With honors.
University honors programs and graduates’ careers

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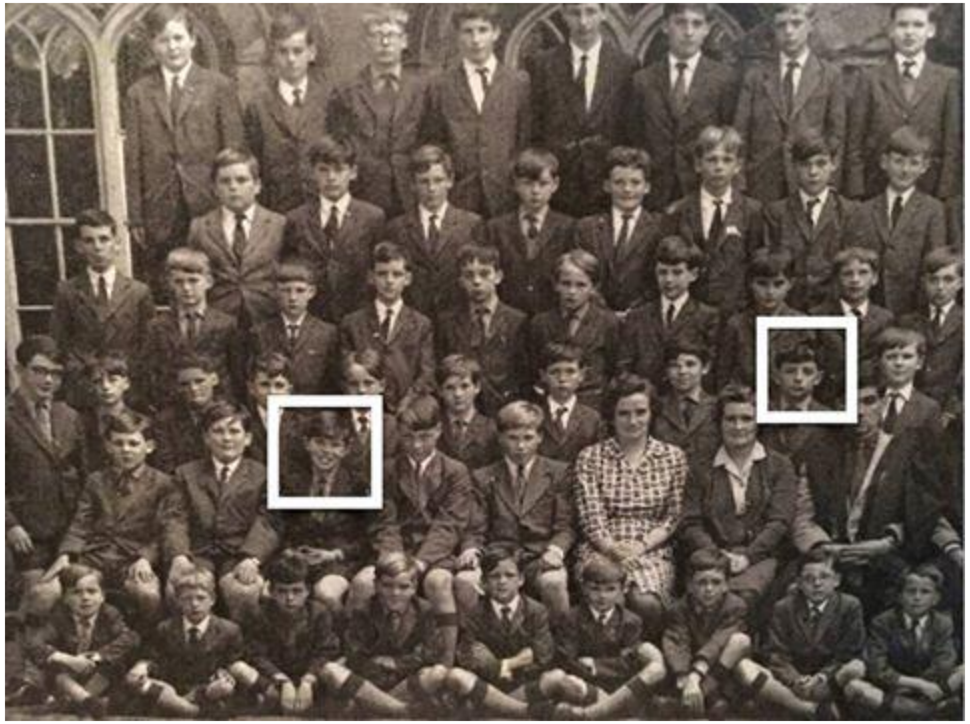
Motivation

Quality in tertiary education pays off
eg Hoekstra (2009), Anelli (2020), Barrera-Osorio et al (2019), Saavedra (2008), Jia et al (2021)



However, attending elite universities is **costly**

- Sistematic under-enrollment of **financially constrained** or **minority** students, however bright
- **Information** and **monetary costs** are salient, especially for first generation university students

Honors programs can then be an option to **improve quality** in education outside of elite institutions

This paper

RQ: Can honors programs be a **viable way to promote talent** outside of elite universities?

We study an honors program targeting **bright students** within a **public Italian university**. **Bundle treatment**:

- Extra classes and **academic requirements**
- An increase in time spent with similarly driven **peers** through classes and accomodation
- **Financial constraints relief** through tuition fee waiver and a small scholarship

Admission threshold creates a discontinuity in enrollment which can be used in a **RDD** setting

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Main **takeaways**:

- Honors students improve their **GPA** (+0.53 points out of 30) and probability of **graduating with honors** (+17pp)
- Honors students are 41pp more likely to **delay their entry into the labour market** and rather pursue a **PhD** (+37pp)
- The honors program affects **low- and high-SES students differently**, leading them to **converge**

Related literature

- Returns to **quality in higher education**

Hoekstra (2009), Anelli (2020), Jia and Li (2021), Saavedra (2008), Barrera-Osorio and Bayona-Rodríguez (2019)

We look at honors programs as a potential **alternative tool** to promote quality in non-competitive universities

- **Merit based aid**

Chakrabarti and Roy (2013), Cohodes and Goodman (2014), Firoozi (2022)

Honors programs can act as a **recruitment device** which offers, among other things, a tuition fee waiver and a small scholaship

- **Peer** effects

Carrieri et al (2015), Canaan and Mouganie (2018)

In our setting, honors students take honors classes together but also **live together** in dedicated accomodations. The honors program could also attract bright students to the university, benefiting the student population as a whole.

Closest to us: Pugatch and Thompson (IZA DP) who study an honors program offered by a non-selective, public US institution

- We are able to investigate **enrollment** and **labour market outcomes**, other than academic achievements

The honors program

Honors program offered by the University of Turin to some of its bright and motivated students

- Similar programs in Italy, continental Europe and the US
- **5-year** program (= tertiary education in the Italian system)
- Targets first-year students at a medium-sized, public university

The program:

- **Dedicated** add-on honors classes (15 credits per year), **on top of** regular university curriculum and irrespective of field of study
- Focus on **multidisciplinarity**
- **Requirements** in terms of GPA and time to graduation
- Students **live together** in dedicated accomodations
- **Tuition fee waiver** and small yearly scholarship

Admission test: Two-stage admission – Written exam and interview

Step one

Written exam:

- **Essay**
- **Grading:** 0 – 10, essays are completely blind to examiners
- **Cut-off:** At least 7
- **Outcome:** Admission to the interview. 44% of all candidates admitted to the interview

123

Step two

Interview:

- **Motivational**
- **Grading:** 0 – 10
- **Cut-off:** At least 7
- **Outcome:** Admission into the program

43

Admission

39

Examples of essay questions

Grading procedure

Applicants by year

Data

Administrative

- **Selection process into the honors program**:
  - List of applicants
  - Application package (basic demographics including motivational letter)
  - Selection logs (test score)
  - Written tests

- **Enrolment registers at UniTO**

Honors program applicants

Almalaurea survey

- **Mandatory at graduation:**
  - Parental and socio-economic background, high school achievement, academic experience at UniTO
  - Prospects on future careers

- **One year after graduation:**
  - First jobs, further studying and training

UniTO graduates

More about data

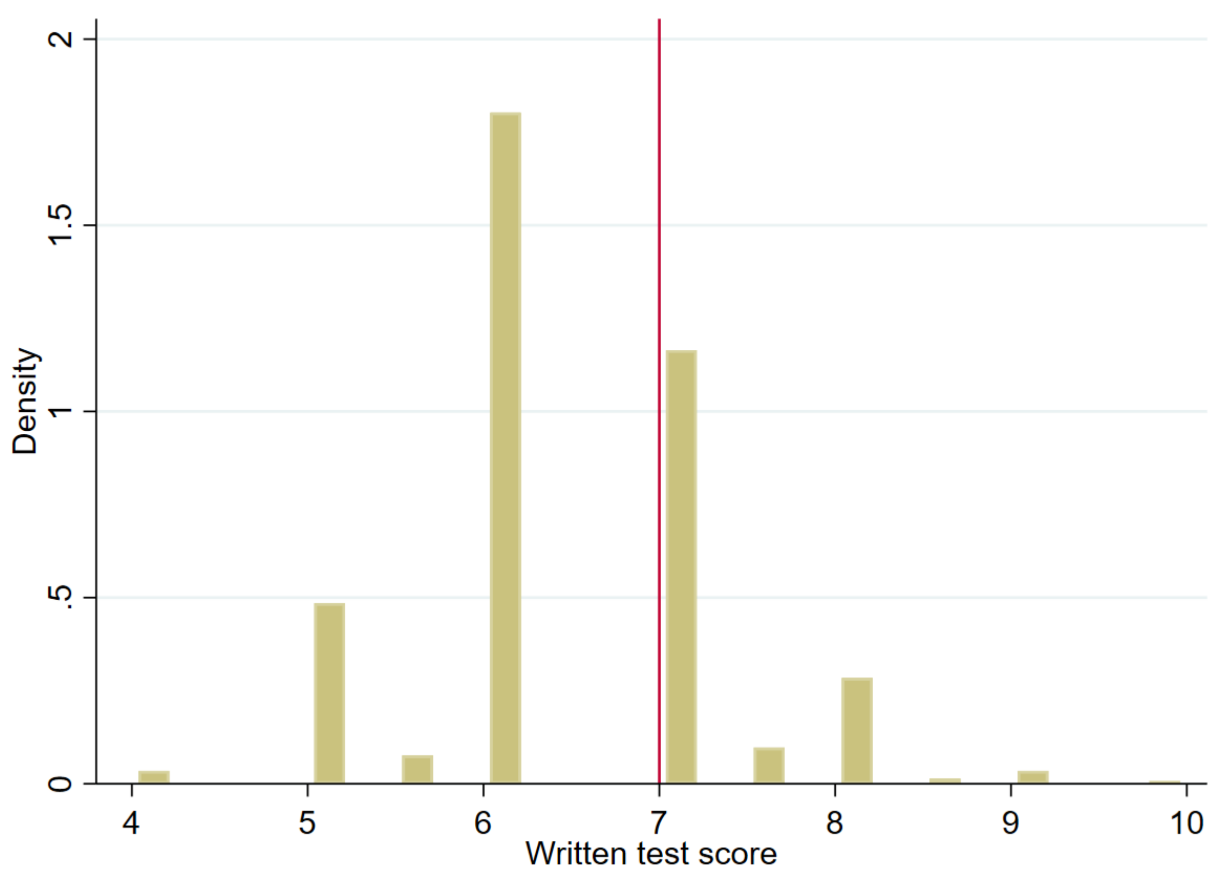
Descriptive statistics

Identification strategy (1/3): Discrete running variable making the assumptions for continuity framework RDD not applicable

- Written test score with integer grades between 4 and 10

- Four clear mass points at 5, 6, 7 and 8

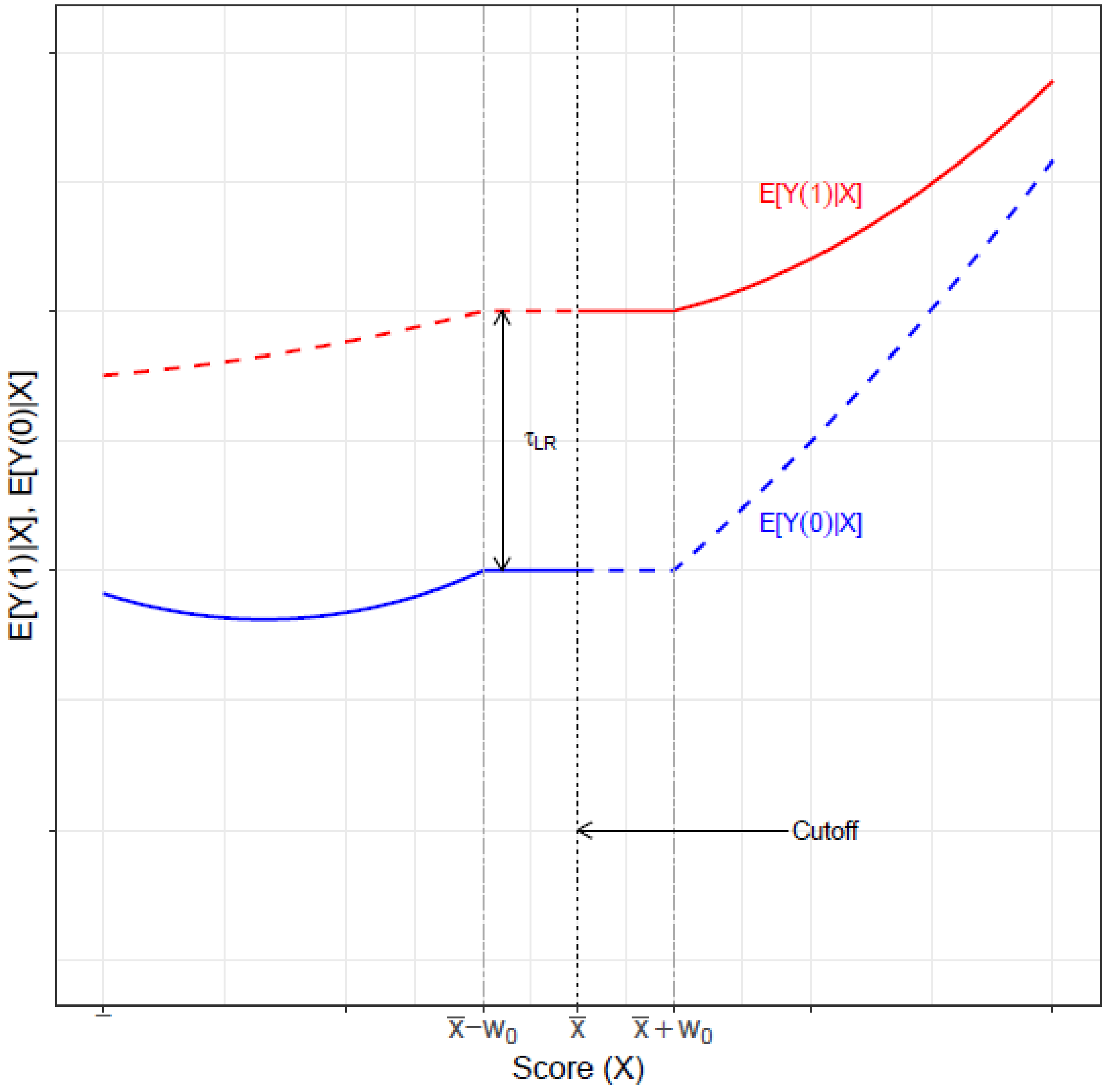
→ RDD local randomization framework (Cattaneo et al. (2015), Cattaneo et al. (2017))



Identification strategy (2/3): Local randomization assumptions impose the score in the window to be as good as randomly assigned

Stricter identifying assumptions imposing potential outcomes to be **flat in the window** (no relationship between potential outcomes and the running variable).

Window: students who scored either 6 (barely failed) or 7 (barely passed) in the written test



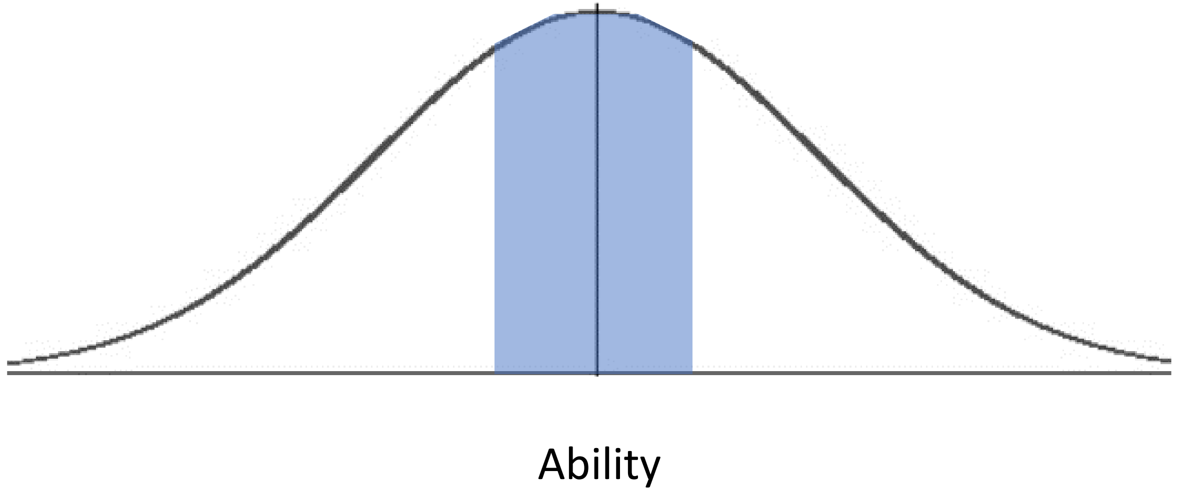
Equations

Identification strategy (2/3): Local randomization assumptions impose the score in the window to be as good as randomly assigned

Stricter identifying assumptions imposing potential outcomes to be **flat in the window** (no relationship between potential outcomes and the running variable). **Violated if**:

- The selection **committee can accurately separate candidates** on the basis of any unobserved ability component

- The score plays any **direct effect** on the outcome of interest (e.g., higher scores as encouragement)



Equations

Identification strategy (3/3): Empirical evidence supporting the identifying assumptions

Validity checks towards our assumptions:

- Balance tests
- RDD plots
- Regrading
- Text analysis on cover letters
- Conceptual framework
- R^2 comparison

Reasons why our assumptions hold:

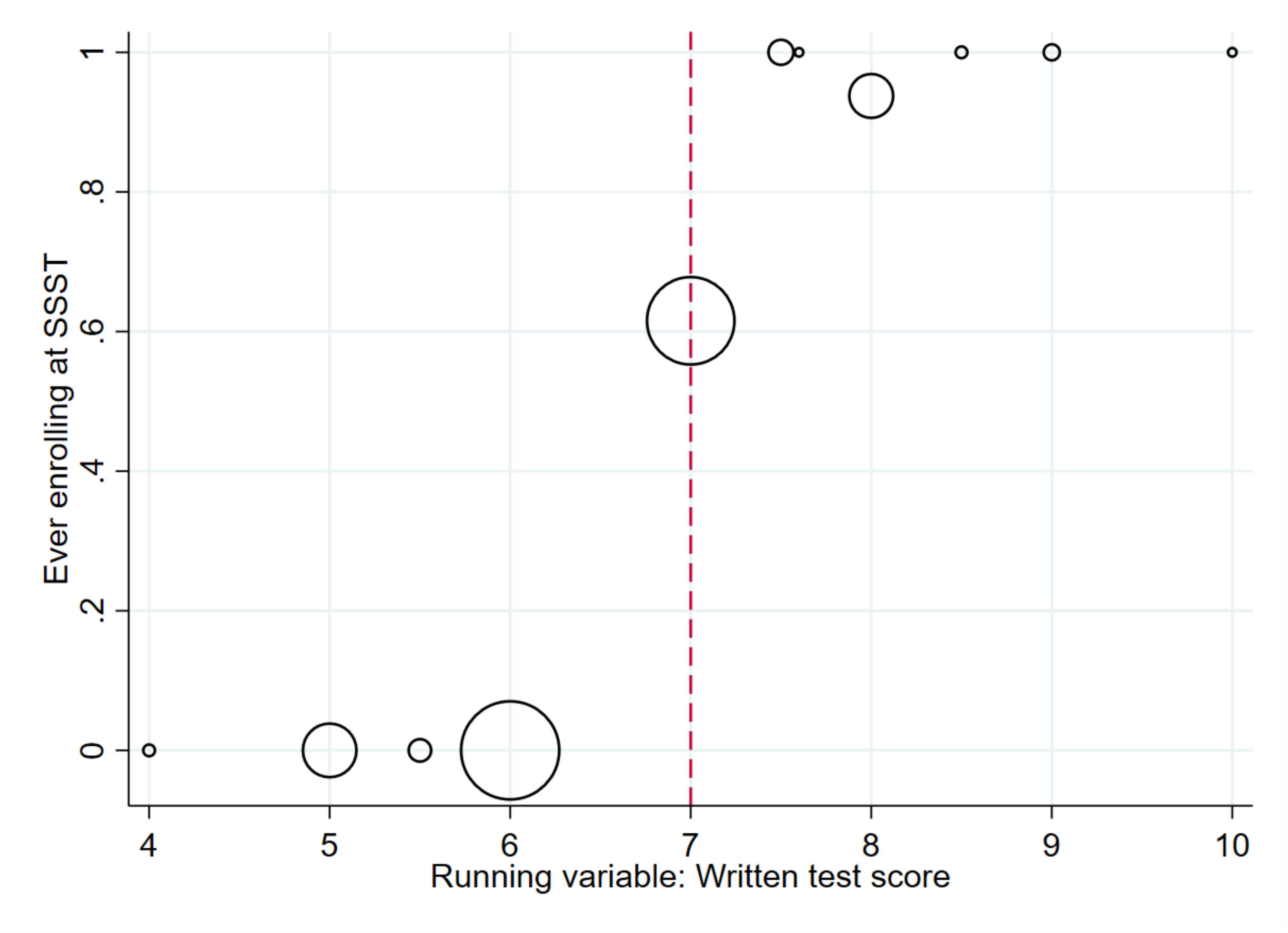
- Essay questions
- Grading procedure

First stage: Strong discontinuity in the probability of **enrolment** into the program

One-sided non compliance

Not all 7 enroll in the honors program as they

- Might **fail the interview step**
- Might **choose not to enroll** in the honors program



Discontinuity in admission

Results: We show positive effects both for academic achievement, career prospects and LM choices 1Y after graduation

- Enrolment at UniTO
- Achievement at UniTO
- Academic experience at UniTO – sanity check
- LM prospects at graduation
- LM outcomes 1 year after graduation
- Heterogeneity analysis: socio-economic status

Robustness: A series of robustness checks do not significantly affect our baseline results

- Adding additional controls
- Oster's δ (Oster 2019)
- Relaxing the exclusion restriction (Conley et al 2012)
- Window selection (Cattaneo et al 2016)

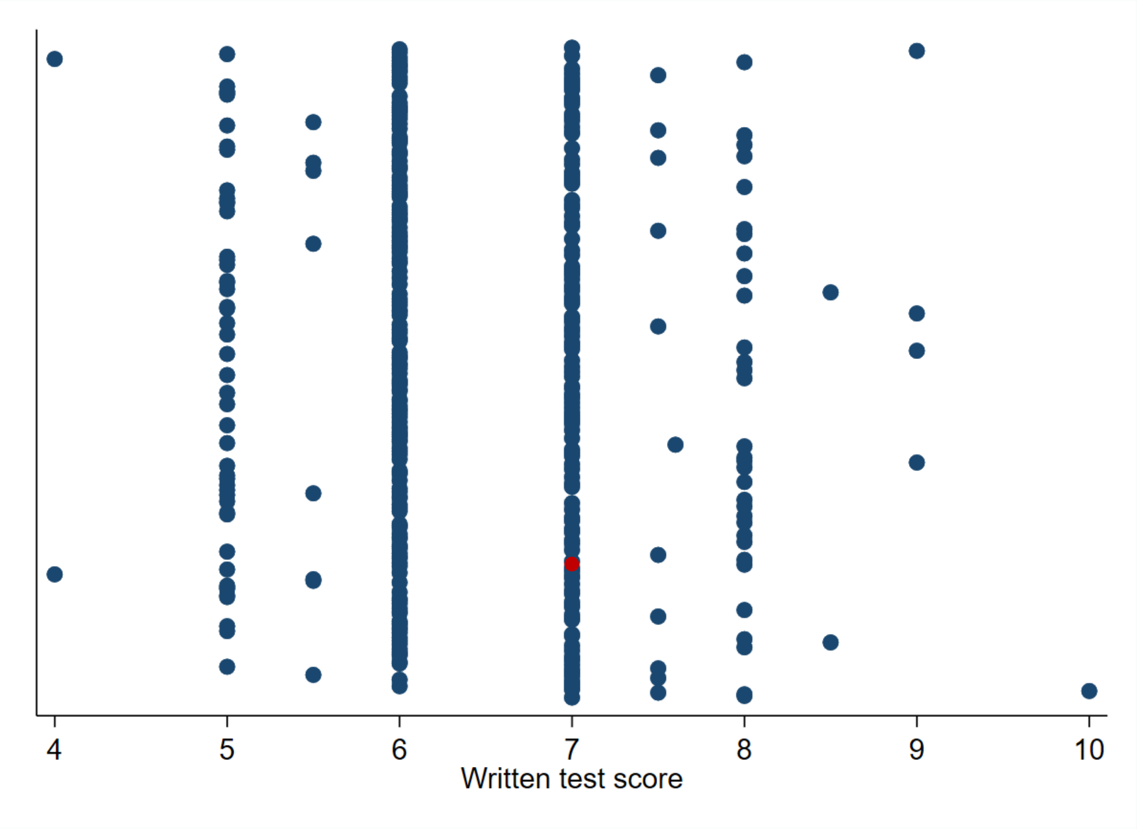
Conclusions

We study an honors program targeting bright students at a non-competitive university.
The program creates a **bundle treatment** including

- Extra classes and **academic requirements**
- An increase in time spent with similarly driven **peers** through classes and accomodation
- **Financial constraints relief** through tuition fee waiver and a small scholarship

Takeaways:

- This honors program **improves students' academic outcomes**
- This honors program fosters human capital accumulation by incentivizing **PhD enrolment** and **delaying entry into the labour force**
- **Heterogeneous effects by socio-economic status** lead students to **converge**



Thank you

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Annex

Graduate data (1/3):

What is AlmaLaurea? What data does it collect?

AlmaLaurea

- **AlmaLaurea** is an Italian nationwide inter-university consortium set up in 1994 which **collects** graduates' **profile** information and then tracks their subsequent **career paths**
- The consortium aims at monitoring graduates' academic careers and analysing graduates' performance on the labour market. It also collects and distributes graduates' CVs to ease their transition to the labour market
- As of 2020, AlmaLaurea partnered with 76 Italian universities collecting information for about **90% of all Italian graduates** each year

Data

- AlmaLaurea collects **microdata** through **two** main **surveys**:
  - Graduates **profile** upon graduation. The profile survey is one of the requirements to graduate
  - Graduates **labour market** outcomes at 1, 3 and 5 years after graduation
- Reports are published every year in June with aggregate data being made available on the AlmaLaurea website

Graduate data (2/3):
The profile survey looks at students upon graduation

Profile upon graduation

- The graduate **profile survey** collects information for students graduating in a given calendar year.
- The data is **particularly detailed** covering:
  - Education background prior to university
  - Performance during university including subject, marks, time to graduation, attendance to classes, scholarships, work experience and mobility (Including previous degrees for master graduates)
  - Perspective towards further studies, including master degrees, master courses, specialization trainings and PhD
  - Labour market intentions and perspectives including:
    - Type of employment (Employees vs Self employed)
    - Economic sector of employment
    - Job characteristics including career perspectives, job stability, free time, independence, etc
    - Attitudes towards geographic mobility, time schedules (Full time vs part time) and type of contract (Including remote working)
  - Socio-economic background looking at education attainment and occupation of graduates’ parents

Graduate data (3/3):
The labour market survey tracks graduates 1, 3 and 5 years after graduating

Labour market outcomes
1, 3 and 5 years after graduation

- Graduates are first contacted by email, and for those who did not complete the survey online, by phone. This ensures the **high rates of response** (73,2% for 2018 graduates 1 year after graduation, 70,4% for 2016 graduates 3 years after graduation and 64,6% for 2014 5 years after leaving university)
- The **labour market** survey asks graduates:
  - Whether they are pursuing further studies or training
  - Whether they are employed, unemployed or inactive in the labour market
  - Type of employment (employee vs self employed), contract, use of smart working, economic sector, type of employer, geographical area of employment
  - Time from graduation to first job search
  - Time from graduation to finding a first job
  - Net salaries
  - How much graduates:
    - Use skills learned during university in their jobs
    - Think their degrees are useful in their jobs
  - Job satisfaction

Essay questions: Selected examples for admission year 2020 - 2021

- **Q1:** Discuss the following statement, attributed to Galileo Galilei: “Scientific truths are not decided by majority vote.”

- **Q2:** 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

- **Q3:** According to Bauman, where does science stand in a liquid society?

- **Q4:** 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.

Back to admission procedure

Back to validation checks

Essay grading

Examiner A

Examiner B

Examiner C

Back to admission procedure

Back to validation checks

Selected results (1/7): Enrolment at UniTO

Dependent Variable	Enroll at UniTO		Graduate on time		Drop out	
	(1)	(2)	(3)	(4)	(5)	(6)
Admitted to HP	0.04	0.08	0.26	0.24	-0.07	-0.07
Asy p-value	0.34	0.04	0	0	0.04	0.04
Exact p-value	0.49	0.04	0	0	0.10	0.07
Controls		✓		✓		✓
AY FE		✓		✓		✓
Mean – score 6	0.93	0.93	0.77	0.78	0.07	0.07
N – score 6	260	217	168	137	242	201
N – score 7	168	145	122	105	160	140
F-stat	217.61	213.65	168.67	152.93	220.98	211.76
Oster's δ		-11.40		26.81		10.95

Note: LATE estimates. Odd columns control for degree type and field of study. Even columns add controls for ability proxy, motivation proxy, gender, socio-economic and geographic background and honors program admission year FE. Endogenous: Ever enrolled in the honors program. Asy SEs robust to heteroskedasticity. Kleibergen-Paap rk Wald F statistic reported. Oster on Reduced Form.

Results: Academic achievements at UniTO

Dependent Variable	College GPA		Final grade		Graduating *cum laude*	
	(1)	(2)	(3)	(4)	(5)	(6)
Ever enrolled in HP	0.52	0.53	1.83	1.56	0.19	0.17
Asy p-value	0.01	0	0	0	0.02	0.03
Exact p-value	0.01	0	0	0.01	0.02	0.03
Controls		✓		✓		✓
AY FE		✓		✓		✓
Mean – score 6	28.27	28.27	107.65	107.73	0.59	0.59
N – score 6	164	154	164	154	164	154
N – score 7	130	112	130	112	130	112
F-stat	196.46	188.21	196.46	188.21	196.46	188.21
Oster's δ		3.15		4.03		3.95

Note: LATE estimates. Odd columns control for degree type and field of study. Even columns add controls for ability proxy, motivation proxy, gender, socio-economic and geographic background and honors program admission year FE. Endogenous: Ever enrolled in the honors program. Asy SEs robust to heteroskedasticity. Kleibergen-Paap rk Wald F statistic reported. Oster on Reduced Form.

Selected results (3/7): Academic experience at UniTO – sanity check

Dependent Variable	Live close to Uni		Work		Rent		Happy with faculty		Happy with students	
	(1)	(2)	(3)	(4)	(5)	(6)	(3)	(4)	(5)	(6)
Ever enrolled in HP	0.23	0.23	-0.24	-0.24	-0.15	-0.26	0.12	0.09	0.04	0.05
Asy 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
Controls		✓		✓		✓		✓		✓
AY FE		✓		✓		✓		✓		✓
Mean – score 6	0.65	0.65	0.28	0.29	0.39	0.39	0.19	0.19	0.44	0.44
N – score 6	155	154	155	154	164	154	164	154	164	154
N – score 7	114	112	130	112	130	112	130	112	130	112
F-stat	196.46	188.21	196.46	188.21	196.46	188.21	196.46	188.21	196.46	188.21
Oster's δ		14.48		-171.92		-9.48		3.61		1.95

Note: LATE estimates. Odd columns control for degree type and field of study. Even columns add controls for ability proxy, motivation proxy, gender, socio-economic and geographic background and honors program admission year FE. Endogenous: Ever enrolled in the honors program. Asy SEs robust to heteroskedasticity. Kleibergen-Paap rk Wald F statistic reported. Oster on Reduced Form.

Results: LM prospects at graduation

Dependent Variable	Into labour force		Into PhD		Reservation wage	
	(1)	(2)	(3)	(4)	(5)	(6)
Ever enrolled in HP	-0.20	-0.21	0.11	0.18	-208.58	-212.27
Asy p-value	0.03	0.02	0.3	0.1	0.01	0.01
Exact p-value	0.03	0.03	0.29	0.12	0.01	0.01
Controls		✓		✓		✓
AY FE		✓		✓		✓
Mean – score 6	0.67	0.67	0.35	0.37	1344.45	1344.45
N – score 6	154	153	72	68	153	153
N – score 7	112	111	73	62	108	107
F-stat	185.45	186.6	186.41	217.39	175.74	181.34
Oster's δ		-15.87		2.72		11.25

Note: LATE estimates. Odd columns control for degree type and field of study. Even columns add controls for ability proxy, motivation proxy, gender, socio-economic and geographic background and honors program admission year FE. Endogenous: Ever enrolled in the honors program. Asy SEs robust to heteroskedasticity. Kleibergen-Paap rk Wald F statistic reported. Oster on Reduced Form.

Results: LM outcomes 1 year after graduation

Dependent Variable	Into labour force		Into PhD	
	(1)	(2)	(3)	(4)
Ever enrolled in HP	-0.34	-0.41	0.29	0.37
Asy p-value	0.02	0	0.04	0.01
Exact p-value	0.03	0.04	0.04	0.03
Controls		✓		✓
AY FE		✓		✓
Mean – score 6	0.65	0.63	0.21	0.22
N – score 6	34	32	34	32
N – score 7	40	38	40	38
F-stat	119.41	75.56	119.41	75.56
Oster's δ		-91.67		-10.47

Note: LATE estimates. Odd columns control for degree type and field of study. Even columns add controls for ability proxy, motivation proxy, gender, socio-economic and geographic background and honors program admission year FE. Endogenous: Ever enrolled in the honors program. Asy SEs robust to heteroskedasticity. Kleibergen-Paap rk Wald F statistic reported. Oster on Reduced Form.

Heterogeneity analysis: Socio-economic status 1

Dependent Variable	GPA				Final grade				Graduate *cum laude*			
	Lower class		Upper class		Lower class		Upper class		Lower class		Upper class	
	(1)	(2)	(3)	(4)	(5)	(6)	(3)	(4)	(5)	(6)	(5)	(6)
Ever enrolled in HP	0.19	0.34	**0.75**	**0.66**	1.36	1.7	**2.43**	**1.83**	0.08	-0.01	**0.3**	**0.25**
Asy 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
Controls		✓		✓		✓		✓		✓		✓
AY FE		✓		✓		✓		✓		✓		✓
Mean – score 6	28.45	28.47	28.10	28.07	107.86	108.04	107.33	107.43	0.62	0.64	0.54	0.54
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
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
Oster's δ		3.81		2.01		16.22		2.66		-0.27		2.75

Note: LATE estimates. Odd columns control for degree type and field of study. Even columns add controls for ability proxy, motivation proxy, gender, socio-economic and geographic background and honors program admission year FE. Endogenous: Ever enrolled in the honors program. Asy SEs robust to heteroskedasticity. Kleibergen-Paap rk Wald F statistic reported. Oster on Reduced Form.

Heterogeneity analysis: Socio-economic status 2

Dependent Variable	Wants to enter LF				Reservation wage			
	Lower class		Upper class		Lower class		Upper class	
	(1)	(2)	(3)	(4)	(5)	(6)	(3)	(4)
Ever enrolled in HP	**-0.34**	**-0.42**	-0.11	-0.10	**-295.23**	**-290.75**	-202.64	-158.05
Asy p-value	0.04	0.01	0.37	0.38	0.01	0.01	0.10	0.18
Exact p-value	0.02	0.01	0.39	0.43	0.01	0.04	0.09	0.18
Controls		✓		✓		✓		✓
AY FE		✓		✓		✓		✓
Mean – score 6	0.71	0.70	0.64	0.63	1312.17	1312.17	1375.5	1375.5
N – score 6	75	74	80	79	75	75	78	78
N – score 7	46	46	66	65	45	45	63	62
F-stat	61.13	71.41	110.45	117.64	57.07	69.12	110.37	117.19
Oster's δ		24.42		-4.92		19.79		3.67

Note: LATE estimates. Odd columns control for degree type and field of study. Even columns add controls for ability proxy, motivation proxy, gender, socio-economic and geographic background and honors program admission year FE. Endogenous: Ever enrolled in the honors program. Asy SEs robust to heteroskedasticity. Kleibergen-Paap rk Wald F statistic reported. Oster on Reduced Form.

Robustness (1/3): Additional controls for ability

- **Main results** for achievement reproduced in column 1 for our reduced form specification

- **Results remain similar** when we **add** controls:
  - o **housing value** in column 2
  - o **linguistic styles** derived from text analysis in column 3
  - o A measure of **essay approachability** derived from the choice of questions in the written test

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

	GPA	GPA	GPA	GPA
Score > cut - off	0.333	0.303	0.376	0.372
	(0.004)	(0.008)	(0.012)	(0.004)
N	266	228	193	232
adj. R^2	0.516	0.514	0.478	0.524
Avg - score 6	28.51	28.62	28.53	28.42
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

Robustness (2/3): Compute the relative degree of selection on unobservables that would be needed to explain away our results

- Compute the **relative degree of selection on unobservables**, based on selection on observables, that would be needed to drive to zero our estimates (Oster's δ, Oster 2019)

- Report results for **RF equation** in our results tables
  → instrument as good as randomly assigned for candidates in the window

- Assess our results to be **robust when** $|\boldsymbol{\delta}| > \mathbf{1}$
  → Selection on unobservables as relevant as selection on observables
  (unlikely given the rich covariate set we observe)

Robustness (3/3): Relaxing the exclusion restriction

The RDD local randomization framework identifying assumptions would be violated if

- The selection **committee can accurately separate candidates** on the basis of any unobserved ability component

- The score plays any **direct effect** on the outcome of interest (e.g., higher scores as encouragement)

$$GPA_{ikt} = \alpha + \beta\, honors\ program_{ik} + \upsilon_{ikt}$$

IV

Encouragement

Passing the written exam

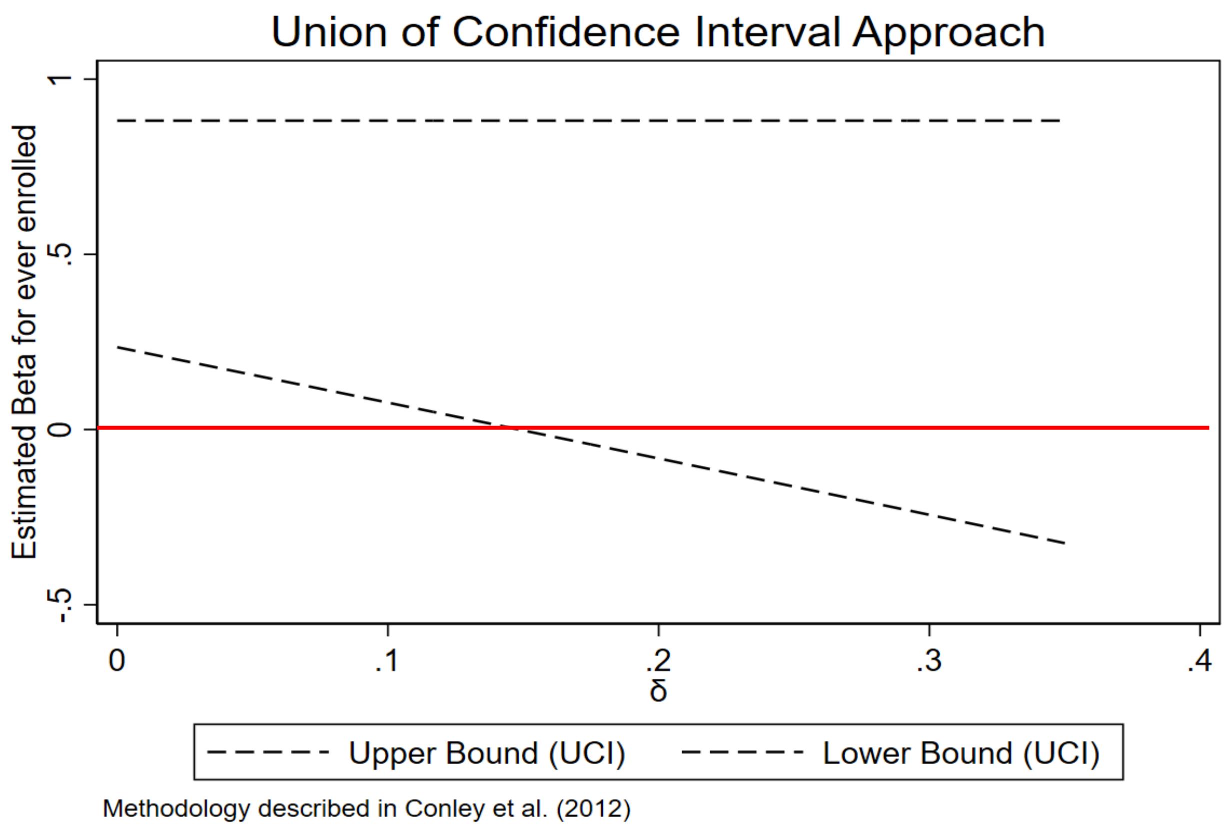
Ability

Robustness (3/3): Relaxing the exclusion restriction

- We **relax the exclusion restriction** by following Conley et al 2012 and assuming a value (δ) for the direct effect the instrument can play on the dependent

- **Confidence intervals of IV estimates exclude zero for values of δ up to a third of the reduced form effect** (0.33)

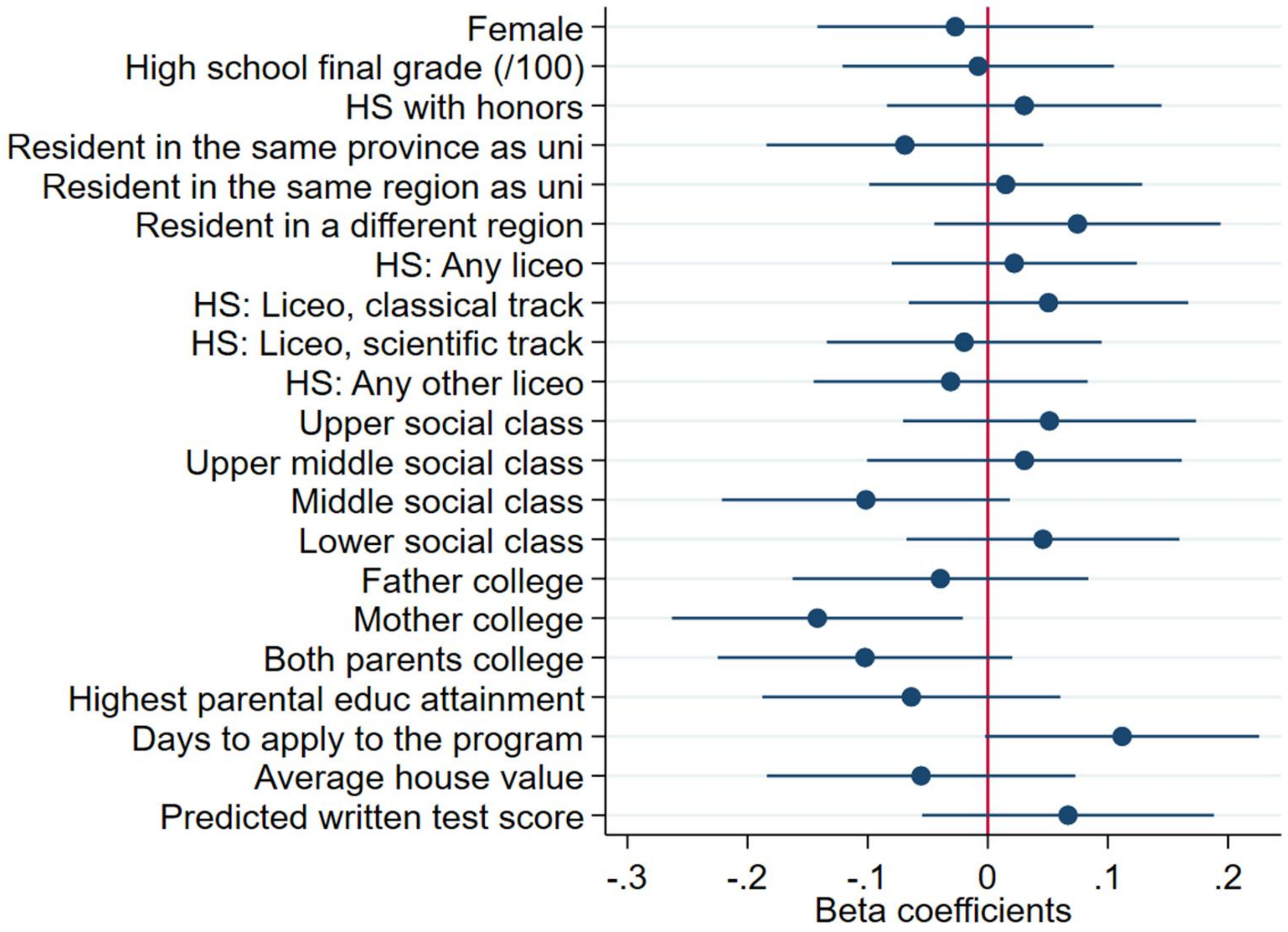
  → Even allowing for a direct effect of the instrument on the dependent (up to 0.14 points on college GPA) we would identify a positive effect of the honors program



Balance test: Pre-determined characteristics are balanced for marginal candidates in the window

- **Balance** across all **pre-determined characteristics** for candidates in the window

- **No evidence of positive selection**



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- **Balance** across all **pre-determined characteristics** for candidates in the window

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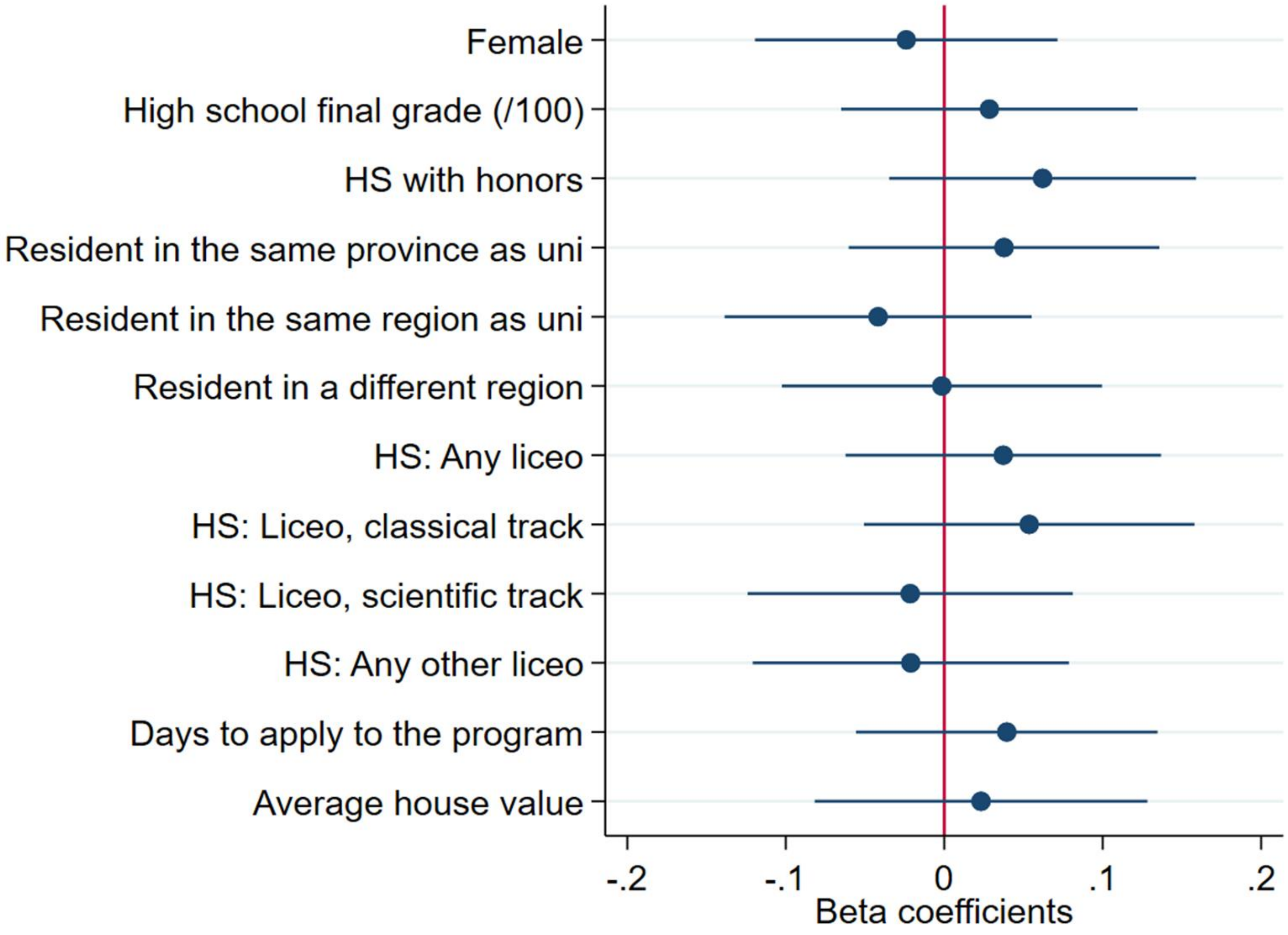


Conceptual framework: Framework to think about the assumptions behind our identification strategy

Intuition:
- **Easy** to separate candidates based on their underlying ability **at the tails** of the ability distribution
- **Harder** to tell candidates apart when we are **in the middle** of the ability distribution

To rationalize this:
- We **assume 4 types of candidates** according to their latent ability level:
  - Low ability, t = L
  - High ability, t = H
  - Medium-low ability, t = ML
  - Medium-high ability, t = MH
- Selection **committee** attempts to **discriminate** candidate types **through the written test**, “c” denotes the profiling of candidates by the selection committee.
- **Assumption**: 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.

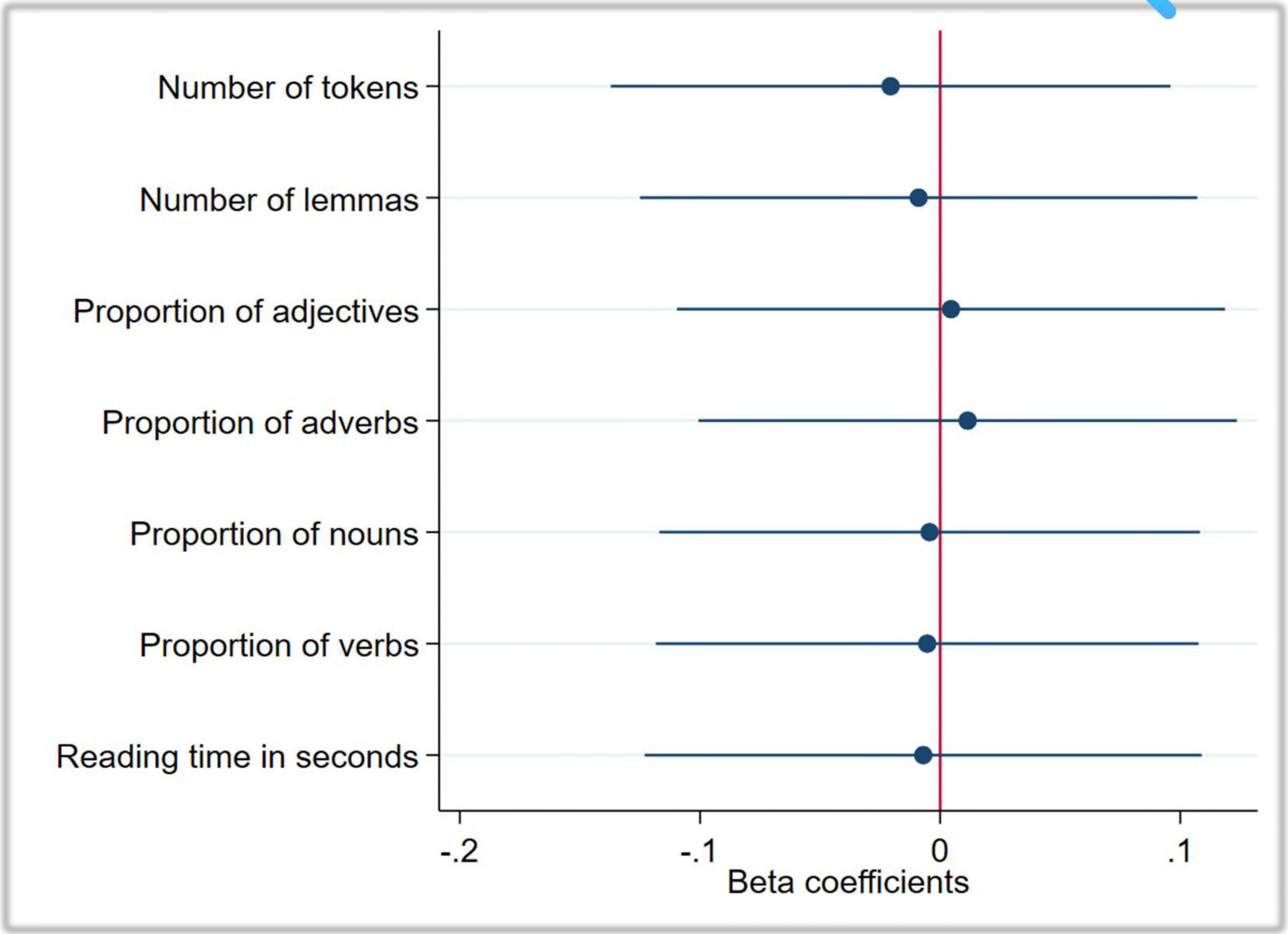
$$\Pr(c = ML \mid t = ML) = \Pr(c = MH \mid t = ML)$$
$$\Pr(c = ML \mid t = MH) = \Pr(c = MH \mid t = MH)$$

Text analysis (1/2): Marginal candidates use more frequently the same words (9/10) in their covering letters compared to candidates at the tails (5/10)

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

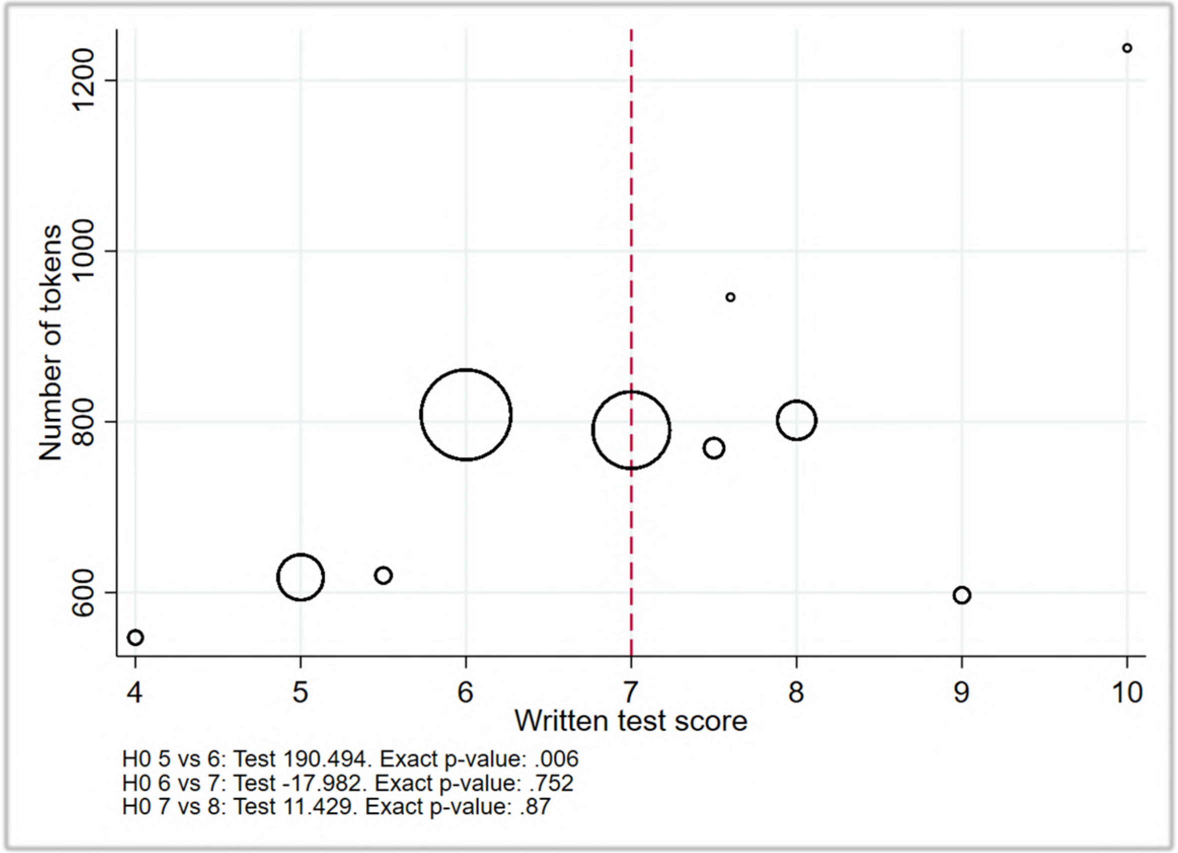
Text analysis (2/2): Linguistic choices in cover letters are also balanced

- **Balance** across all **linguistic choices**
- **RDD plots**

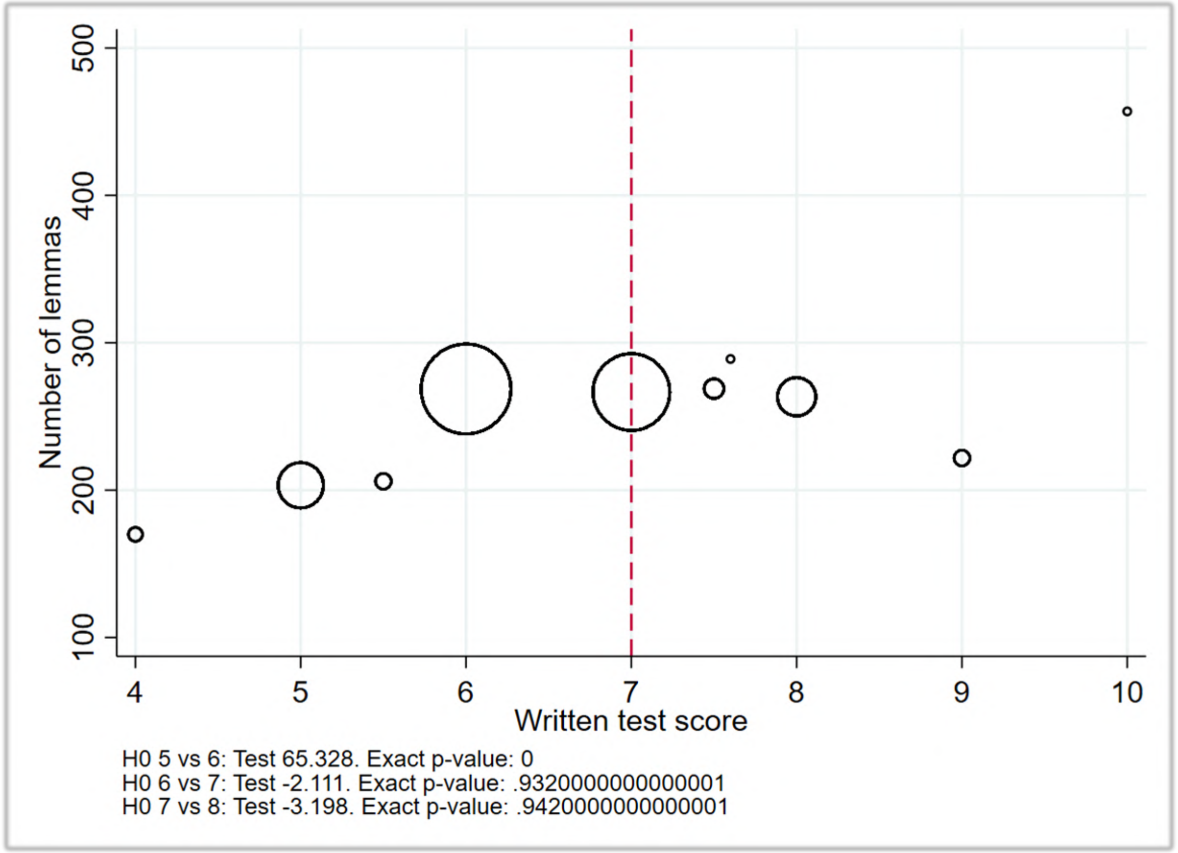


RDD plots – Text analysis (1/4): 2012 – 2017 SSST AY

Number of tokens

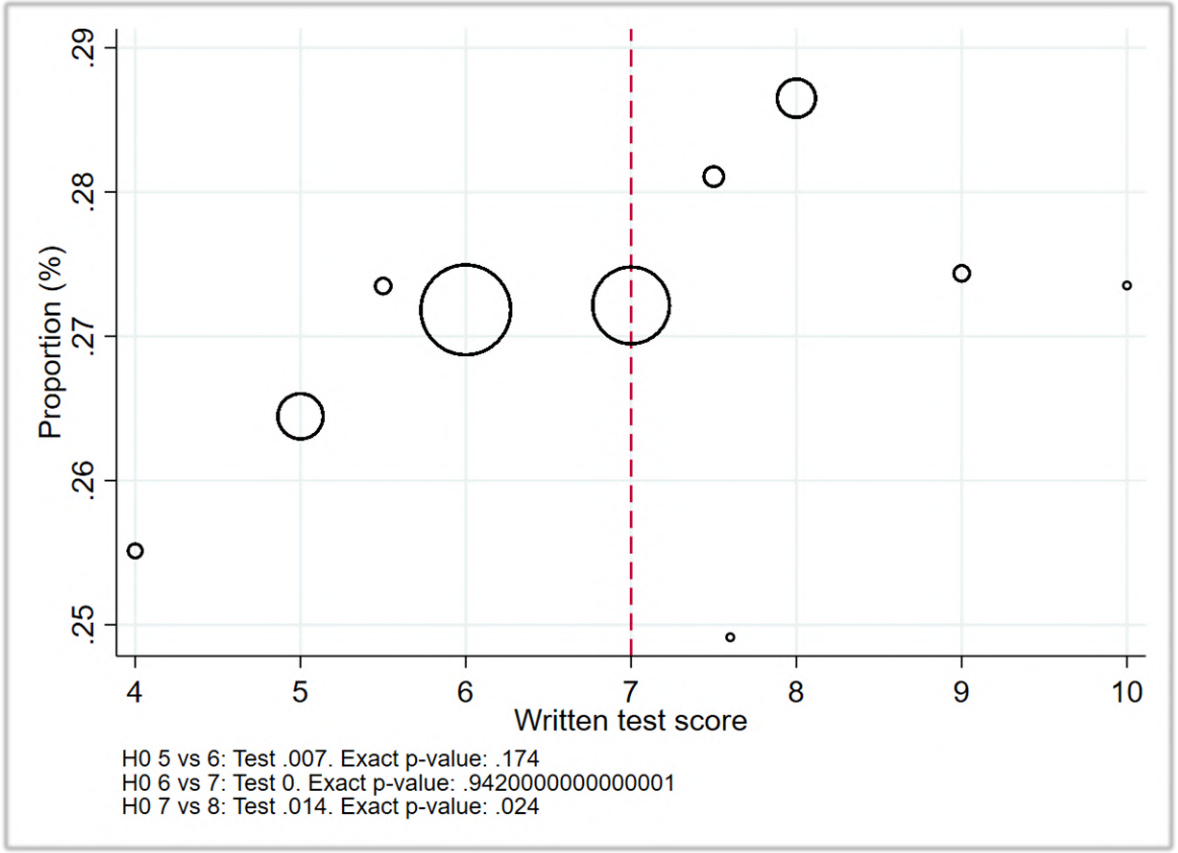


Number of lemmas

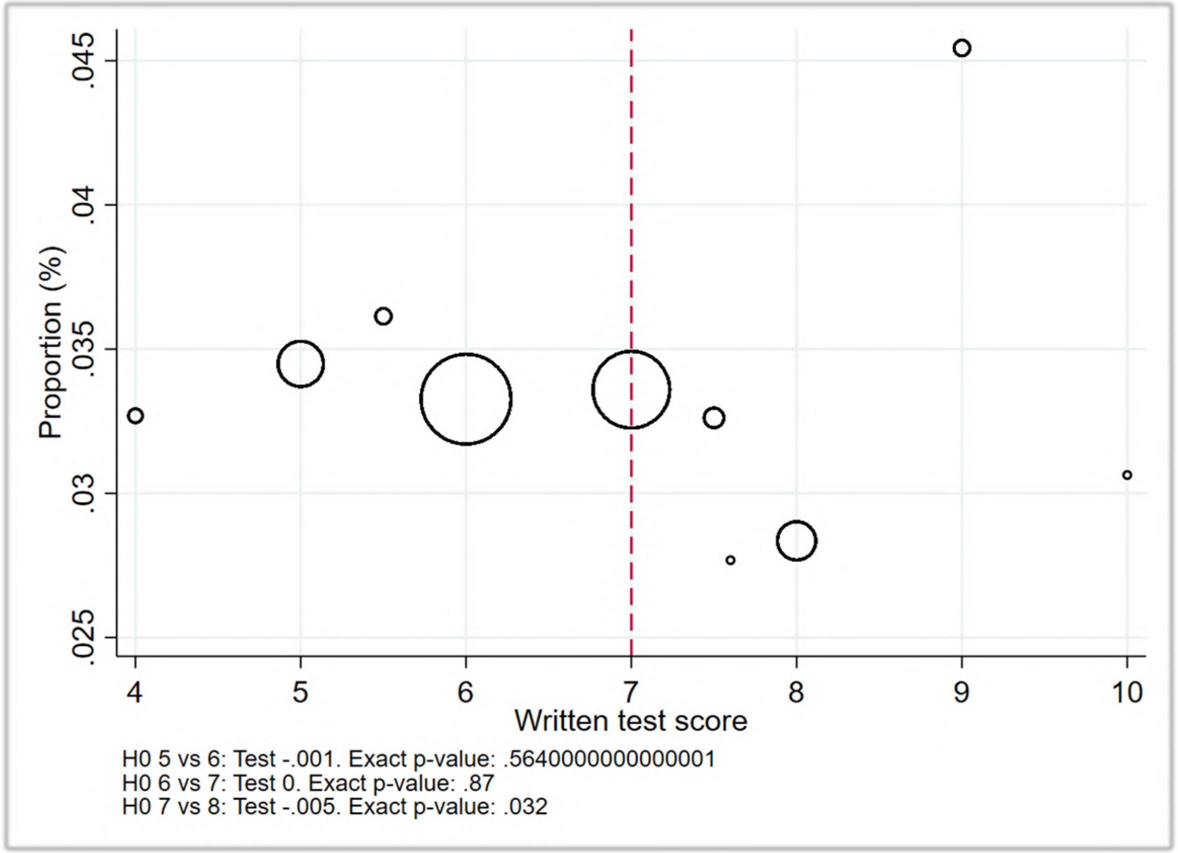


RDD plots – Text analysis (2/4): 2012 – 2017 SSST AY

Proportion of adjectives over lemmas

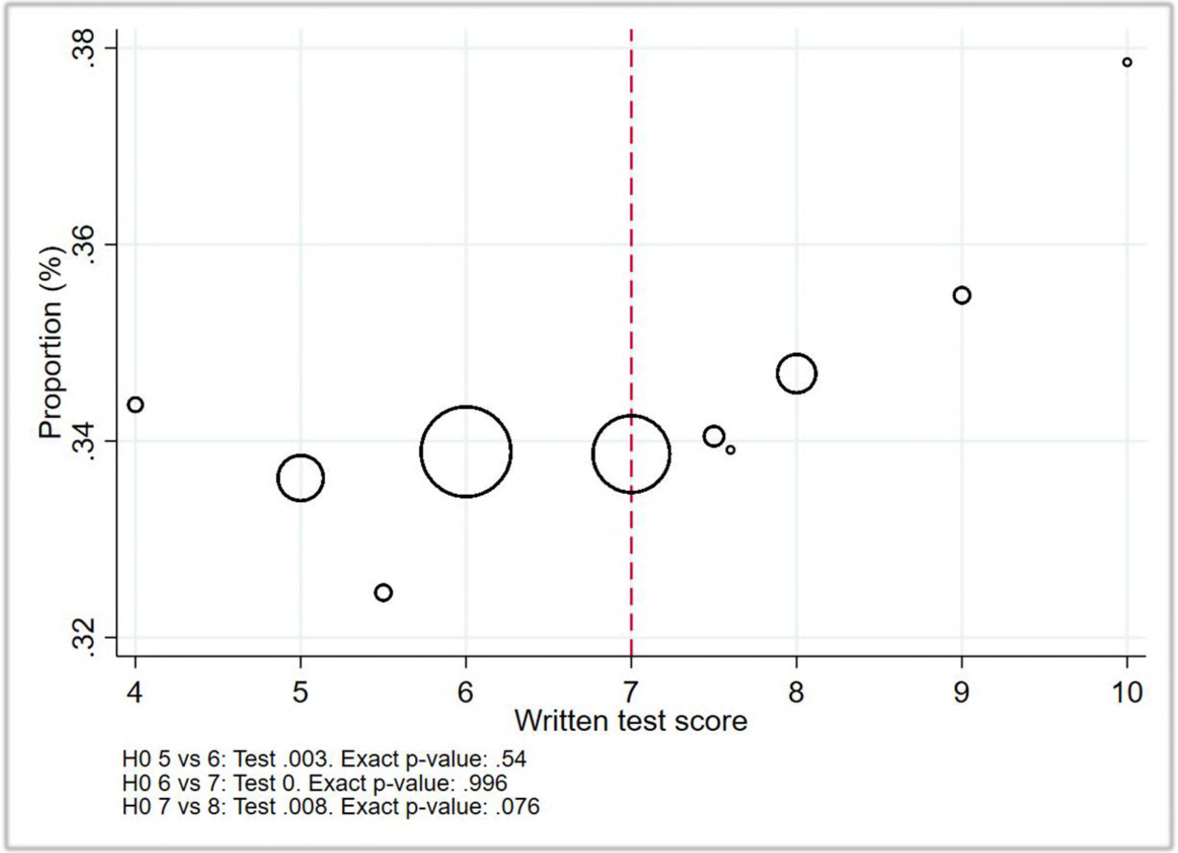


Proportion of adverbs over lemmas

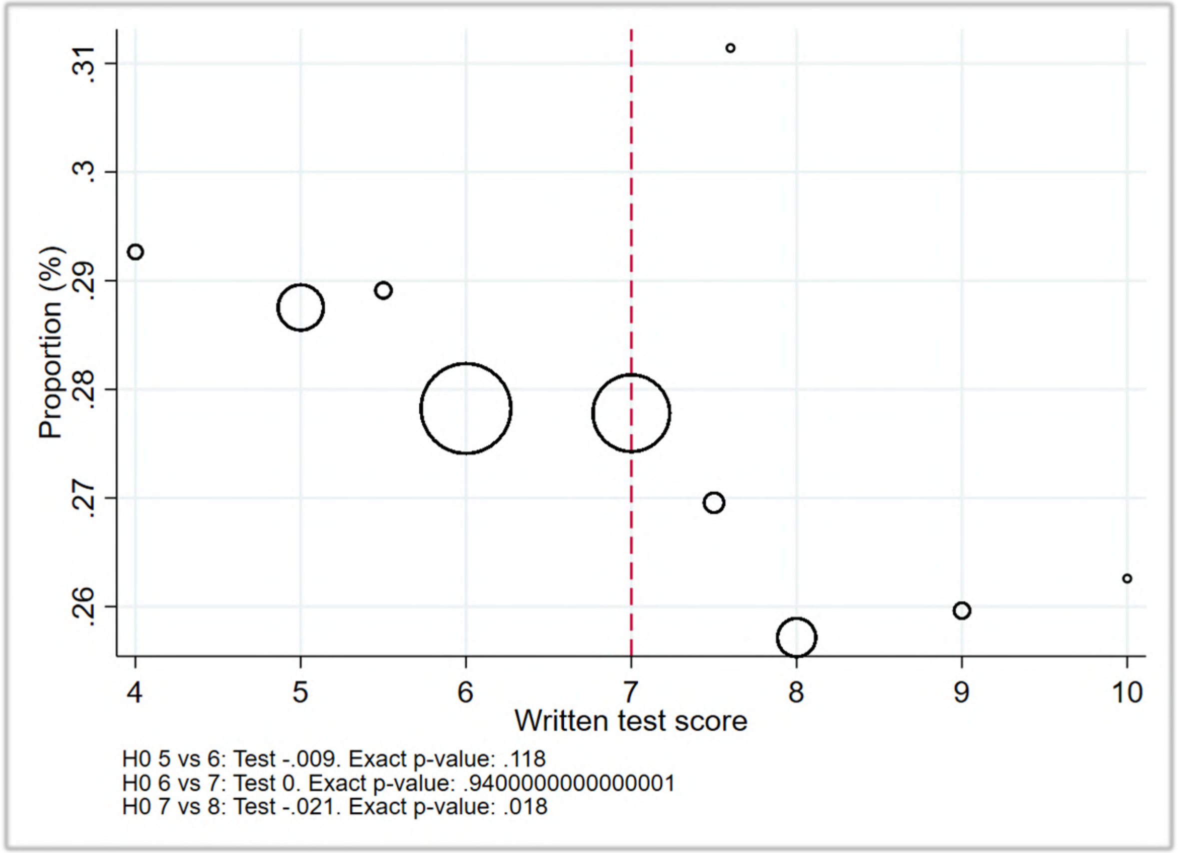


RDD plots – Text analysis (3/4): 2012 – 2017 SSST AY

Proportion of nouns over lemmas

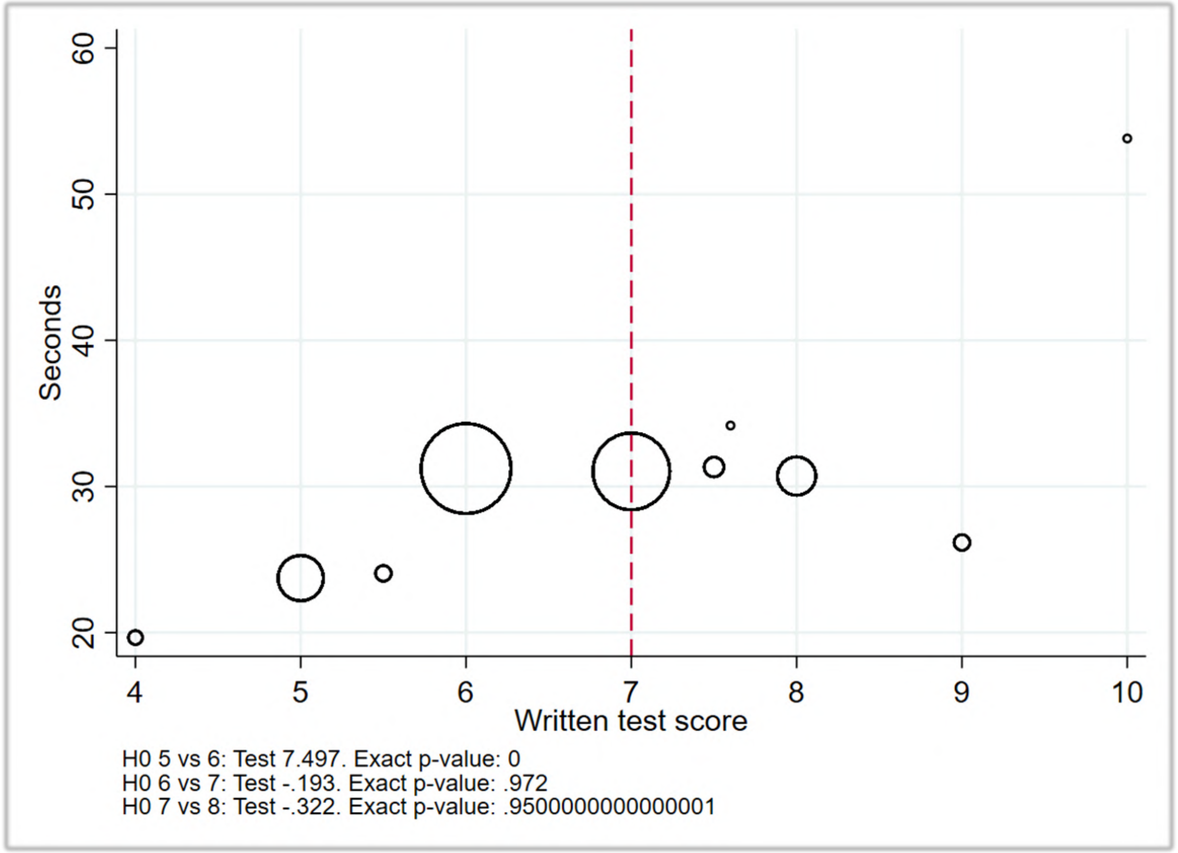


Proportion of verbs over lemmas



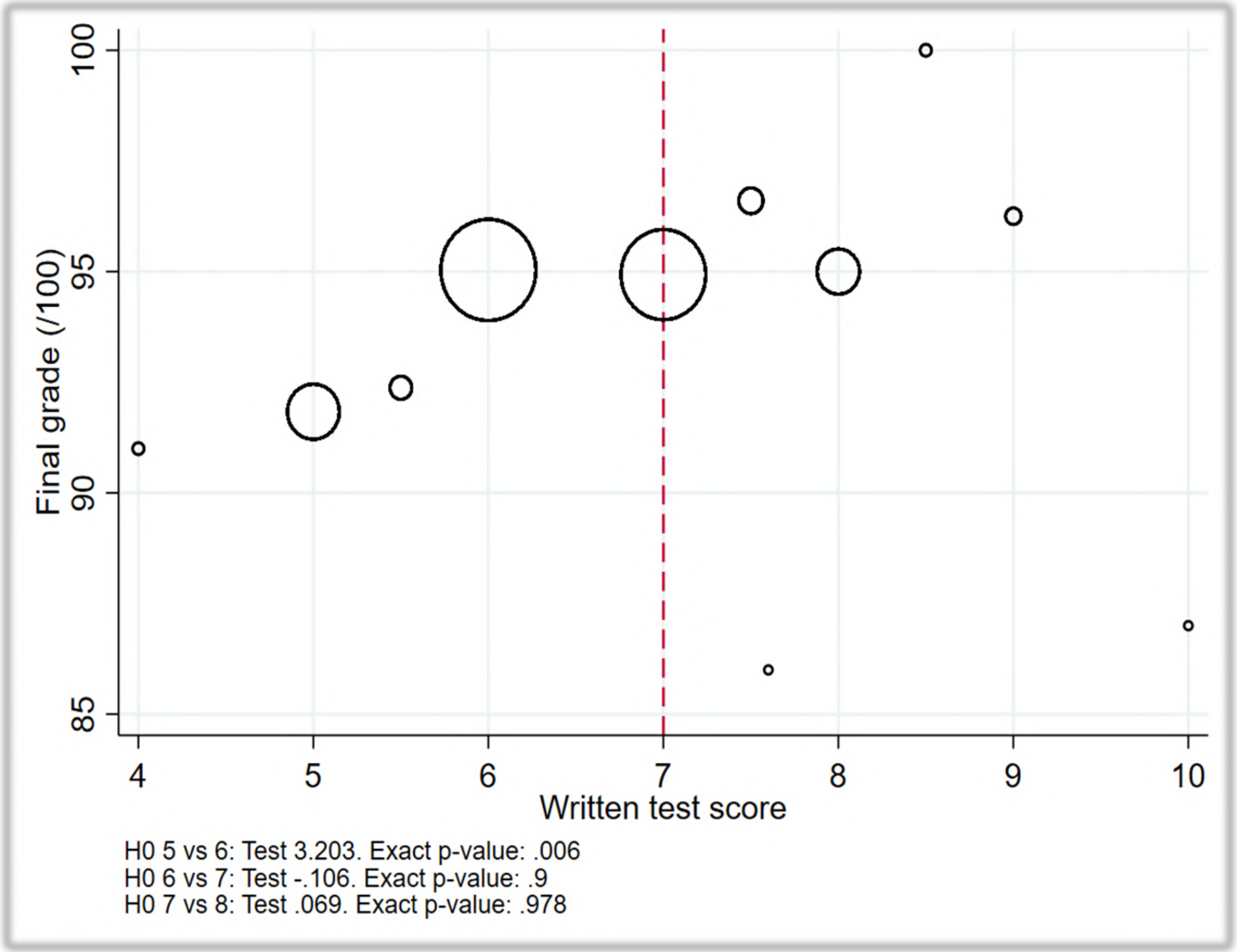
RDD plots – Text analysis (4/4): 2012 – 2017 SSST AY

Reading time in seconds



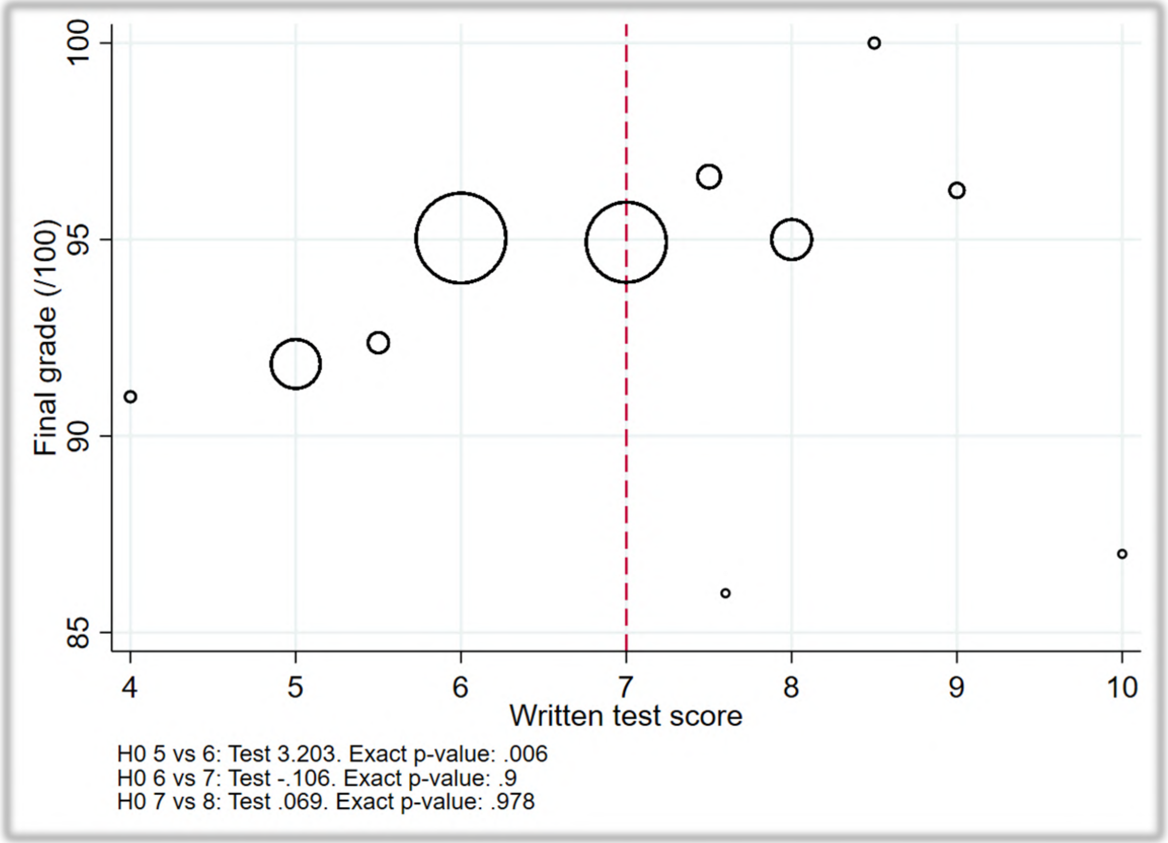
RDD plots

Ability proxy: High school final grade

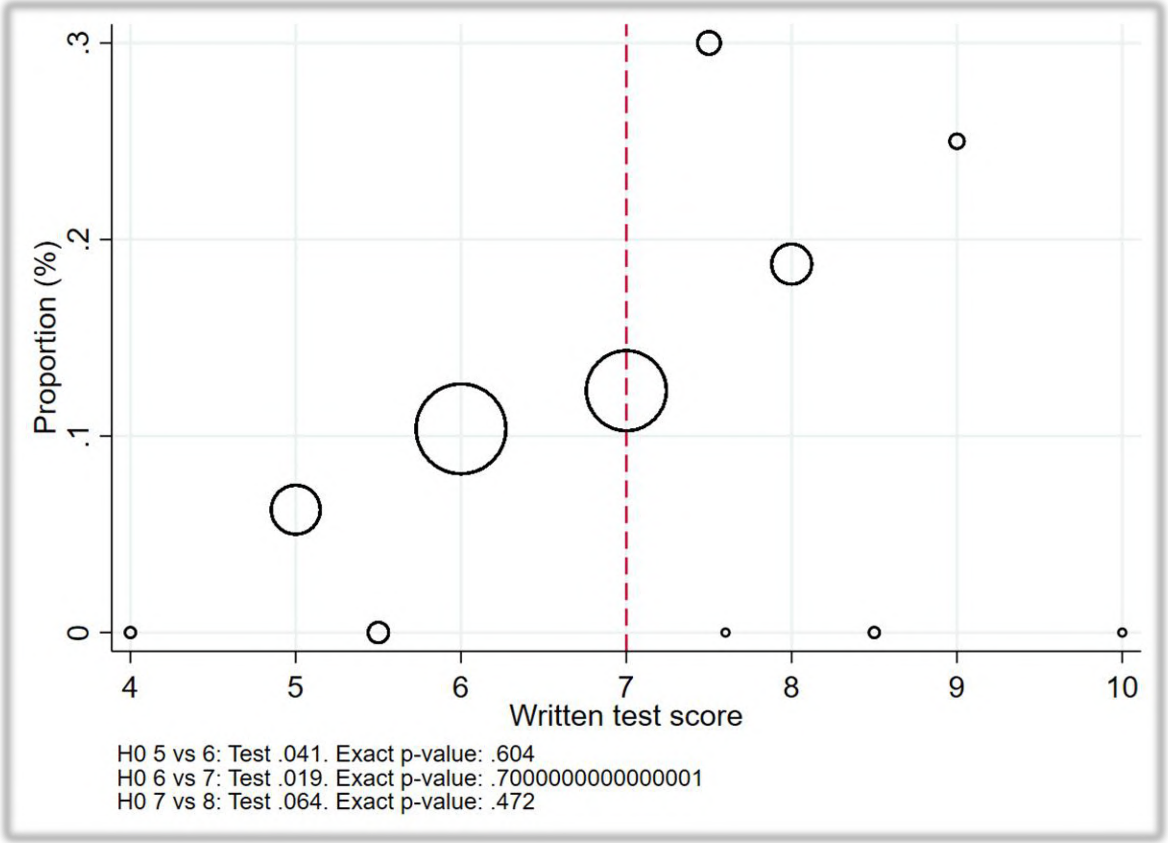


RDD plots - Graduate (1/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

Ability proxy: High school final grade

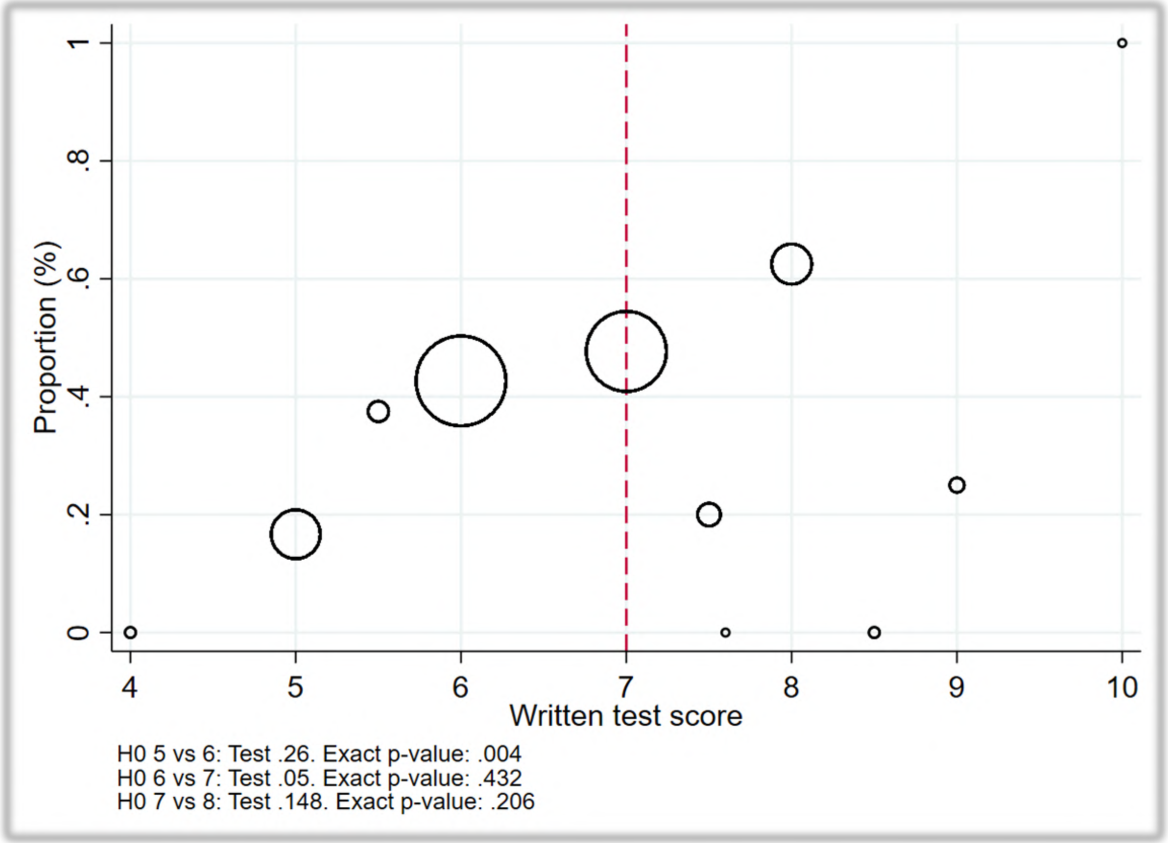


Ability proxy: Graduating with honors from high school

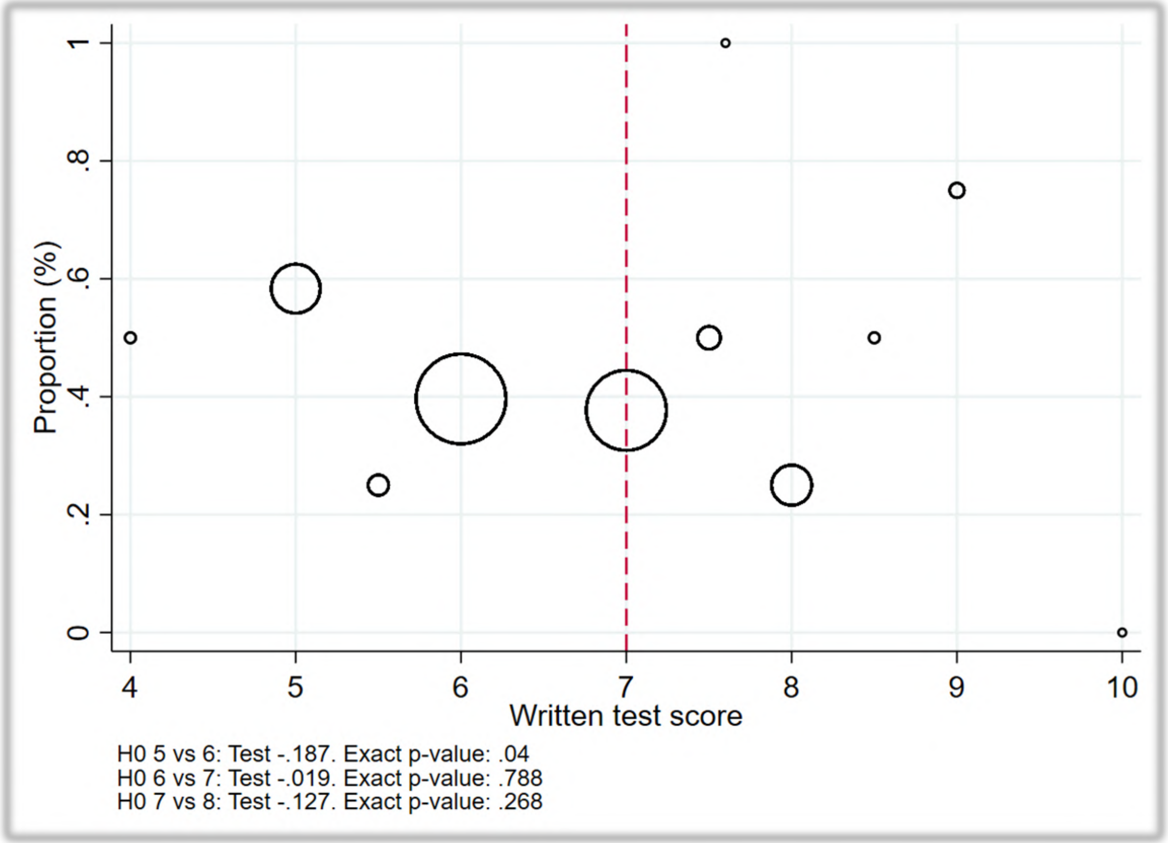


RDD plots - Graduate (2/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

Ability proxy: classical high school

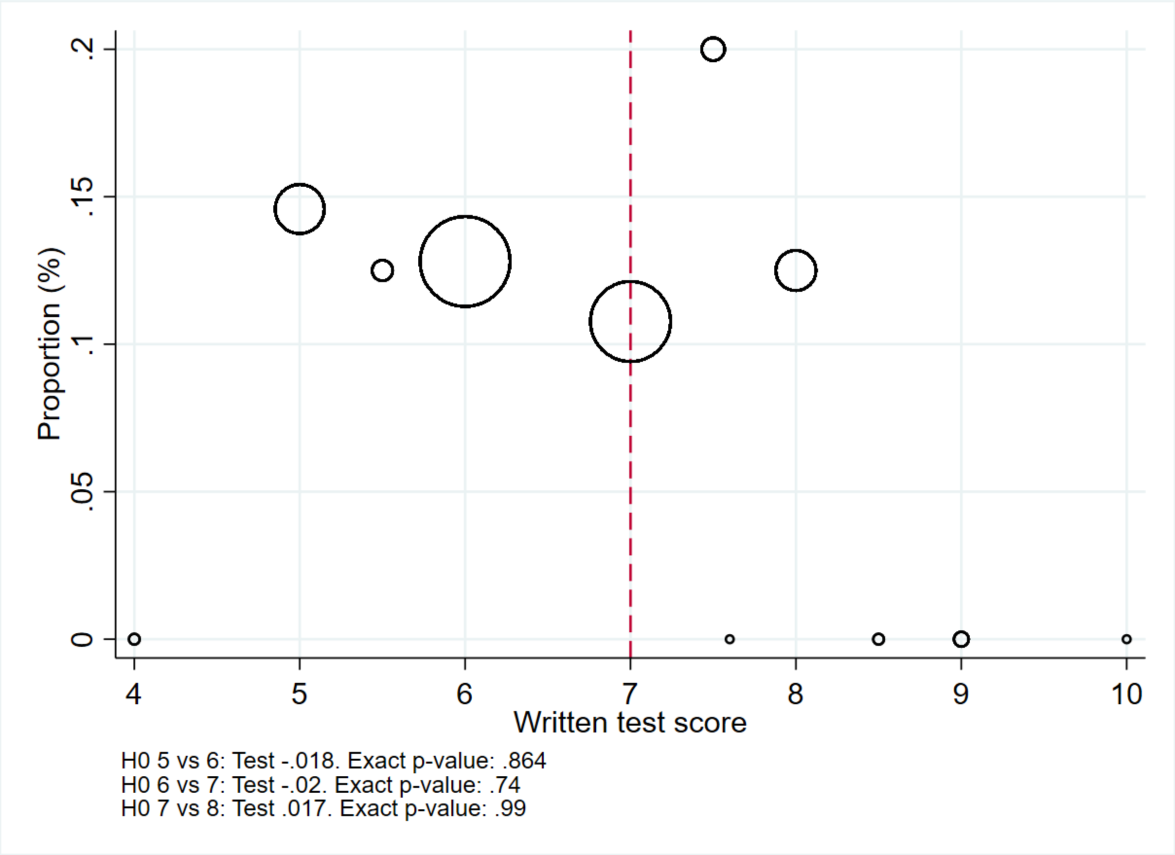


Ability proxy: scientific high school



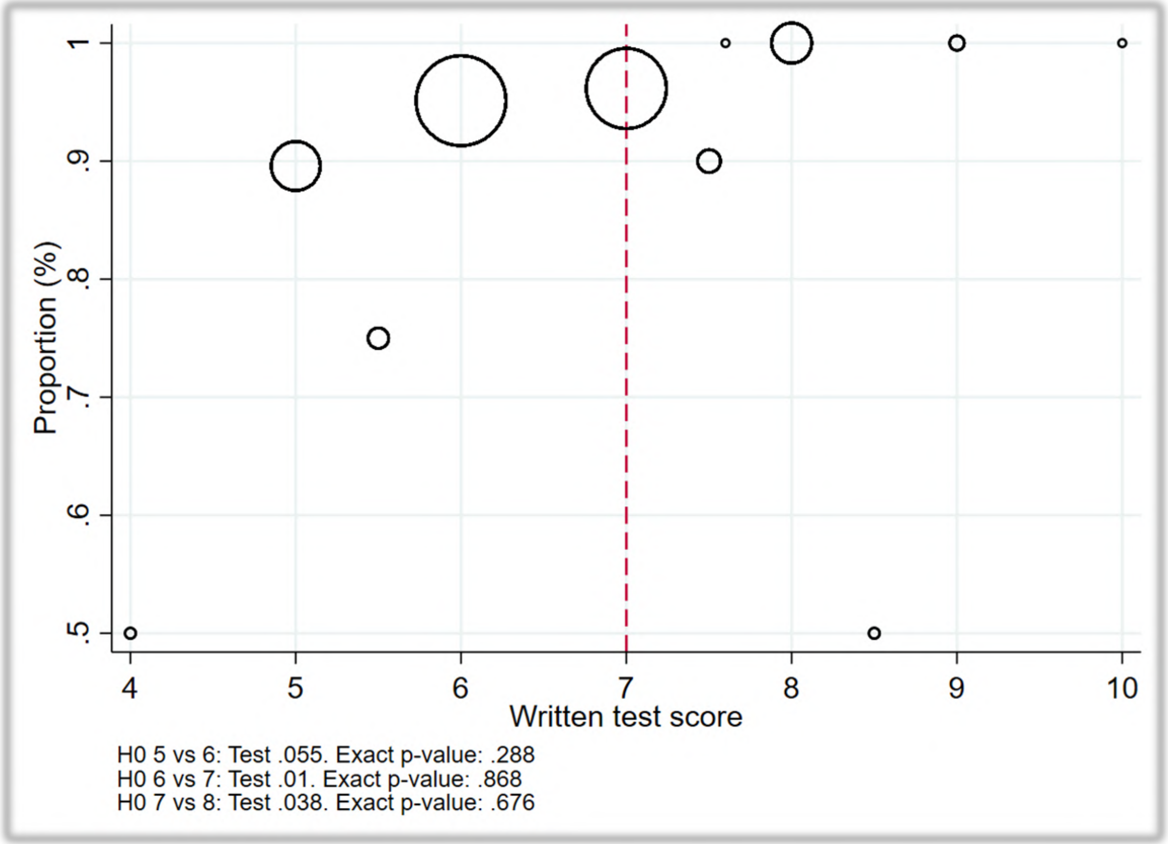
RDD plots - Graduate (3/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

Ability proxy: Any other liceo

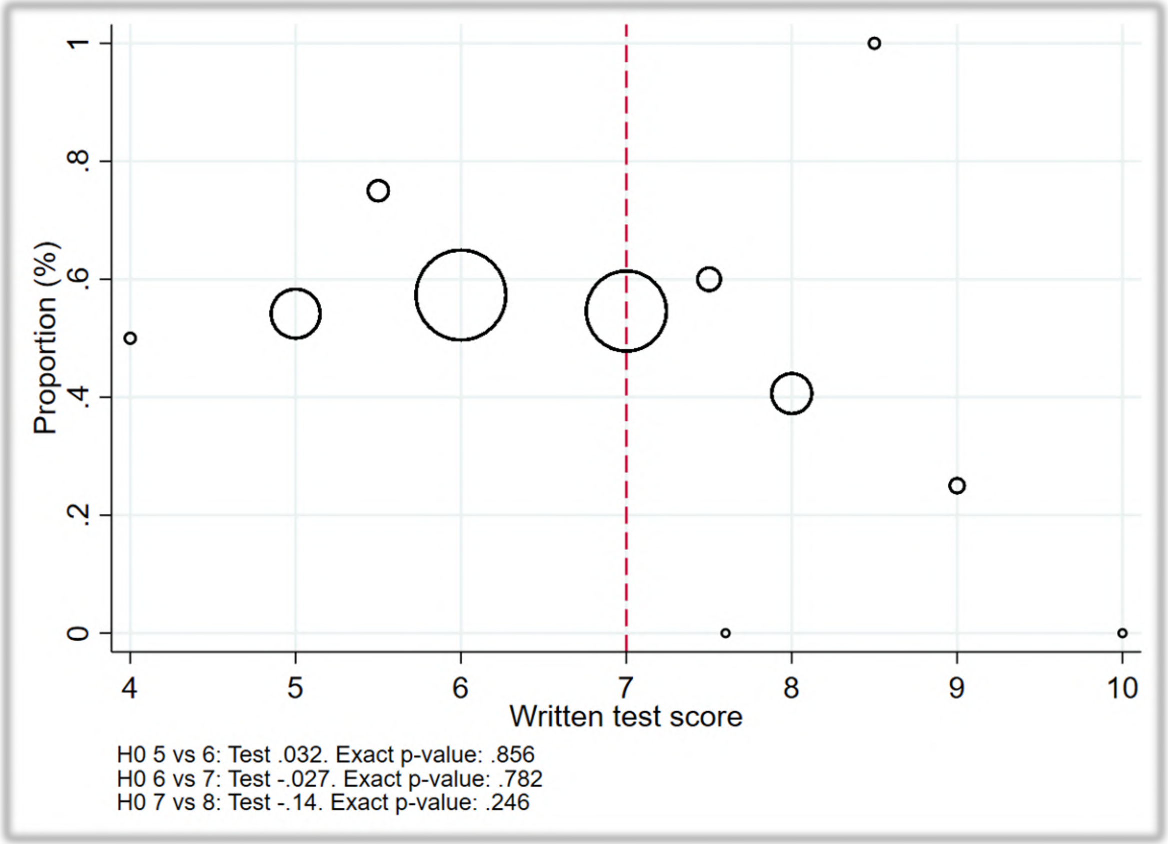


RDD plots - Graduate (4/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

Ability proxy: Any liceo

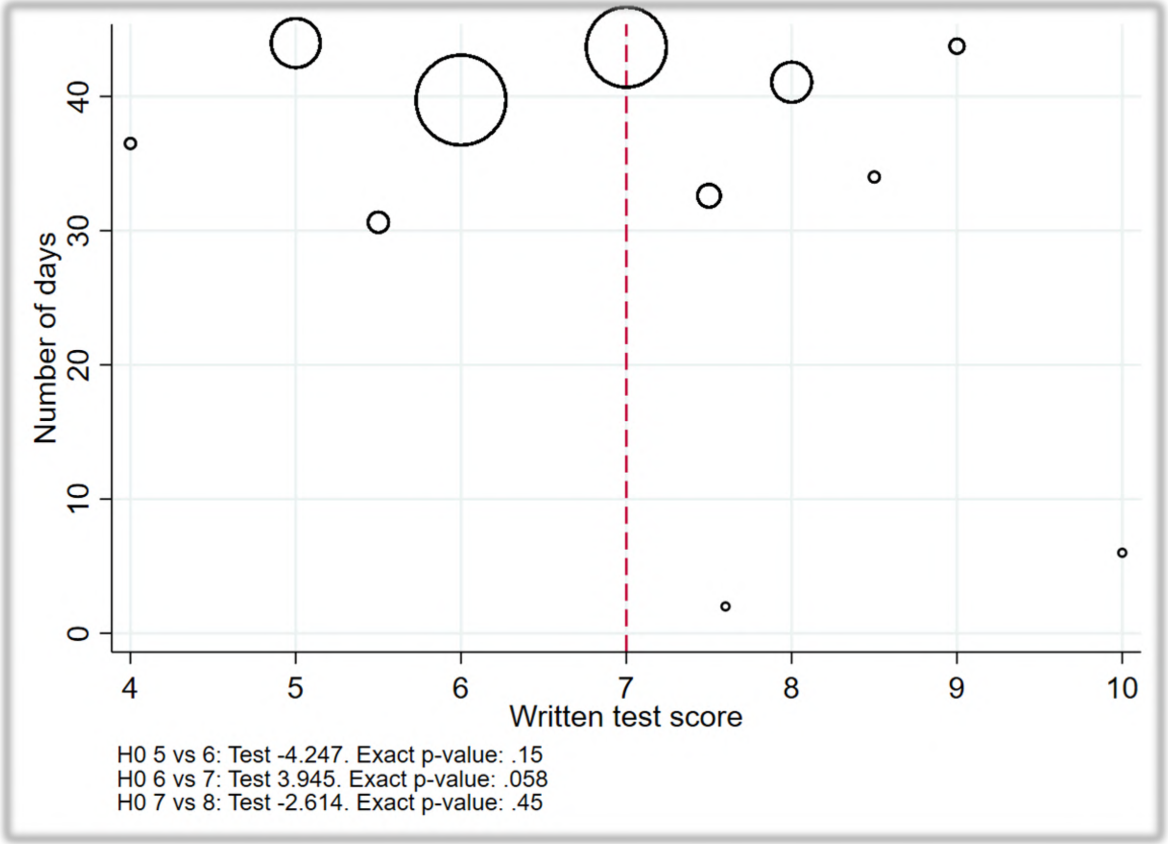


Female

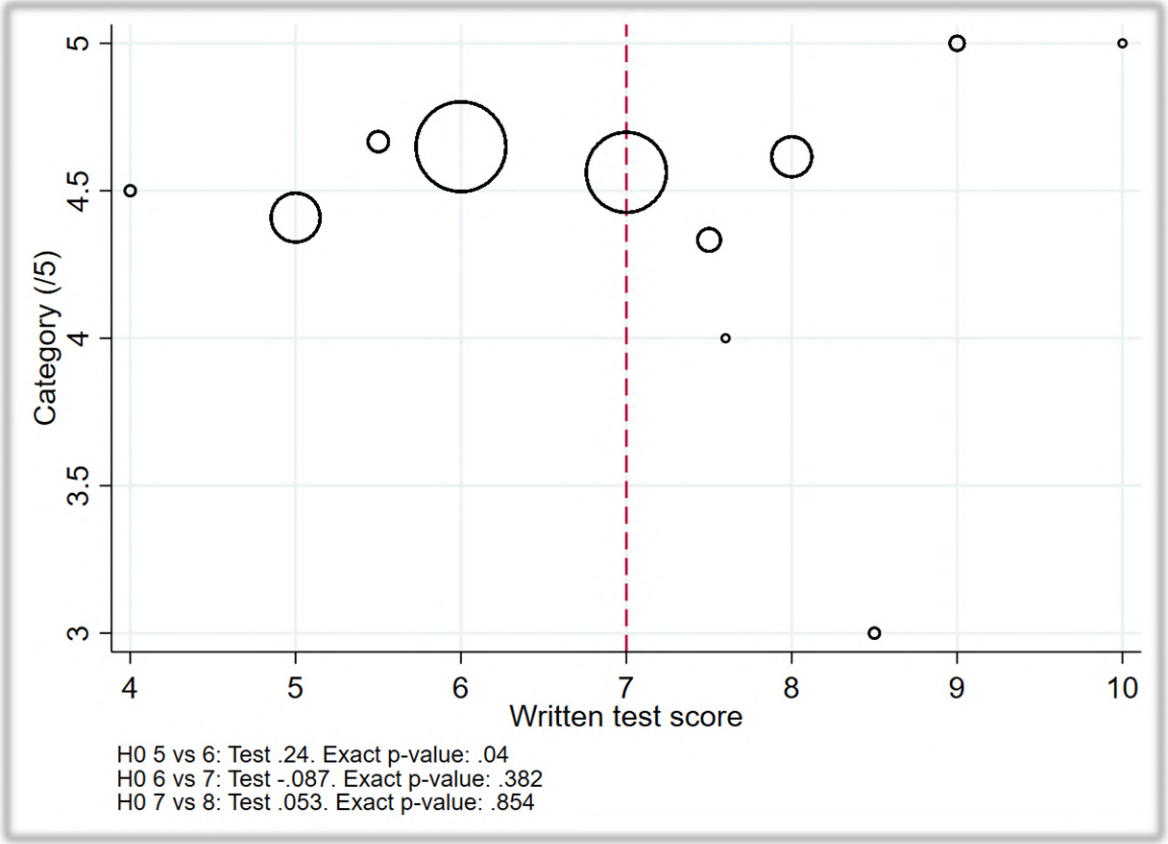


RDD plots - Graduate (5/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

Motivation proxy: Time to apply

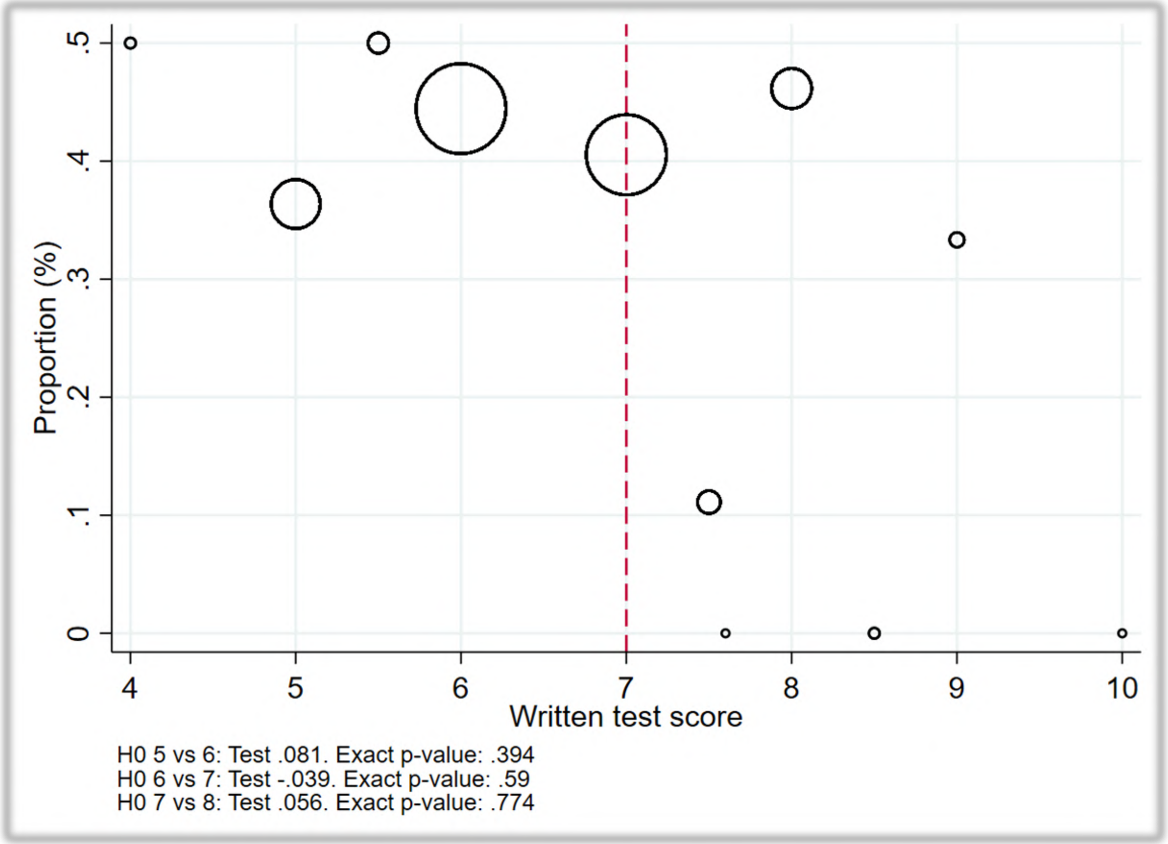


Socio-economic background: Parental education

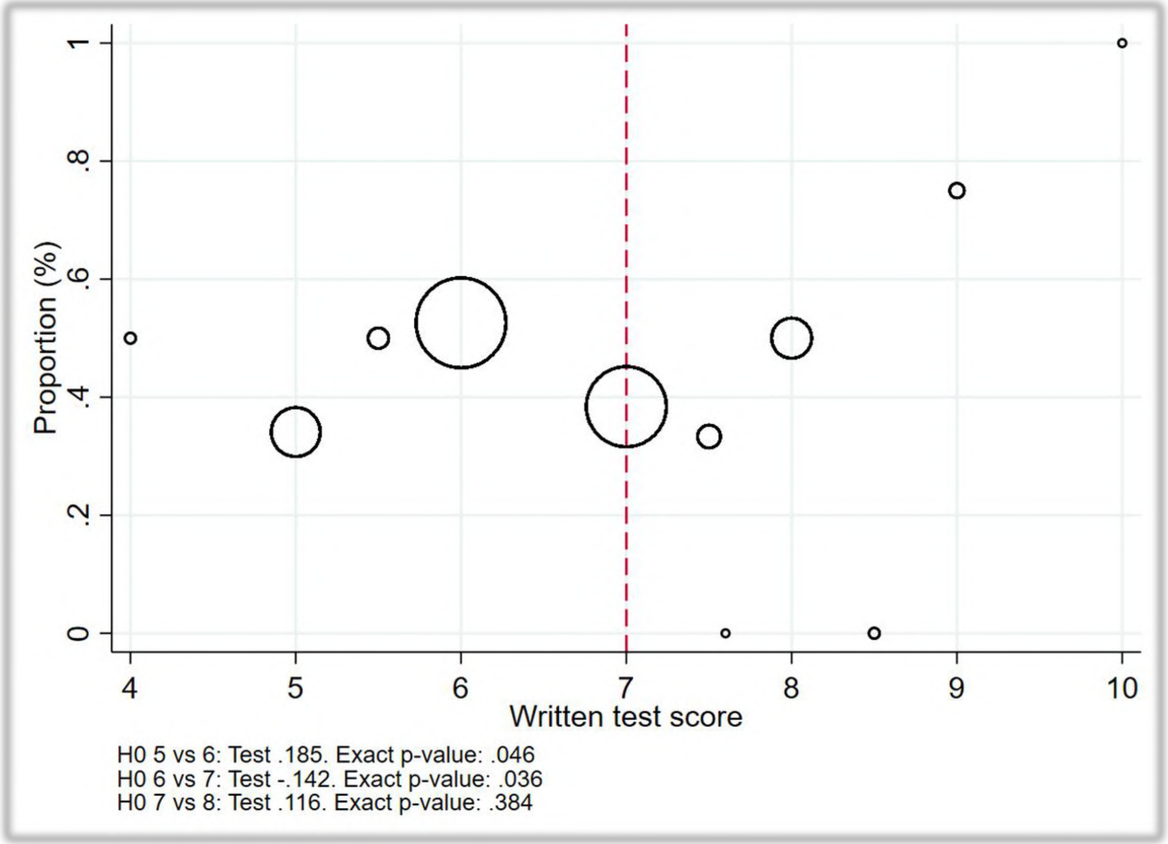


RDD plots - Graduate (6/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

Socio-economic background: Father college

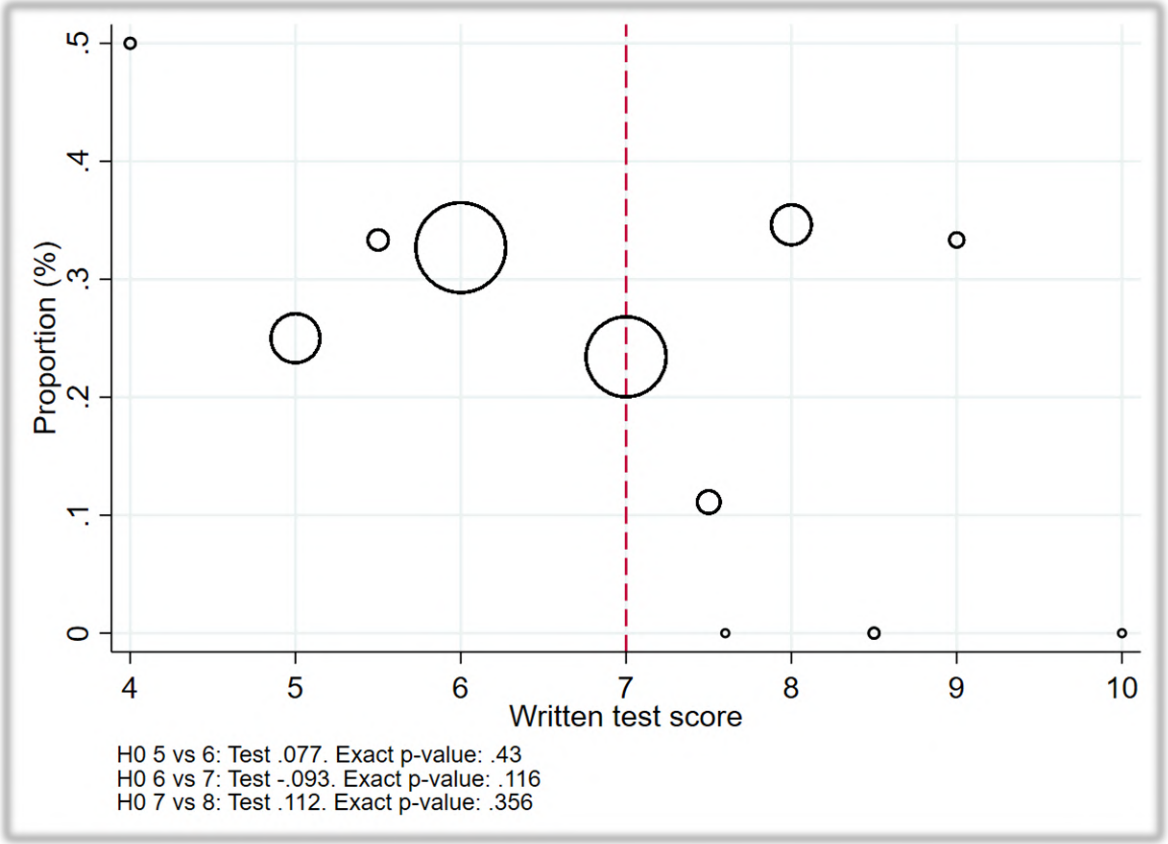


Socio-economic background: Mother college

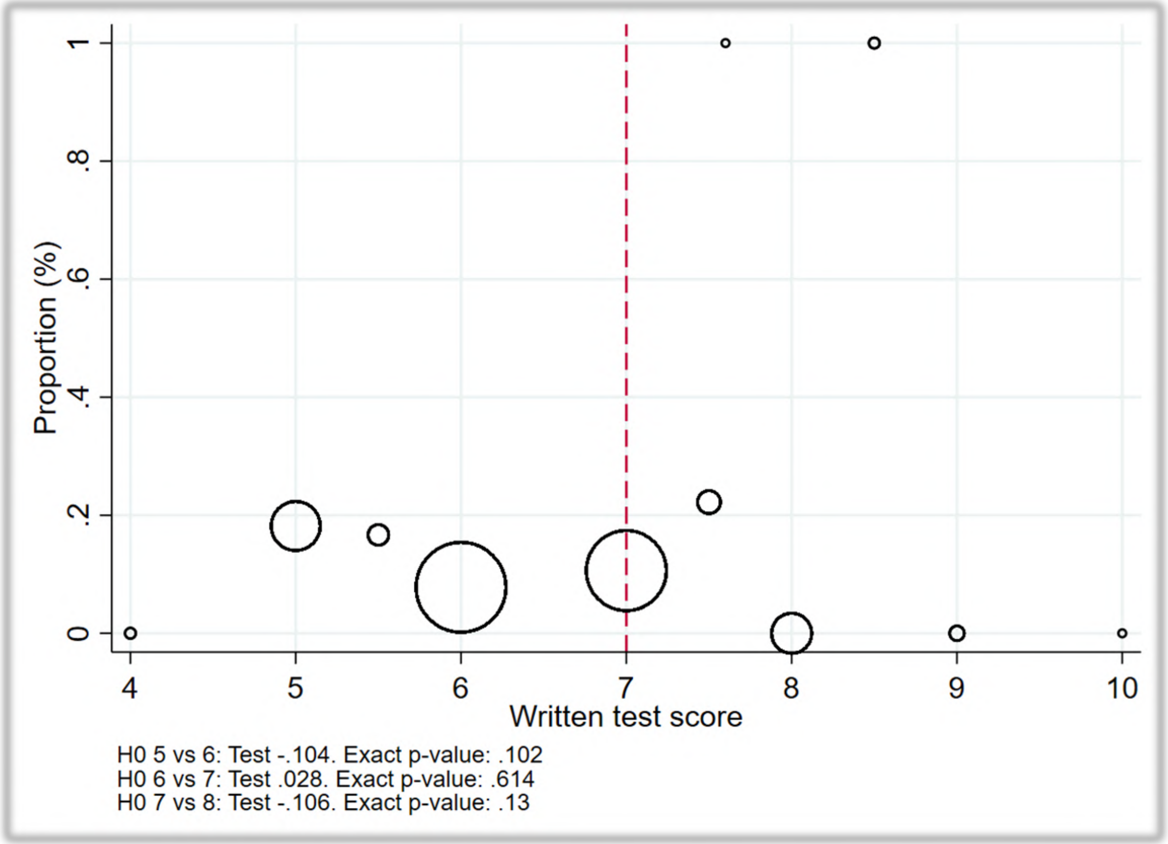


RDD plots - Graduate (7/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

Socio-economic background: Both parents college

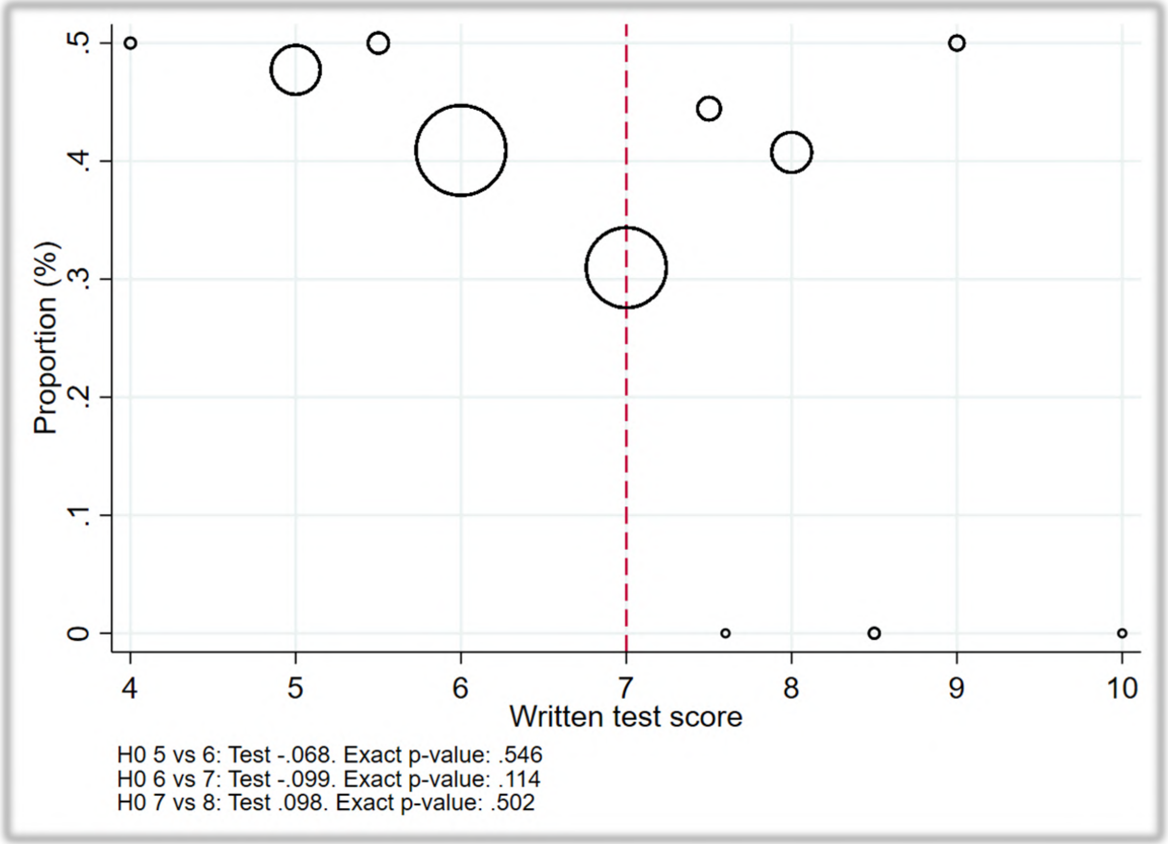


Socio-economic background: lower social class

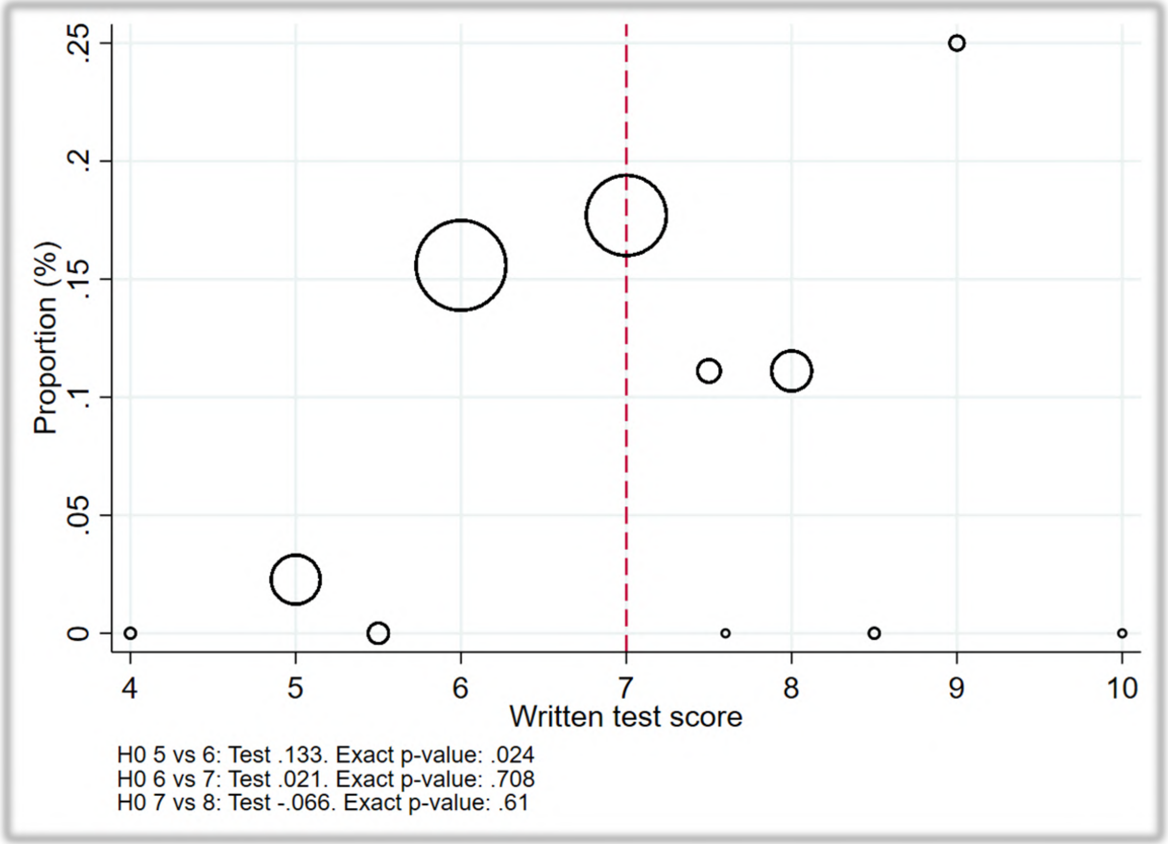


RDD plots - Graduate (8/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

Socio-economic background: Middle social class

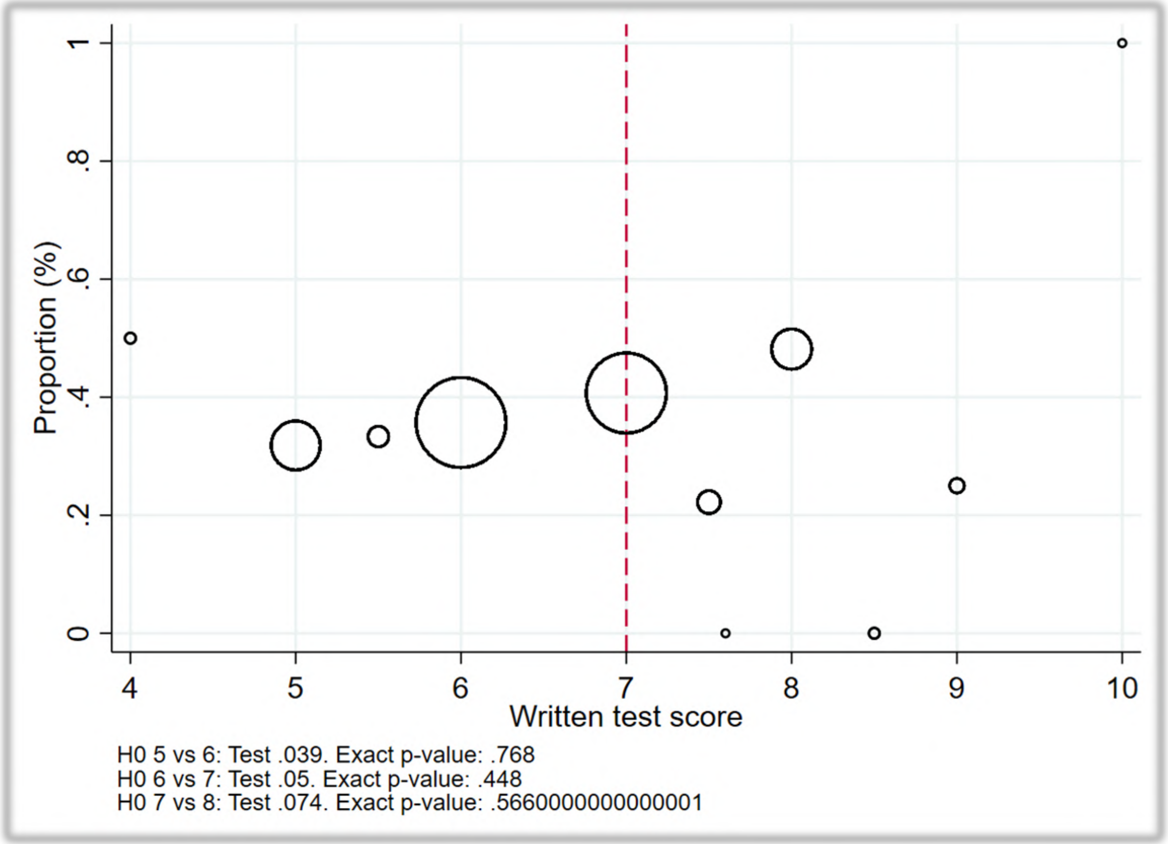


Socio-economic background: Upper middle social class

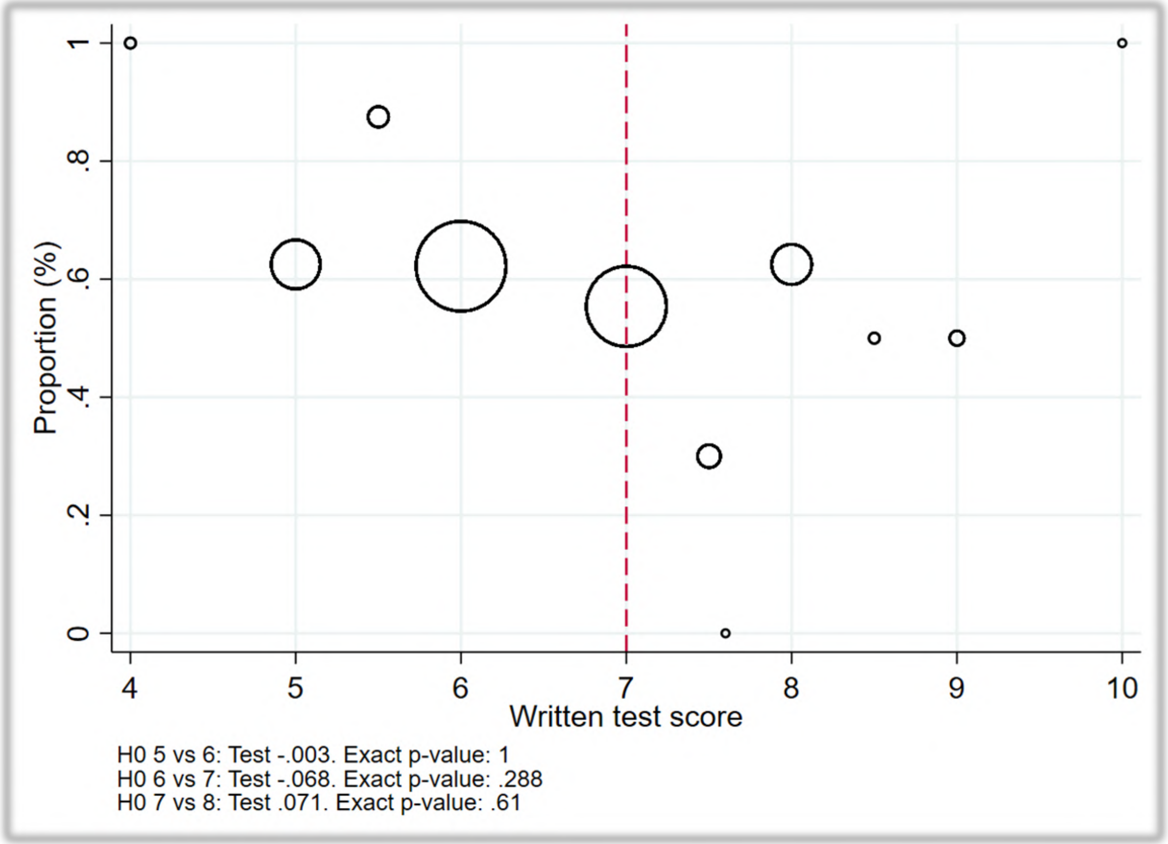


RDD plots - Graduate (9/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

Socio-economic background: Upper social class

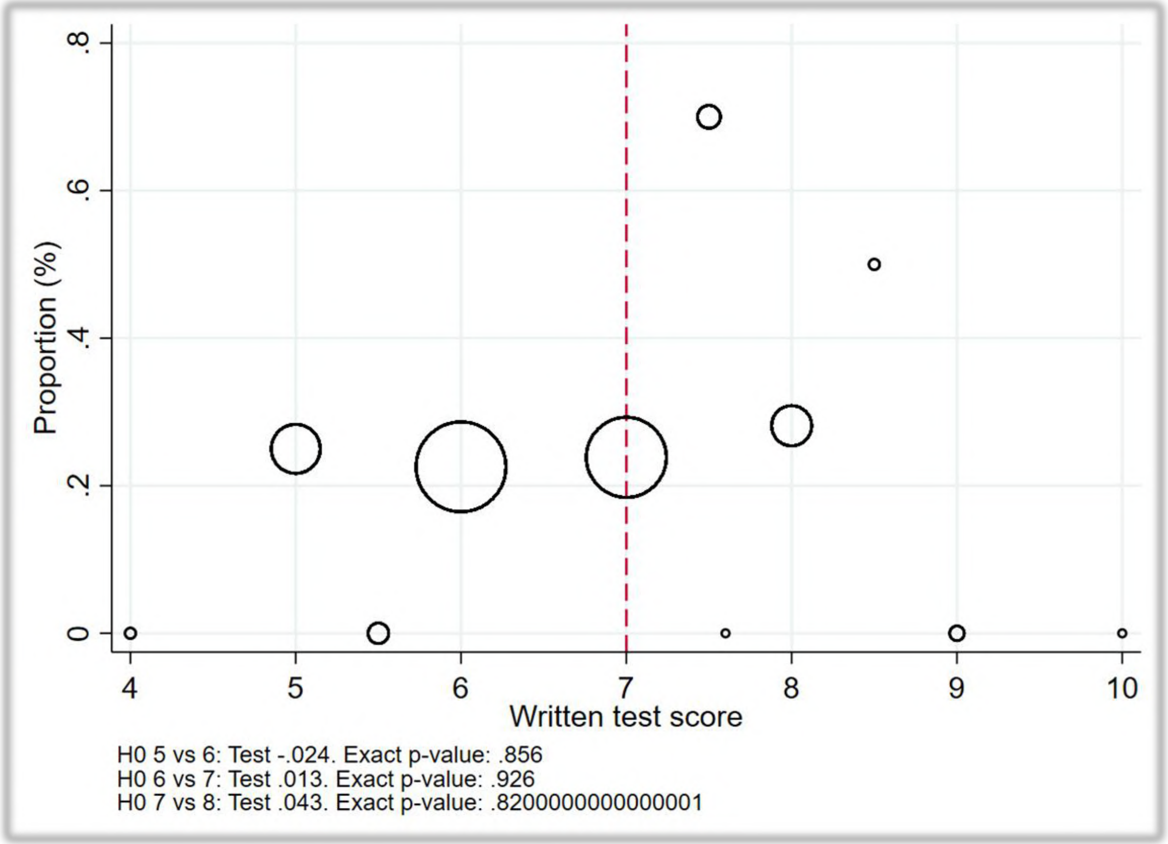


Socio-economic background: From Turin

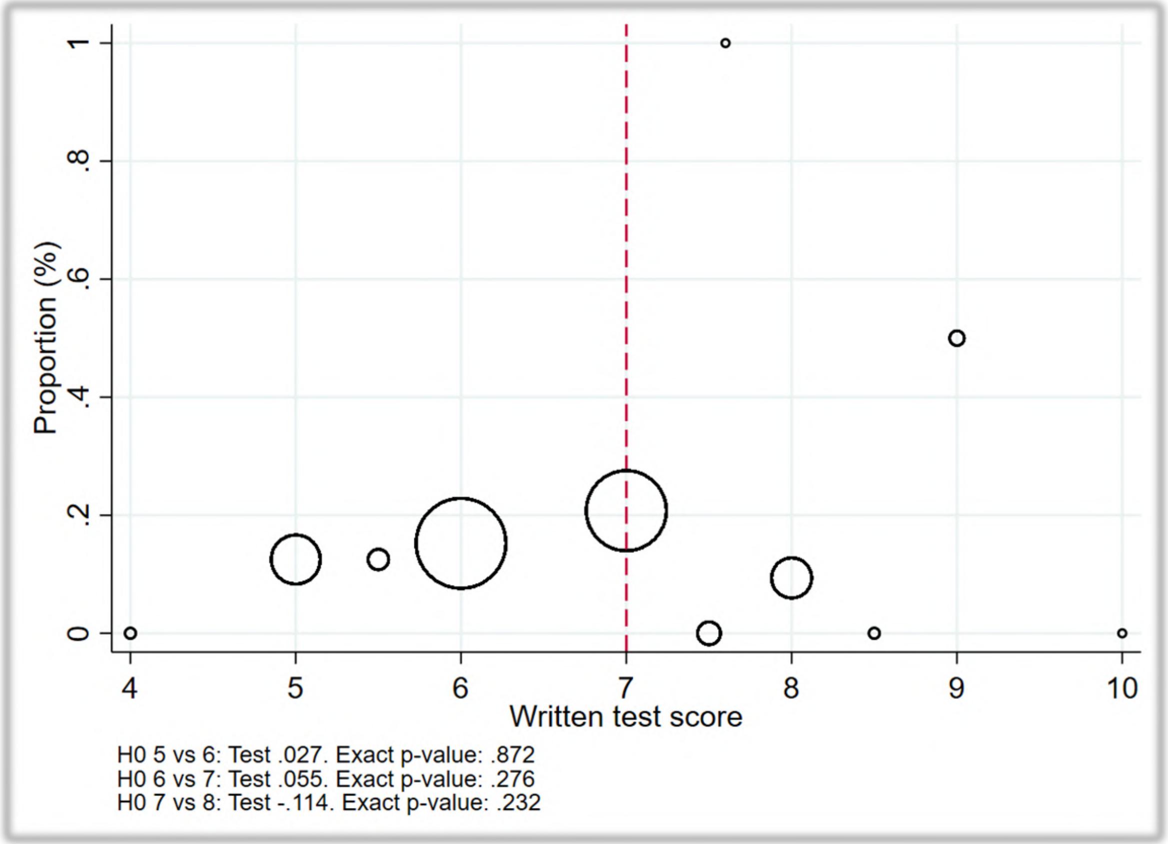


RDD plots - Graduate (10/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

Socio-economic background: From Piedmont (No Turin)

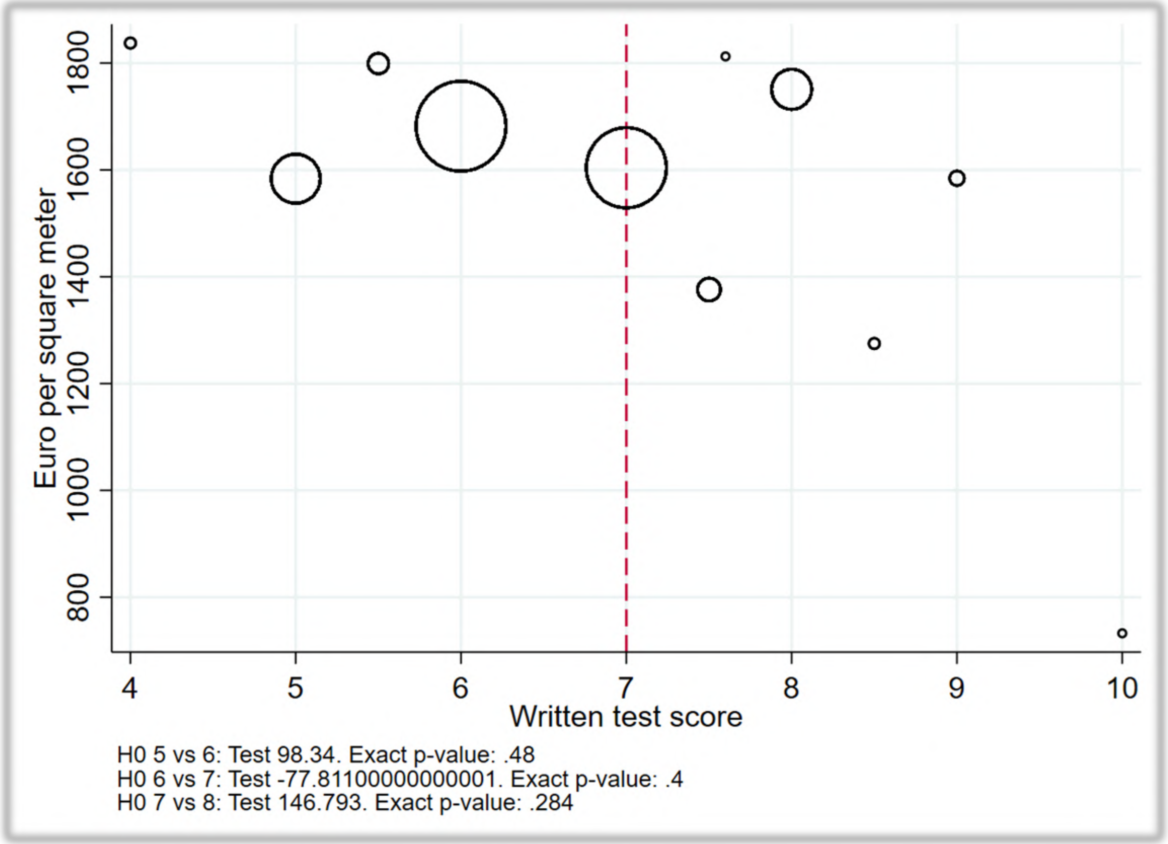


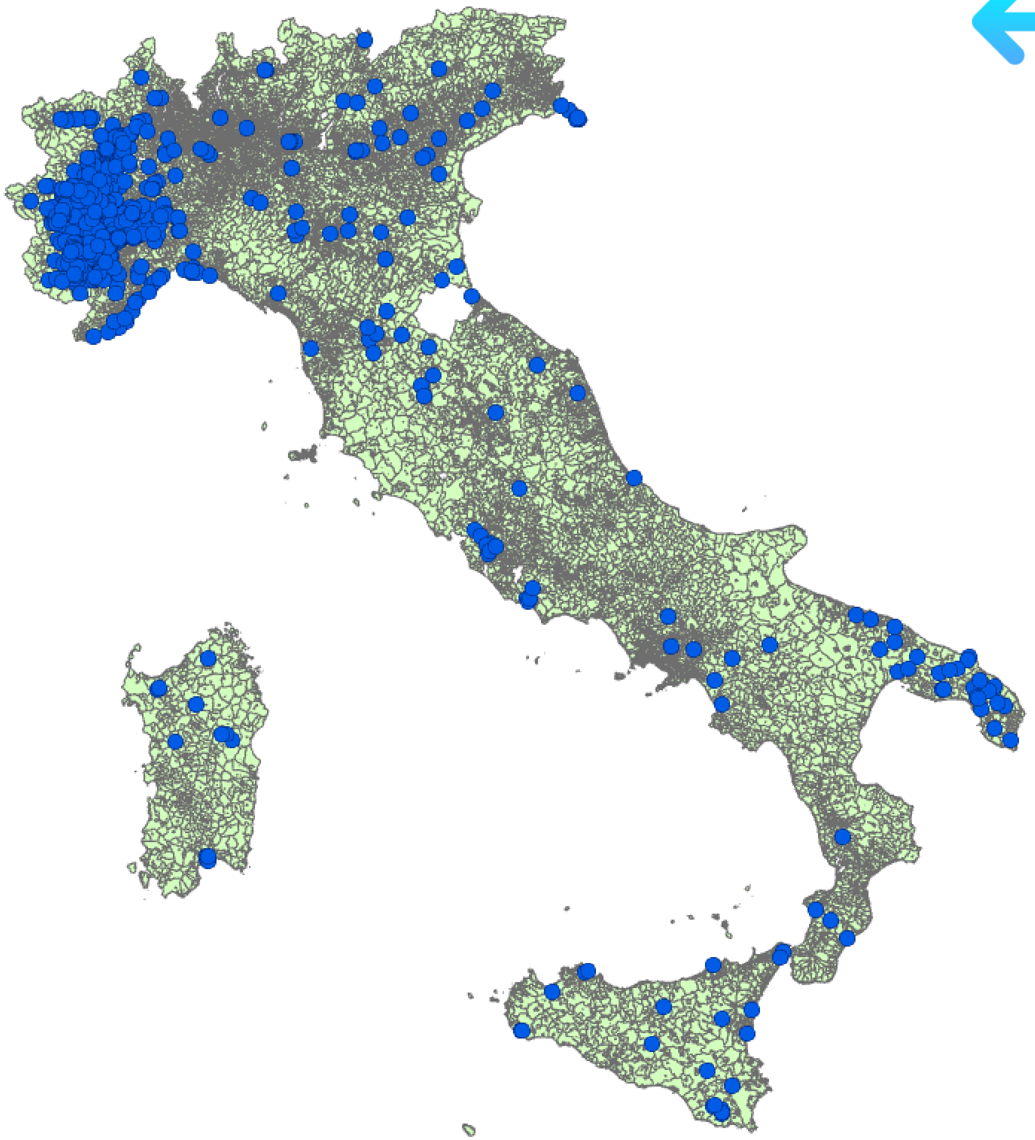
Socio-economic background: From rest of Italy



RDD plots - Graduate (11/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

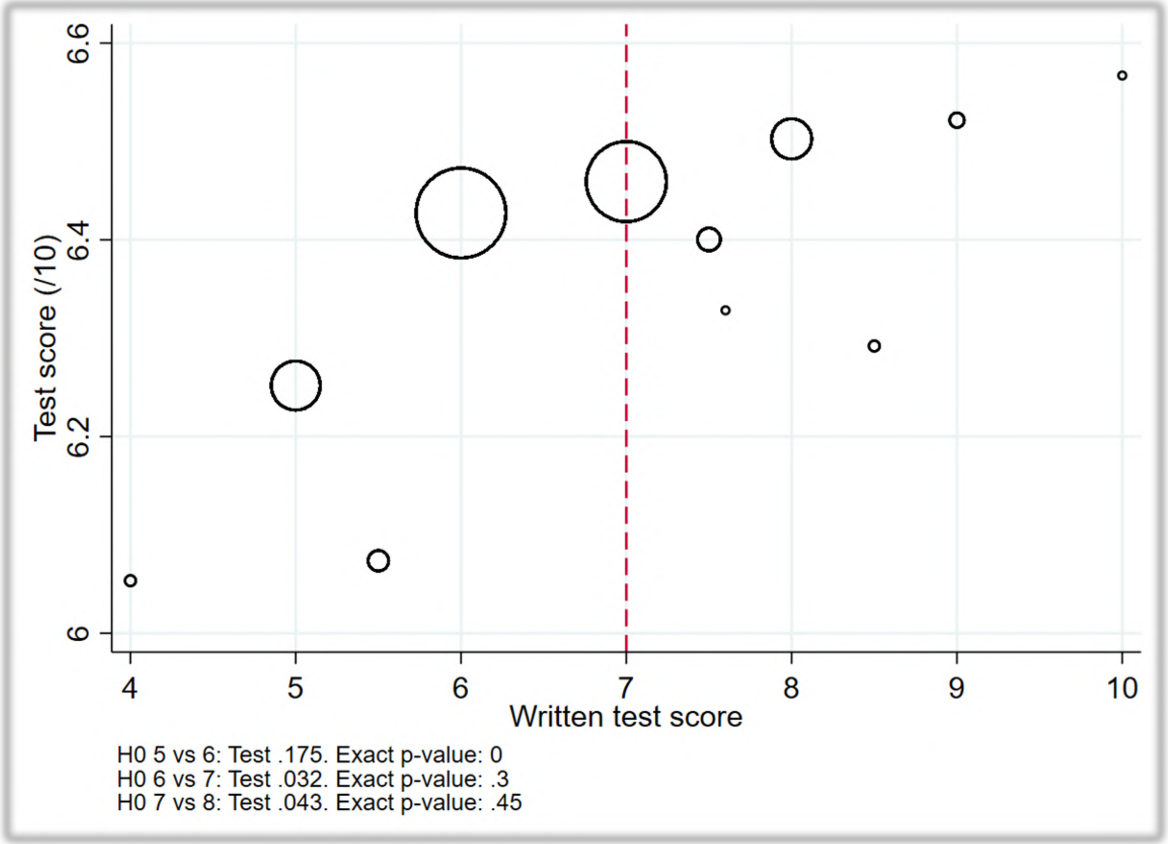
Socio-economic background: Property value in neighbourhood





RDD plots - Graduate (12/12): AlmaLaurea data (UniTO graduates) 2012 – 2017 SSST AY

Predicted test score

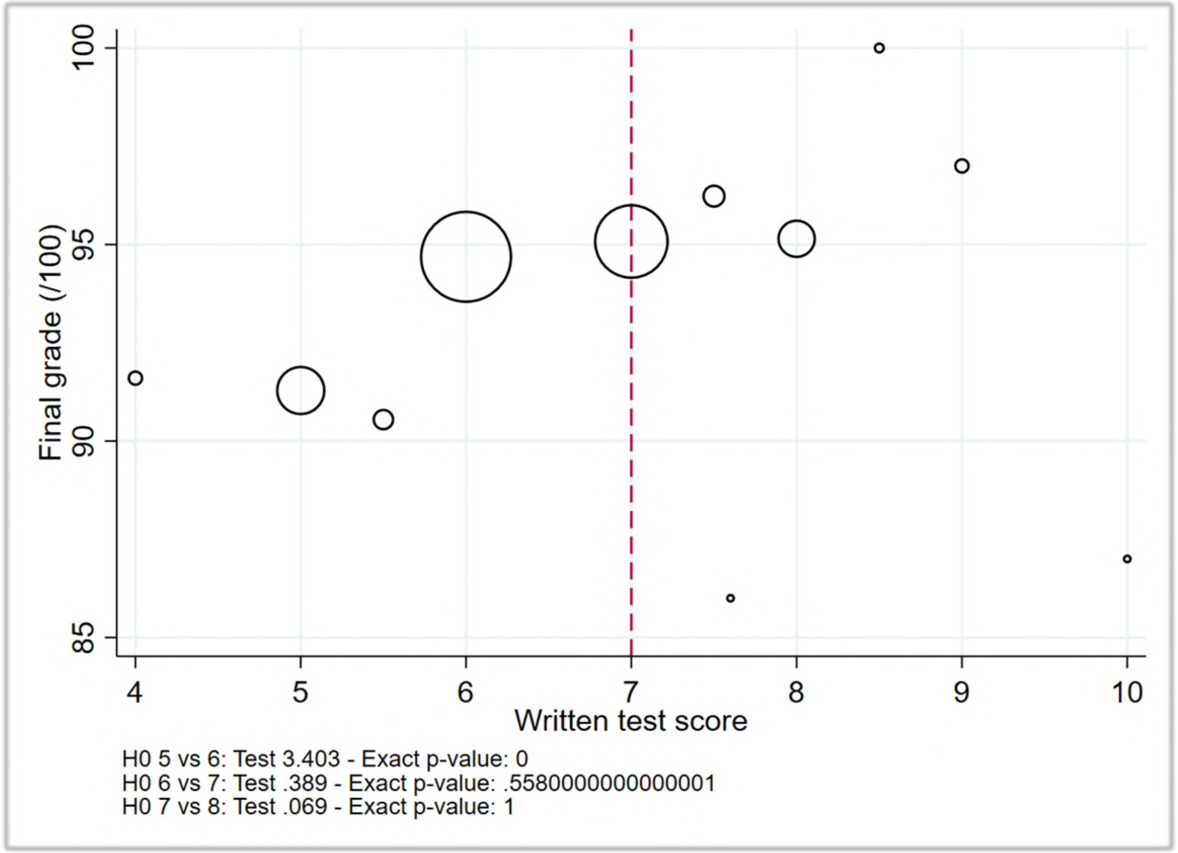


Predicted written test score by regression on:

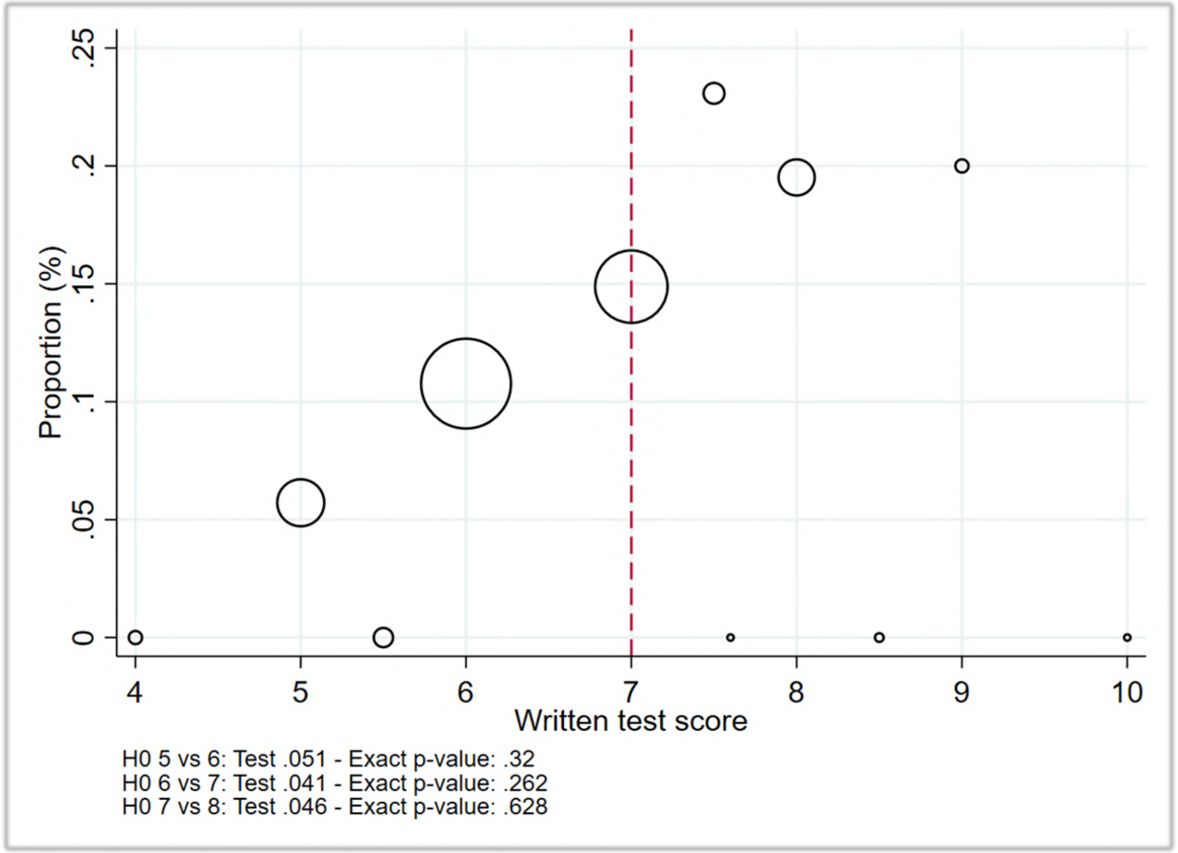
- Gender
- High school final grade
- Graduating with honors from high school
- Area of residence
- Liceo high school
- Father and mother university attainment
- Parental occupation (Socio economic class in AlmaLaurea)
- Motivational proxy: Time to apply

RDD plots - Admin (1/6): Admin data 2012 – 2017 Honors program AY

Ability proxy: High school final grade

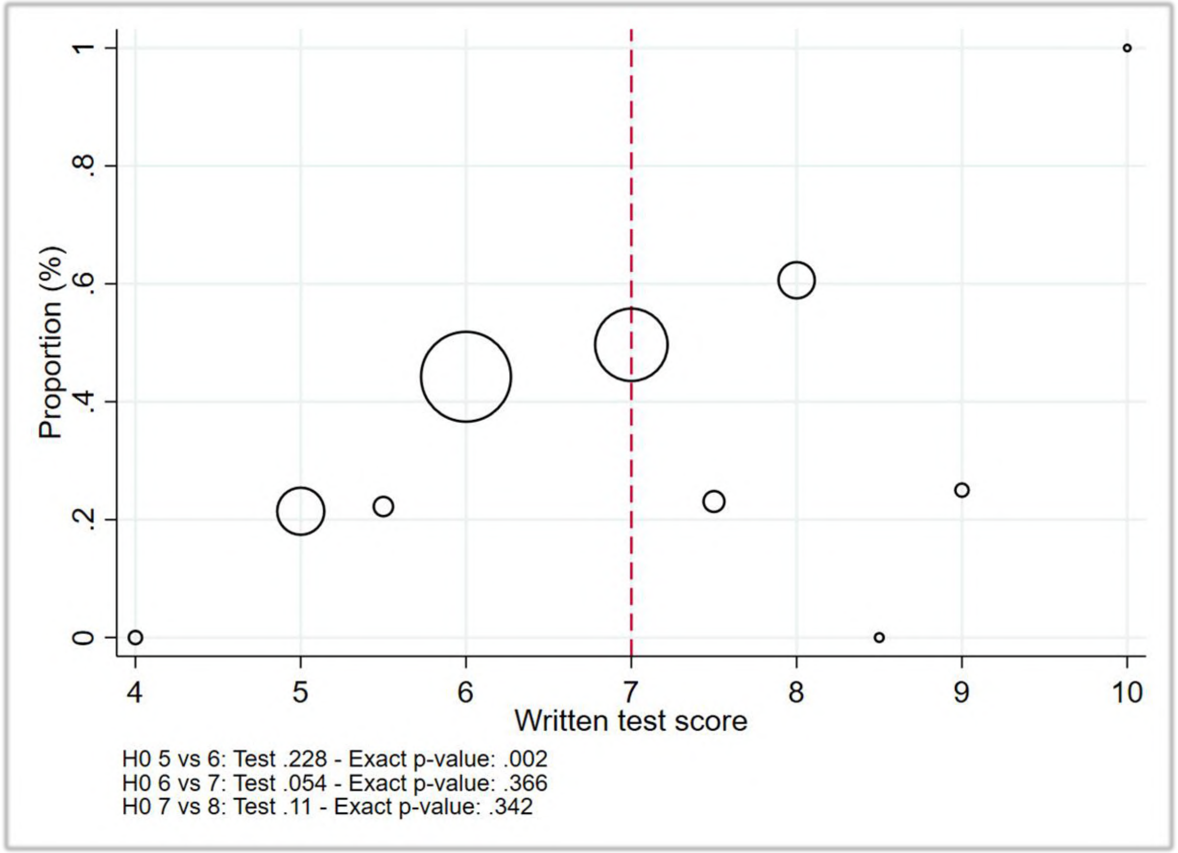


Ability proxy: Graduating with honors

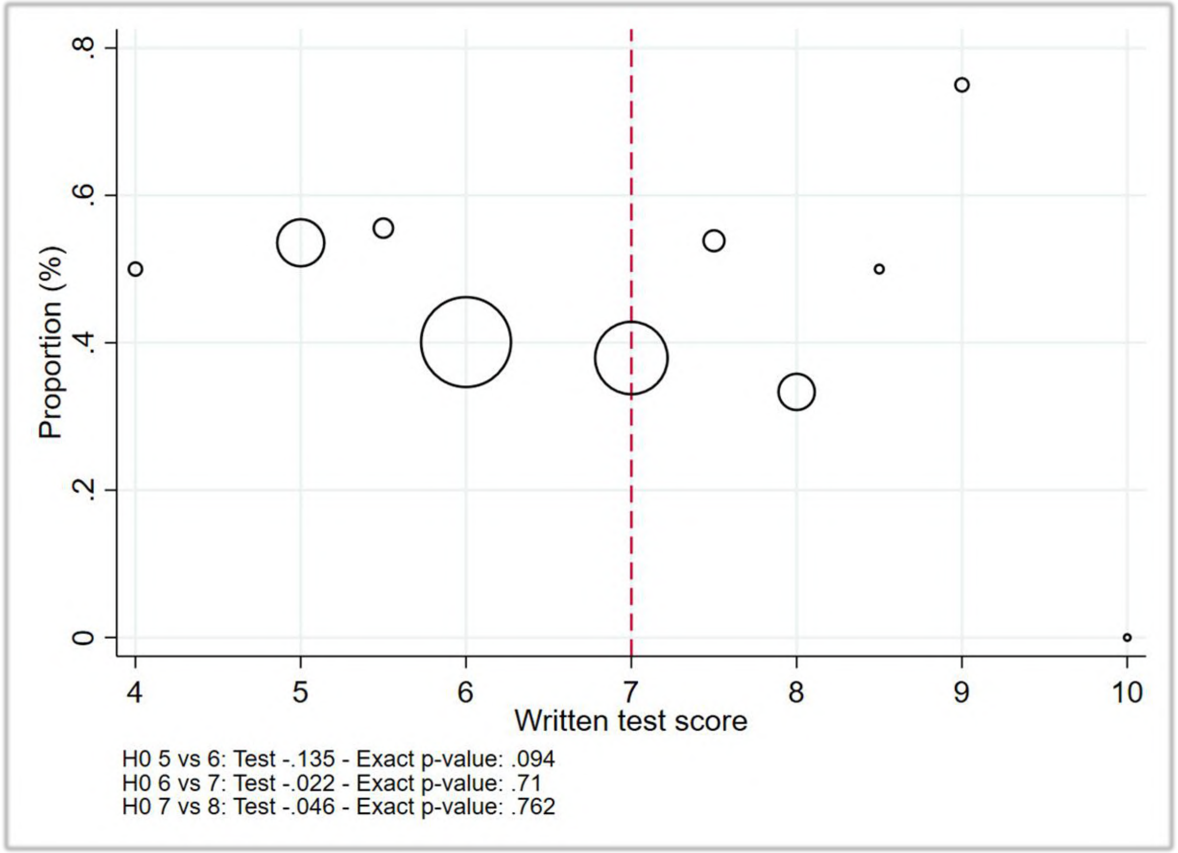


RDD plots - Admin (2/6): Admin data 2012 – 2017 Honors program AY

Ability proxy: classical high school

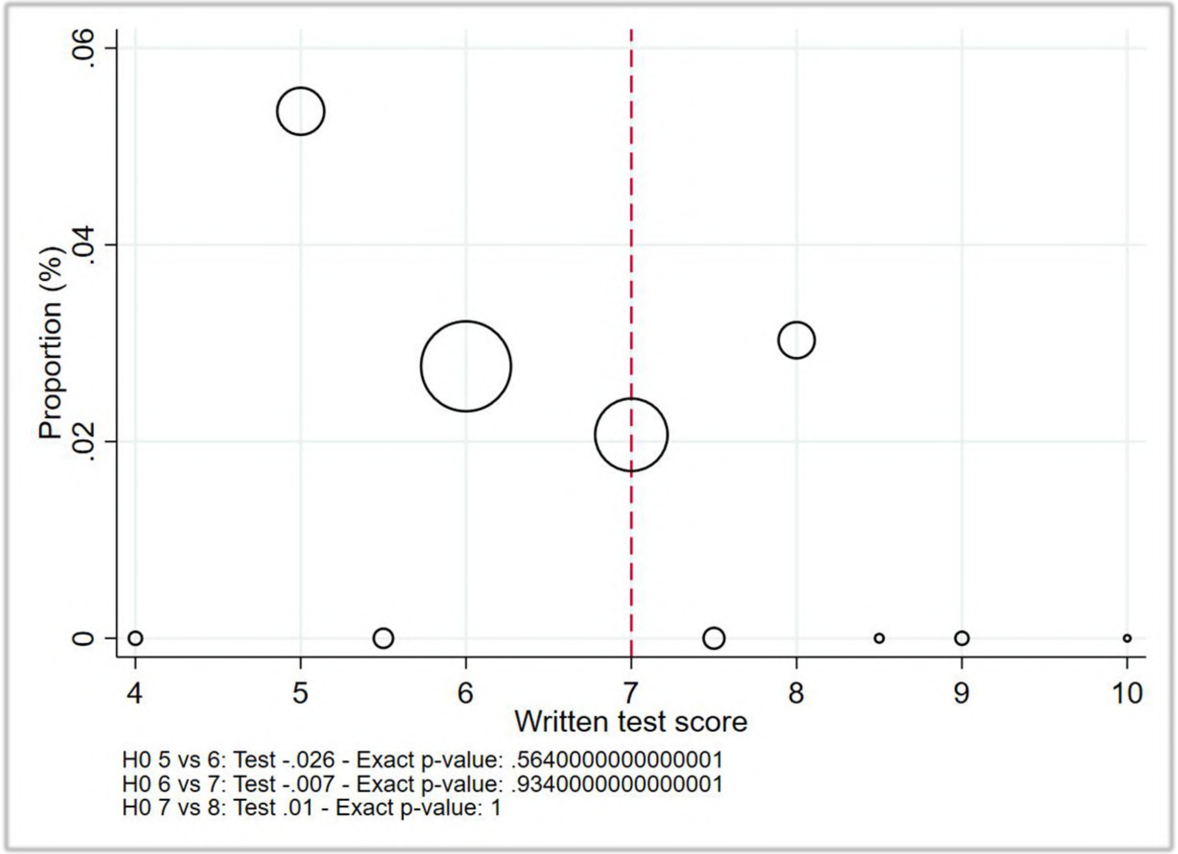


Ability proxy: scientific high school

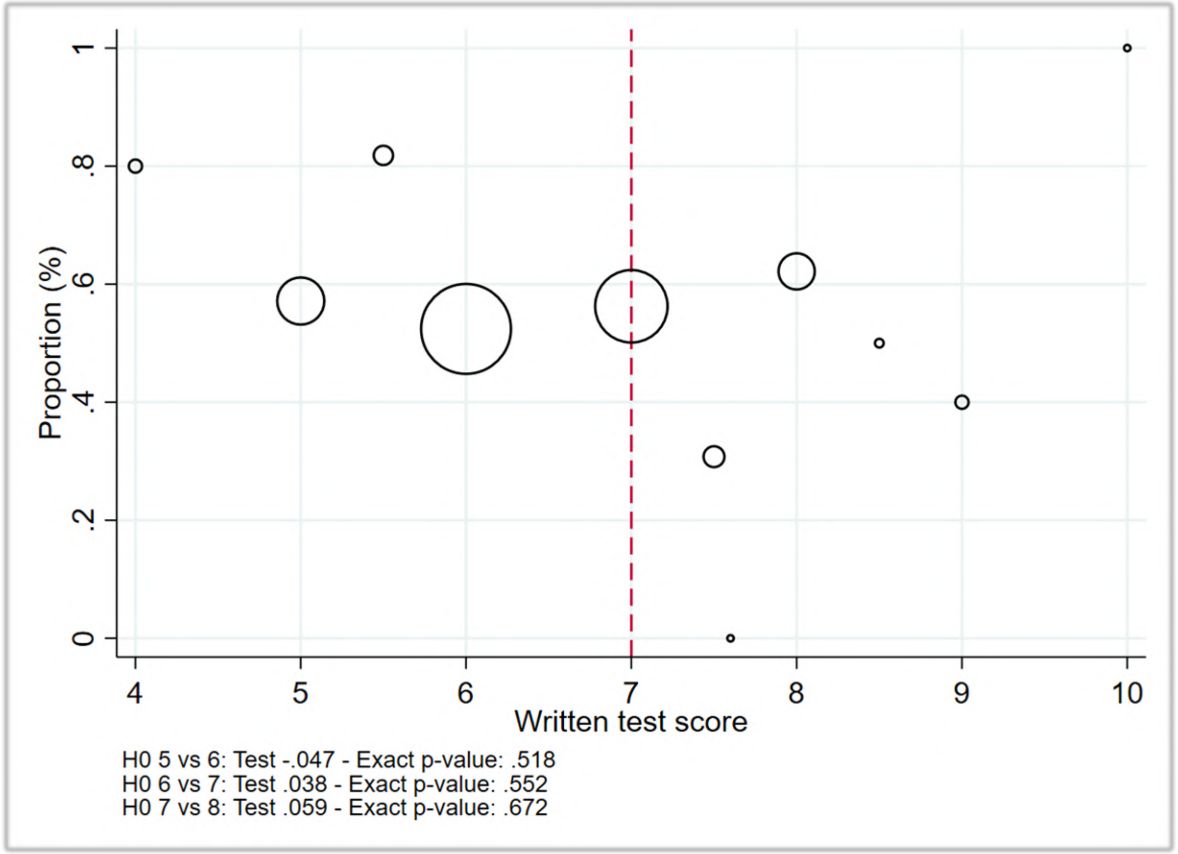


RDD plots - Admin (3/6): Admin data 2012 – 2017 Honors program AY

Ability proxy: Any other liceo

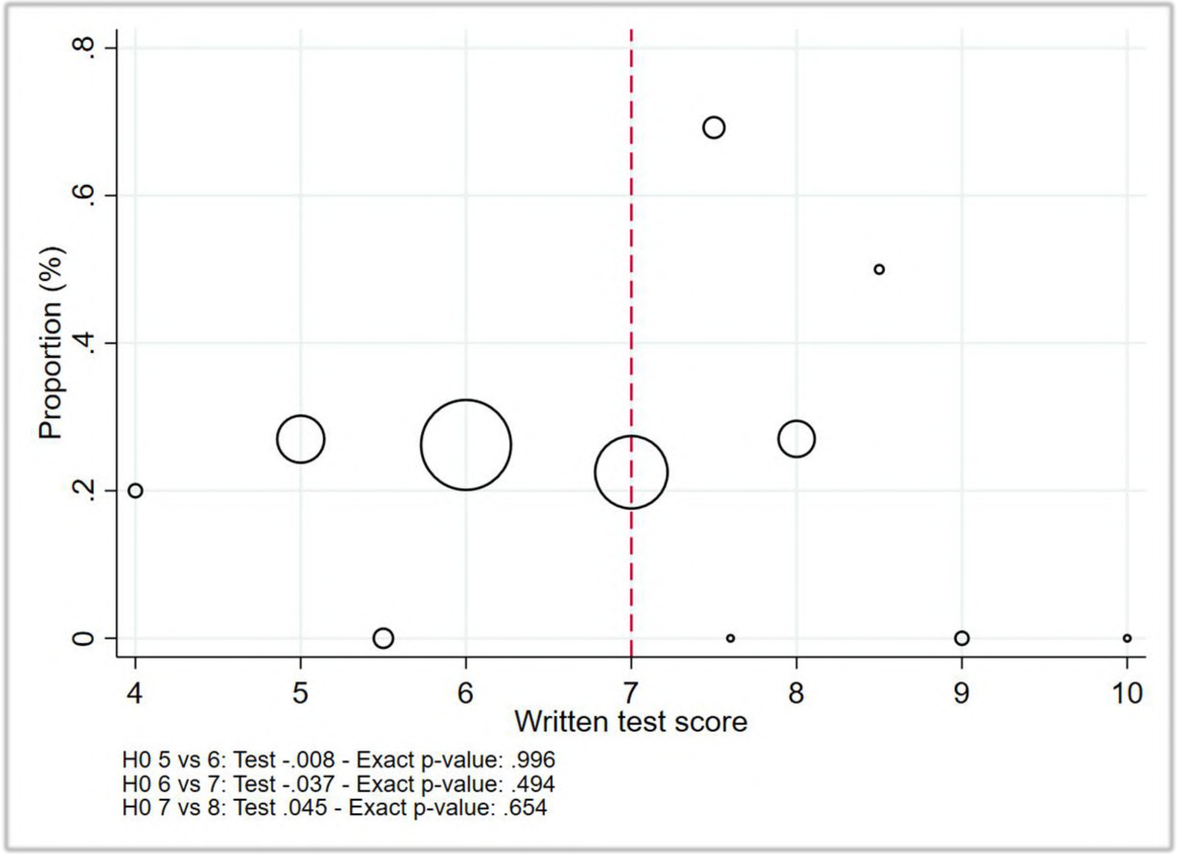


Socio-economic background: From Turin

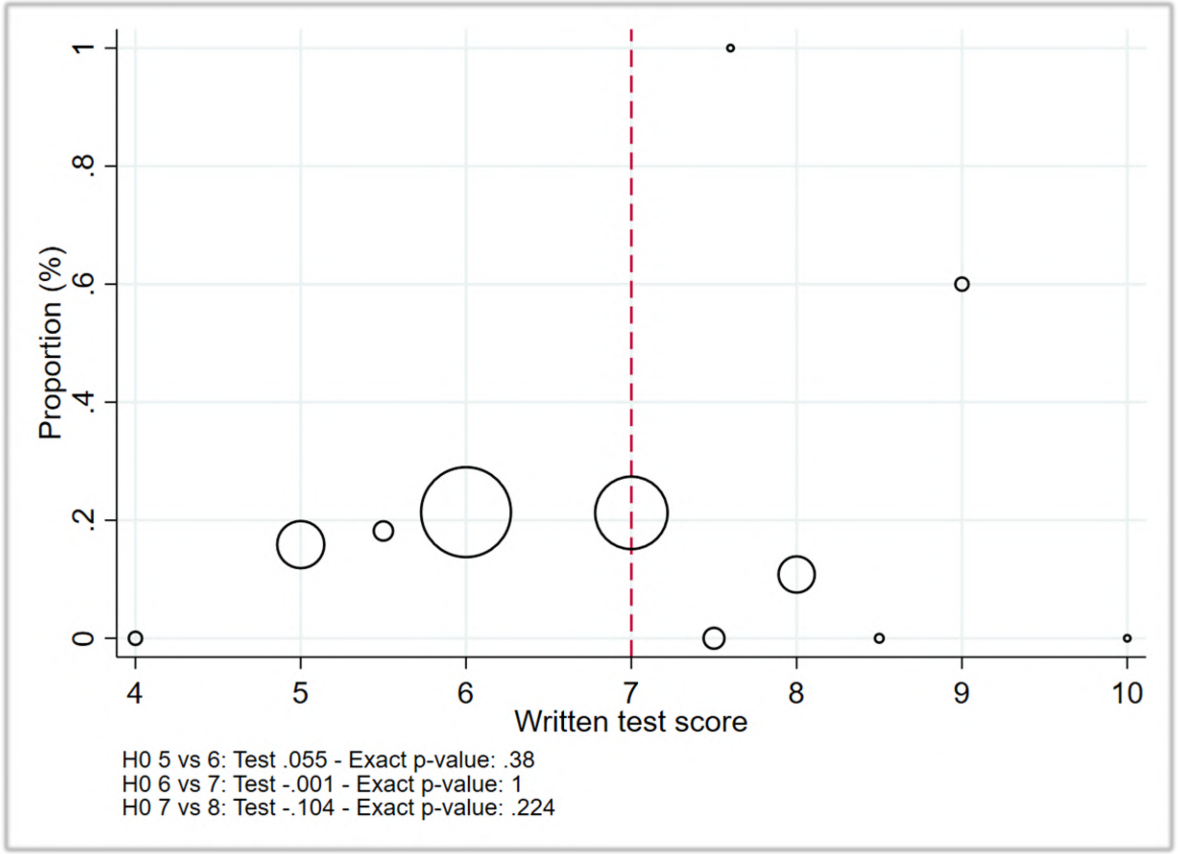


RDD plots - Admin (4/6): Admin data 2012 – 2017 Honors program AY

Socio-economic background: From Piedmont (No Turin)

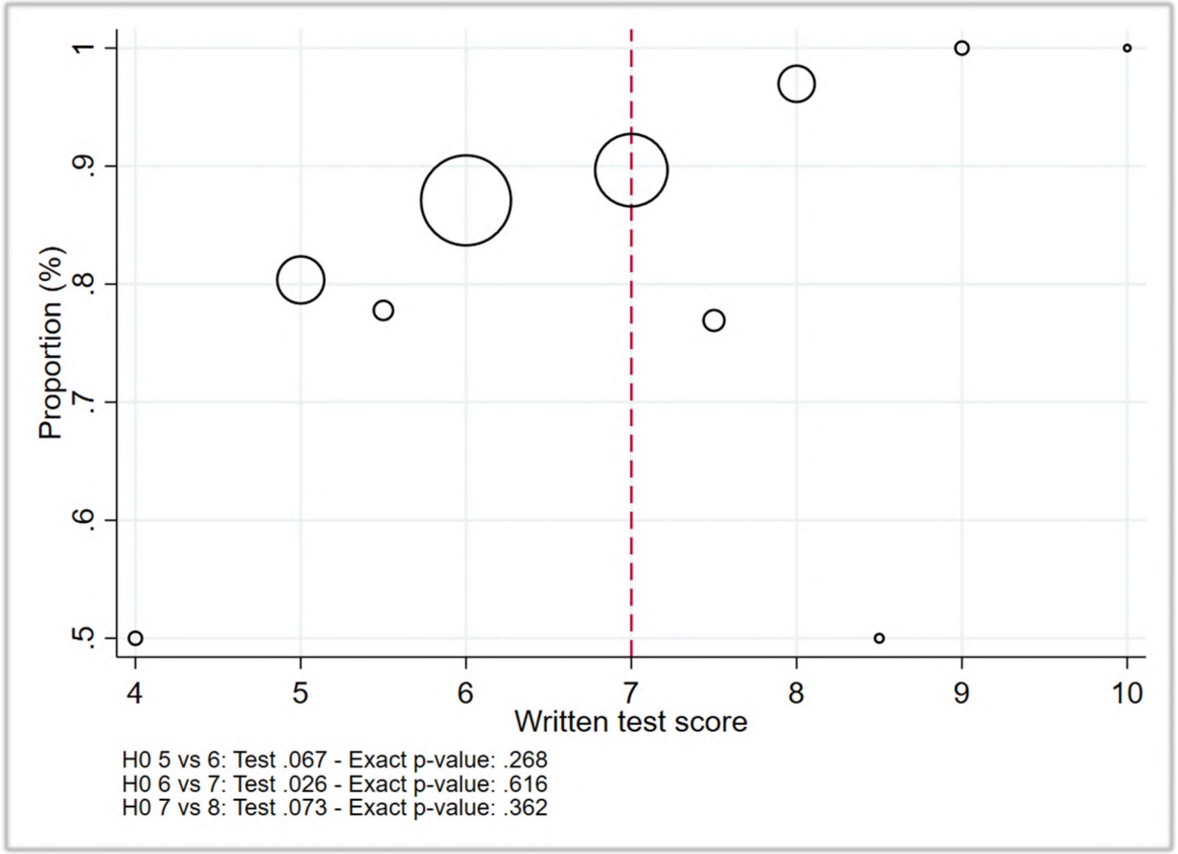


Socio-economic background: From rest of Italy

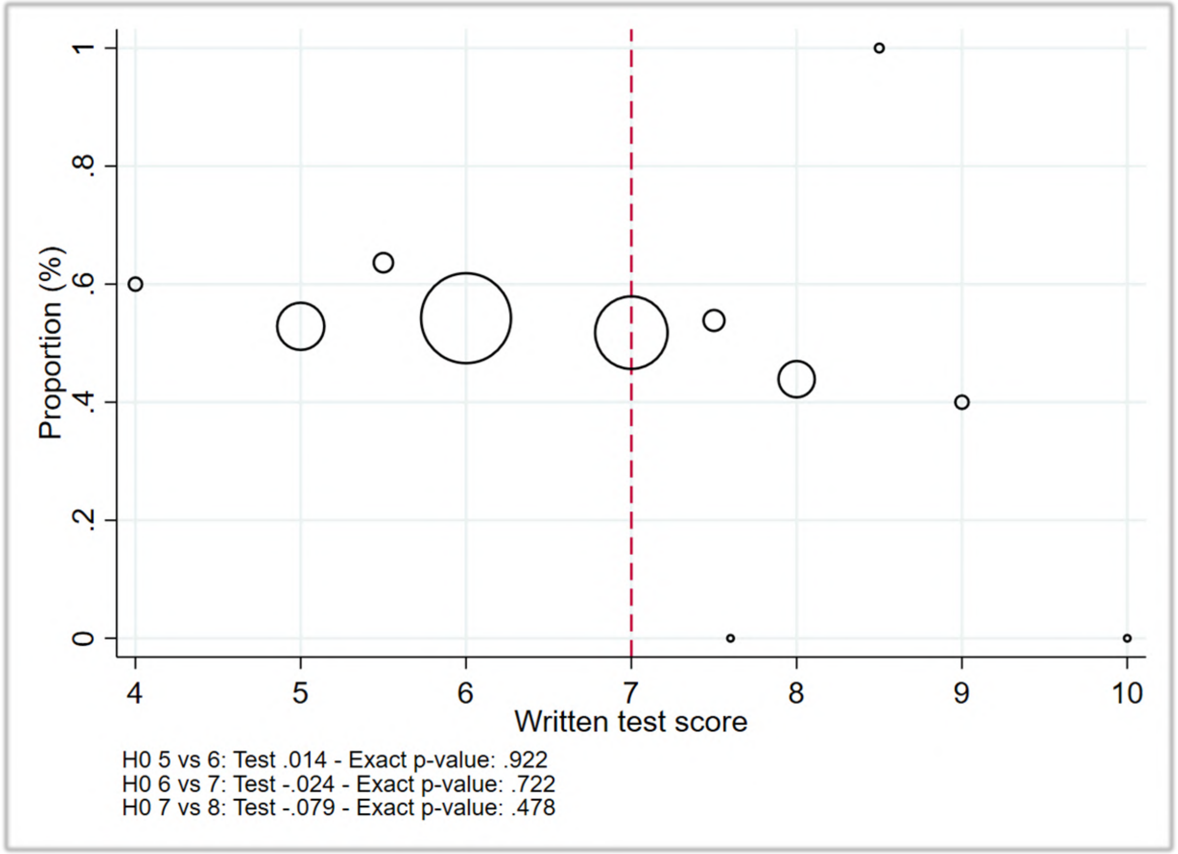


RDD plots - Admin (5/6): Admin data 2012 – 2017 Honors program AY

Ability proxy: Any liceo

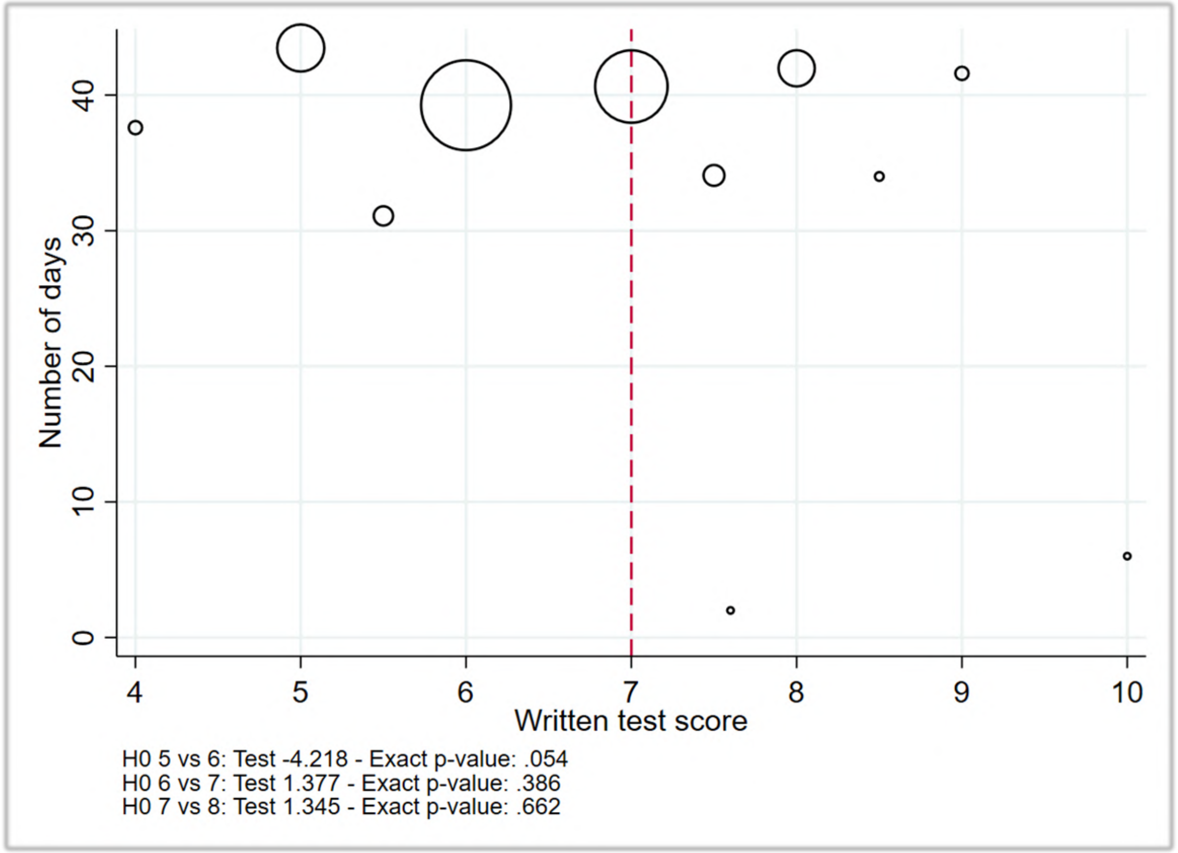


Female

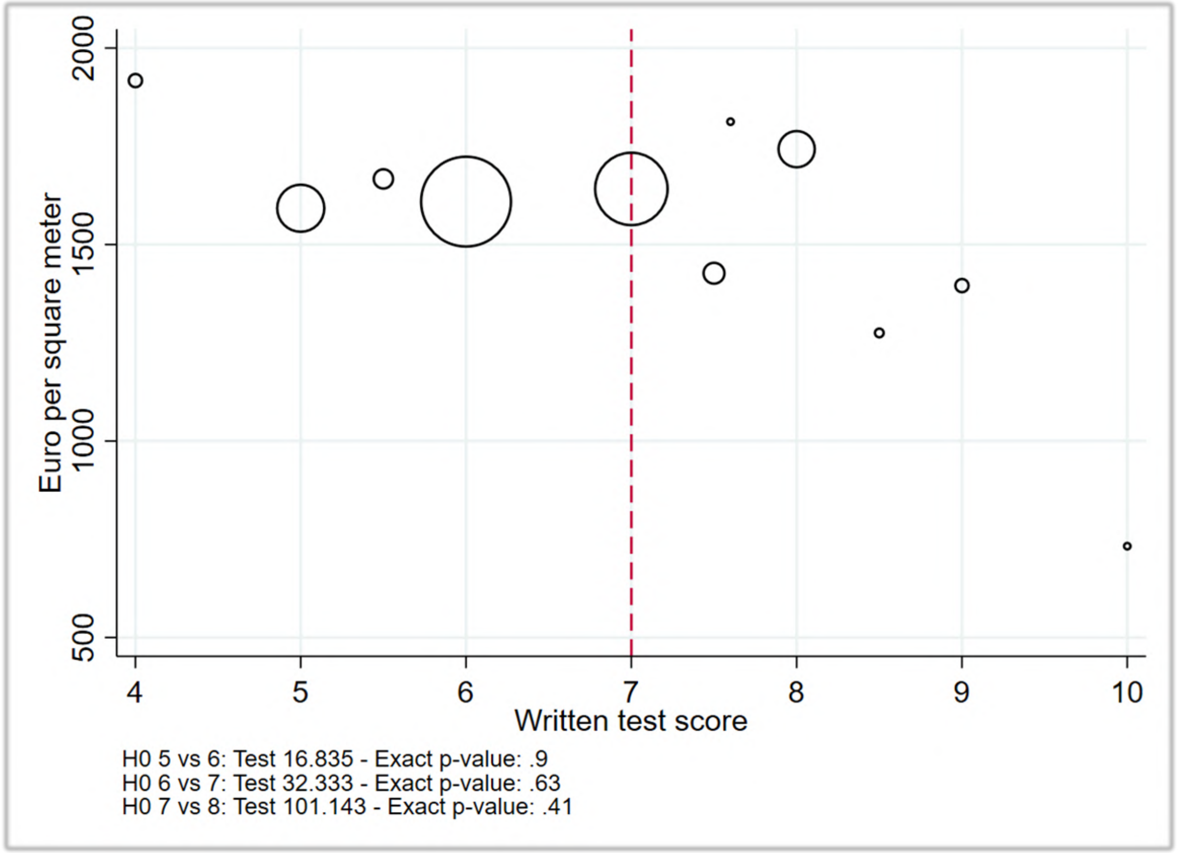


RDD plots - Admin (6/6): Admin data 2012 – 2017 Honors program AY

Motivation proxy: Time to apply



Socio-economic background: Property value in neighbourhood



R^2 (1/4): We derive testable implications in terms of the portion of variance in the dependent variable that our different proxies for ability should explain

In our setting:

- HS final grade → **Pre-determined** proxy for individual **ability**
- Written test score → Contemporaneous proxy for **individual ability** as measured by the **selection committee**
- GPA at Uni → **Post-determined** proxy for individual **ability**

Based on the above we formulate the following testable implications:

1) Reg post-determined proxy for ability (GPA at Uni) on **admission test score:**
   → Admission **test score** should **explain little in-window** variability **compared to** explained variability **outside the window**

2) Reg post-determined proxy for ability (GPA at Uni) on **pre-determined** proxy for **ability** (HS final grade):
   →Fraction of **outcome variability explained by HS final** score should be **similar** across the admission test score distribution **both inside and outside the window**.

R^2 (2/4): We derive testable implications in terms of the portion of variance in the dependent variable that our different proxies for ability should explain

Based on the above we formulate the following **testable implications**:

1) Reg post-determined proxy for ability (GPA at Uni) on **admission test score**:
→ Admission **test score** should **explain little in-window** variability **compared to** explained variability **outside the window**

2) **Reg post-determined** proxy for **ability** (GPA at Uni) on **pre-determined** proxy for **ability** (HS final grade):
→ Fraction of **outcome variability explained by HS final** score should be **similar** across the admission test score distribution **both inside and outside the window**.

Outcome	List of controls	Support	Adjusted R2
GPA	HS final score, constant	Full	7.70
GPA	Admission test score, constant	Full	11.55
GPA	HS final score, constant	Only in window	5.69
GPA	Admission test score, constant	Only in window	4.47
GPA	HS final score, constant	Only outside the window	9.87
GPA	Admission test score, constant	Only outside the window	24.14

R^2 (3/4): We derive testable implications in terms of the portion of variance in the dependent variable that our different proxies for ability should explain

Based on the above we formulate the following **testable implications**:

1) **Reg post-determined** proxy for **ability** (GPA at Uni) on **admission test score:**
   → Admission **test score** should **explain little in-window** variability **compared to** explained variability **outside the window**

2) Reg post-determined proxy for ability (GPA at Uni) on **pre-determined** proxy for **ability** (HS final grade):
   → Fraction of **outcome variability explained by HS final** score should be **similar** across the admission test score distribution **both inside and outside the window**.

Outcome	**List of controls**	**Support**	**Adjusted R2**
GPA	HS final score, constant	Full	7.70
GPA	Admission test score, constant	Full	11.55
GPA	HS final score, constant	Only in window	5.69
GPA	Admission test score, constant	Only in window	4.47
GPA	HS final score, constant	Only outside the window	9.87
GPA	Admission test score, constant	Only outside the window	24.14

R^2 (4/4): We derive testable implications in terms of the portion of variance in the dependent variable that our different proxies for ability should explain

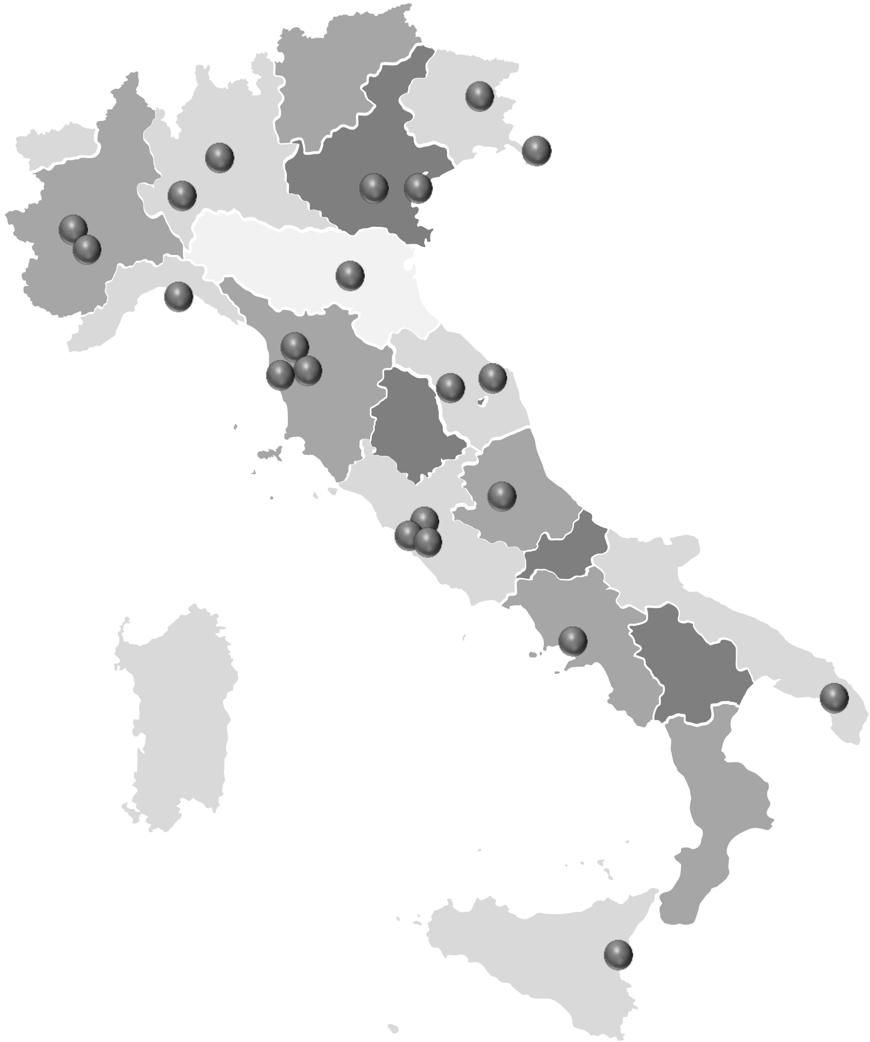
Based on the above we formulate the following **testable implications**:

1) **Reg post-determined** proxy for **ability** (GPA at Uni) on **admission test score:**
   → Admission **test score** should **explain little in-window** variability **compared to** explained variability **outside the window**

2) **Reg post-determined** proxy for **ability** (GPA at Uni) on **pre-determined** proxy for **ability** (HS final grade):
   → Fraction of **outcome variability explained by HS final** score should be **similar** across the admission test score distribution **both inside and outside the window**.

Outcome	List of controls	Support	Adjusted R2
GPA	HS final score, constant	Full	7.70
GPA	Admission test score, constant	Full	11.55
GPA	HS final score, constant	Only in window	5.69
GPA	Admission test score, constant	Only in window	4.47
GPA	HS final score, constant	Only outside the window	9.87
GPA	Admission test score, constant	Only outside the window	24.14

Institutional Setting: There are 22 *Scuole Superiori Universitarie* scattered across Italy offering additional academic training to highly selected students

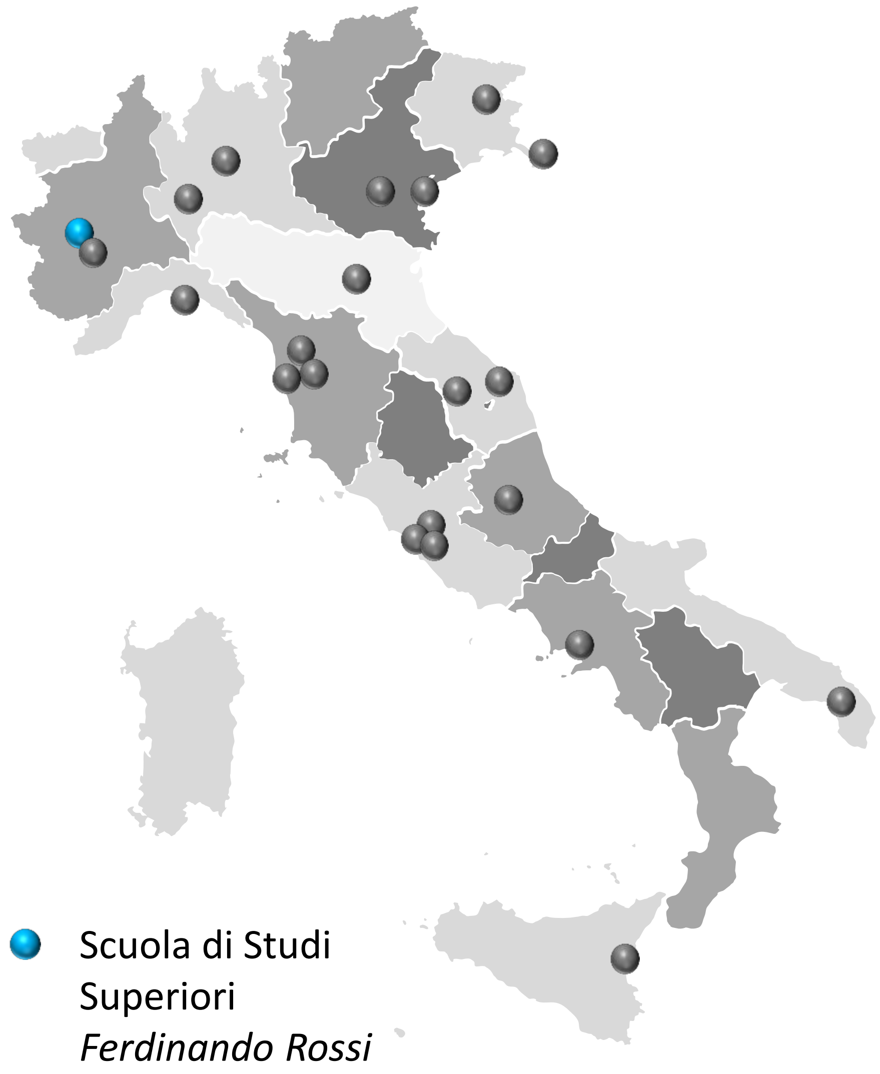


Scuole Superiori Universitarie

- *Scuole Superiori Universitarie* are 22 free, merit-based **honors university** programs targeting high-achieving students.
- Students complete additional **academic activities on top** of their regular degree program.
- Selected individuals benefit from a closer relationship with faculty and from a community of highly-motivated peers, living in dedicated accommodation. They usually enjoy a tuition fee waiver and receive an additional scholarship but are expected to maintain a high GPA and keep on track with their exams

- A **selective entry examination** recruits high-performing students as they first enrol into a university program. Admission requirements and exam are institution specific. These schools generally require:
    - High achievement in high school final exam or bachelor
    - Age and timing requirement
    - Score above a cut off for written test and interview

Focus *Scuola di Studi Superiori* Ferdinando Rossi – Torino: Set up in 2009 with strict admission requirements demanding students to meet high academic standards



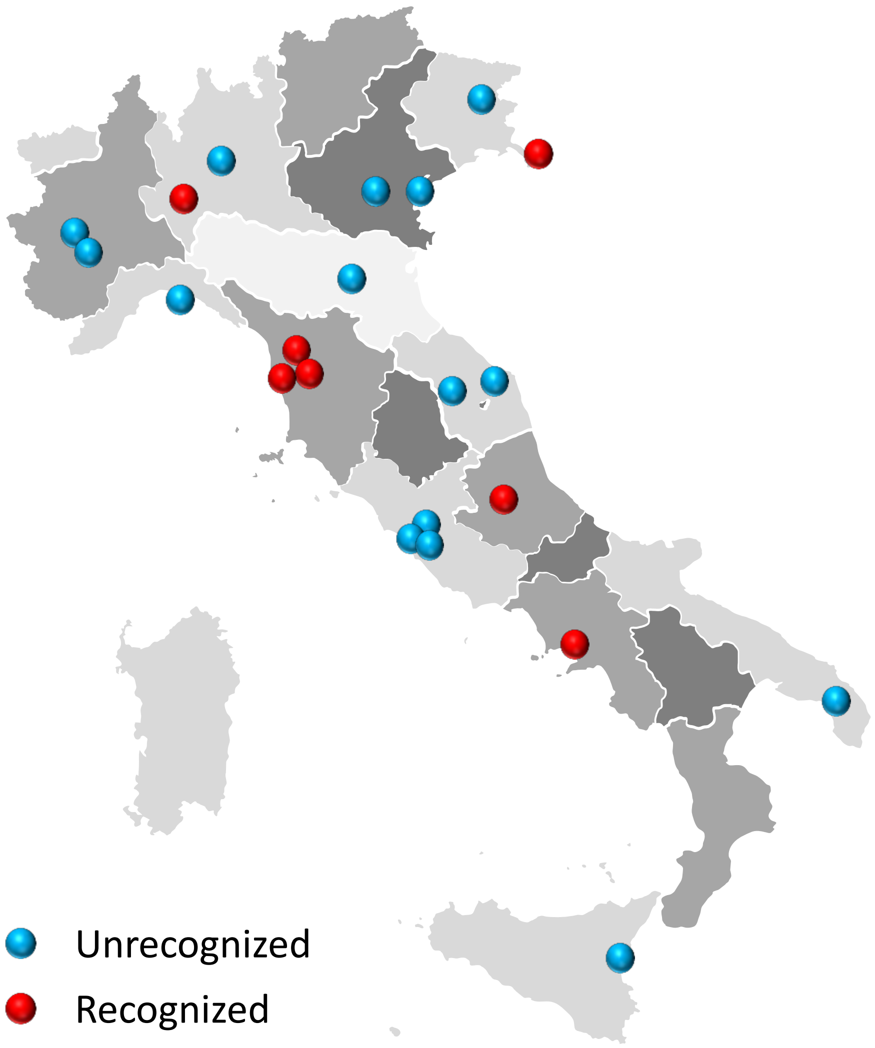
The School in key figures

- Set up in **2009**
- Up to **30** admitted first year **students** per academic year
- **Academic commitments**:
  - take 3 additional courses per year (15 ECTS) designed by the School
  - maintain a GPA ≥ 27/30
  - pass all university exams on time
- Strong focus on **multidisciplinarity**
- Live in **dedicated accommodation** near campus

Admission requirements

- **High** high-school **final grade** >80/100
- <21 years old
- First university enrolment
- **Motivation** and reference **letters**
- B1 level English proficiency
- Pass the **examination test**

Institutional Setting: There are two types of schools with different missions and academic profiles, both offering only limited places every year



Types of school

- **7 oldest institutions** (in red) are **recognized** by the Ministry of Education and granted autonomous university status. These are **research centres** offering programs focusing on *post lauream* training at PhD level. While also offering non-PhD courses, **training** is usually aimed at fostering **research skills to ease the transition to PhD**
- **15 more recent institutions** (in blue) are direct **offshoot of parent universities** offering complementary training at undergraduate and master level. All schools offer comparable **interdisciplinary training** supplementing university standard degree courses
- **Our analysis** would **focus on the impact** of attending programmes offered by the more recent **unrecognized institutions**

Honors courses example: The 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

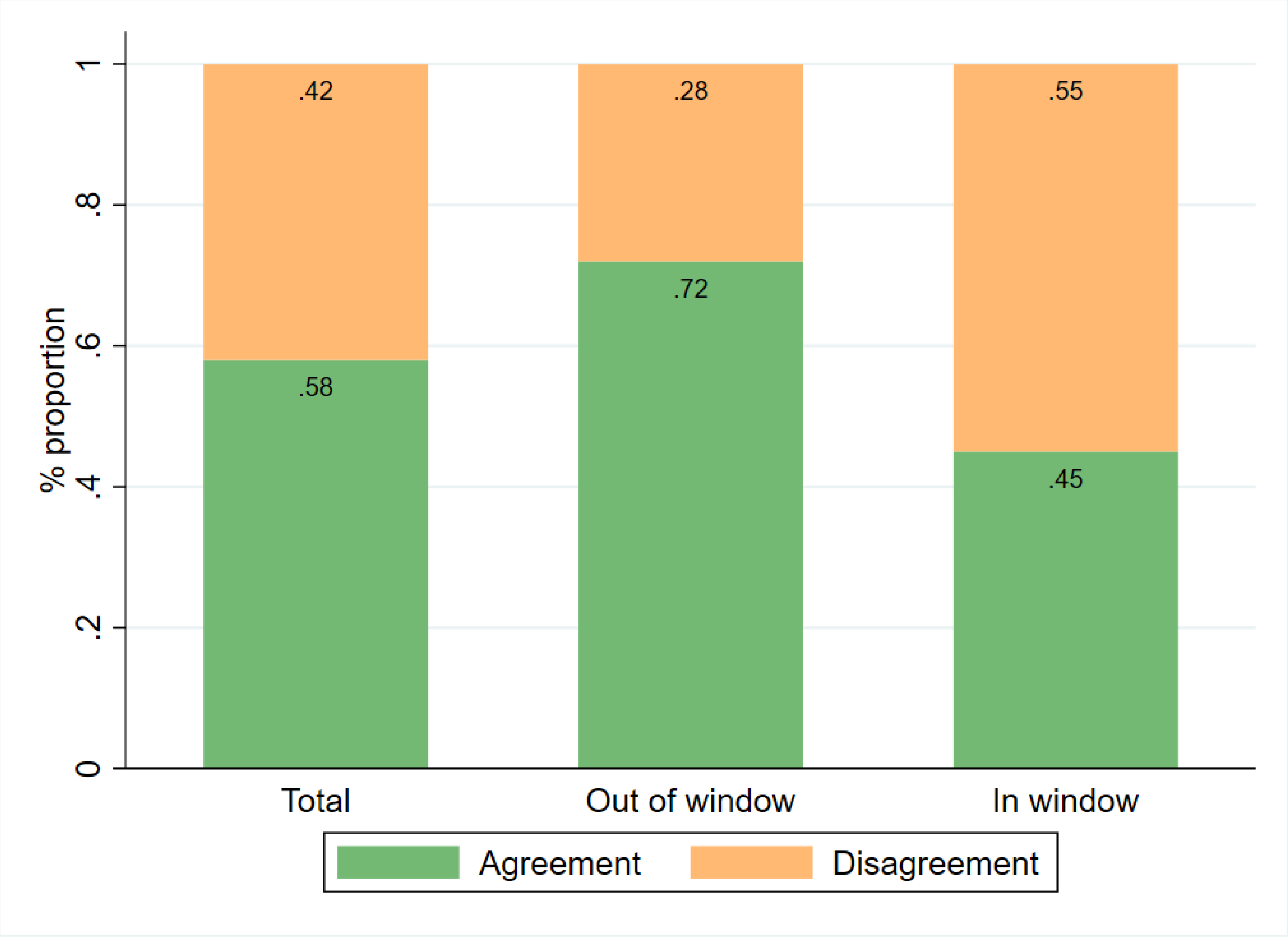
Course overview

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. (…)

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.

Regrading exercise

- Randomly selected 20 applicants, 10 in the window (graded 6 or 7) and 10 outside the window (graded less than 6 or more than 7)
- Submitted their entry exams to 6 Economics professors for **blind grading**
- Provided regraders with **istructions** on how to carry out the regrading, so as to **recreate the original process** as much as possible



Identification strategy

$$Graduated_{ikt} = \alpha_0 + \alpha_1 \mathrm{cutoff}_{ik} + \mathbf{X}'_{\mathbf{ikt}}\theta + \gamma_k + \eta_{ikt}$$

$$Y_{ikt} = \delta_0 + \delta_1 \widehat{\mathrm{graduated}}_{it} + \mathbf{X}'_{\mathbf{ikt}}\rho + \gamma_k + \xi_{ikt}$$

where

- Y_{ikt} is the outcome for individual *i* applying to the program in year *k* and graduating in calendar year *t*
- $Cutoff_{ik}$ is an indicator variable for students passing the written test
- X_{ikt} is a vector of individual, observed in application year k, and academic controls, observed in graduating year t
- γ_k is a set of admission year FE

Descriptive statistics – Administrative data

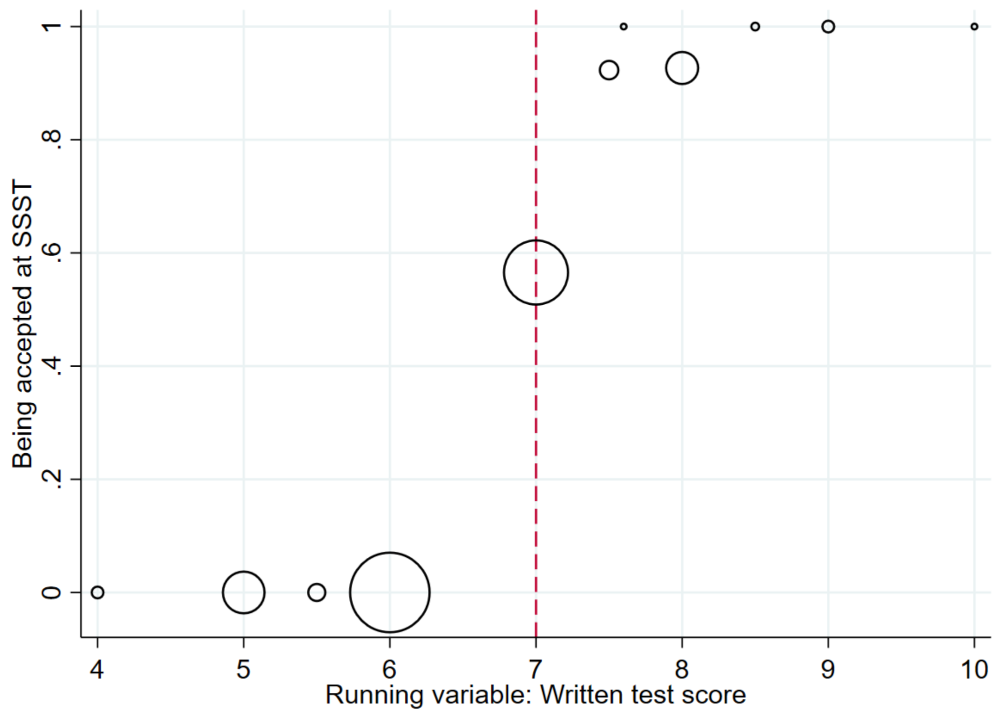
	Applicants		Admitted		Enrolled		Window	
	N	Mean	N	Mean	N	Mean	N	Mean
Female	577	0.53	154	0.48	144	0.49	428	0.53
High school final grade (/100)	577	94.36	154	95.65	144	95.53	428	94.84
Graduated HS with honors	577	0.12	154	0.19	144	0.17	428	0.12
HS: Any liceo	484	0.87	138	0.93	128	0.93	362	0.88
HS Liceo: 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

Descriptive statistics – Administrative data

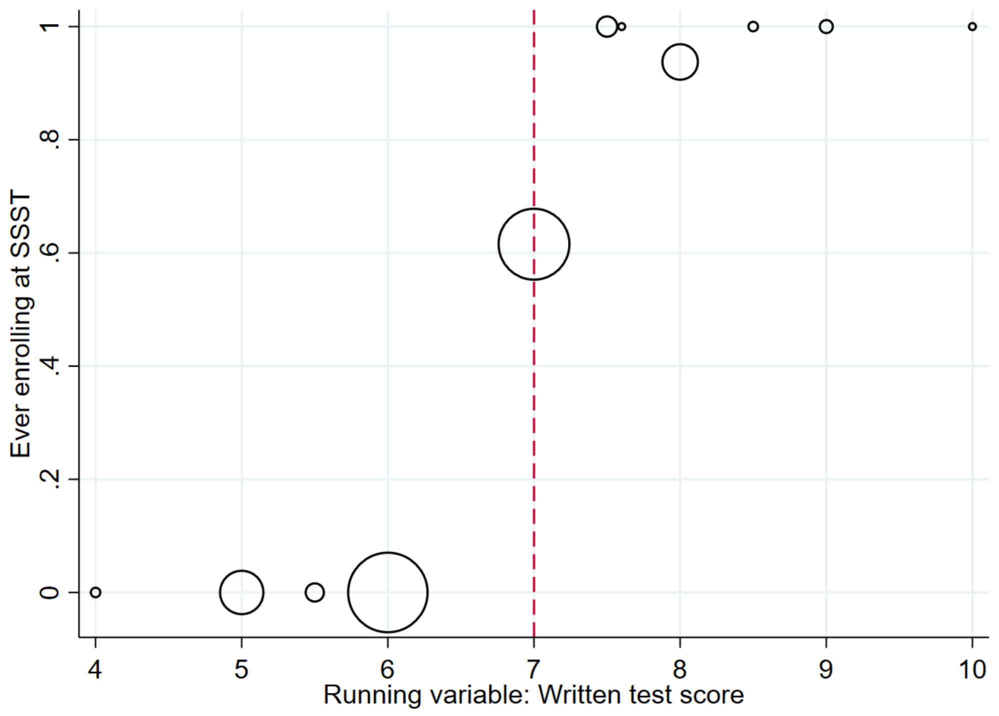
	Honors program		University	
	Applicants	In window	Eligible	Overall
Female	0.55	0.56	0.72	0.63
High school final grade (/100)	94.58	94.99	88.90	79.98
Graduated HS with honors	0.11	0.11	0.03	0.02
HS: Any liceo	0.94	0.96	0.81	0.78
HS Liceo: classical	0.42	0.45	0.16	0.15
HS Liceo: scientific	0.41	0.39	0.38	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		

First stage: Strong discontinuity in the probability of admission, enrolment into the program

Acceptance



Enrolment



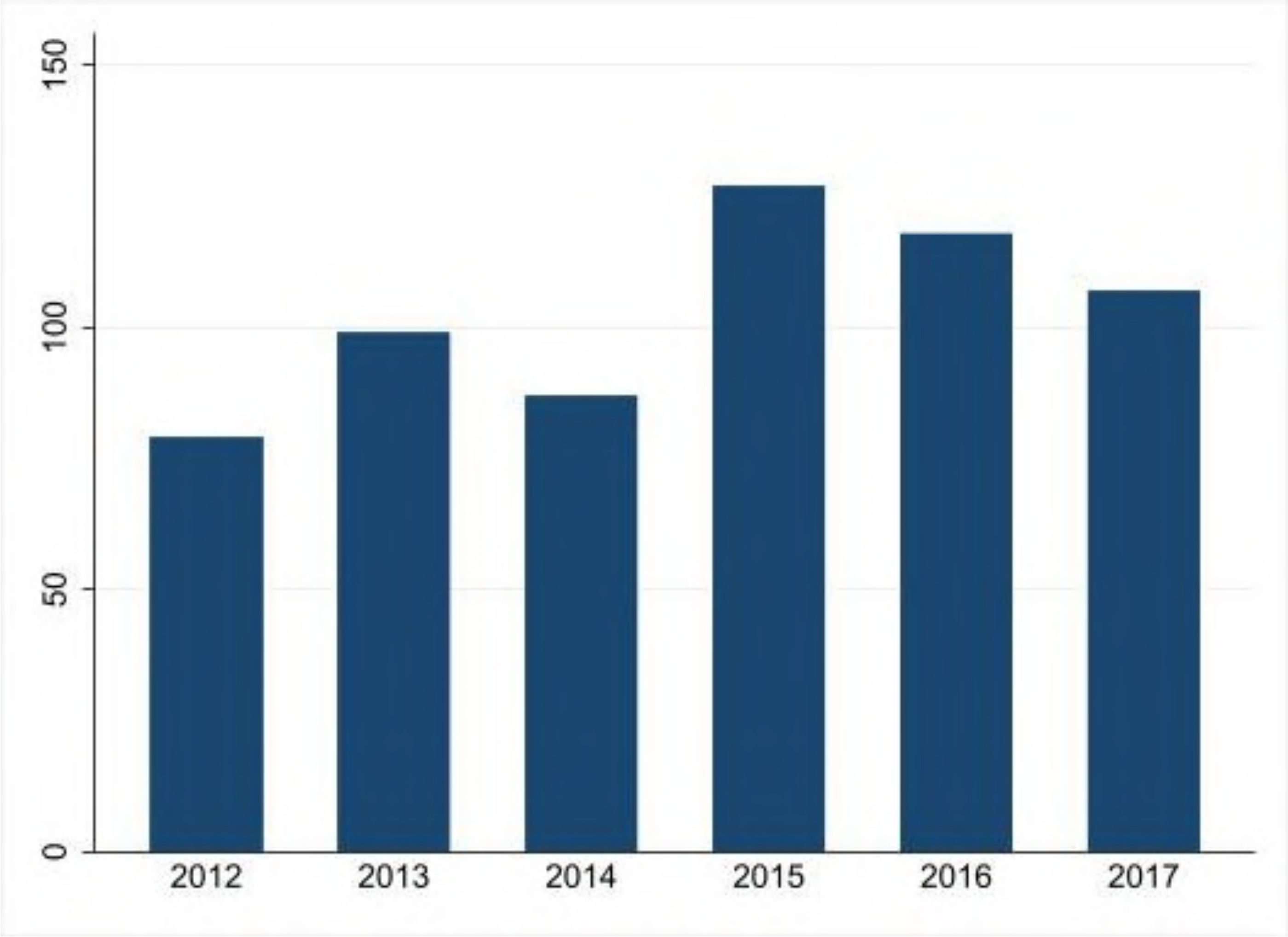
Approachability table: We derive a measure of how "approachable" each essay was based on empirical choice of exam questions

- Table A.12 reports the **proportion of candidates** who **chose** each **essay question** over the total of applicants in each admission year
- For each essay we build an **"approachability" index** by averaging the empirical frequency of the exam questions chosen
- Sample refers to first year candidates who completed 3 exam questions.

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

Applicants by admission year



Robustness to window selection

Administrative data

- Assess window choice following Cattaneo et al 2016's algorithm and choice of **alpha at 0.15**
- The smallest window with balanced covariates is selected

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

Column 4 refers to the variable displaying the smallest p-value in the regression

Robustness to window selection

Graduate data

Panel A

Window		Balance test p-value	Variable	Obs < cutoff	Obs ≥ 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

Panel B

Window		Balance test p-value	Variable	Obs < cutoff	Obs ≥ 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

Column 4 refers to the variable displaying the smallest p-value in the regression. Panel A includes Days to apply to the program among the regressors, while Panel B does not.

- Days to apply to the program (motivation proxy) marginally unbalanced as in balance tests, though in a direction which is inconsistent with positive selection