	0.67	1344.45	1344.45	0.35	0.37	0.83	0.83	0.83	0.83
<i>Panel B: ITT</i>										
Score > cut - off	-0.13	-0.13	-129.37	-132.24	0.08	0.14	0.07	0.07	0.06	0.06
P-value	0.03	0.03	0.01	0.01	0.32	0.15	0.11	0.11	0.2	0.15
Exact p-value	0.03	0.03	0.01	0.01	0.29	0.12	0.15	0.16	0.2	0.15
Oster's delta		-15.87		11.25		2.72		16.01		-5.66
<i>Panel C: FS</i>										
<i>Dependent: Pr(Enrolling at SSST)</i>										
Score > cut - off	0.62	0.62	0.62	0.62	0.73	0.79	0.62	0.62	0.63	0.62
P-value	0	0	0	0	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0	0	0	0	0
F-stat	185.45	186.6	175.74	181.35	186.41	217.39	188.35	188.21	191.68	188.21
Degree characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N score 6	154	153	153	153	72	68	154	154	155	154
N score 7	112	111	108	107	73	62	113	112	114	112

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using AlmaLaurea survey data for UniTO graduates. Dependent variable for “Into LF” is a dummy equal to one for graduates who are willing to either look for a job, accept a job offer or continue a pre-existing job, “Reservation wage” records the minimum salary a graduate is willing to accept to start a full time occupation, “PhD” is a dummy equal to one for graduates who want to pursue PhD studies, “Work abroad” is dummy equal to one for graduates who would accept a job abroad, “Further studies” is a dummy equal to one for graduates who are planning to continue studying. “PhD” is only defined for master (including single cycles) degree holders who are hence eligible for postgraduate studies. Odd columns include controls for degree characteristics: type of degree and field of studies. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates’ geographical area of residence, a proxy for candidates’ motivation (time from SSST call release and submitting an application to the honors program), family background variables (socio-economic status based on parental occupation and parental highest educational attainment) and admission year FE. We report Oster’s δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2017 and candidates within the chosen window (6 vs 7). SSST drop outs excluded from the sample. Endogenous variable: Enrolled at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

Table 8: One year after graduation

	In PhD		In labour force		In Master	
<i>Panel A: LATE</i>						
Enrolled at SSST	0.29	0.37	-0.34	-0.41	0.28	0.05
P-value	0.04	0.01	0.02	0	0.09	0.78
Exact p-value	0.04	0.03	0.03	0.04	0.14	0.86
Mean - score 6	0.21	0.22	0.65	0.63	0.8	0.8
<i>Panel B: ITT</i>						
Score > cut - off	0.22	0.29	-0.26	-0.32	0.12	0.02
P-value	0.05	0.02	0.03	0.02	0.11	0.83
Exact p-value	0.04	0.03	0.03	0.04	0.14	0.86
Oster's delta		-10.47		-91.67		0.82
<i>Panel C: FS</i>						
<i>Dependent: Pr(Enrolling at SSST)</i>						
Score > cut - off	0.76	0.77	0.76	0.77	0.43	0.44
P-value	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0
F-stat	119.41	75.56	119.41	75.56	22.46	14.62
Degree characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes
N score 6	34	32	34	32	41	40
N score 7	40	38	40	38	31	29

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using AlmaLaurea survey data for UniTO graduates one year after graduation. Dependent variable for “In PhD” is a dummy equal to one for graduates who are pursuing a PhD, “In labour force” is a dummy equal to one for graduates who are either working or looking for a job, “In Master” is a dummy equal to one for graduates who are studying towards a master degree. “In PhD” is only defined for master (including single cycle) degree holders who are hence eligible for postgraduate studies. “In Master” is only defined for bachelor degree holders. Odd columns include controls for degree characteristics: type of degree and field of studies. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates’ geographical area of residence, a proxy for candidates’ motivation (time from SSST call release and submitting an application to the honors program), family background variables (socio economic status based on parental occupation and parental highest educational attainment) and admission year FE. We report Oster’s δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2016 and candidates within the chosen window (6 vs 7). SSST drop outs excluded from the sample. Endogenous variable: Enrolled at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

Table 9: Academic outcomes and intentions: Heterogeneous treatment effects

	GPA				Final grade				Graduated <i>cum laude</i>			
	Lower class		Upper class		Lower class		Upper class		Lower class		Upper class	
<i>Panel A: LATE</i>												
Enrolled at SSST	0.19	0.34	0.75	0.66	1.36	1.7	2.43	1.83	0.08	-0.01	0.3	0.25
P-value	0.53	0.28	0	0	0.18	0.14	0	0	0.51	0.92	0.01	0.02
Exact p-value	0.58	0.36	0.01	0	0.24	0.2	0	0.02	0.58	0.99	0.01	0.04
Mean - score 6	28.45	28.47	28.1	28.07	107.86	108.04	107.33	107.43	0.62	0.64	0.54	0.54
<i>Panel B: ITT</i>												
Score > cut - off	0.11	0.2	0.45	0.41	0.74	1.02	1.44	1.13	0.04	-0.01	0.18	0.16
P-value	0.55	0.35	0.01	0	0.21	0.21	0	0.01	0.53	0.93	0.01	0.04
Exact p-value	0.58	0.36	0.01	0	0.24	0.2	0	0.02	0.58	0.99	0.01	0.04
Oster's delta		3.81		2.01		16.22		2.66		-0.27		2.75
<i>Panel C: FS</i>												
<i>Dependent: Pr(Enrolling at SSST)</i>												
Score > cut - off	0.55	0.6	0.59	0.62	0.55	0.6	0.59	0.62	0.55	0.6	0.59	0.62
P-value	0	0	0	0	0	0	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0	0	0	0	0	0	0
F-stat	72.03	73.82	125.14	117.64	72.03	73.82	125.14	117.64	72.03	73.82	125.14	117.64
Degree characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N score 6	85	75	89	79	85	75	89	79	85	75	89	79
N score 7	64	47	83	65	64	47	83	65	64	47	83	65

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using AlmaLaurea survey data for UniTO graduates. Break downs by social class based on parental occupation and educational attainment. Dependent variable for “GPA” is measured out of 30 points, “Final grade” is measured out of 110 points, “Graduating *cum Laude*” is a dummy equal to one for graduates receiving a *Laude* in their degree. Odd columns include controls for degree characteristics: type of degree and field of studies. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates’ geographical area of residence, a proxy for candidates’ motivation (time from SSST call release and submitting an application to the honors program), family background variables (socio economic status based on parental occupation and parental highest educational attainment) and admission year FE. We report Oster’s δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2017 and candidates within the chosen window (6 vs 7). SSST drop outs excluded from the sample. Endogenous variable: Enrolled at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

Table 10: Academic outcomes and intentions: Heterogeneous treatment effects (continued)

	Wants to enter LF				Reservation wage			
	Lower class		Upper class		Lower class		Upper class	
<i>Panel A: LATE</i>								
Enrolled at SSST	-0.34	-0.42	-0.11	-0.1	-295.23	-290.75	-202.64	-158.05
P-value	0.04	0.01	0.37	0.38	0.01	0.01	0.1	0.18
Exact p-value	0.02	0.01	0.39	0.43	0.01	0.04	0.09	0.18
Mean - score 6	0.71	0.7	0.64	0.63	1312.17	1312.17	1375.5	1375.5
<i>Panel B: ITT</i>								
Score > cut - off	-0.2	-0.25	-0.07	-0.06	-170.58	-169.2	-128.66	-98.73
P-value	0.03	0.01	0.4	0.44	0.01	0.02	0.11	0.24
Exact p-value	0.02	0.01	0.39	0.43	0.01	0.04	0.09	0.18
Oster's delta		24.42		-4.92		19.79		3.67
<i>Panel C: FS</i>								
<i>Dependent: Pr(Enrolling at SSST)</i>								
Score > cut - off	0.59	0.59	0.63	0.62	0.58	0.58	0.63	0.62
P-value	0	0	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0	0	0
F-stat	61.13	71.41	110.45	117.64	57.07	69.12	110.37	117.19
Degree characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes	No	Yes
N score 6	75	74	80	79	75	75	78	78
N score 7	46	46	66	65	45	45	63	62

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using AlmaLaurea survey data for UniTO graduates. Break downs by social class based on parental occupation and educational attainment. Dependent variable for “Wants to enter LF” is a dummy equal to one for graduates who are willing to either look for a job, accept a job offer or continue a pre-existing job, “Reservation wage” records the minimum salary a graduate is willing to accept to start a full time occupation. Odd columns include controls for degree characteristics: type of degree and field of studies. Even columns add controls for: gender, a set of pre-determined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates’ geographical area of residence, a proxy for candidates’ motivation (time from SSST call release and submitting an application to the honors program), family background variables (socio economic status based on parental occupation and parental highest educational attainment) and admission year FE. We report Oster’s δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2017 and candidates within the chosen window (6 vs 7). SSST drop outs excluded from the sample. Endogenous variable: Enrolled at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

6 Robustness checks

A series of robustness checks do not significantly affect our baseline results. First, estimates remain very similar without controls as we show in odd columns. We then explore the relationship between observable characteristics and the running variable along the full support of the running. Figure A.5 in the Appendix provides visual evidence of this relationship and reports results from balance tests where we contrast individuals outside the window and candidates within the 6-7 window from the main specification. Our results show how there appears to be little to no evidence of association between observable characteristics and the running variable for units within the window. This finding however does not hold for candidates awarded low or high scores, which are contrasted at arbitrary cutoff values following the masspoints in the running variable. The clear imbalances we find are suggestive of a meaningful relationship between observable characteristics and the running variable outside the window. This relationship, which might also capture some unobserved heterogeneity connected to our outcomes of interest, explains why we cannot investigate treatment effects at placebo cutoffs.

We assess our choice of window by applying Cattaneo et al. (2016)'s algorithm to select the window based on a series of balance tests on nested windows. We apply this procedure separately across our administrative sample and then on our sample of graduates from AlmaLaurea. We perform balance tests using all the main control variables used in our main specification (equation 2) and follow Cattaneo et al. (2016) in choosing a conservative threshold of α equal to 0.15. The procedure runs, for each nested window, a series of balance tests and reports the smallest p-value associated with the test. The selected window is the smallest possible window with a p-value greater than the threshold level of α .

As we show in Table A.13 in the Appendix, the procedure yields back our original window of 6 to 7 as the largest possible one for administrative data. Applying it to graduate data, in Table A.14 in the Appendix, leads to an initial failure to select a valid window due to an imbalance for our motivation proxy, which measures the number of days it takes candidates to apply to the program. As noted also in our balance tests above, see Figure 4b, while our motivation proxy shows signs of imbalance, selection into treatment does not align with expectations. It is marginally rejected students who appear to be more eager to apply, or to exert less effort, and it is hence unlikely to be indicative of a stronger motivation component picked up by the selection committee. Once we repeat the window selection procedure on the sample, but removing our motivation proxy, we get back our original 6 to 7 window.

We also check the robustness of our results by adding more proxy for individual ability to mitigate concerns over the selection committee discriminating against students based on any ability component unobserved to the econometrician. We focus on our reduced form specification, in equation 2, where we regress our ex post measure of ability (GPA) on the ability proxy as measured by the selection committee (having crossed the cutoff). Table A.11 in the Appendix presents our estimates. We start by first replicating our main

results in column 1, we then add a control in column 2 for the average property value in the neighborhoods where each applicants resides. Finally, we add to our original specifications a set of control variables⁴¹ derived from an application of text analysis to candidates' admission letters. Looking across columns our results are very similar and remain stable as we add these finer controls. We take this as additional evidence towards the validity of our design.

Lastly, we investigate the robustness of our results by relaxing the exclusion restriction and allowing for a direct effect of having a score of 7 instead of 6 on our ex post measure of ability (GPA). We follow the methodology developed by Conley et al. (2012) which allows to bound IV estimation by assuming the degree of violation of the exclusion restriction. We show in Figure A.8 in the Appendix that even allowing for a direct effect of the instrument on GPA between 0 and a third of the ITT, the lower bound of the coefficient estimate for our LATE would still be above zero, suggesting that our results are robust to plausible violations of the identifying assumptions.

7 Conclusion

This paper investigates the impact of first being accepted, and then of enrolling, in an honors program on academic choices, achievements and labour market outcomes by exploiting a plausibly exogenous discontinuity along the main admission score. We study the honors program offered by the University of Turin, Italy, in a context of non-competitive, universalist tertiary education. Honors students are selected on the basis of a written exam, an interview and an application package. Admitted students are granted access to dedicated multidisciplinary honors courses, which they are required to attend on top of their university curriculum. They are also requested to maintain a high GPA and fulfill all academic commitments on time. Honors students live together on complimentary accommodation on campus and enjoy monetary benefits.

We achieve identification by leveraging on a natural experiment arising from the admission procedure to the honors program. We exploit plausible exogenous variation in a regression discontinuity design, local randomization framework and provide empirical evidence to support the required exogeneity claims. This is possible thanks to the blind nature of the written test, a coarse grading scheme and the positioning of the admission cutoff. We argue that the admission cutoff lies in a subset of the applicant's ability distribution where the selection committee is unable to perfectly discriminate between candidates and provide extensive evidence towards the required assumptions.

We find that the honors program acts as both a recruitment and a commitment device. Indeed, being admitted to the program increases the probability of enrolling at the parent

⁴¹We add the same controls we used in our balance tests in fig A.7: the number of tokens in the letter, the number of lemmas, the proportion of adjectives, adverbs, nouns, verbs and average reading time in seconds.

university, while reducing drop out rates and increasing the probability to graduate on time. Enrolling in the honors program leads to an increase in GPA, final graduation grade and in the probability of graduating *cum laude*.

Next, we document how enrolment in the honors program changes labour market prospects and outcomes. Through mandatory survey data assessing students' future intentions, we show a sizeable change on future plans, which shift away from immediate labour market entry and towards pursuing PhD-level studies. We find that enrolling in the honors program leads to a decrease in the probability of reporting the intention to enter the labour market after graduation, closely matched by an increase in interest towards doctoral programs. Consistently, reservation wage at graduation drops roughly to the level of PhD stipends in the country. Through the same survey one year after graduation, we are able to follow graduates as they enter the labour market and check whether their intentions are verified. We find that actions match stated intentions: one year after graduation, enrolling in the honors program leads to a reduction in the proportion of senior graduates in the labour force and to a matching increase in those enrolled in a PhD program. Finally, we investigate heterogeneous effects across socio-economic backgrounds. We find that both lower class and upper class students benefit from the program. Lower class students adjust their expectations by driving the decrease in intention to enter the labour market and reservation wage, while upper class students drive the effects found in academic achievements. These effects lead the two groups to converge to a similar post-treatment mean across all the aspects above.

When comparing our results on academic achievements with those in Pugatch and Thompson (2022) it is important to take into account the differences in context across the two programs. While both honors programs are offered by institutions of comparable quality⁴², Pugatch and Thompson (2022) study an honors program in the US, where the tertiary education system is heavily stratified, with abundant options for fostering excellence across all fields. We instead look at a European setting, where the educational system is dominated by public institutions, ensuring higher level of universalism with no clear flagship institution. Beyond the institutional setting, our program is also different as it is regarded as a public investment towards excellence, hence it comes with a full tuition waiver and a scholarship. In comparison, honors students in Pugatch and Thompson (2022) are charged additional tuition fees, on top of regular university fees, to participate in the honors program. Moreover the honors courses in our setting do not substitute traditional learning but they are designed to complement the academic activities offered within the degree courses at the University of Turin. Indeed, honor classes in Turin are designed with a strong multidisciplinary component, as discussed in Appendix A, and are only available to honor students. For these reasons, prior exposure to honors coursework is not possible in our setting, removing the key mechanism found in Pugatch and Thompson (2022).

Adding to the literature investigating the returns to quality in higher education, we

⁴²Both universities ranking within the top 500 QS ranking

study whether honors programs could be an effective tool to promote talent in a non-competitive setting. We argue that similar honors programs effectively improve admitted students' academic achievement. Moreover, we provide unique causal evidence on their effects in fostering aspirations and actions towards pursuing postgraduate education. Such beneficial action could qualify as an alternative way to foster talent for policymakers and university administrators. Overall, honors programs are particularly attractive, compared to establishing flagship institutions, given that they promote human capital accumulation and are relatively cheap to set up by pooling together the necessary resources across university departments.

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A Appendix

A.1 Written test: Examples of essay questions

We report below the six essay questions first year candidates could chose from in the 2020-2021 admission test. Applicants are asked to pick and write three out of the six essays. Applicants have two hours to complete the written exam.

1. Discuss the following statement, attributed to Galileo Galilei: “Scientific truths are not decided by majority vote.”
2. Most of us are fascinated by astronomic discoveries trying to fathom the origins and limits of the universe; many of us admire Newton because of his discovery of the law of gravity, which underlies the movement of astronomical objects. Did this reduce our enthusiasm and our curiosity towards the universe? Absolutely not. Why should, then, knowledge on creativity, on reward area neurotransmitters, on the physiology of the disappointment area reduce our enthusiasm for the works of Richard Wagner or Thomas Mann or Michelangelo?’ Discuss the statement by British neuroscientist Semir Zeki (*Splendors and Misteries of the Brain*. 2011)
3. According to Hans Jonas, responsibility should be thought of as a future-oriented moral imperative, which can be summarized in the formula: “Act so that the effects of your action are compatible with the permanence of genuine human life on Earth” (*The Imperative of Responsibility*. 1979). Considering the ongoing pandemic emergency, express your considerations on limits and resources of this principle, focusing on the problematic relationship between freedom and responsibility.
4. According to Bauman, where does science stand in a liquid society?
5. The self and the other, the self with the other: can we see relationships as a meeting ground? Discuss, considering the repercussions on the single person and on the social fabric, other than on politics and the economy.
6. Remote and near causes lead to historical events. Illustrate and discuss said distinction though the use of what you consider being a model instance.

A.2 Honors courses offered by *Scuola di Studi Superiori “Ferdinando Rossi”*

We report below the syllabus of one of the honors courses offered to selected students.

Course: Determinants of decision-making: the concept of free will

Instructors

- M.D. Professor A. Department of Neurosciences - Psychiatry
- Professor B. Department of Philosophy
- Professor C. Department of Law
- M.D. Professor D. Department of Neurosciences - Psychiatry
- Professor E. Department of Psychology
- Dr. F. Department of Neurosciences

Course overview

The aim of this course, that will be divided in four modules, is to deepen the key determinants of decision-making. Particularly, the process and the concept of decision making will be addressed from the point of view of neuroscience, cognitive science, law and philosophy.

Decision making is a process of generating, evaluating and selecting among a set of at least two choice alternatives. In real-life situations, the choices involve a variable of uncertainty. In recent years, growing knowledge, new technologies, and progress in science have broadened existing definitions and concept of decision making. Recent functional imaging and clinical evidence indicates that a remarkably consistent network of brain regions is involved in decision making, in decisions made in the context of social interactions and in moral cognition. More recent work emphasizes the role of intuitive and emotional processes in decision making.

The challenge to address this issue is that it requires extensive cross-field integration of neuroscience, psychology, evolutionary biology and anthropology.

The exploration of the neurobiology of decision making and its implications for the legal system has highlighted the complexity of the interaction between the two. The theories of free will in a philosophical perspective will be considered.

Schedule

Module 1. Free will and neurosciences

Instructors: Dr. F, Prof. A, Prof. D

- Introduction: determinism; cognitivism; freedom from our brain
- Neurological fundamentals of decision making: neural fundamentals of decision making and social behaviour; neural fundamentals of moral awareness; decision making and emotions
- Decision making and psychiatry: decision making and psychopathology; mental competence; forensic psychopathology

Module 2. Choices: cognitive processes and fundamentals in evolution

Instructor: Prof. E

- Introduction; choices in organisms; choosing under uncertainty; utility theory; from utility to biological fitness; risk and risk aversion.
- Prospect theory; framing effects; evolution and prospect theory; inter-temporal choice; time discounting models; evolution and time discounting.
- Heuristics and bias; standard approach; ecological approach; bounded rationality; "fast and frugal" heuristics; adaptive toolbox.

Module 3. Neurosciences and Law

Instructor: Prof. C

- Anthropological and legal origins of trust
- Complex choices and risk
- Neuroimaging and evidence during trial

Module 4. Free will and intentionality

Instructor: Prof. B

- Theories on free will
- Theories on intentionality

Student evaluation

Oral examination

Table A.1: Descriptive statistics: Administrative data

	Applicants		Admitted		Enrolled		Window	
	N	Mean	N	Mean	N	Mean	N	Mean
Female	577	0.53	154	0.48	144	0.49	428	0.53
High school final grade (/100)	577	94.36	154	95.65	144	95.53	428	94.84
Graduated HS with honors	577	0.12	154	0.19	144	0.17	428	0.12
HS: Any liceo	484	0.87	138	0.93	128	0.93	362	0.88
HS Liceo: classical	484	0.43	138	0.49	128	0.48	362	0.46
HS Liceo: scientific	484	0.42	138	0.42	128	0.42	362	0.39
HS Liceo: any other liceo	484	0.03	138	0.02	128	0.02	362	0.02
Resident in same province as uni	546	0.55	147	0.54	138	0.55	408	0.54
Resident in same region as uni	546	0.25	147	0.27	138	0.27	408	0.25
Resident in different region	546	0.20	147	0.19	138	0.18	408	0.21
Time to apply to honors program (days)	577	39.95	154	41.75	144	41.31	428	39.79
Average house value	489	1620.33	136	1608.49	128	1613.67	363	1621.81

Note: The table reports descriptive statistics for a subset of predetermined variables. Applicants refers to all individuals who took the entry test, Admitted refers to all individuals who successfully passed the entry test, Enrolled refers to all students ever enrolled in the honors program, In Window refers to students who obtained a 6 or a 7 in the written phase of the selection process. The class of *Resident in* variables refer to where the applicant resided as she was applying to the program: in Turin, in other cities in the same region (Piedmont), or outside the region. The dummy *HS: Liceo* indicates whether the applicant graduated from *Liceo* high schools, i.e. high schools meant to prepare students for university. *HS Liceo: classical* and *HS Liceo: scientific* show which *Liceo* track applicants attended, provided they graduated from a *Liceo* high school. *Time to apply to honors program* measures days between the student's application and when the call was published.

Table A.2: Descriptive statistics: AlmaLaurea data

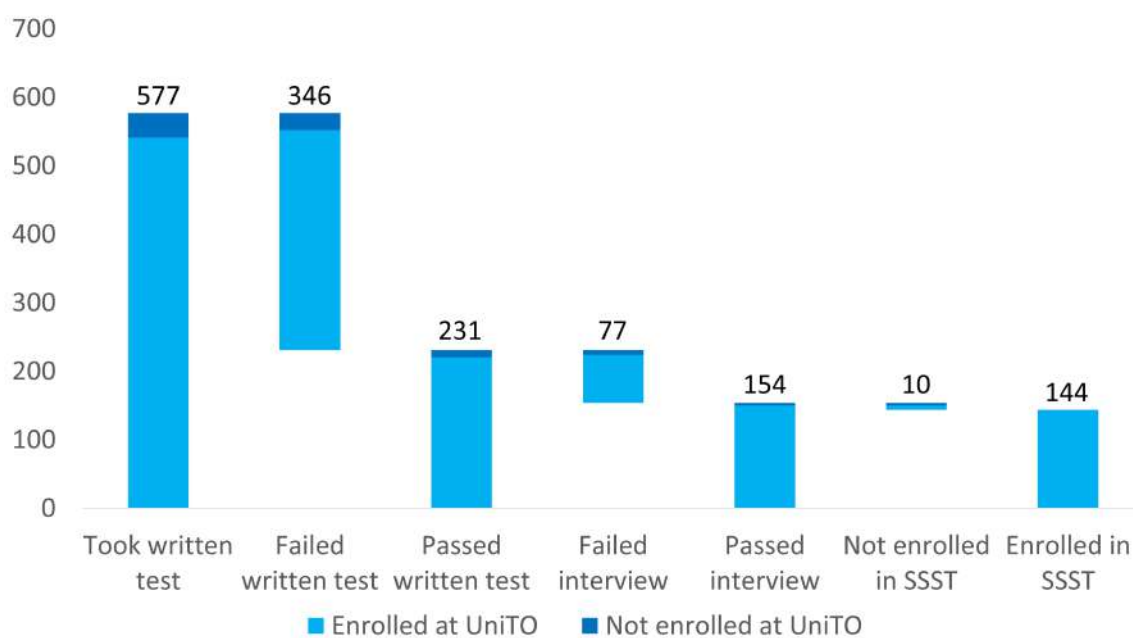
	Honors program		University	
	Applicants	In window	Eligible	Overall
Female	0.55	0.56	0.72	0.63
High school final grade (/100)	94.58	94.99	88.90	79.98
Graduated HS with honors	0.11	0.11	0.03	0.02
HS: Any liceo	0.94	0.96	0.81	0.78
HS Liceo: classical	0.42	0.45	0.16	0.15
HS Liceo: scientific	0.41	0.39	0.38	0.43
HS Liceo: any other liceo	0.12	0.12	0.27	0.21
Resident in same province as uni	0.60	0.59	0.60	0.58
Resident in same region as uni	0.24	0.23	0.25	0.21
Resident in different region	0.16	0.18	0.15	0.21
Lower social class	0.10	0.09	0.21	0.20
Middle social class	0.39	0.37	0.33	0.33
Upper-middle social class	0.14	0.16	0.24	0.24
Upper social class	0.37	0.38	0.22	0.22
Both parents college	0.28	0.29	0.12	0.11
Highest parental educational attainment (/5)	4.58	4.61	4.15	4.13
Average house value	1638.06	1647.08		

Note: The table reports descriptive statistics for the subset of predetermined variables contained in the AlmaLaurea dataset, comprising all graduates. The class of *Resident in* variables refer to where the applicant resided as she was applying to the program: in Turin, in other cities in the same region (Piedmont), or outside the region. The dummy *HS: Liceo* indicates whether the applicant graduated from *Liceo* high schools, i.e. high schools meant to prepare students for university. *HS Liceo: classical* and *HS Liceo: scientific* show which *Liceo* track applicants attended, provided they graduated from a *Liceo* high school. *Both parents college* takes value one if both parents graduated from college. *Highest parental educational attainment* is the maximum value between parents' educational levels and ranges between 1 (no title) and 5 (completed college education).

Table A.3: Honors program: Admitted and drop outs

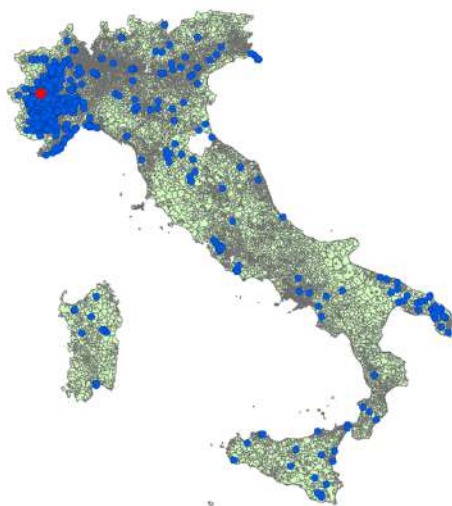
Admission year	Applicants	Admitted	Enrolled	Drop out
2012	79	39	39	9
2013	99	35	33	10
2014	87	30	26	3
2015	127	35	33	6
2016	118	25	23	5
2017	107	30	30	7

Notes: All columns refer to students admitted, enrolled and dropped out from the honors program. While enrollment in the honors program is conditional on enrollment at the parent university, a student could drop out from the program without dropping out from the parent university. Similarly, a student who was admitted to the honors program could decide not to enroll into the honors program, while still enrolling at the parent university.

Figure A.1: Outcomes of the admission process

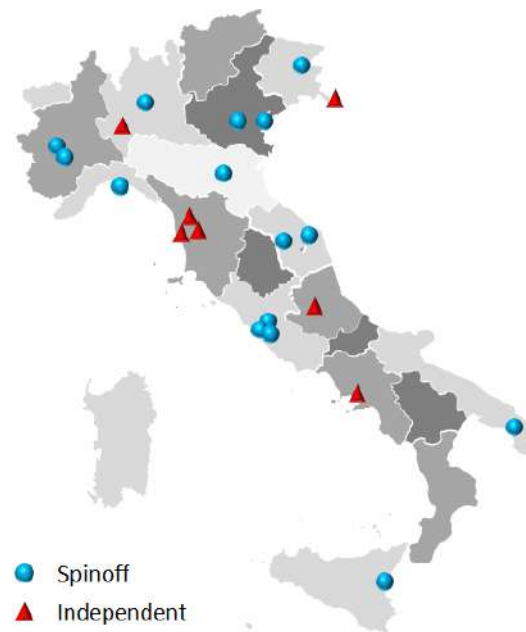
Notes The figure breaks down the total number of students taking the written entry test in the subsequent selection phases, including a breakdown of enrolled (light blue) or not enrolled (dark blue) at the University of Turin.

Figure A.2: Applicants' area of residence



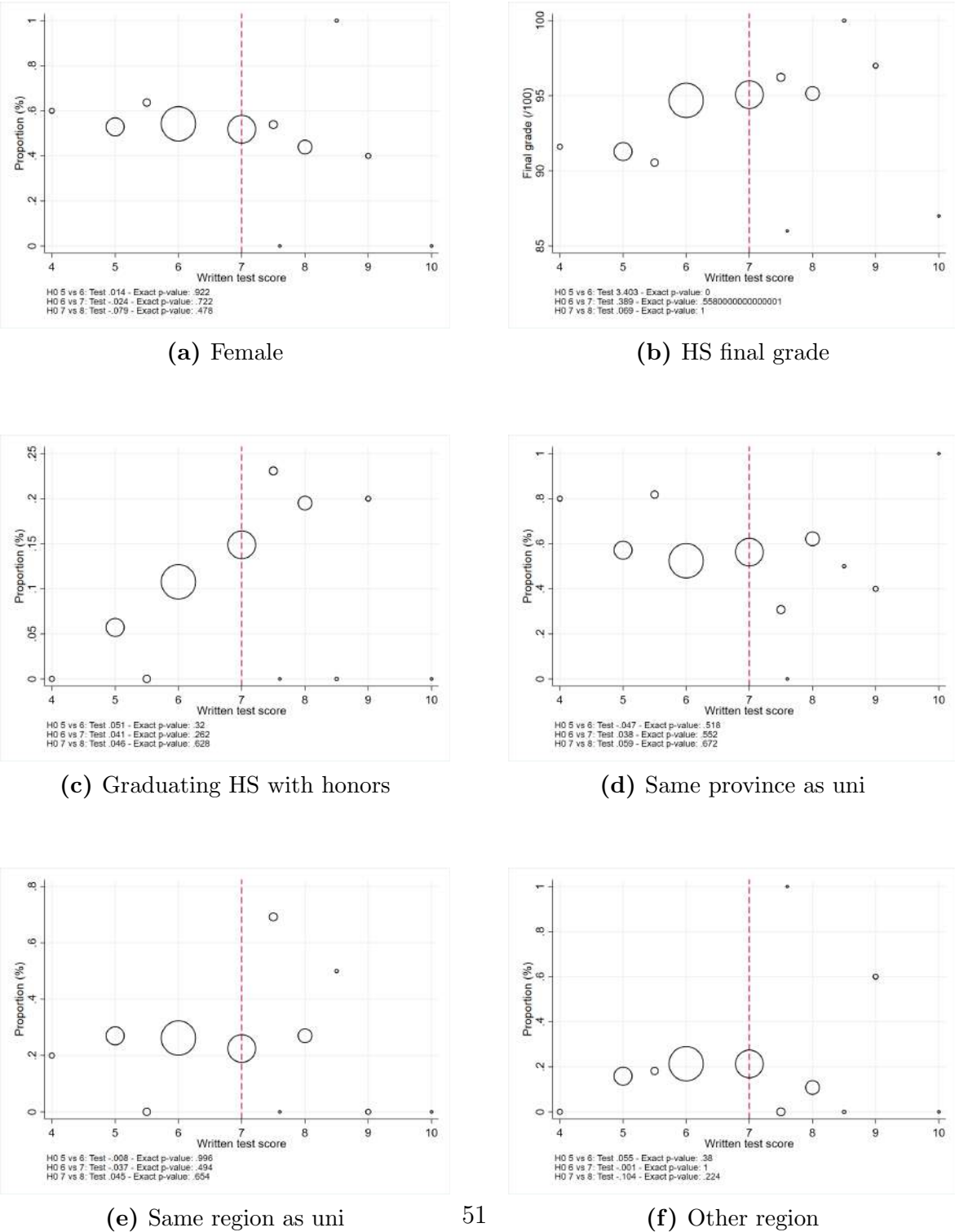
Notes The figure maps the area of residence of applicants to the honors program, as retrieved from the application package. Note data is only available for candidates who included an address in their application package. We show with a red dot Turin, where both the honors program and the parent university are located.

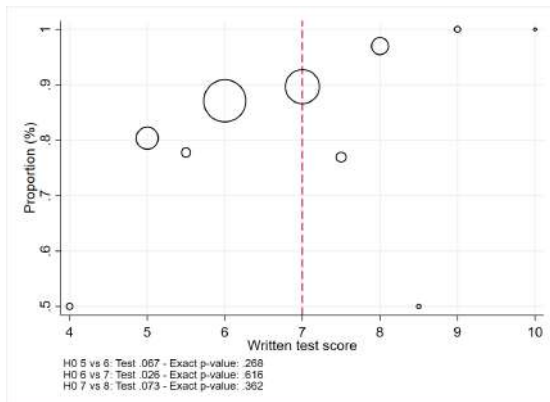
Figure A.3: Honors programs in Italy



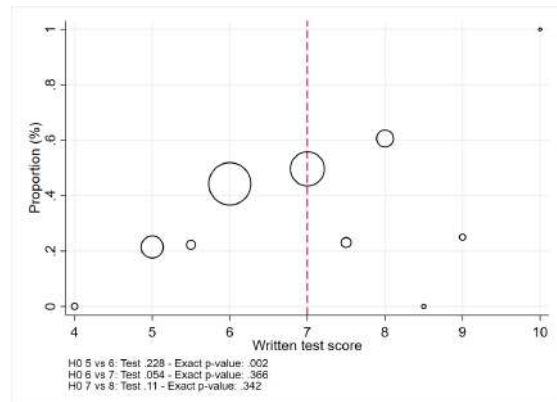
Notes The figure maps honors programs in Italian universities and research bodies. The generic name in the Italian university system is *Scuole Superiori Universitarie* (SSU). The system distinguishes between 7 older institutions, which are recognized (independent) by the Ministry of Education and granted autonomous university status, and over 15 unrecognized SSUs (spinoffs of a parent university). *Spinoff* institutions are comparable to SSST being direct offshoots of parent universities. *Independent* institutions are older institutions, recognized by the Italian Ministry of University and Research, focusing on advanced classes, usually at postgraduate level only.

Figure A.4: RDD plots of pre-determined variables over the running - Administrative dataset

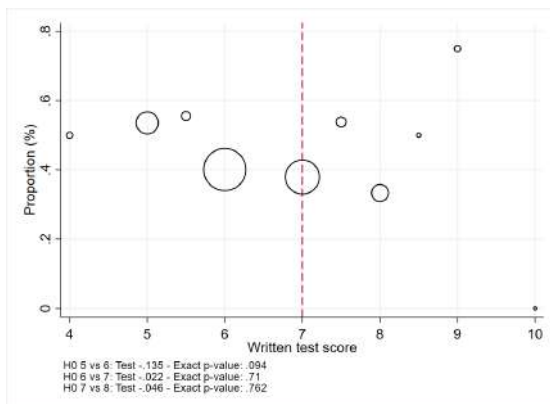




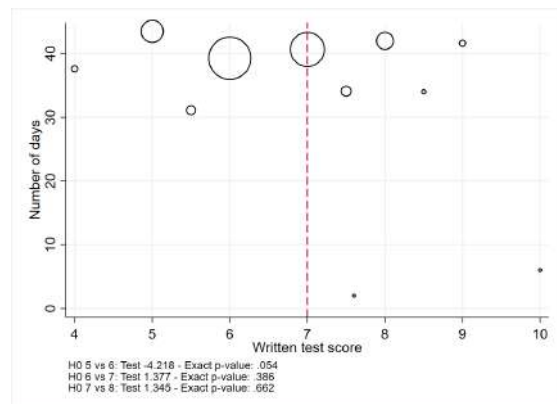
(g) HS: any liceo



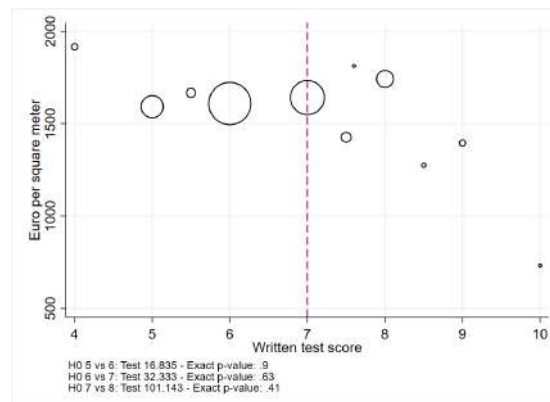
(h) HS Liceo: classical track



(i) HS Liceo: scientific track



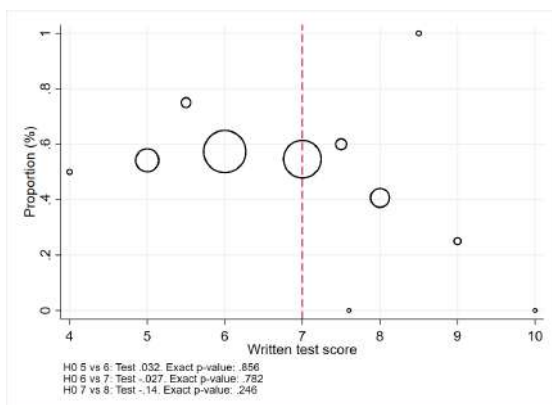
(j) Days to apply to the program



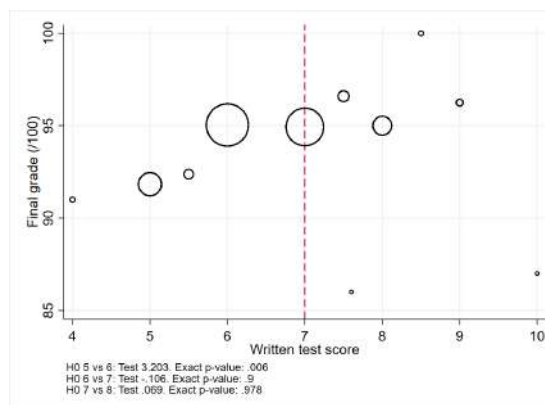
(k) Average house value

Notes The graphs show RDD plots of a series of pre-determined characteristics on the running variable (written test scores). Each circle's radius is proportional to the number of candidates in that class. Exact p-values for two by two difference-in-means comparisons are reported in the bottom left corner.

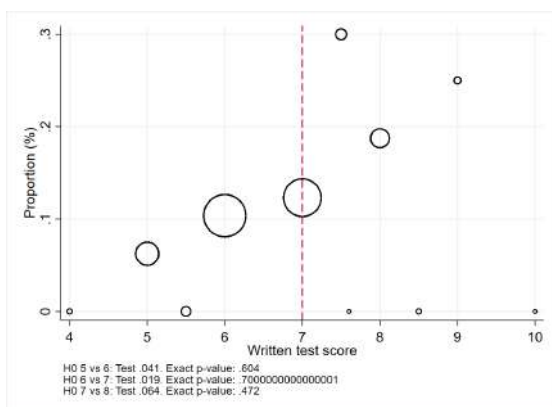
Figure A.5: RDD plots: Graduate dataset



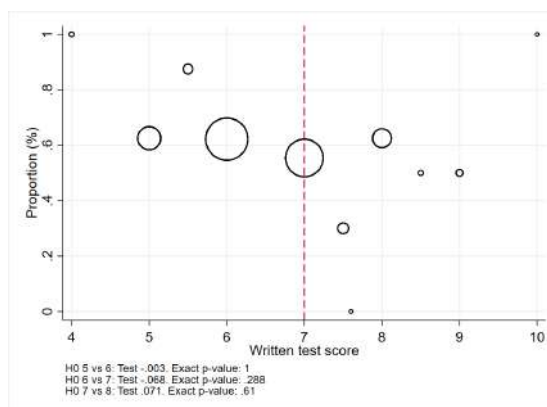
(a) Female



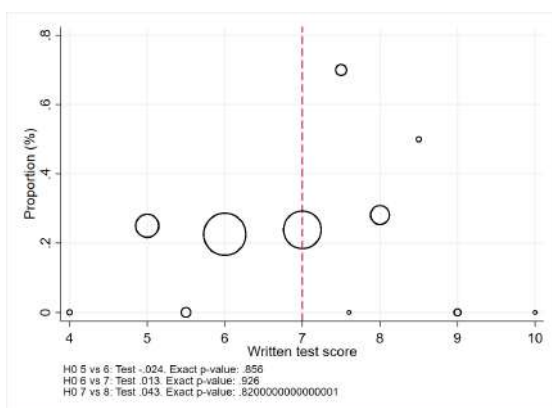
(b) High school final grade (/100)



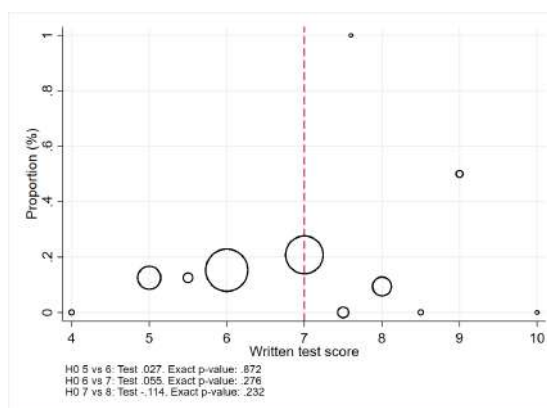
(c) Graduated HS with honors



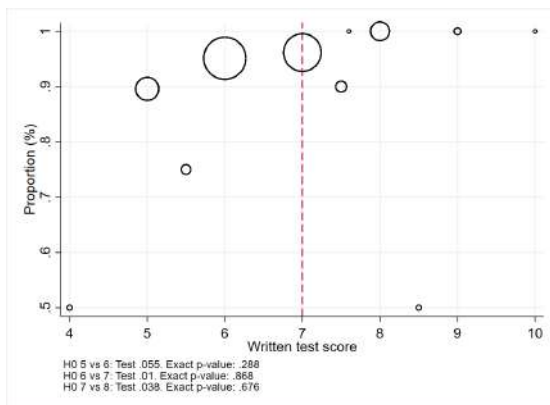
(d) Same province as uni



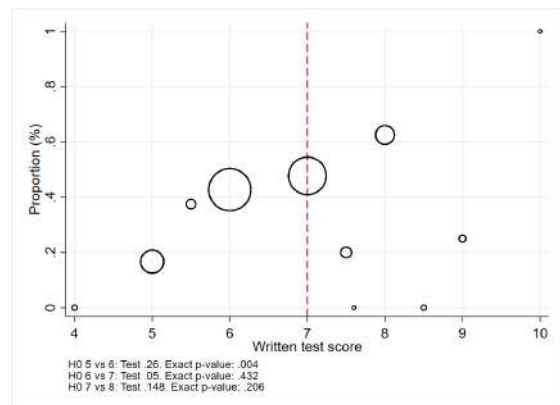
(e) Same region as uni



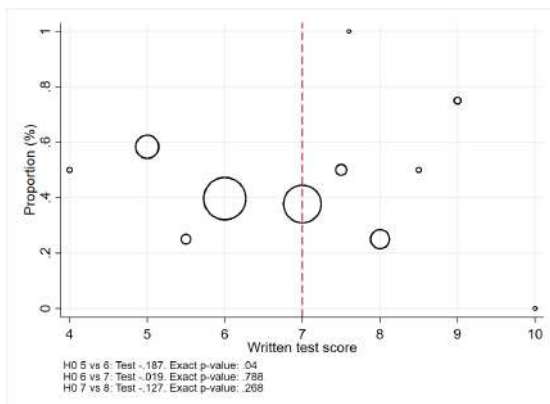
(f) Different region



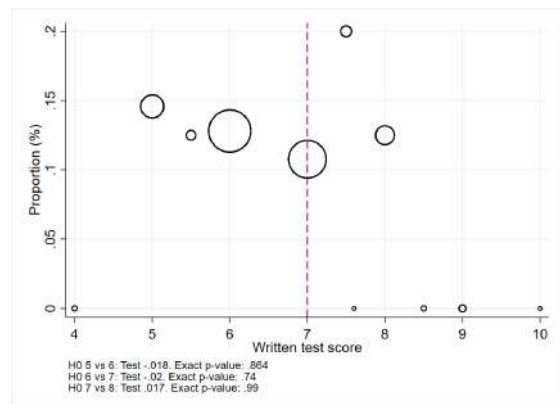
(g) HS: Any liceo



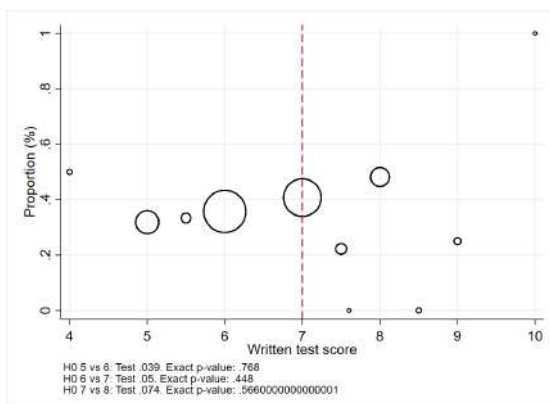
(h) HS Liceo: classical track



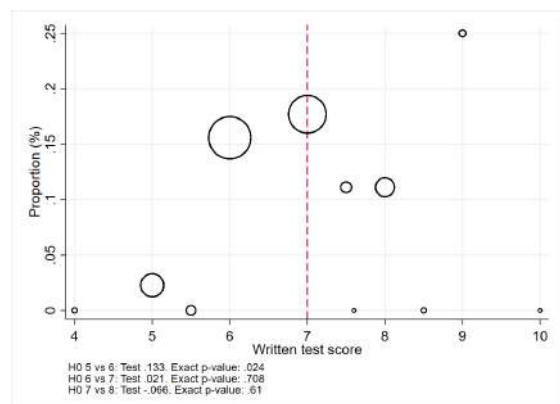
(i) HS Liceo: scientific track



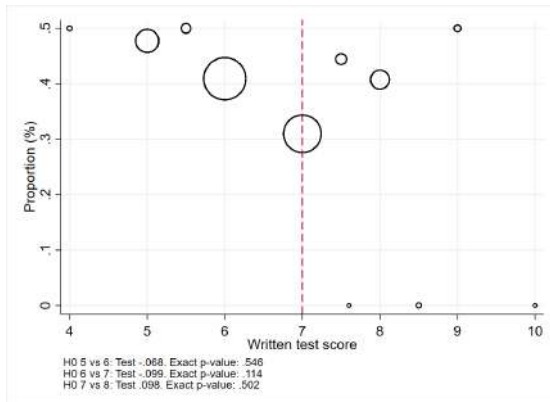
(j) HS Liceo: Any other liceo



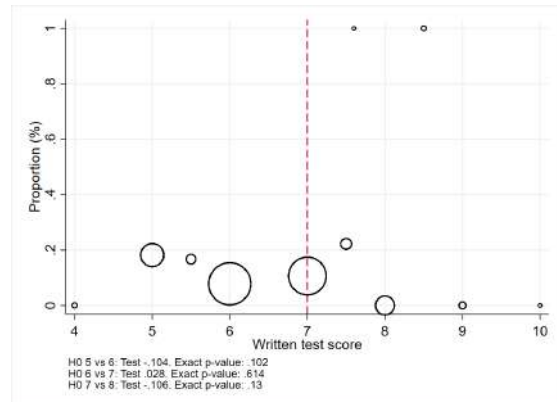
(k) Upper social class



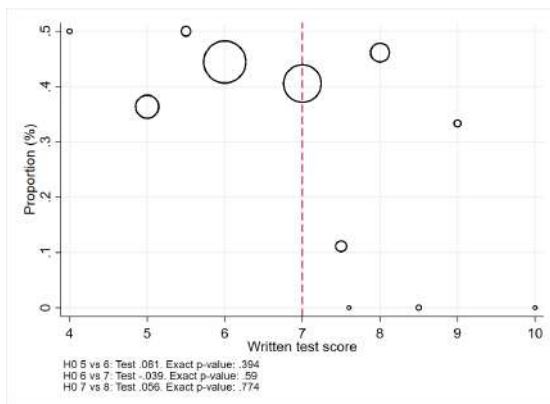
(l) Upper-middle social class



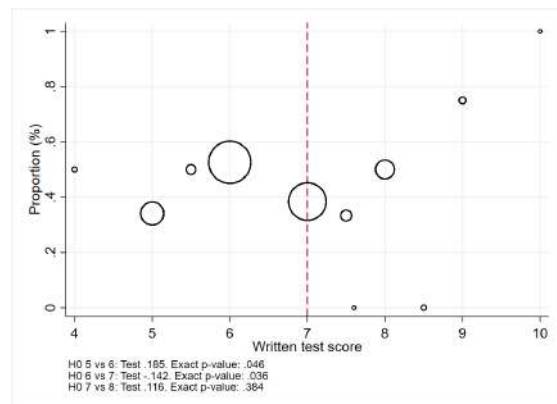
(m) Middle social class



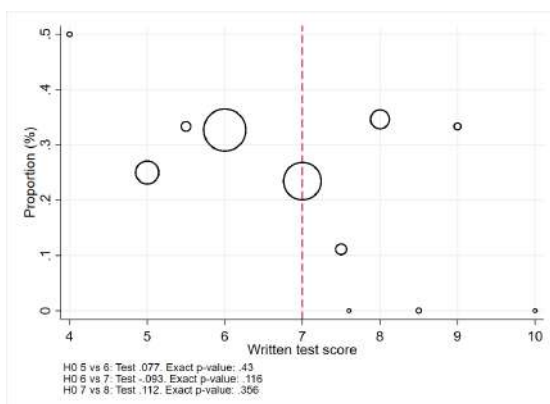
(n) Lower social class



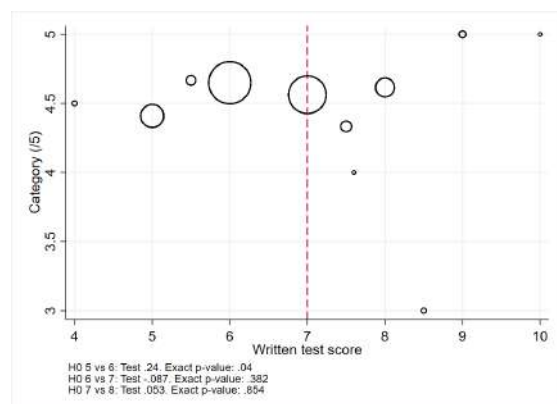
(o) Father college



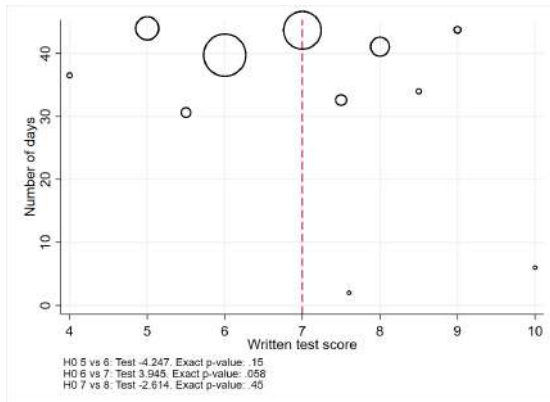
(p) Mother college



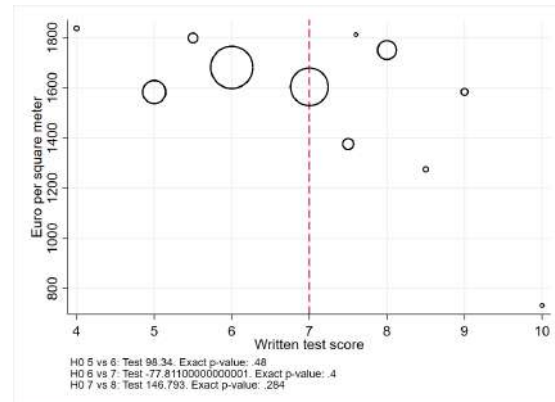
(q) Both parents college



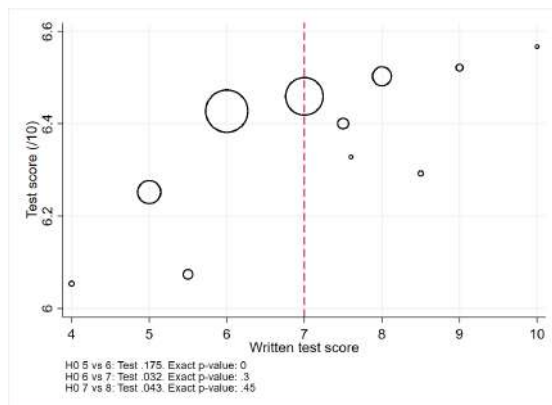
(r) Highest parental educational attainment



(s) Days to apply to the program



(t) Average house value



(u) Predicted written test score

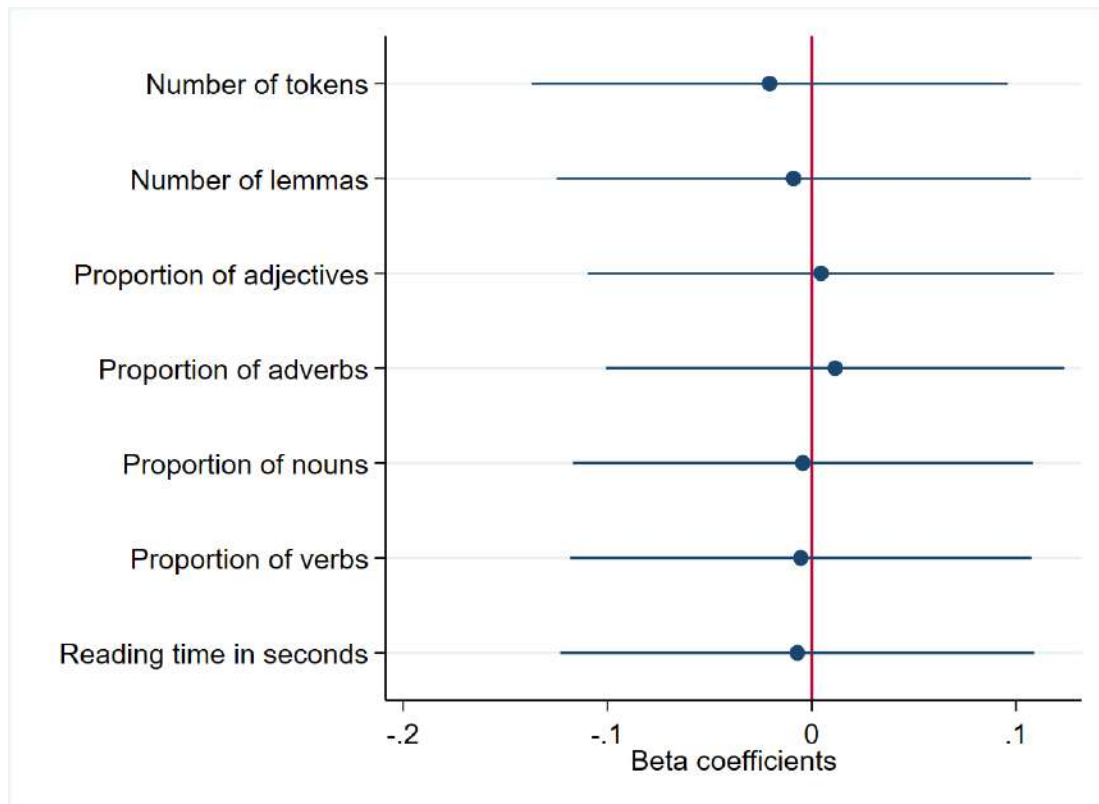
Notes The graphs show RDD plots of a series of pre-determined characteristics on the running variable (written test scores). Each circle's radius is proportional to the number of candidates in that class. Exact p-values for two by two difference-in-means comparisons are reported in the bottom left corner

Table A.4: Most common words in cover letters

Written test score							
5		6		7		8	
English	Italian	English	Italian	English	Italian	English	Italian
Degree	Corso	Path	Percorso	Scientific	Scientifico	Education	Formazione
Turin	Torino	To be	Stare	Path	Percorso	Philosophy	Filosofia
Scientific	Scientifico	Knowledge	Conoscenza	University	Universit(à)	Academic	Universitario
To be	Stare	Experience	Esperienza	To be	Stare	Knowledge	Conoscenza
Knowledge	Conoscenza	Scientific	Scientifico	Knowledge	Conoscenza	Setting	Ambito
To believe	Ritenere	Academic	Universitario	Setting	Ambito	Experience	Esperienza
Academic	Universitario	To allow	Permettere	To believe	Ritenere	To be	Stare
To allow	Permettere	University	Universit(à)	Academic	Universitario	Scholastic	Scolastico
Experience	Esperienza	To believe	Ritenere	Experience	Esperienza	Classical	Classico
Student	Studente	Setting	Ambito	Opportunity	Possibilit(à)	To believe	Ritenere

Notes: TF - IDF rescaled counts by mass points of the running variable. Top 10 words reported. We report common words in green for candidates in the window and in orange for candidates outside the window. The actual TF-IDF rescaled Italian words are reported in full form and accompanied by their English equivalent.

Figure A.6: Balance tests: Text analysis variables



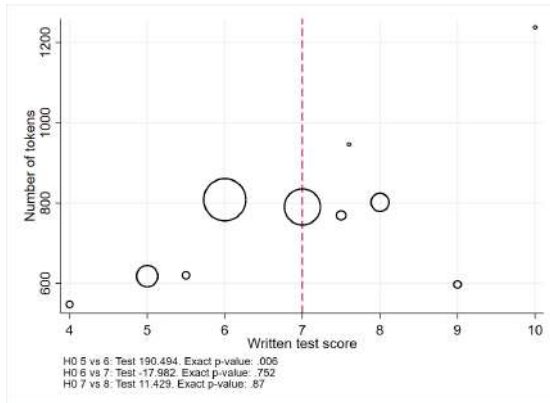
Notes Figure shows beta coefficients from regression models where we regress variables, derived from application letters, on a dummy for having crossed the admission cutoff. We applied text analysis tools to extract number of tokens (text length), number of lemmas (meaningful base form of a word), reading time in seconds, proportions of nouns, verbs and adjectives over the number of all lemmas used in the letter. Sample includes all SSST applicants which were merged to their application letter.

Table A.5: Enrolment, graduation and drop out outcomes - SSST drop outs included

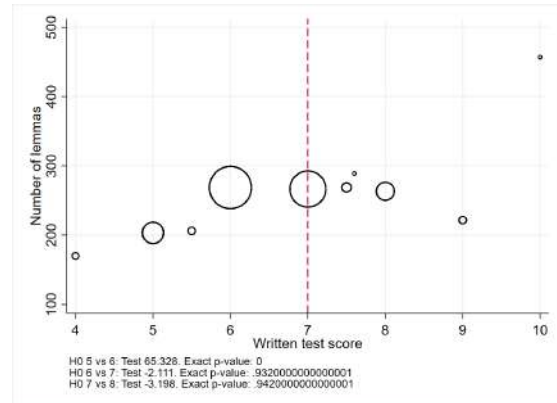
	Enroll in UniTO		Graduate on time		Drop out	
<i>Panel A: LATE</i>						
Enrolled at SSST	0.04	0.07	0.19	0.16	-0.04	-0.05
P-value	0.33	0.05	0.01	0.02	0.21	0.22
Exact p-value	0.45	0.45	0.01	0.01	0.3	0.3
Mean - score 6	0.93	0.93	0.77	0.78	0.07	0.07
<i>Panel B: ITT</i>						
Score > cut - off	0.02	0.05	0.12	0.1	-0.03	-0.03
P-value	0.33	0.05	0.01	0.03	0.21	0.22
Exact p-value	0.45	0.45	0.01	0.01	0.3	0.3
Oster's delta		-11.50		15.23		18.50
<i>Panel C: FS</i>						
<i>Dependent: Pr(Enrolling at SSST)</i>						
Score > cut - off	0.61	0.64	0.63	0.64	0.63	0.64
P-value	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0
F-stat	298.99	298.41	233.87	220.05	302.14	293.18
Controls	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes
N score 6	260	217	168	137	242	201
N score 7	189	165	138	120	180	159

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using administrative data for applicants to the program. Dependent variable for “graduate on time” is a dummy equal to 1 if students complete their degree program within nominal degree length plus an additional six months, “drop out” include both students who leave the university system and students transferred to another institution. “graduate on time” only defined for candidates who enrolled at UniTO and have exceed completion time to graduate. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates’ geographical area of residence, a proxy for candidates’ motivation (time from SSST call release and submitting an application to the honors program) and admission year FE. We report Oster’s δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2017 and candidates within the chosen window (6 vs 7). SSST drop outs included in the sample. Endogenous variable: Admitted at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

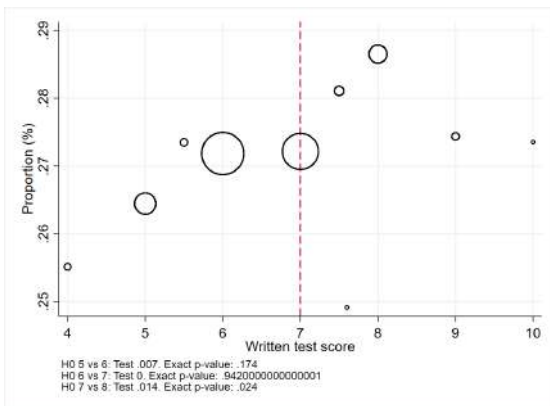
Figure A.7: RDD plots - Text analysis



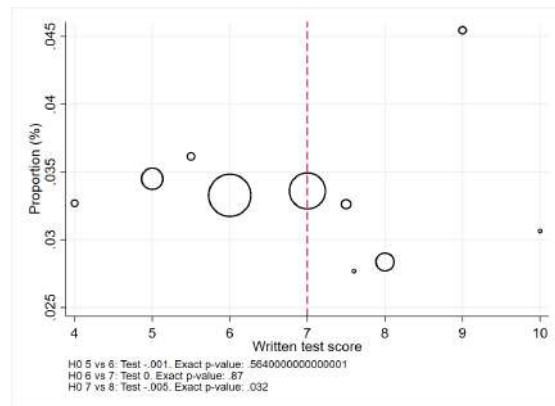
(a) Number of tokens



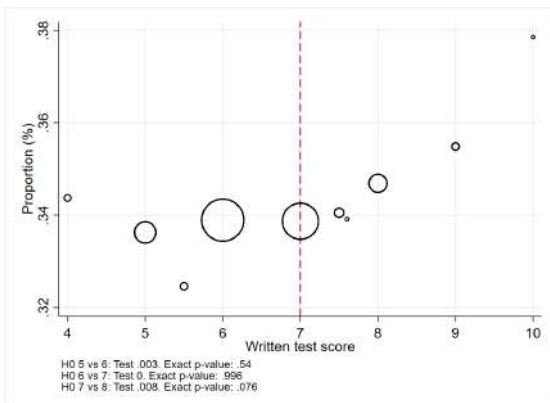
(b) Number of lemmas



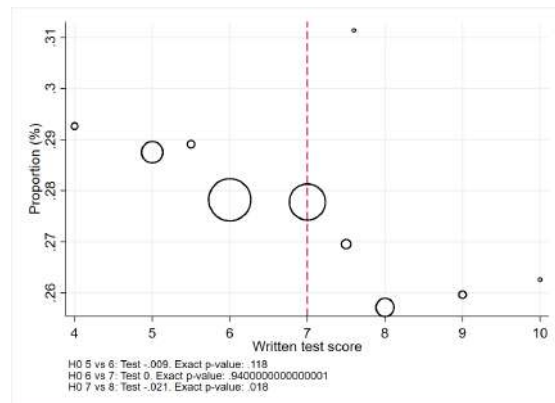
(c) Proportion of adjectives



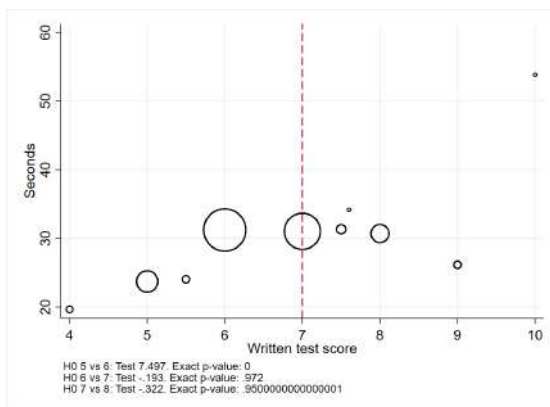
(d) Proportion of adverbs



(e) Proportion of nouns



(f) Proportion of verbs



(g) Reading time in seconds

Notes The graphs show RDD plots of a series of variables, derived from application letters, on the running variable (written test scores). Depicted variables are number of tokens (text length), number of lemmas (meaningful base form of a word), reading time in seconds, proportions of nouns, verbs and adjectives over the number of all lemmas used in the letter. Each circle's radius is proportional to the number of candidates in that class. Exact p-values for two by two difference-in-means comparisons are reported in the bottom left corner

Table A.6: Graduates' experience at university - SSST drop outs included

	Lived close to Uni		Working		Renting		Happy with faculty		Happy with students	
<i>Panel A: LATE</i>										
Enrolled at SSST	0.2	0.19	-0.23	-0.22	-0.13	-0.25	-0.05	-0.04	0	0.03
P-value	0.02	0.01	0	0	0.13	0	0.41	0.45	0.97	0.57
Exact p-value	0.01	0.02	0	0	0.12	0	0.41	0.5	0.98	0.58
Mean - score 6	0.65	0.65	0.28	0.29	0.39	0.39	0.9	0.9	0.88	0.88
<i>Panel B: ITT</i>										
Score $\hat{\epsilon}$ cut - off	0.13	0.13	-0.15	-0.14	-0.08	-0.16	-0.03	-0.03	0	0.02
P-value	0.02	0.02	0	0.01	0.14	0	0.42	0.49	0.97	0.6
Exact p-value	0.01	0.02	0	0	0.12	0	0.41	0.5	0.98	0.58
Oster's delta'		17.65		30.83		-8.86		64.53		-5.93
<i>Panel C: FS</i>										
<i>Dependent: Pr(Enrolling at SSST)</i>										
Score > cut - off	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66
P-value	0	0	0	0	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0	0	0	0	0
F-stat	240.45	235.82	240.45	235.82	236.37	235.82	240.45	235.82	240.45	235.82
Degree characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N score 6	155	154	155	154	155	154	155	154	155	154
N score 7	125	122	125	122	124	122	125	122	125	122

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using AlmaLaurea survey data. Odd columns include controls for degree characteristics: type of degree and field of studies. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates' geographical area of residence, a proxy for candidates' motivation (time from SSST call release and submitting an application to the honors program), family background variables (socio economic status based on parental occupation and parental highest educational attainment) and admission year FE. We report Oster's δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2017 and candidates within the chosen window (6 vs 7). SSST drop outs included in the sample. Endogenous variable: Enrolled at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

Table A.7: Academic outcomes - SSST drop outs included

	GPA		Final grade		Graduating with honors		Time to graduate	
<i>Panel A: LATE</i>								
Enrolled at SSST	0.38	0.4	1.41	1.2	0.14	0.13	-0.1	-0.07
P-value	0.04	0.01	0.02	0.03	0.07	0.07	0.27	0.42
Exact p-value	0.06	0.02	0.03	0.05	0.08	0.08	0.25	0.46
Mean - score 6	28.27	28.27	107.65	107.73	0.59	0.59	3.34	3.32
<i>Panel B: ITT</i>								
Score > cut - off	0.24	0.27	0.88	0.79	0.09	0.08	-0.06	-0.05
P-value	0.04	0.02	0.02	0.04	0.07	0.09	0.28	0.45
Exact p-value	0.06	0.02	0.03	0.05	0.08	0.08	0.25	0.46
Oster's delta		3.36		4.56		4.30		0.93
<i>Panel C: FS</i>								
<i>Dependent: Pr(Enrolling at SSST)</i>								
Score > cut - off	0.63	0.66	0.63	0.66	0.63	0.66	0.63	0.66
P-value	0	0	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0	0	0
F-stat	241.16	235.82	241.16	235.82	241.16	235.82	241.16	235.82
Degree characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes	No	Yes
N score 6	164	154	164	154	164	154	164	154
N score 7	141	122	141	122	141	122	141	122

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using AlmaLaurea survey data for UniTO graduates. Dependent variable for “GPA” is measured out of 30 points, “Final grade” is measured out of 110 points, “Graduating *cum Laude*” is a dummy equal to one for graduates receiving a *Laude* in their degree and “Time to graduate” measures time to degree in years. Odd columns include controls for degree characteristics: type of degree and field of studies. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school *cum laude* and type of high school), candidates’ geographical area of residence, a proxy for candidates’ motivation (time from SSST call release and submitting an application to the honors program), family background variables (socio economic status based on parental occupation and parental highest educational attainment) and admission year FE. We report Oster’s δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2017 and candidates within the chosen window (6 vs 7). SSST drop outs included in the sample. Endogenous variable: Enrolled at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

Table A.8: Prospects at graduation - SSST drop outs included

	Into LF		Reservation wage		PhD		Work abroad		Further studies	
<i>Panel A: LATE</i>										
Enrolled at SSST	-0.18	-0.18	-208.68	-203.79	0.09	0.12	0.08	0.07	0.08	0.09
P-value	0.04	0.03	0	0.01	0.36	0.25	0.18	0.22	0.22	0.14
Exact p-value	0.04	0.05	0.01	0.01	0.35	0.27	0.21	0.31	0.22	0.19
Mean - score 6	0.67	0.67	1344.45	1344.45	0.35	0.37	0.83	0.83	0.83	0.83
<i>Panel B: ITT</i>										
Score > cut - off	-0.12	-0.12	-136.36	-133.71	0.07	0.1	0.05	0.05	0.05	0.06
P-value	0.04	0.04	0.01	0.01	0.38	0.31	0.19	0.25	0.24	0.17
Exact p-value	0.04	0.05	0.01	0.01	0.35	0.27	0.21	0.31	0.22	0.19
Oster's delta		3391.71		11.02		2.04		6.99		-7.03
<i>Panel C: FS</i>										
<i>Dependent: Pr(Enrolling at SSST)</i>										
Score > cut - off	0.65	0.65	0.65	0.66	0.74	0.81	0.66	0.66	0.66	0.66
P-value	0	0	0	0	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0	0	0	0	0
F-stat	229.06	231.41	224.59	230.31	208.48	254.28	236.66	235.82	240.45	235.82
Degree characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N score 6	154	153	153	153	72	68	154	154	155	154
N score 7	122	120	119	117	76	65	124	122	125	122

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using AlmaLaurea survey data for UniTO graduates. Dependent variable for “Into LF” is a dummy equal to one for graduates who are willing to either look for a job, accept a job offer or continue a pre-existing job, “Reservation wage” records the minimum salary a graduate is willing to accept to start a full time occupation, “PhD” is a dummy equal to one for graduates who want to pursue PhD studies, “Work abroad” is dummy equal to one for graduates who would accept a job abroad, “Further studies” is a dummy equal to one for graduates who are planning to continue studying. “PhD” is only defined for senior (master or single single) degree holds who are hence eligible for postgraduate studies. Odd columns include controls for degree characteristics: type of degree and field of studies. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates’ geographical area of residence, a proxy for candidates’ motivation (time from SSST call release and submitting an application to the honors program), family background variables (socio economic status based on parental occupation and parental highest educational attainment) and admission year FE. We report Oster’s δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2017 and candidates within the chosen window (6 vs 7). SSST drop outs included in the sample. Endogenous variable: Enrolled at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

Table A.9: One year after graduation - SSST drop outs included

	In PhD		In labour force		In Master	
<i>Panel A: LATE</i>						
Enrolled at SSST	0.29	0.37	-0.34	-0.41	0.17	-0.05
P-value	0.04	0.01	0.02	0	0.28	0.78
Exact p-value	0.04	0.03	0.03	0.04	0.36	0.79
Mean - score 6	0.21	0.22	0.65	0.63	0.8	0.8
<i>Panel B: ITT</i>						
Score > cut - off	0.22	0.29	-0.26	-0.32	0.08	-0.02
P-value	0.05	0.02	0.03	0.02	0.31	0.83
Exact p-value	0.04	0.03	0.03	0.04	0.36	0.79
Oster's delta		-10.47		-91.67		-1.25
<i>Panel C: FS</i>						
<i>Dependent: Pr(Enrolling at SSST)</i>						
Score > cut - off	0.76	0.77	0.76	0.77	0.48	0.5
P-value	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0
F-stat	119.41	75.56	119.41	75.56	30.55	23.37
Degree characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes
N score 6	34	32	34	32	41	40
N score 7	40	38	40	38	36	34

Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using AlmaLaurea survey data for UniTO graduates one year after graduation. Dependent variable for “In PhD” is a dummy equal to one for graduates who are pursuing a PhD, “In labour force” is a dummy equal to one for graduates who are either working or looking for a job, “In Master” is a dummy equal to one for graduates who are studying towards a master degree. “In PhD” is only defined for senior (master or single single) degree holders who are hence eligible for postgraduate studies. “In Master” is only defined for junior (bachelor) degree holders. Odd columns include controls for degree characteristics: type of degree and field of studies. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates’ geographical area of residence, a proxy for candidates’ motivation (time from SSST call release and submitting an application to the honors program), family background variables (socio economic status based on parental occupation and parental highest educational attainment) and admission year FE. We report Oster’s δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2016 and candidates within the chosen window (6 vs 7). SSST drop outs included in the sample. Endogenous variable: Enrolled at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

Table A.10: Reservation wage by PhD prospects

	Reservation wage		Reservation wage		Reservation wage	
	All graduates	All graduates	PhD prospect - No	PhD prospect - No	PhD prospect - Yes	PhD prospect - Yes
<i>Panel A: LATE</i>						
Enrolled at SSST	-105.58	-105.15	-7.67	-0.63	-292.04	-117.69
P-value	0.18	0.21	0.93	1	0.06	0.48
Exact p-value	0.15	0.18	0.94	0.96	0.04	0.58
Mean - score 6	1294.62	1294.62	1247.59	1247.59	1375.5	1375.5
<i>Panel B: ITT</i>						
Score > cut - off	-79.12	-81.4	-6.32	-0.49	-193.73	-69.46
P-value	0.2	0.28	0.94	1	0.07	0.61
Exact p-value	0.15	0.18	0.94	0.96	0.04	0.58
Oster's delta		3.19		0.03		0.57
<i>Panel C: FS</i>						
<i>Dependent: Pr(Enrolling at SSST)</i>						
Score > cut - off	0.75	0.77	0.82	0.78	0.66	0.59
P-value	0	0	0	0	0	0
Exact p-value	0	0	0	0	0	0
F-stat	186.17	193.53	120.38	97.34	51.4	19.72
Degree characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
AY FE	No	Yes	No	Yes	No	Yes
N score 6	68	68	43	43	25	25
N score 7	58	58	24	24	34	34

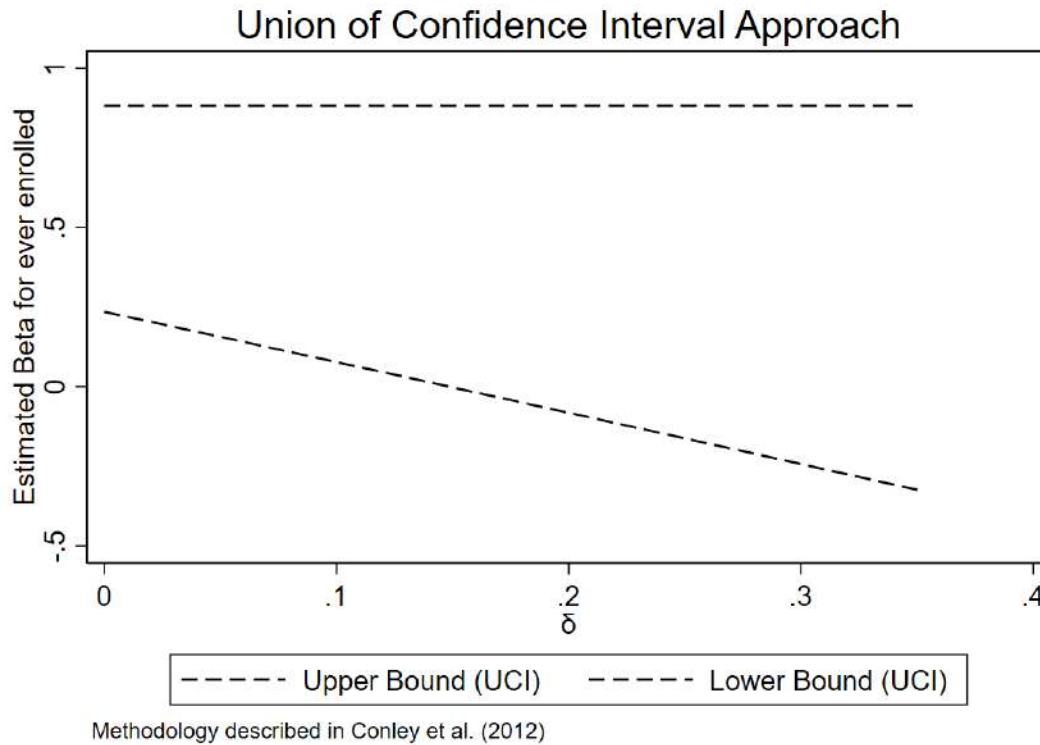
Note: Table reports LATE (Panel A), ITT (Panel B) and First Stage (Panel C) estimates using AlmaLaurea survey data for UniTO graduates who completed a master degree (including single cycles). Break downs by PhD prospects. Dependent variable for “Reservation wage” records the minimum salary a graduate is willing to accept to start a full time occupation. Odd columns include controls for degree characteristics: type of degree and field of studies. Even columns add controls for: gender, a set of predetermined proxy variables for individual ability (high school final grade, having graduated from high school cum laude and type of high school), candidates’ geographical area of residence, a proxy for candidates’ motivation (time from SSST call release and submitting an application to the honors program), family background variables (socio-economic status based on parental occupation and parental highest educational attainment) and admission year FE. We report Oster’s δ for specifications with controls. Sample restricted to SSST admission years 2012 - 2017 and candidates within the chosen window (6 vs 7). SSST drop outs excluded from the sample. Endogenous variable: Enrolled at SSST. F-stat refers to Kleibergen-Paap rk Wald F statistic. Standard errors robust to heteroskedasticity. Exact p-values for LATE estimates are derived from permuting treatment assignment 1,000 times in ITT equation.

Table A.11: Robustness check: Adding controls in RF

	GPA	GPA	GPA	GPA
Score > cut - off	0.333 (0.004)	0.303 (0.008)	0.376 (0.012)	0.372 (0.004)
N	266	228	193	232
adj. R^2	0.516	0.514	0.478	0.524
Avg - score 6	28.27	28.42	28.20	28.21
Oster's delta	3.150	3.586	1.931	4.567
Degree characteristics	Y	Y	Y	Y
Controls	Y	Y	Y	Y
House value	N	Y	N	N
Text analysis controls	N	N	Y	N
Essay approachability	N	N	N	Y
AY FE	Y	Y	Y	Y

Notes: The table presents coefficient estimates for RF equation using data for AlmaLaurea graduates. Column 1 replicates our main result from Equation 2. Column 2 adds control for housing value retrieved from applicants geo-coded residence address. Column 3 adds controls retrieved from applying text analysis techniques on graduates' application letters. We compute text length, number of lemma used in letters, proportion of adjectives, proportion of adverbs, proportion of nouns, proportion of verbs and a measure for the required reading time on lemmas. Column 4 adds the essay approachability measure as discussed in Appendix A.3. We report asymptotic p-values in parenthesis computed through Heteroskedasticity-robust standard errors. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure A.8: Relaxing the exclusion restriction



Notes The graph shows results from applying a procedure developed by Conley et al. (2012) on our LATE estimates for academic achievement. δ on the x-axis measures the degree of violation of the exclusion restriction allowed in estimation, the y-axis shows the estimated beta for each degree of violation. We allow for different estimates with violations from 0 to 0.35 corresponding to roughly the full effect found in our reduced form estimate (0.33) from the model with controls in Table 5. Setting $\delta = 0$ replicates our main result. As the graph shows the lower bound for beta excludes zero up to a delta of 0.14, slightly more than a third of our Reduced Form estimate ($0.33 / 3 = 0.11$).

A.3 Essay questions: Analysis

In this section we analyse the essay questions candidates picked for the written test and check whether applicants differed in terms of their choices. We remind the reader that candidates were asked to select three out of six questions and to develop an argument for each of them⁴³. Figure A.9 below reports, for each admission year, the proportion of candidates who selected each question across the four mass points we discussed in Section 4. Although imprecisely estimated, partly because of the small sample sizes for each admission year, we feel reassured by the relative similarity in the questions chosen by candidates awarded 6 or 7 compared to applicants scoring 5 or 8.

An additional concern over different choices of exam questions, arises from the several combinations of the three questions applicants can pick. It might be possible that candidates select similar proportions of exam questions but combine them differently, focusing on either more approachable questions or more challenging ones. To investigate this issue further we build an empirical measure of question “approachability” by inspecting the proportion of candidates selecting each question by admission year. The intuition behind this measure lies in candidates revealing their preferences towards the different questions by selecting them during the written exam. Had candidates been indifferent across the six questions, we would expect them to select every question with probability equal to $1/6$. Summing over the three questions each candidate is required to pick, the expected probability of every question would then be equal to $1/2$. Table A.12 below reports the empirical frequency according to which each question has been selected by admission year. In 2015 for instance, question 1 was very popular, having been chosen by 80% of all candidates, while question 5 was only developed in 18% of exams. We take this difference to proxy the different degree of approachability across the two questions, which can derive from several factors, such as candidates’ backgrounds or their different exposure to the topic. As an illustrative example, question 1 in 2015 asked candidates to reflect on a common European strategy to handle immigration, an highly debated topic in Italian politics at the time. Question 5, instead, required applicants to summarize what is currently known on the complex phenomenon of the origin and development of life on planet Earth, which requires a more in-depth knowledge or interest. With this mind we proceed to construct, for each essay, an average approachability measure by averaging the empirical frequency of the chosen questions across every written test. Figure A.10a below shows the RDD plot contrasting the average value of our approachability measure for candidates along the support of the running variable. Comparing candidates in the window, there is some weak evidence of imbalance in the average approachability of their exams, with candidates scoring 7 writing exams with a slightly lower level of approachability compared to applicants awarded a 6. Although running contrary to our assumptions, this finding worries us little for a series of reasons. First, the much larger and neater jump in approachability between candidates awarded 5 and 6 is counter-intuitive as it does not match our RDD plots on

⁴³The wording of each question can be made available upon request

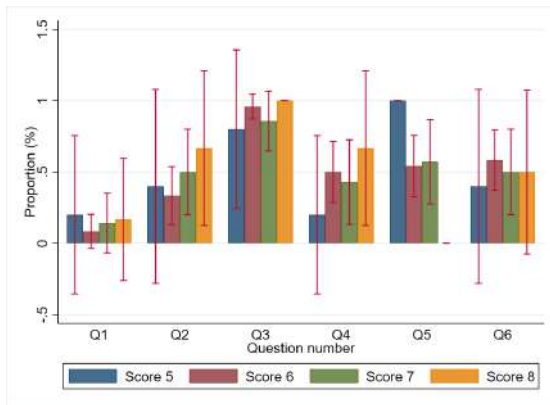
individual ability, it is candidates awarded a 6 who are more frequently found to leave high school with a higher grade as show in Figure A.4b. Second, close inspection of Figures A.9a - A.9f, reveals that most of the imbalance is likely to derive from admission year 2015. Figure A.10b corroborates this insight by showing much more similar approachability values for candidates in the window once we exclude admission year 2015 from the analysis. Finally, as we show in Table A.11, our results on academic achievement, which would be most likely to be affected by any endogeneity concerns over ability, are unaffected once we include our measure of approachability as a control.

Table A.12: Frequency of essay questions

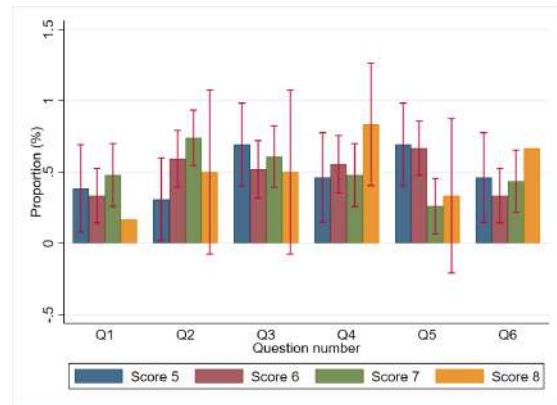
Admission year	Q1	Q2	Q3	Q4	Q5	Q6	N
2012	18%	40%	87%	45%	57%	53%	60
2013	38%	59%	59%	52%	51%	41%	73
2014	59%	84%	59%	19%	18%	62%	73
2015	80%	70%	78%	37%	18%	18%	108
2016	78%	44%	25%	50%	53%	51%	112
2017	53%	37%	70%	66%	54%	21%	99

Notes Table reports the proportion of candidates who chose each essay question over the total of applicants in each admission year. Sample refers to first year candidates who completed 3 exam questions.

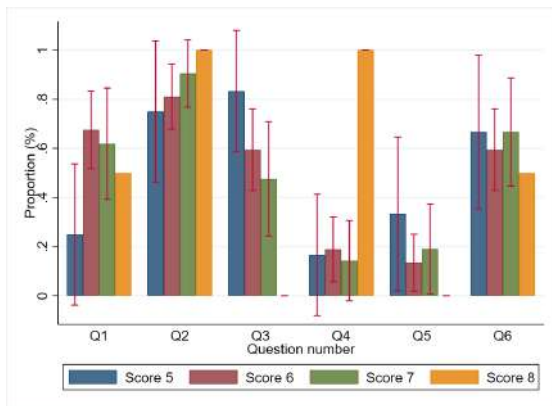
Figure A.9: Essay questions - Yearly graphs



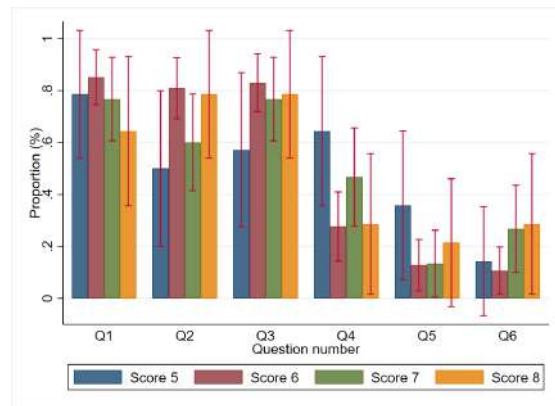
(a) 2012



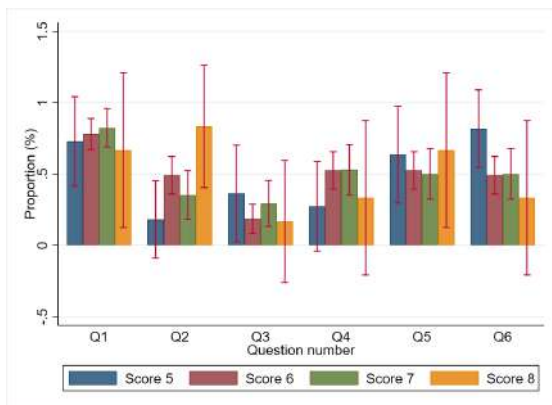
(b) 2013



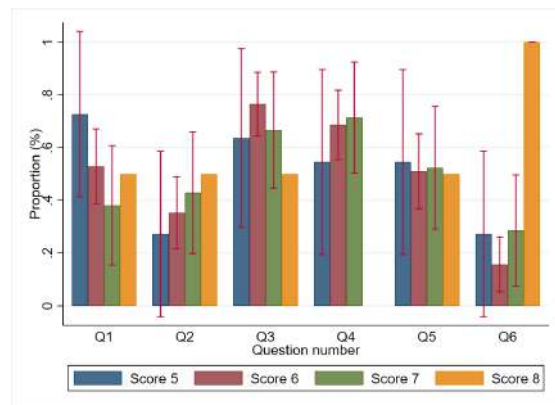
(c) 2014



(d) 2015



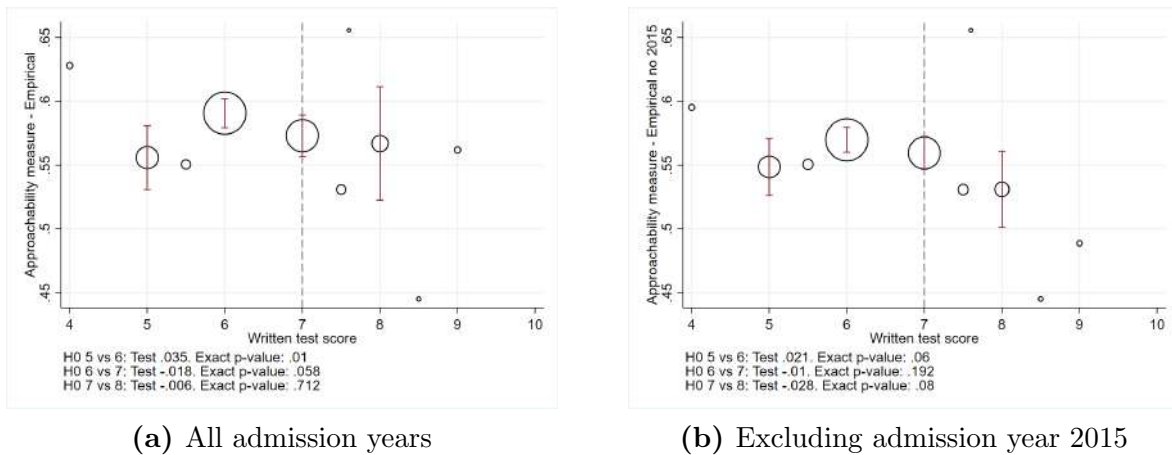
(e) 2016



(f) 2017

Notes The graphs show the proportion of candidates who chose each essay question by year and mass point of our running variable. We only compute figures for first year candidates to keep the set of exam questions comparable. 95% confidence intervals reported across all graphs. We remove confidence intervals for candidates awarded an 8 selectively across questions to avoid very large confidence intervals produced by tiny cells and ensure readability of the results. Sample refers to first year candidates who completed 3 exam questions. Electronic copy available at: <https://ssrn.com/abstract=4189859>

Figure A.10: Approachability measure - RDD plots



Notes The graphs show RDD plots of our approachability measure on the running variable (written test scores). Each circle's radius is proportional to the number of candidates in that class. Exact p-values for two by two difference-in-means comparisons are reported in the bottom left corner. Sample refers to first year candidates who completed 3 exam questions.

Table A.13: Window selection: Administrative data

Window		Balance test p-value	Variable	Obs < cutoff	Obs \geq cutoff
6	7	0.274	HS with honors	217	145
5.5	7.5	0.13	HS with honors	226	158
5	7.6	0.03	High school final grade (/100)	282	158
4	8	0.004	High school final grade (/100)	286	191
4	8.5	0.008	High school final grade (/100)	286	193
4	9	0.004	HS with honors	286	197

Note Column 4 refers to the variable displaying the minimum p-value in the regression.

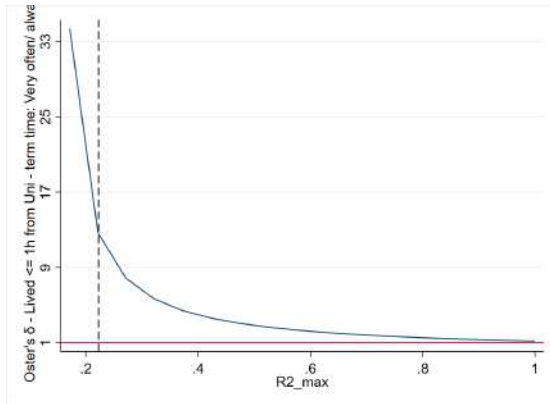
Table A.14: Window selection: Graduate data

<i>Panel A</i>					
Window		Balance test p-value	Variable	Obs < cutoff	Obs \geq cutoff
6	7	0.03	Days to apply to the program	154	112
5.5	7.5	0.07	Days to apply to the program	160	121
5	7.6	0.06	Resident in the same province as uni	204	122
4	8	0.05	HS: Liceo, classical track	206	148
4	8.5	0.66	HS: Liceo, classical track	206	150
4	9	0.08	Resident in the same province as uni	206	154
<i>Panel B</i>					
Window		Balance test p-value	Variable	Obs < cutoff	Obs \geq cutoff
6	7	0.2	Middle social class	154	112
5.5	7.5	0.1	Resident in the same province as uni	160	121
5	7.6	0.1	Resident in the same province as uni	204	122
4	8	0.1	HS: Liceo, classical track	206	148
4	8.5	0.1	HS: Liceo, classical track	206	150
4	9	0.1	Resident in the same province as uni	206	154

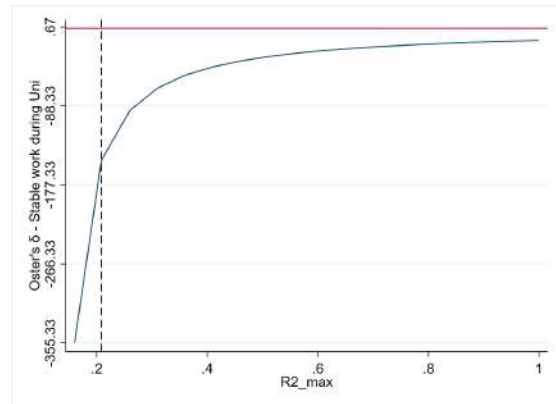
Note Column 4 refers to the variable displaying the minimum p-value in the regression. *Panel A* includes the variable Days to apply to the program as a control, while *Panel B* does not.

A.4 Selection on unobservables

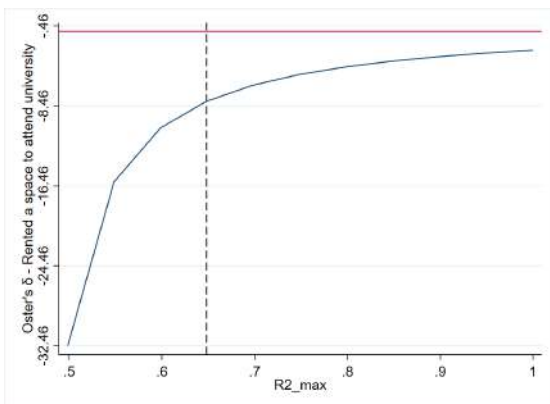
Figure A.11: Oster's delta



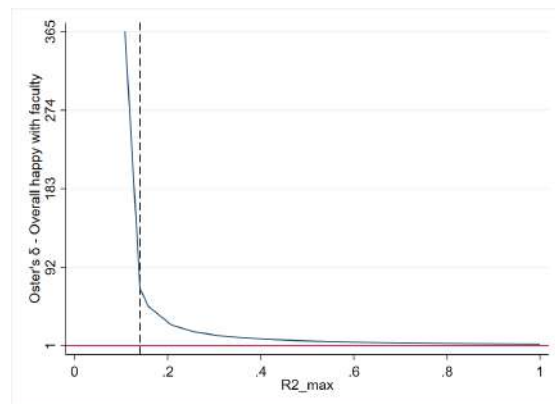
(a) Lived close to university



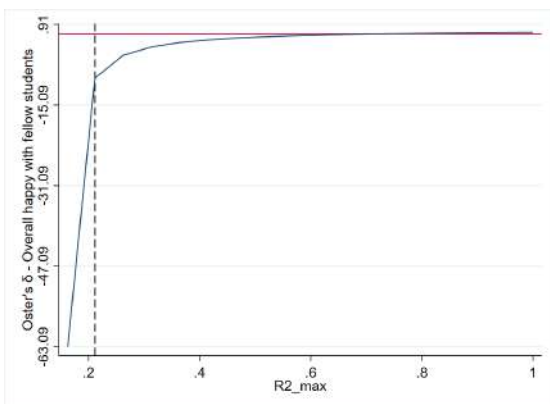
(b) Worked during university



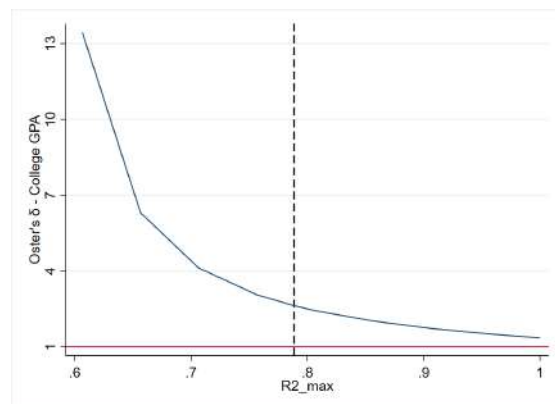
(c) Rented during university



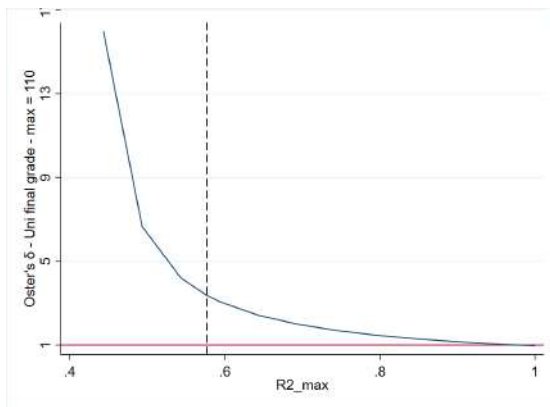
(d) Happy with faculty



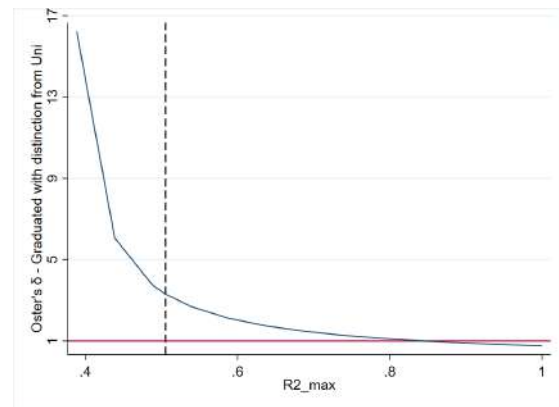
(e) Happy with students



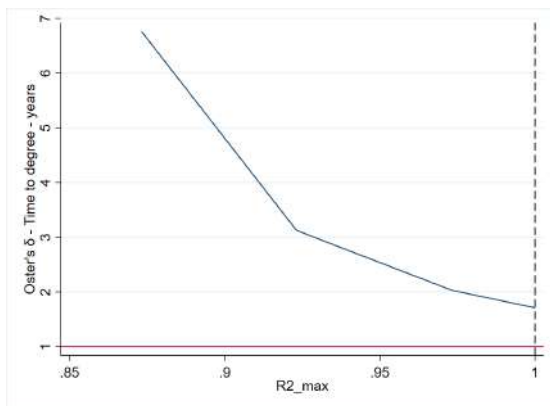
(f) GPA



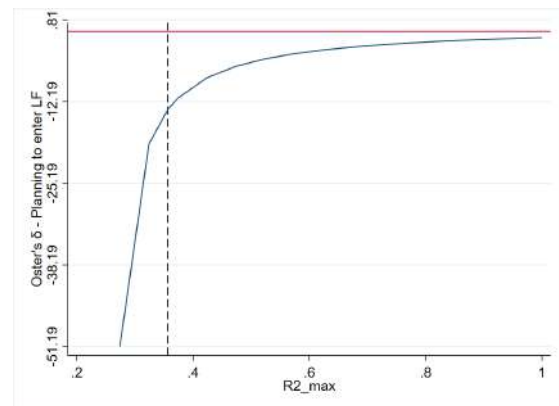
(g) Final grade



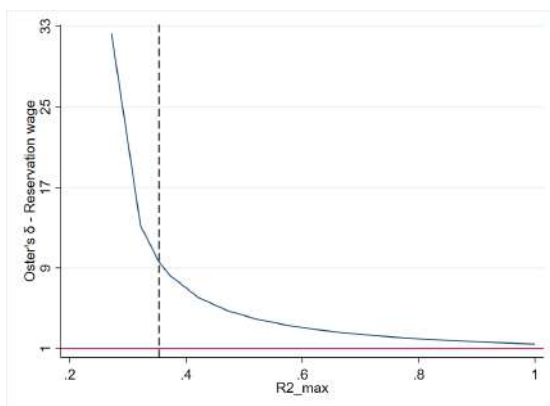
(h) Graduating with honors



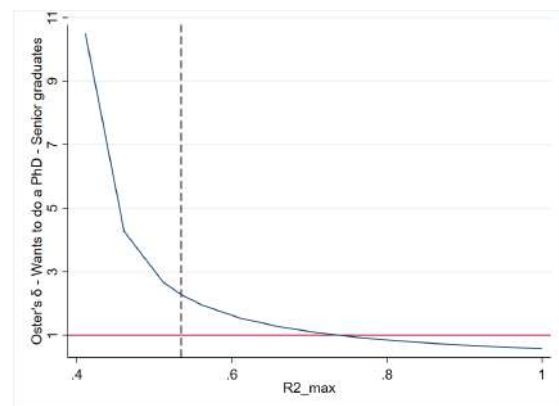
(i) Time to graduate



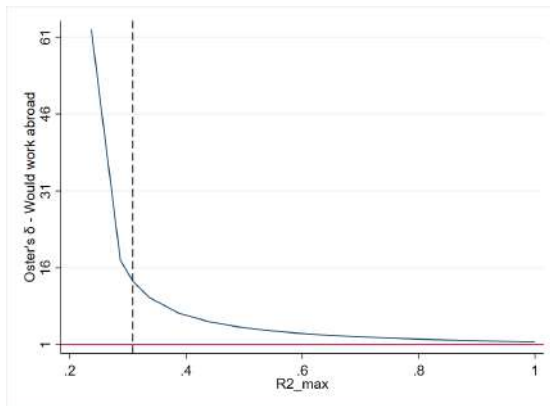
(j) Into Labour Force



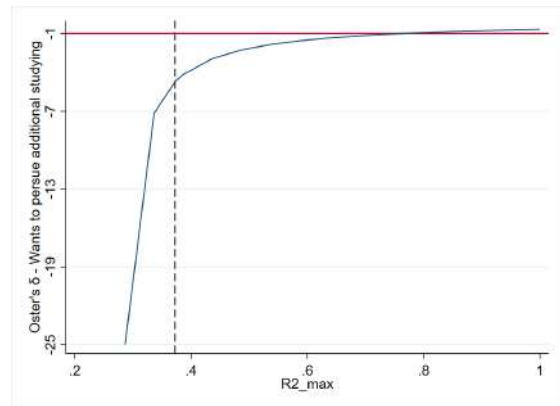
(k) Reservation wage



(l) Into PhD



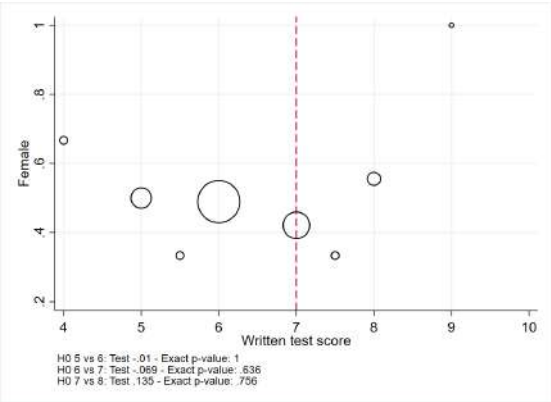
(m) Work abroad



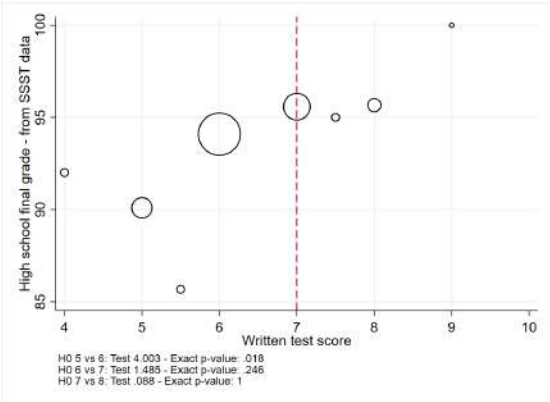
(n) Further studies

Notes Figures report results for Oster's δ where we allow for different input values of R^2 max until the value of one. The magenta horizontal line corresponds to the threshold value of one for δ while the dashed vertical line reports the value of R^2 max as suggested by Oster (2019) and reported in our result tables.

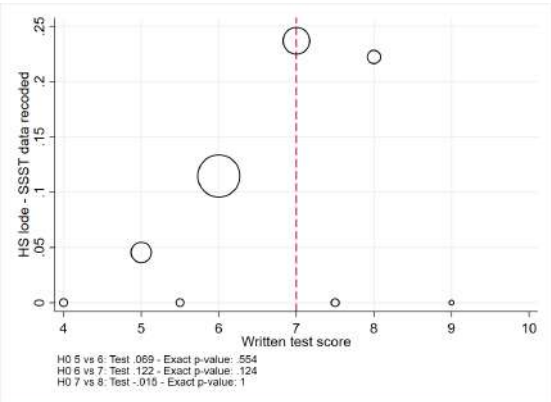
Figure A.12: Balance tests: students in Administrative dataset but not in Graduate dataset



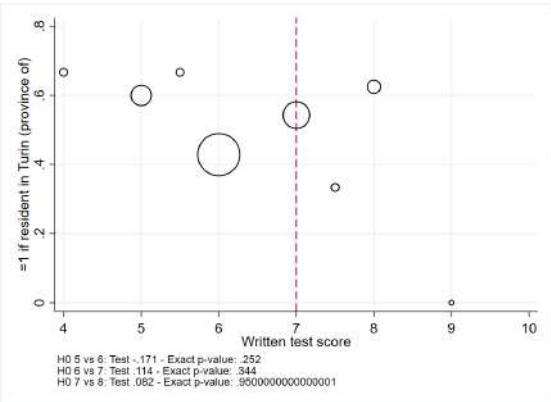
(a) Female



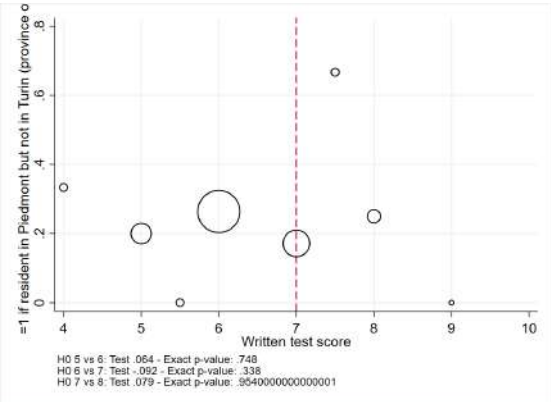
(b) High school final grade (/100)



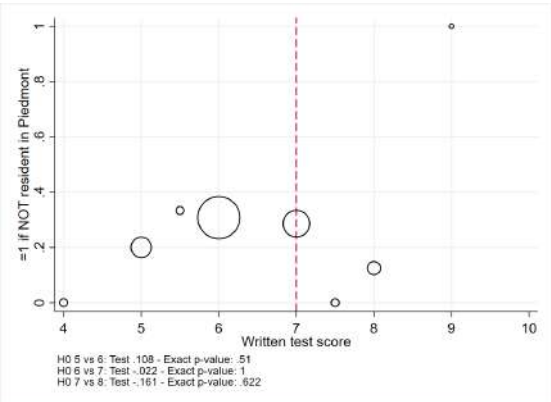
(c) Graduated HS with honors



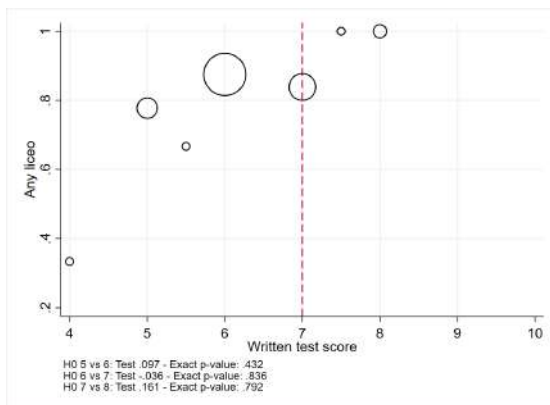
(d) Resident in the same province as uni



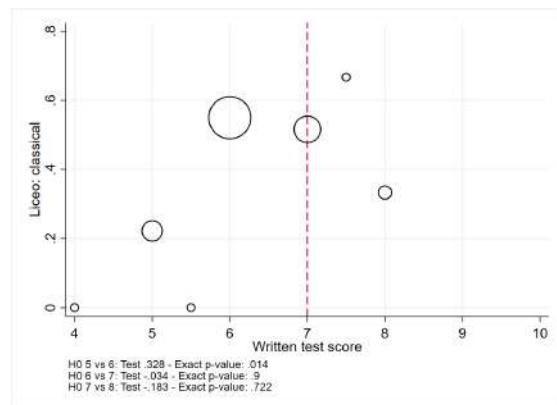
(e) Resident in the same region as uni



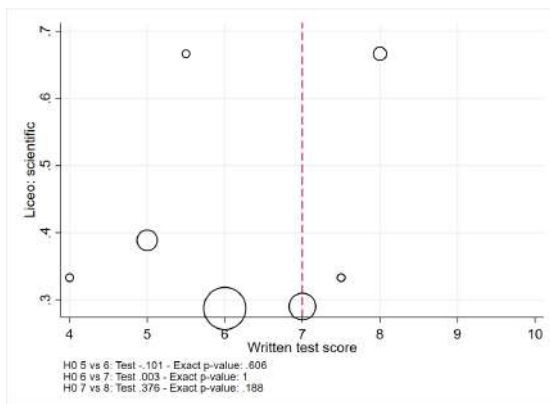
(f) Resident in a different region



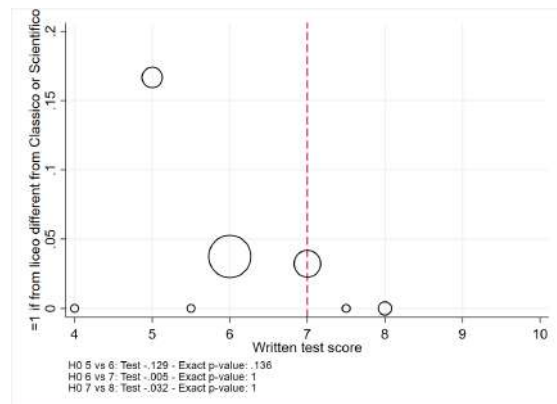
(g) HS: Any liceo



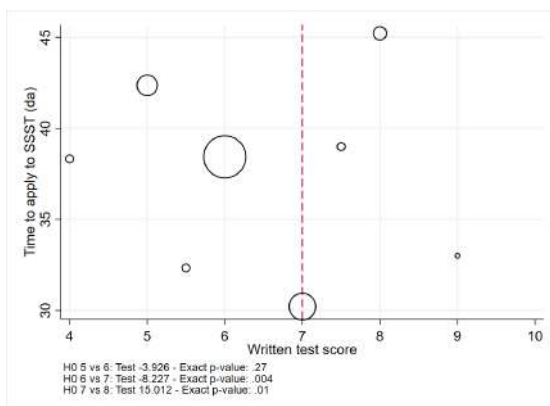
(h) HS Liceo: classical track



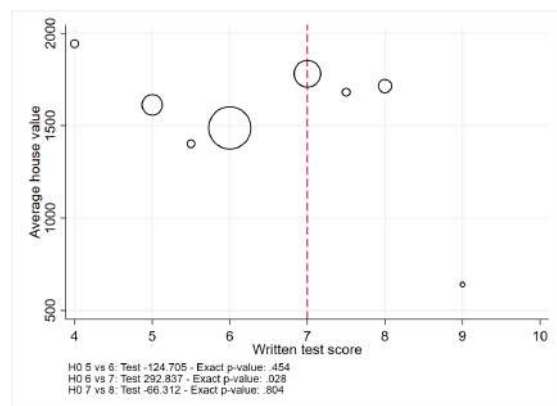
(i) HS Liceo: scientific track



(j) HS Liceo: any other liceo



(k) Days to apply to the program



(l) Average house value

Notes The graphs show RDD plots of a series of pre-determined characteristics on the running variable (written test scores). Each circle's radius is proportional to the number of candidates in that class. Exact p-values for two by two difference-in-means comparisons are reported in the bottom left corner. Sample refers to candidates which we lose when switching from our administrative dataset to the AlmaLaurea dataset.