Tracking and academic prospects*

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First version: 16/7/2024
Revised: 18/10/2024

Abstract

This paper investigates the impact of secondary school tracking on students' transitions to higher education (HE) in Italy. Using data from INVALSI and PISA surveys, we explore how track allocation—whether students attend academic, technical, or vocational schools—affects their academic outcomes and aspirations for higher education. There are significant disparities in transition rates between tracks, with students from vocational schools facing lower prospects of accessing higher education compared to their peers in academic tracks. These students not only demonstrate weaker skill growth over time but also lower aspirations for college, exacerbated by selective university admission policies based on standardized testing. The findings suggest that tracking reinforces social inequalities, with vocational students experiencing lower probabilities of entering tertiary education, especially under selective university admission policies. Revising vocational curricula, postponing track selection, or adjusting admission processes are policy measures that could improve equity in higher education access. Targeted interventions to support students in vocational tracks might also be needed to mitigate the long-term consequences of early academic tracking.

Keywords: higher education access; vocational education; educational inequality; university admission policies

JEL codes: I21; I24; I28; J24.

* This paper was prepared as part of UNICREDIT Foundation research project on transition from secondary to tertiary education. We would like to thank Gabriele Ballarino, Massimiliano Bratti, Giuseppe Marotta, and Elena Meschi for their constructive comments on an earlier draft of this paper. The usual disclaimer applies.

1. Introduction

The transition from secondary to tertiary education is typically socially selective in countries where secondary education is organized by tracks. Italy is an interesting example in this respect since transition rates are significantly differentiated by tracks despite universal admission to universities for anyone successfully completing upper secondary education. In the most recent report on Italian universities (ANVUR 2023), we can compute some interesting statistics on the average educational careers of Italian youngsters (see table 1, based on flow data reported in table A.1 in the Appendix). Irrespective of the age of attainment, the fraction of the population obtaining a secondary school degree that allows the enrolment in higher education (HE) is equal to 77% for the cohort born in 2001. This percentage is on a rising trend, when we consider that for the generation ten years older the same percentage was 50%.[1] When we compare these statistics to the graduation rate of regular students, the same statistics drops to 67%.[2] This suggests that a significant fraction of Italian students complete secondary education at a later age than foreseen by the law due to irregular careers (later entry, differential year of admission for non-citizen students, retentions). If we stick to regular students, the vast majority enrols in universities (a rough estimate corresponds to 87% of the 19-year-old graduates).[3]

These transitions can be appropriately studied using longitudinal administrative data, which are unfortunately not yet available for research purposes in Italy. In their absence, one can rely on gross rates, namely graduation and enrolment in the same year, irrespective of the age of the individuals. Under the assumption of a constant share of irregular careers across age cohorts[4], these gross rates constitute a reasonable estimate of transition rates. Going back to table 1, almost 60% of all secondary school graduates make a transition to HE, but this average hides huge differences associated with school tracks: the same transition rate is 76% for students coming from academic oriented high schools (*licei*), 46% from technical schools (*istituti tecnici*) and 24% from vocational schools (*istituti professionali*). If we take into account an estimate of the drop-out rate between the first and second year of enrolment (bottom part of table 1), we end up with an estimated transition and survival rate of 50%, ranging from almost 70% in high schools to 20% in vocational schools.

[1] Statistics computed by the authors on SILC survey sampled in 2021.

[2] The Italian educational cycles last 13 years (5 in primary education, 3 in lower secondary and 5 in upper secondary), with an entry age at 6. Thus, a regular student who has not experienced any failure should complete secondary education at the age of 19.

[3] As a result of the ratio between 0.589 (transition rate) and 0.673 (secondary school graduation rate).

[4] Ballarino et al 2011 show that the fraction of dropout remains approximately constant in Italy across age cohorts, though it moves from lower secondary to upper tertiary when passing from cohorts born in the 40's to cohorts born in the '70s.

Table 1 – Relevant transition rates in secondary education – Italy – year 2022

graduation rate of population born in 2001 observed in 2021 (from SILC 2021)	0.770
graduation rate of regular students – 19-year-old in 2022 - born in 2003 (from administrative data)	0.673
transition rate of regular students – 19-year-old in 2022	0.589
transition rate of repeating students - older than 19 in 2022	0.612
gross transition rate - high schools (enrolled/graduates) in 2022	0.766
gross transition rate - technical schools (enrolled/graduates) in 2022	0.462
gross transition rate - vocational schools (enrolled/graduates) in 2022	0.246
gross transition rate (enrolled/graduates) in 2022	0.595
drop-out rate (end 1st year) - graduate from high schools - in 2021	0.093
drop-out rate (end 1st year) - graduate from technical schools - in 2021	0.211
drop-out rate (end 1st year) - graduate from vocational schools - in 2021	0.268
drop-out rate (end 1st year) - in 2021	0.145
estimated survival rate (start of second year) - graduate from high schools - in 2022	0.694
estimated survival rate (start of second year) - graduate from technical schools - in 2022	0.365
estimated survival rate (start of second year) - graduate from vocational schools - in 2022	0.180
estimated survival rate (start of second year) - in 2022	0.509

Source: ANVUR 2023, figures 1.2.11-1.2.12-1.2.15

We can summarise previous evidence by saying that out of 100 members of the recent birth cohorts, 23 do not gain the possibility of accessing tertiary education, 31 choose not to enrol, and 46 enter a BA course, but more than 6 abandon after one year.[5] The share of potential achievers of a BA in the recent cohorts is 39%, well below the European Lisbon 2030 target of 45% HE graduates in the population aged 25-34.[6] From this perspective, the Italian educational system is rather selective, especially when compared to other educational systems where the fraction of HE graduates exceeds half of the population. The real problem is whether it is excessively selective: according to EC (2023 - see figure 27), Italy is the country with the lowest HE attainment in the adult population after Romania. In 2022 the fraction of the population aged 25-34 was 29% against a European average of 42% and countries like France or Spain at 50%. In addition, the Italian educational system is at risk of social selectivity (Ballarino and Panichella 2021). In the sequel of the present paper, we will explore the extent of social selectivity, along four mechanisms: track allocation and track attendance, using longitudinal information on student testing (INVALSI 2013 and 2018 survey); track allocation and aspiration to college, using cross-sectional data on students (PISA 2018 survey); college admissions via ability testing (TOLC test at the University of Milan). The next three sections deal with each of these mechanisms, while the concluding section draws some policy implications.

[5] These number are obtained as follow: 23 comes from $100 \times (1 - 0.77)$, the fraction of population without a secondary degree; 31 is the difference between 77 (potential applicants) and $77 \times 0.595 = 45.8$ (effective applicants); and 6 is the fraction of drop-outs as result of $45.8 \times 0.145 = 6.6$. The survivors are then $45.8 - 6.6 = 39.2$.

[6] See EC 2023 and also their website https://op.europa.eu/webpub/eac/education-and-training-monitor-2023/en/comparative-report/chapter-5.html.

2. Is vocational tracking detrimental to prospective academic careers?

The Italian educational system is organized into two cycles: a comprehensive segment including 5 years of primary and 3 years of lower secondary, followed by a tracked segment of 5 years of upper secondary education. Education is compulsory until age 16, including the first cycle and the initial years of the second cycle (Eurydice Italia 2014). The tracking is usually classified as tripartite (academic oriented high school, technical and vocational), but the distinction has become blurred in recent years since many technical schools have been converted into high schools.[7] Completing 5 years of upper secondary education allows enrolment in any university course.

In order to properly answer the question of the title (*Is vocational tracking detrimental to prospective academic careers?*), we would need an exogenous (random) assignment to track of otherwise almost identical pupils, who are then followed in their development of cognitive and non-cognitive abilities. Since random assignment is opportunely precluded in democratic societies, pupils will likely be sorted across school tracks according to their observable and unobservable characteristics, like parental education, teacher evaluation, peer pressure, and the like. However, we can still infer some of the effects of the treatment (i.e., of tracking) by comparing the differences between the treated before and after the treatment. In order to do so, we have made use of Italian student test scores, linking them across different survey years in order to obtain longitudinal information. We collected information on test achievement of the entire population of Italian pupils in grade 8 (before the track allocation) and in grade 13 (at the end of a 5-year treatment of being allocated to a specific track). Given the longitudinal nature of our data and taking into account non-random attrition, we can shed additional light on the impact of differences associated with track allocation, which then matter in the HE transition.

Italian students are tested in their literacy and numeracy competences by INVALSI, the national testing agency, in grades 2, 5, 8, 10 and 13. Since 2012-13, INVALSI has introduced a unique identifier for each pupil to track them in their educational career. It is, therefore, possible to use their survey conducted in the school year 2013-14 for 8th graders, matched on individual identifiers with the survey conducted in the school year 2018-19 for 13th graders. Given the non-negligible retention rate during the initial years of upper secondary school, it would have been advisable to add data collected in the school year 2019-2020 for grade repeaters, but unfortunately this survey did not take place due to the Covid pandemic. More recent surveys are then contaminated by the effects of Covid, and we have preferred to limit ourselves to pre-Covid data, convinced that these phenomena are persistent across years.

[7] See the discussion in Ballarino and Panichella 2021, pg.154-166.

Over a population of 512,876 8th graders in 2013-14, we are able to trace 67.2% five years later in grade 13th. One-third of our initial sample has either been retained or has dropped out of school. Conversely, if we consider that in grade 13th, one-fourth of the students do not have a match in five years earlier data, we may conclude that our population of interest is clearly positively self-selected since the weakest students have been either retained at least once during secondary education or have abandoned their schools.[8] This is confirmed by comparing the descriptive statistics of the matched sample against the unmatched ones (see column 2 of table 2). Girls are over-represented, as are pupils in their modal year of birth (2000). The fraction of natives is ten percentage points higher when compared to first- or second-generation migrants. By construction, almost all report a regular career without retention (97%). Pupils of the matched sample are also characterized by more educated parents, working more frequently in non-manual occupations.[9] Consistently with these observables, the matched sample exhibits higher test scores both in literacy and numeracy compared to the unmatched samples.[10] Statistical evidence of these claims is reported in table A.2 in the Appendix, where we estimate a linear probability model of the correlates to disappearing from 8th graders five years later (columns 1 and 2) as well as to appearing among 13th graders, coming from older age cohorts (columns 3 to 5).

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[8] The early school leaving rate in the population aged 118-24 for Italy provided by Eurostat for these years goes from 15% in 2013 to 14.7% in 2018 (https://ec.europa.eu/eurostat/databrowser/view/sdg_04_10/default/table?lang=en&category=t_educ.t_educ_outc).

[9] Over the years, Invalsi has changed the information collected on family background. In the initial years they collected information on parental education and occupation, while in more recent years they expanded the list of items in order to include number of books at home and other educational resources. Based on these pieces of information, they replaced parental education and occupation with a synthetic index of cultural and socio-economic condition (ESCS), which is standardized with zero mean and unitary standard deviation. In both cases, this information is missing in almost 30% of the observations.

[10] INVALSI presents three measures of student achievements: the raw score (corresponding to the count of correct answers to items), the Rasch estimate of the inner ability of each student (that takes into account the different difficulty of each item as well as the number of correct answers of each pupil) and a corrected Rasch estimate (accounting for potential cheating of teachers, according to similarities in the classes – see Bertoni et al 2013). Since we ignore the potential bias introduced by cheating, we have preferred to adopt the second measure (the uncorrected Rasch estimate) as proxy for student ability.

Table 2 – Descriptive statistics – Invalsi 2013-14 (8th graders) and 2018-19 (13th graders

	grade 8th not found in grade 13th	grade 8th matched in grade 13th	grade 13th without match in grade 8th
observations	168 100	344 776	117 499
gender:			
female	0.418	0.537	0.404
birth year:			
<=1997	0.006	0.000	0.094
1998	0.044	0.003	0.145
1999	0.166	0.026	0.474
2000	0.711	0.858	0.260
2001	0.072	0.112	0.025
>=2002	0.000	0.000	0.000
citizenship:			
native	0.818	0.939	0.882
born abroad from foreign parents (G1)	0.104	0.026	0.057
born inland from foreign parents (G2)	0.075	0.033	0.061
school career:			
regular or anticipatory	0.784	0.970	0.286
at least one retention year	0.216	0.030	0.714
Parental education (highest in the couple):			
illiterate or primary education	0.034	0.007	
lower secondary	0.400	0.211	
vocational degree	0.112	0.081	
high school degree	0.335	0.456	
tertiary degree	0.119	0.245	
Parental occupation (highest ISCO):			
manager	0.002	0.005	
entrepreneur	0.008	0.010	
professional	0.030	0.058	
self-employed	0.065	0.068	
white collar	0.127	0.268	
blue collar	0.215	0.173	
unemployed/housewife/retired	0.553	0.418	
Socio-economic status (ESCS)		0.132	-0.119
		0.996	*1.028*
Test scores (Rasch without cheating correction)			
Literacy grade 8th	181.18	212.11	
	(35.65)	*(37.83)*	
Numeracy grade 8th	184.13	212.59	
	(35.53)	*(38.89)*	
Literacy grade 13th		204.47	179.00
		(40.91)	*(40.90)*
Numeracy grade 13th		206.75	185.48
		(40.03)	*(37.84)*

We now focus on the matched sample, described in the second column of table 2. Thanks to the match, we know the final track allocation of these 344,776 students, which does not necessarily correspond to the initial track allocation since students may change track during their career, typically towards less academically oriented tracks. If we compare administrative data on total enrolment in 9th grade (which includes repeating students) with total enrolment in 13th grade five years later (which also includes repeaters - see table 3), we can notice the differential dropout rate that increases when passing from high schools to vocational schools.[11] When compared to our matched sample, we confirm the evidence of non-random attrition, with a larger share of students from high schools (58.4%) and a minority share of students who have "survived" in the vocational track (12.8%).[12]

Table 3 – Track enrolment – comparison with administrative data

	9th grade enrolment 2014-15 (MIUR data)	%	13th grade enrolment 2018-19 (INVALSI data)	%	implicit drop-out from admin. data	13th grade enrolment 2018-19 (matched sample)	%
High schools (licei classici/scientifici)	116 044	21.6	108 763	23.5	6.3%	95 354	27.6
High schools - applied (licei scientifici scienze applicate/ linguistici/ scienze umane/ musicale/ artistico/ europeo)	151 502	28.2	131 103	28.3	13.5%	106 321	30.8
Technical schools (istituti tecnici economico/tecnologico)	165 471	30.8	142 860	30.9	13.7%	98 899	28.7
Vocational schools (industria/artigianato/servizi/sussidiarietà)	104 225	19.4	79 549	17.2	23.7%	44 202	12.8
	537 242	100.0	462 275	100.0	14.0%	344 776	100.0

Source: first column from administrative data on enrolment from MIUR (2014) Focus "*Le iscrizioni al primo anno delle scuole primarie, secondarie di primo e secondo grado del sistema educativo di istruzione e formazione*" Anno Scolastico 2014/2015 – second column from INVALSI 2018-19 sample – third column from match of 2013-14 and 2018-19 INVALSI data

Track allocation is chosen by parents during 8th grade, taking into account the teachers' suggestions (*consiglio orientativo*). As a consequence, track choice is based on school results (driving teachers' advice) but also determined by the social origins of the students (via opinion/expectations of parents). In table 4 we report the estimates of a statistical model predicting the track allocation of pupils based on their observable characteristics: the highest parental education and the socio-economic status in the couple are negatively correlated to the choice of technical or vocational tracks (column 1). However, the choice is also negatively correlated to school marks, as witnessed by the improvement of the predicting ability of the model (according to the pseudo-R^2 statistics). Parents and teachers do not observe the literacy and numeracy test scores, which are correlated to school marks (0.60 for Italian/literacy and 0.59 for Mathematics/numeracy). If, however, we add this piece of information, which is likely to reflect part of the unobservable abilities of the students, we observe a negative correlation with track allocation and a modest improvement in the goodness of fit. We can, therefore, infer that track allocation reflects social origin, school performance and unobservable ability in proportions that are hard to quantify. One could object that track allocation may also be driven by local labour market conditions affecting the attractiveness of early employment. For this reason, in

[11] Invalsi provides a fourfold classification of upper secondary schools, distinguishing between traditional high schools (intended to college enrolment without any professional content: *licei classici* and *licei scientifici*) and recently introduced high schools (with some applied contents: *licei scientifici scienze applicate*, *licei linguistici*, *licei delle scienze scienze umane* - formerly teaching schools -, *licei musicali* – conservatoire -, *licei artistici* - academy of arts- and *licei europei*). This second group attracts students that are rather similar to students attending technical schools (as evident in the sequel) and could therefore be grouped with them. However, since PISA survey utilizes a tripartite classification (50.2 % in high schools, 29.8% in technical schools and 20% in vocational ones) we have kept them separate.

[12] Note also that some vocational training courses have a duration of three or four years. Therefore, some of the students in the vocational track that we do not find in 13th grade may also have regularly completed their education.

column 4 we have introduced province fixed effects, which fully capture local labour markets' characteristics. Results are substantially identical to column 3, suggesting that track allocation is relatively independent from local job opportunities for the youth.

Despite the non-random selection into tracks, we may wonder whether such treatment (track assignment) modifies the level of competences of students. We have two measures of competences: the teachers' marks and the test scores. The former indicator corresponds to the subjective evaluation of teachers, which may reflect their biases due to stereotypes. The latter is a more objective measure (in its Rach estimate, it incorporates each question's different degree of difficulty) that is comparable across all students. We, therefore, compare students in terms of their relative test score position before the entry into secondary education and at the exit five years later. Suppose we find that the relative position of those at the bottom of the distribution has improved (conversely, relative positions at the top have worsened). In that case, we might conclude that tracks reduce the differences created by selection into tracks, leading to greater equality in achievements. If selection is also driven by social origins, then tracks would help in reducing social differences (for example allocating better resources on disadvantaged students). On the contrary, if spending five years in different tracks, learning different contents and forming different aspirations yields a widening of the pre-existing test score differences, then we could argue that tracks contribute to amplifying skill differences that are not independent of social origin.[13]

Table 4 – Probability of track allocation – ordered probit model

	1	2	3	4
dependent variable: track allocation (%)				
1.high schools (classico/scientifico)	*29.54*	*29.40*	*29.40*	*29.40*
2.other high schools	*30.28*	*30.22*	*30.22*	*30.22*
3.technical schools	*29.02*	*29.14*	*29.14*	*29.14*
4.vocational schools	*11.17*	*11.23*	*11.23*	*11.23*
highest parental education=primary	0.588***	0.443***	0.422***	0.388***
highest parental education=lower secondary	0.390***	0.297***	0.286***	0.230***
highest parental education=vocational	0.314***	0.245***	0.233***	0.175***
highest parental education=high school	0.033***	0.043***	0.044***	0.005
highest parental education=non academic tertiary	-0.074***	-0.077***	-0.073***	-0.117***
highest parental education=BA or MA	-0.339***	-0.262***	-0.240***	-0.270***
ESCS (cultural-socio-economic conditions)	-0.253***	-0.206***	-0.197***	-0.195***
Marks in Italian (oral)		-0.227***	-0.171***	-0.176***
Marks in Mathematics (oral)		-0.262***	-0.201***	-0.204***
Literacy test score			-0.003***	-0.003***
Numeracy test score			-0.004***	-0.004***
Observations	253 786	224 138	224 138	224 138
Pseudo R^2	0.064	0.142	0.151	0.156

Robust standard errors in parentheses - *** p<0.01, ** p<0.05, * p<0.1

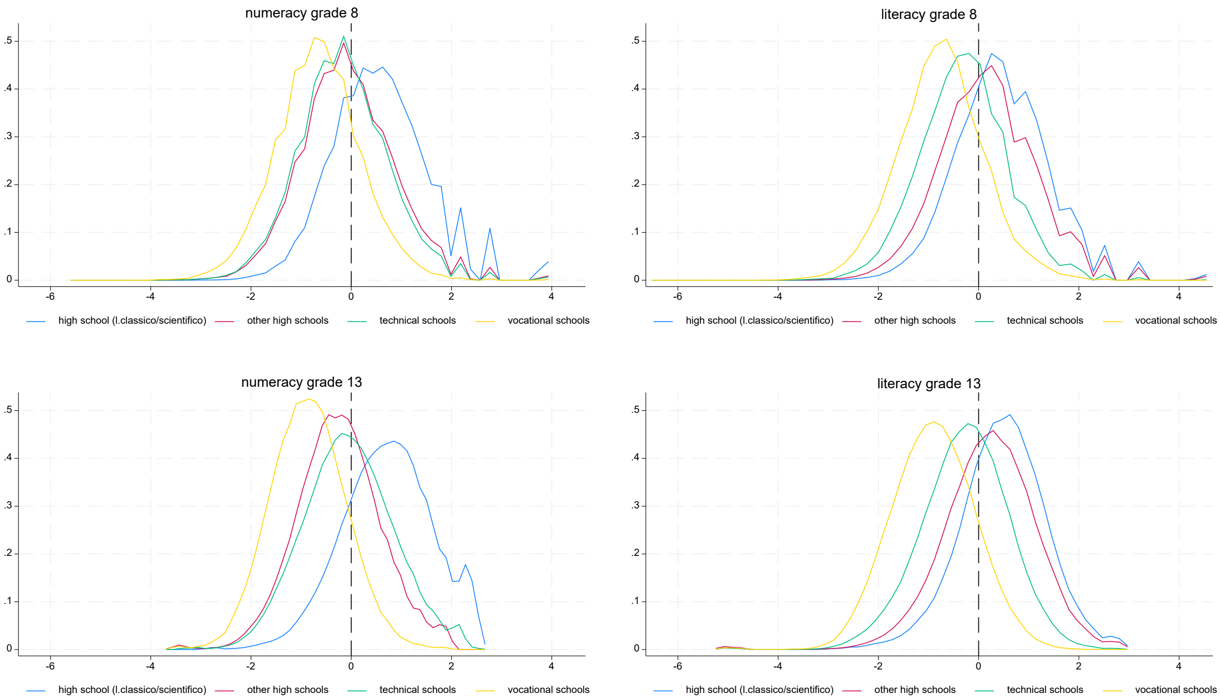
Controls include gender, birth year, citizenship and macro-region of residence (replaced by province fixed effects in column 4) – full model is reported in Table A.3 in the Appendix

[13] This is sometimes indicated in the sociological literature as Matthew effect (Merton 1968).

Figure 1 plots the kernel densities of numeracy and literacy test scores in grade 8 (before the track allocation – top panels) and in grade 13 (at the end of five years of track treatment – bottom panels) for the same population of the matched panel. Recall that because of the non-random attrition, weaker students, often allocated to vocational tracks, are underrepresented in these graphs (since they constitute the unmatched samples), and therefore, the distributions appear more compressed than they actually are. Test scores have been standardized in order to have zero mean and unitary standard deviation.

Two comments are at hand. The first one is that track allocation does indeed reflect differences in students' competences since (expected) high school students possess, on average, a higher level of competences before entry into upper secondary education. However, despite track differences, the distributions have largely common support since there are high-skill students assigned to vocational tracks and, conversely, low-ability students assigned to high-skill tracks.[14] Five years later, the differences among tracks have widened, but it is still possible to find high-skill students in vocational schools and low-skill ones in high schools.

Figure 1 – Distribution of test score – Invalsi matched sample (2013-14 and 2018-19)

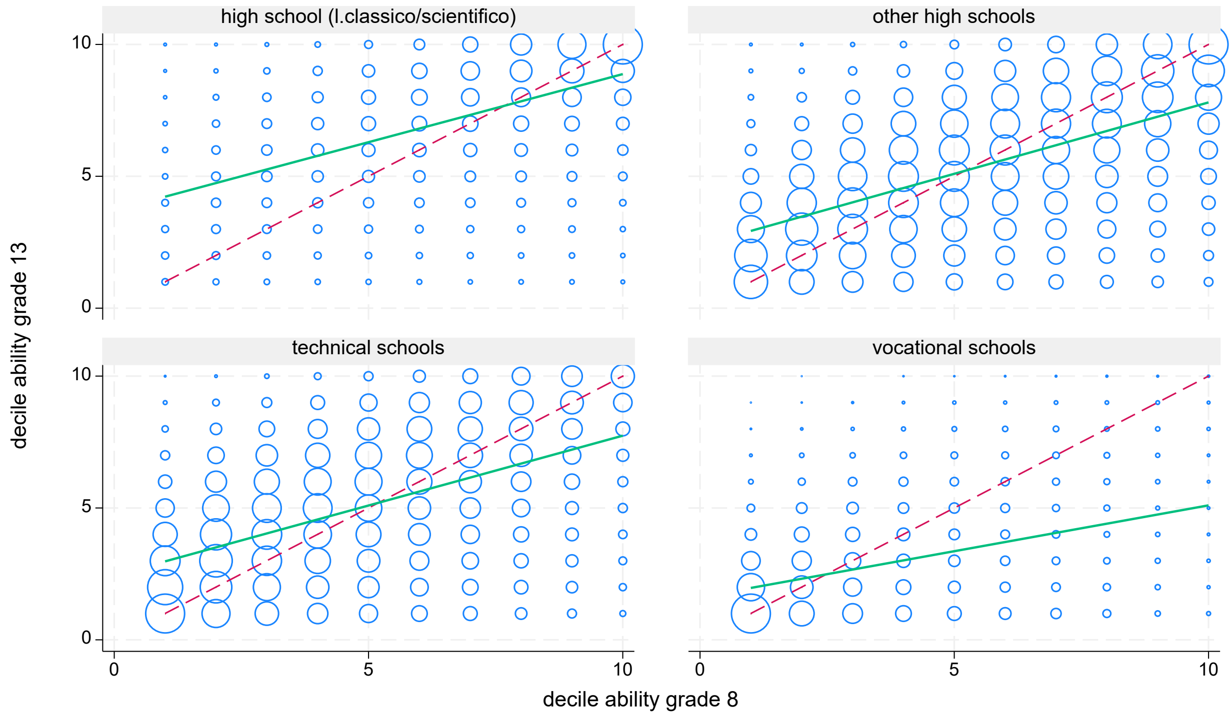


In order to appreciate the mobility in the relative position of each student, we have proxied *individual ability* with the standardized sum of literacy and numeracy test scores, both in the 8th and 13th grades,

[14] The comparison between track allocation in Italy and Germany using this type of graphs is originally presented in Checchi and Flabbi 2013.

and then we have partitioned each distribution into deciles. We can, therefore, build a "curricular" mobility matrix, where each row corresponds to the test score distribution in 8th grade, and each column corresponds to the arrival decile in grade 13. A graph corresponding to this curricular mobility matrix by track is depicted in figure 2, where one can visualize the distribution of students by tracks since the size of each circle is proportional to the frequency of cases. All circles above the (ideal) 45-degree line represent cases where the students improve their relative position in the distribution, while the opposite applies to cases below a 45-degree line.

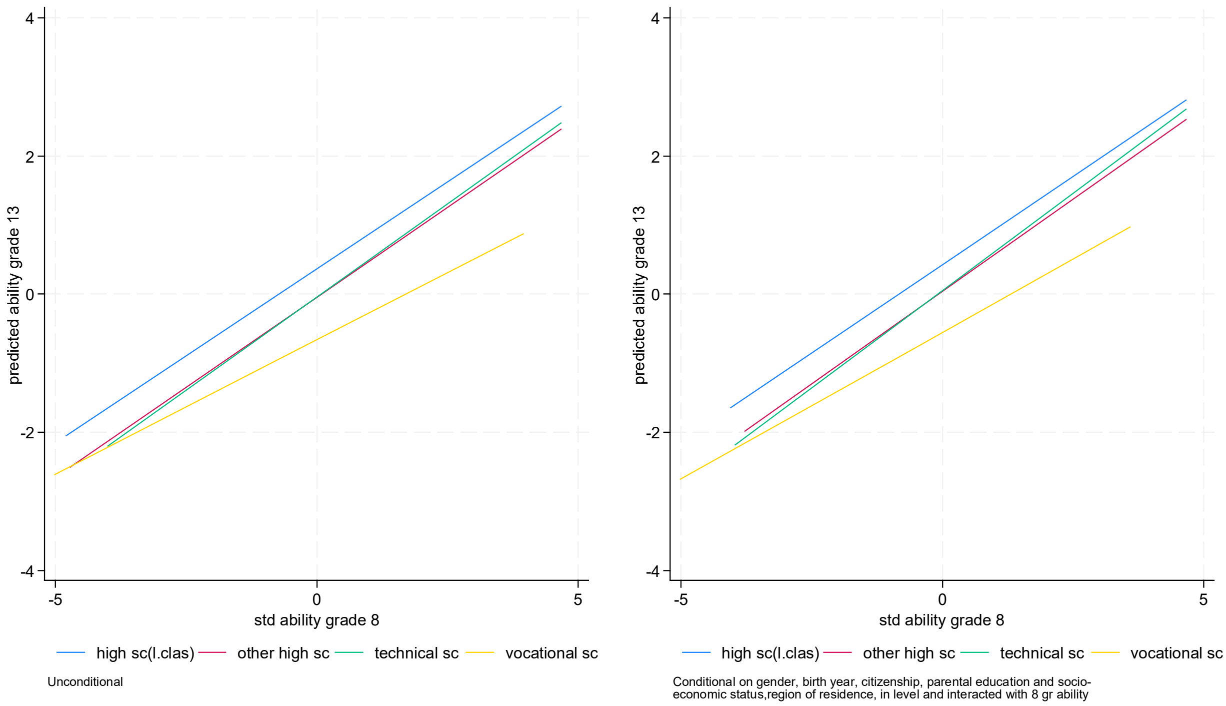
Figure 2 – Individual mobility in relative score position during five years of tracking – Invalsi matched sample (2013-14 and 2018-19)



It is apparent that attending a high school is associated with upward curricular mobility, given that the regression line crosses the bisector at a higher decile than in the other school types. Conversely, the vocational track corresponds to downward curricula mobility, as fewer students who were in the top deciles in 8^{th} grade end up in the bottom decile five years later.

One potential objection to this approach is that students are inherently different in terms of social origins. However, even when we consider these effects, differences in track effectiveness persist. In figure 3, we have regressed ability in grade 13 onto ability in grade 8, separately by track. In the left panel, the regressions are unconditional, while in the right panel, we control for observables (gender, birth year, parental background and region of residence). In both cases, it is evident that attending vocational schools is associated with slower progress in relative ability, the detrimental effect being more apparent in numeracy than in literacy (see figure A.1 in the Appendix).[15] Since this is true irrespective of the social origins of the students, we may infer that this detrimental effect has to be associated with what occurs within the classes: teaching contents (which are statutorily different), class climate, teacher selection and motivation, peer effects and more generally school environment. We do not have adequate information on all these dimensions, but we can claim that they are independent of the students' willingness to learn. Thus, being assigned to a high school track or a vocational track makes a significant difference in the level of skills each student achieves, irrespective of their level of initial ability and social origins. If university admissions are based on tests correlated to numeracy or literacy, then two identical students in terms of initial ability and family background who are assigned to two different tracks would experience different ex-post probabilities of being admitted to HE institutions.

Figure 3 – Cumulative effects of tracking



[15] Using the economic jargon, we can say that competence score exhibits β-convergence (i.e. regression to the mean), but not σ-convergence (i.e. the dispersion among tracks widens over the school years).

3. Aspirations by tracks

Test scores are not the unique variable driving student choices. Unfortunately, Invalsi does not collect information from 13th graders about their intention to pursue further education. For this reason, we have been forced to rely on a different survey that contains this information, though collected among 10th graders. The OECD PISA survey conducted in 2018 surveys 15-year-old students born in 2003 and includes information on students' literacy, numeracy, and science abilities, as well as aspirations over further education and occupations (PISA 2019). Parents are also interviewed about their aspirations about their children's prospects. An extensive array of items allows for precise measures of students' socio-economic background, including parental education and occupation, books at home and a summary indicator of socio-economic and cultural conditions. After excluding 15-year-old students still in lower secondary, we are left with 11,710 student observations randomly drawn from 508 schools, which are representative of tracks in secondary education. Given their selection rule, we encounter in the sample both a fraction of 13% of repeaters (therefore attending 9th grade) and a smaller fraction of 7% of students who entered primary education one year earlier than usual (thus attending 11th grade). PISA survey gathers all high schools into a single group, making up half of the sample. Students in technical schools add another 30%, and vocational schools add the complementary 20%. These shares are entirely consistent with the administrative data of earlier years reported in table 3.

Table 5 – Italian PISA sample (weighed) - 2018

	repeaters 9th graders	regular 10th graders	early student 11th grade	Total	%
high school	346	4910	622	5877	50.19%
technical schools	571	2726	192	3489	29.80%
vocational schools	679	1569	95	2343	20.01%
Total	1596	9205	910	11710	100.00%

Table 6 – Descriptive statistics (weighed) – Italy – PISA 2018

	high school	technical schools	vocational schools	Total	# cases	std.dev.	min	max
female	0.60	0.29	0.47	0.48	11710	0.50	0.00	1.00
age	15.78	15.77	15.74	15.77	11710	0.28	15.25	16.33
ESCS index	0.11	-0.39	-0.73	-0.21	11401	0.91	-5.92	3.07
Highest occup.prestige	54.07	42.89	36.74	47.42	10991	21.28	11.74	88.96
numeracy	522.17	482.00	409.75	487.70	11710	88.00	191.82	746.77
literacy	521.05	457.52	397.65	477.43	11710	93.34	175.34	754.42
science	502.70	460.19	398.01	469.08	11710	84.98	128.31	742.00
Child expects HE	0.87	0.64	0.46	0.72	11262	0.45	0.00	1.00
Parents expect HE	0.82	0.58	0.35	0.66	11528	0.47	0.00	1.00

When looking at the descriptive statistics of this sample (table 5 and table A.4 in the Appendix), it is evident that high schools gather the best students both in terms of cognitive skills (literacy, numeracy and science) and social background (parental education and occupation, educational resources). Girls and natives are overrepresented in high schools, while boys concentrate in technical schools and non-citizens in vocational schools.

The PISA survey investigates students' and families' aspirations regarding future educational careers. Based on their answers, we have created two dichotomous variables, one elicited from students[16] and the other from their parents.[17] Aspirations to HE are rather different across tracks: while on average, almost three out of four (72%) 15-year-old students declare their intention to progress to HE three years later, this percentage varies from 87% in high schools to 46% in vocational schools. Parental aspirations are lower but ordered similarly (see again table 6).

In this section, we aim to study why college aspirations markedly differ among tracks and whether there is a genuine contribution of the tracks in shaping these aspirations. In Figure 4, we introduce a summary measure of student skills by averaging the three scores in literacy, numeracy and science.[18] The distribution of this measure, which we term "student ability", is displayed by school track. We distinguish between students in high school (academic track, black line), technical schools (red line), and vocational track (green line). The figure clearly shows that the three distributions are different: students in high school generally have higher abilities than those in technical schools, who are, in turn, followed by vocational school students. Differences in abilities between students across tracks can be traced down to (i) differences in family and parental background, (ii) differential sorting into tracks by ability, and (iii) the differential effect of each school track on students' ability. We remove the effect of family background and selection on observable characteristics in the school track by regressing individual ability on student and family characteristics and studying the residuals of this regression, which we denote as "residual ability."[19]

[16] The question ST225 in the student questionnaire lists all ISCED attainment and asks "Which of the following do you expect to complete?". We have identified as student aspiring to HE those who answer ISCED 4 or ISCED 5B or ISCED 5A or ISCED 6.

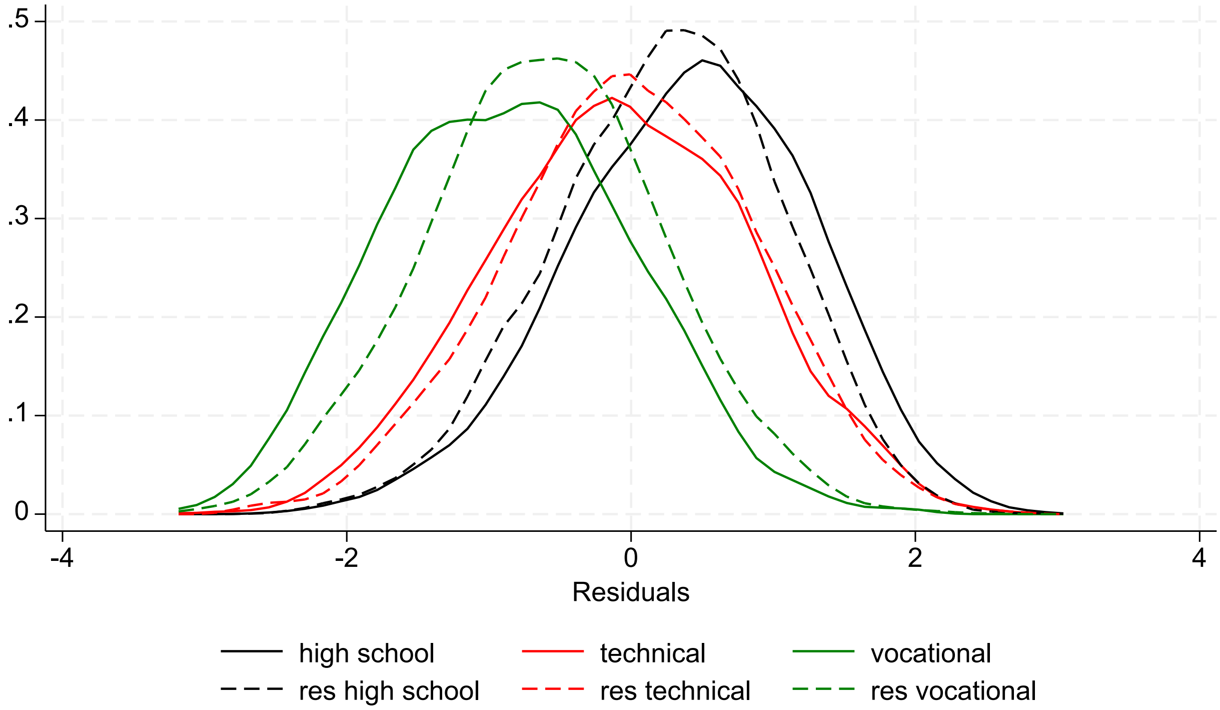
[17] The question PA172 in the parent questionnaire lists all ISCED attainment and asks "Which of the following do you expect your child to complete?" We have identified as parents aspiring their children progressing to HE those who answer ISCED 4 or ISCED 5B or ISCED 5A or ISCED 6.

[18] To be more precise, we have measured each skill (literacy, numeracy and science) by taking the mean value across their 10 plausible values. Then our measure of ability is the average score across these three skills, standardized in order to have zero mean and unitary standard deviation. The existence of 10 plausible values is used to obtain unbiased estimate of the standard errors in regressors, but given the descriptive nature of the present exercise we have decided not to follow bootstrap techniques in order to produce the present statistics.

[19] Specifically, we include the following students' characteristics: age, gender, and immigrant status, where the latter is captured by a set of dummies that identify native students (who have at least one parent born in the country), first-generation students (those born abroad from foreign-born parents) and second-generation ones (those born in Italy but whose parents were born abroad). Family characteristics, instead, include the PISA index of economic, social, and cultural

The kernel density estimates of the distribution of residual ability by school track, reported as dashed lines in Figure 4, are closer to each other than the distributions of actual ability: the distribution of residual ability for students in high school (vocational schools) has shifted to the left (to the right) relative to the actual one. This indicates that parental and family background and individual observable characteristics explain part of the differences in ability. The remaining differences are partly due to the selection of students across school tracks based on unobservable characteristics and partly due to the effect of school track (as we have argued in the previous section). Under the – admittedly extreme - assumption of no selection on unobservables, all differences in residual ability distribution are driven by the effect of the specific track choice; thus, two students with initially the same "innate" ability (proxied in this case by residual ability) end up with differences in their measured ability as a result of different tracking,

Figure 4 - Actual and residual ability by school track



Our data provide a snapshot of the student population at age 15 and do not have a longitudinal dimension, so we cannot observe which students will apply for admission to a university program upon completing secondary education or whether they will do so for an open-access or restricted-

status (ESCS), a composite index that jointly accounts for parental education, occupational status, and home possessions; a set of dummies for the number of books at home; the highest parents' socio-economic index (HISEI); and the highest education of parents, measured on the ISCED classification (HISCED). The relevant regression is in table A.5 in the Appendix. Note, however, that since tests are taken in the second year after tracking, they may also partly reflect the effect of tracking itself.

access degree. However, PISA has information about students' and parents' expectations about attendance at HE programs, which we use to construct as a proxy for potential university application. Specifically, we define students as potentially applying for university if both they and their parents expect them to receive tertiary education.

Table 7 – Child aspirations to HE, by "ability" or "residual ability" – Italy – PISA 2018

decile of ability	high school	technical schools	vocational schools	Total	decile of residual ability	high school	technical schools	vocational schools	Total
1	0.486	0.229	0.166	0.224	1	0.681	0.313	0.175	0.337
2	0.666	0.325	0.161	0.350	2	0.706	0.413	0.203	0.470
3	0.607	0.318	0.273	0.407	3	0.647	0.392	0.217	0.460
4	0.650	0.381	0.296	0.485	4	0.726	0.364	0.286	0.535
5	0.701	0.408	0.246	0.534	5	0.706	0.382	0.168	0.497
6	0.689	0.525	0.189	0.590	6	0.741	0.476	0.255	0.594
7	0.725	0.557	0.331	0.642	7	0.740	0.490	0.415	0.639
8	0.788	0.427	0.399	0.673	8	0.778	0.465	0.348	0.660
9	0.791	0.544	0.455	0.732	9	0.811	0.499	0.139	0.681
10	0.889	0.687	0.497	0.855	10	0.873	0.540	0.307	0.774
Total	0.738	0.415	0.220	0.543	Total	0.753	0.426	0.222	0.560

In table 7, we report the share of students who intend to go to university by national decile of ability (columns 1-3) or residual ability (columns 5-7) and by school track. The table shows that school track matters above and beyond ability in determining one's probability of going to university. In fact, among students in the top decile of the national ability distribution, 89% of those attending a high school intend to apply to university. However, the corresponding share is 69% for those in the technical track and only 50% for those in vocational schools. Likewise, in all residual ability deciles (i.e. at the same level of ability, gross or net of family background), the share of students planning to apply for tertiary education is highest for those in high schools and lowest for those in vocational education. If the goal of an efficient university admission mechanism is to select the highest-ability students, then table 7 shows that the system leaves inefficiently out of tertiary education some high-ability students in vocational and technical tracks while admitting instead lower-ability high-school students. Since measured ability is also determined by tracking, this implies that the inefficiency is even higher, as some "initially high ability" students will experience a decline in their ability because of tracking, as we have shown in the previous section.

A different way of assessing the influence of track choice on the probability of enrolling in tertiary education is to compute the likelihood of applying to university by school track. We do this in column (1) of table 8, which shows that 74% of high school students will apply to university, whereas the share is almost half as large for technical school students (42%) and about one-third as large for students in vocational education (22%). These differences by school track reflect differences in ability, family background, observable and unobservable individual characteristics of students, as well as the causal effect of attending a specific school track.

In column (2) of the same table, we instead report the average probability of applying for college by school track if the probability of applying to college was only determined by individual characteristics and family background (obtained through a probit regression – see table A.6 in the appendix). Also, in this case, the probability of applying for university has a clear gradient across school tracks, which reflects a positive selection of students into the more academically oriented tracks, but the cross-track differentials are smaller. Based only on their pre-determined characteristics, high school students' probability of going to college would be 60%. In contrast, the corresponding probability for students in technical and vocational schools would be 45% and 40%, respectively. In other words, based on their own and their families' observable characteristics, the probability of vocational school students applying to university would be almost twice as high as the actually observed probability.

Table 8 - Actual and predicted probability of going to university by school track

School track	**Actual probability** of going to college	**Predicted probability** of going to college
high schools	0.738	0.596
technical schools	0.415	0.447
vocational schools	0.220	0.401

In order to assess the relative contribution of groups of covariates, we apply a Gelbach decomposition (Gelbach, 2016) to the differential probability of college attendance between school tracks into a part due to individual characteristics, a part driven by family background, and a part due to ability. In table 9, we compute the differential probability of going to college between high school and technical school students relative to vocational training students, unconditional and conditional on individual and family characteristics and ability. For instance, in the case of high school vs vocational one, the unconditional difference in college application probability is 0.53 (that is the estimated coefficient associated with attending a high school track versus the excluded case, the vocational track). When we include the other covariates, the conditional difference in college application declines to 0.32 since differences in individual characteristics (gender, age, and immigrant status) explain 1% of the decline, differences in family background (ESCS, HISEI, parental education and books at home) explain 16%, and differences in ability explain 22% of the decline in the gap. Overall observables of the students account for 39% of differences in college aspirations, the remaining part being attributable to unobserved individual characteristics and to the track (teaching contents, teacher selection, peer effects and the like).

Table 9 – Gelbach decomposition of track differences in college aspirations, against vocational

child and parent aspiration to college	Coefficient	Std. err.	Initial differences	% explained
High School			**0.5308**	
individual	0.0067	0.0023		1%
family of origin	0.0853	0.0058		16%
ability	0.1176	0.0070		22%
Unexplained			**0.3211**	**61%**
Technical			**0.2037**	
individual	-0.0188	0.0024		-9%
family of origin	0.0374	0.0035		18%
ability	0.0666	0.0044		33%
Unexplained			**0.1186**	**58%**

If all university programs were open access, these predicted probabilities would represent the actual shares of students in each track attending tertiary education. In reality, however, many university programs restrict access to only "the best" students, i.e., those who perform better in some types of standardized tests (sometimes considering them alongside other factors such as the GPA in secondary school). Since these standardized test scores somehow resemble those administered in PISA, we can gain insights into the effects of a policy that restricted access to university only to the top performers of all university applicants on the selection of students from different secondary school tracks. We have seen in section 2 that in Italy, about 60% of all students graduating from upper secondary schools enrol in a university degree. For this reason, we can simulate the effect of a policy that only gave access to tertiary education to students in the top 50% of the ability distribution measured by PISA.

In table 10, we have partitioned the student ability into 20 percentile intervals (ventiles), and we have provided the distribution of the expected choice of applying or not to college by tracks attended by the students. Column (1) of table 10 shows the share of students (and their parents) not intending to go to college (which corresponds to the complement of column (4) in table 7), whereas columns (2) to (4) provide the distribution by tracks of those intending to go to college. For example, among the top performers in the 20th ventile, 91.3% intend to go to college: this share is obtained as 81% from high schools, 10% from technical and 0.2% from vocational ones. Conversely, in the bottom ventile, only 19.1% expect to go to college, and these potential applicants originate mainly from vocational schools (10.8%). In column (6), we provide the cumulated frequency from the highest to the lowest ventile of those intending to apply for college, while columns (7) to (9) report the partition by tracks of the applicants. If we now suppose that the admission policies of universities intending to restrict access were to admit students with a test performance above the median, we would obtain the situation in the grey area of table 10.

Table 10 – Share of students that would be admitted to college if the admission threshold would have been the median performance (weighed) – Italy – PISA 2018

	cross-sectional frequency distribution					cumulated from bottom (highest ventile in ability)			
ventile in the distribution of actual ability	child and parents not expecting application to college – all schools (1)	child expecting application to college - high school (2)	child expecting application to college - technical school (3)	child expecting application to college - vocational school (4)	Total (5)	child and parents expecting application to college – all schools (6)	child expecting application to college - high school - incidence among applicants (7)	child expecting application to college - technical school - incidence among applicants (8)	child expecting application to college - vocational school - incidence among applicants (9)
1	80.9	4.1	4.3	10.8	100.0	54.9	69.9	22.6	7.4
2	73.8	9.0	7.9	9.3	100.0	56.8	70.8	22.6	6.6
3	69.5	14.0	10.0	6.4	100.0	58.5	71.7	22.5	5.8
4	60.3	19.1	15.2	5.4	100.0	60.2	72.5	22.1	5.4
5	62.1	19.6	10.8	7.5	100.0	61.5	73.4	21.5	5.1
6	56.8	22.5	14.4	6.4	100.0	63.0	74.3	21.2	4.5
7	58.6	24.5	9.3	7.6	100.0	64.4	75.4	20.6	4.0
8	44.7	34.0	16.5	4.8	100.0	66.2	76.2	20.6	3.3
9	50.8	31.3	13.6	4.3	100.0	67.1	77.2	19.9	2.9
10	42.7	39.5	15.1	2.7	100.0	68.7	78.1	19.4	2.5
11	44.6	39.1	14.1	2.2	100.0	**69.9**	**78.8**	**18.8**	**2.3**
12	37.4	41.5	19.8	1.3	100.0	71.5	79.5	18.3	2.2
13	38.4	43.6	15.6	2.4	100.0	72.6	80.9	16.8	2.2
14	33.0	46.8	16.7	3.5	100.0	74.2	82.1	15.8	2.0
15	34.3	52.0	11.4	2.3	100.0	75.4	84.0	14.5	1.6
16	31.0	56.1	11.6	1.4	100.0	77.3	84.8	14.0	1.2
17	27.5	56.7	13.5	2.4	100.0	79.4	85.5	13.4	1.1
18	26.0	65.9	7.6	0.4	100.0	81.7	87.7	11.9	0.4
19	20.2	68.0	11.3	0.5	100.0	85.6	87.1	12.5	0.4
20	8.7	81.0	10.1	0.2	100.0	91.3	88.8	11.1	0.2
Total	45.7	37.8	12.4	4.2	100				

The cumulated share of applicants in the top half of the test distribution would be 70% at the median, but they would reach 35% of the total population if the bottom half were prevented from applying since they would not pass the test. Cumulating the choices of the applicants by track, 79% would be attending high schools, 19% technical schools, and only 2% vocational ones. However, if applications were granted on the basis of applicants' ability "pre-tracking," i.e., based on their residual ability after accounting for their personal and family characteristics, then the shares of admitted students across school tracks would be slightly more equalized, even though high school students would still be substantially more likely to enter tertiary education. In fact, if only applicants in the top 50% of the distribution of residual ability were admitted, this would lead to 76% of successful applications from high schools (a 3% reduction), 2% of successful applications from technical schools (a 6% increase), and 3.6% of successful applications from vocational schools (an increase of 50%) (see table A.7 in the Appendix). A benevolent government that intends to respect students' and families' aspirations and tolerates selective university admission policies would pressure universities to lower the admission threshold. If the policy target were 40% of the total population, according to table 10 (and abstracting from college drop-out), the admission threshold should be lowered to the 8th ventile (since $67.1 \times 0.60 = 40.3$). If the target were 50% of the population, the threshold should be even lower, at the 4th ventile (since $61.5 \times 0.80 = 49.2$), making the admission test almost irrelevant.

4. The effect of testing

We have shown that using standardized tests to decide on admissions to restricted-access bachelor programs gives high school students an advantage relative to those in technical and – especially - vocational tracks. However, our analysis so far has been based on data from INVALSI or PISA, neither of which directly measures students' performance in university admission tests or has information on university outcomes.

We repeatedly tried without success to gain access to the test-taking data from CISIA, the leading Italian test provider.[20] Eventually, we ended up obtaining administrative data on students enrolled in restricted-access bachelor programs at the University of Milan in the academic year 2022/2023. This anonymised dataset contains information on the bachelor program they enrolled in, the type of secondary school they graduated from (classical or scientific high school; other high schools; technical school; vocational school; foreign institutions) and the final marks obtained at the end of secondary school.[21] Table 11 presents descriptive statistics of this sample. This is clearly a selected sample since it contains the applicants that were admitted (first selection) and that actually enrolled (second selection). Unfortunately, the University does not possess information on other applicants, either those who did not pass the admission threshold or those who passed it but eventually chose to enrol in a different university. Nevertheless, these data allow us to study the correlation between observables (and, in particular, the test score)[22] and possible outcomes. Unsurprisingly, most of the admitted and enrolled students are from high schools, but their graduation marks seem undistinguishable from a statistical point of view. On the contrary, High school graduates obtain higher scores and perform better during the initial year of BA courses (more exams, better GPA and lower drop-out rates, i.e. lower rates of non-enrolment in the second year of study). Notice that there

[20] CISIA stands for Consorzio Interuniversitario Sistemi Integrati per l'Accesso (https://www.cisiaonline.it/area-tematica-cisia/home-cisia), an association of 62 Italian universities created in the 90's to coordinate admissions to the engineering schools. They began offering online tests in 2012. In their latest report (Filippi and Falco 2024) they provide the following data: in 2023 263,923 students took a test from CISIA, for a total of 329,274 tests (since 18.8% of the participants took the test at least twice). The most frequently accessed are engineering, economics, psychology and humanities entry tests.

[21] We thank the Rector of the University of Milan (Marina Brambilla) for making the data available to us.

[22] It is important to remind that the admission scores are not strictly comparable across BA programs, since they mix contents in different proportions. However, this is dealt with in regression by using BA program fixed effects.

are 2,660 students (corresponding to 26% of our sample) who did not obtain any ECTS during the first year. Even assuming that all the students who drop out after the first year originate from this group, there is still a 5% of the students who keep on enrolling without passing any exams.

Table 11 – Descriptive statistics – Student enrolled in restricted access BA courses - University of Milan – academic year 2022-23

	high school (clas/sci e)	other high schools	technic al schools	vocatio nal schools	foreign schools	Total	# cases	sd	min	max
secondary school attended	33.41%	37.88%	22.14%	4.72%	1.85%	100.0%	9993			
female	0.54	0.65	0.38	0.54	0.57	0.55	9993	0.50	0	1
graduation marks	82.83	82.06	80.52	81.14	45.79	81.26	9986	14.54	0	100
admission test score	31.90	27.83	23.79	21.12	21.28	27.86	9993	9.10	-5	50
ECTS obtained in the 1st year (if ECTS>0)	57.98	54.76	50.55	42.41	45.53	54.47	7333	26.93	3	194
GPA obtained in the 1st year (if ECTS>0)	25.84	25.36	24.44	23.90	23.94	25.27	7333	2.56	18	30
drop-out	0.18	0.21	0.22	0.32	0.17	0.21	9353	0.41	0	1

We focus on three outcomes: whether they dropped out of the program before entering the second year of study, the number of ECTS obtained during the first year, and the GPA obtained. These data allow us to study whether students' performance is correlated with their performance in the admission tests and whether such a correlation varies across different school tracks. Specifically, we run regressions of the type:

$$y_i = \alpha + \beta ltest_i + \sum_{t=2}^{5} \gamma_t track_{it} + \sum_{t=2}^{5} \delta_t ltest_i \times track_{it} + \theta female_i + \mu_p + u_i$$

Where y_i is, alternatively, a dummy for dropping out of the program, or for students who did not drop out, the number of ECTSs completed, or the GPA of student i; $ltest_i$ is the logarithm of the score obtained in the university admission test, recentered so that it has mean zero in each regression; $track_{it}$ are four dummies denoting the type of secondary school attended (with high school being the reference category), $female_i$ is a dummy that identifies female student; and μ_p are dummies identifying the bachelor program students have enrolled into.

Of particular interest in our research are the estimates of β, which quantify the relationship between the score on admission tests and students' outcomes for high school graduates. We also focus on δ_t, which indicates how this relationship differs for students in other school tracks. These estimates are crucial to understanding the predictive power of admission test scores on future outcomes and how this impact varies across different educational backgrounds.[23]

[23] Cisia (2017) studies the predictive ability of the TIP (*test in presenza*) for students enrolled in the engineering schools using the same outcomes. Using contour plots, it shows that test scores and graduation marks both correlate with

Column (1) of table 12 reports estimated coefficients when the dependent variable is a dummy that identifies students who dropped out of their study program before enrolling in the second year of study. There are no significant differences across school tracks in the probability of dropping out, except for students from vocational schools, who are 9.4 percentage points more likely to drop out than students from high schools. This is a sizable difference since the dropout rate in the whole sample is less than 20%. A higher score on the admission test is associated with a lower dropout probability: a 10% increase in the admission test score leads to a 1.6 p.p. lower dropout probability. The effect is homogeneous across all secondary school backgrounds, except for students holding a foreign degree, for whom the test score has no significant effect on dropout probability.

Column (2) shows results when the dependent variable is the number of ECTSs obtained at the end of the first year of university studies for students who did not drop out. The number of ECTSs obtained at the end of the first year is higher (58 on average) for students from classical and scientific high schools. It is 2.3 points lower for students from other high schools, 4.2 points lower for students from technical schools, and 13.3 lower for students from vocational schools. The score on the admission test is positively correlated with a higher number of ECTSs completed: for students who come from any high school, a 10% increase in the admission test score is associated with 2.6 more CFU completed. However, such a relationship is weaker for technical and, especially, vocational school students. A 10% higher admission test score for these students is associated with an extra 2 and 1.9 CFU, respectively. Finally, in column (3), we show results for GPA at the end of the first year for students who did not drop out, where the GPA is set to zero for students who have acquired no CFUs. These regressions paint a similar picture to those of column (2): not only do we observe the same gradient in terms of secondary school type, but also a 10% higher score on the admission test is associated with a 7.2 higher GPA for high school graduates (the mean GPA across all students is 25.27). Additionally, the association between entry test scores and GPA is lower for graduates of technical and vocational schools. For these students, a 10% higher test score is associated with a 5.5 and 4.7 lower GPA, respectively.

Overall, these results suggest that standardized test scores are a worse predictor of university program performance for students from vocational schools than for students from other secondary school tracks.

outcomes. In our data the rank correlation among the two is relatively low (0.25), suggesting that these signals offer different rankings if used as alternative predictors of initial careers.

Table 12 – University outcomes and test scores

dependent variable:	Dropout	ECTS	GPA
Other high	0.012	-2.331**	-0.703**
	(0.011)	(0.768)	(0.221)
Technical	0.025	-4.155***	-1.417***
	(0.013)	(0.927)	(0.266)
Vocational	0.094***	-13.332***	-4.435***
	(0.027)	(1.863)	(0.535)
Foreign school	0.002	-17.039***	-5.304***
	(0.038)	(2.719)	(0.781)
log test score	-0.164***	26.011***	7.180***
	(0.028)	(1.904)	(0.547)
other high # log test score	0.042	-2.667	-0.718
	(0.032)	(2.168)	(0.623)
technical # log test score	0.050	-5.594*	-1.670*
	(0.035)	(2.341)	(0.673)
vocational # log test score	0.064	-7.096*	-2.472*
	(0.047)	(3.493)	(1.004)
foreign # log test score	0.239***	-21.535***	-4.848***
	(0.043)	(3.475)	(0.998)
female	0.015	4.343***	1.442***
	(0.009)	(0.667)	(0.192)
Obs	9.346	7.409	7.409

The table reports regressions results from regressions where the dependent variable is, alternatively, a dummy for dropping out of the bachelor program after the first year (column 1), the number of ECTS obtained at the end of the first year for students who have not dropped out (column 2), and the GPA at the end of the first year for students who have not dropped out (column 3). All regressions include fixed effects for the BA program they are enrolled in. Sample: students enrolled in the first year of restricted access programs at the University of Milan in the academic year 2022/2023. Heteroscedasticity-robust standard errors in column 1. * p<0.05, ** p<0.01, *** p<0.001

5. Conclusions and policy suggestions

This paper examines the impact of secondary school tracking on the transition to tertiary education of Italian students. We start by examining longitudinal data on the cohort of students born in the year 2000, observed in junior high school before tracking choice in 2014, and for those who survived at the end of 5 years of upper secondary education in 2019. We use INVALSI data that contain measures of competences (literacy and numeracy) as well as information on family background. We show that track assignment implies a different evolution of competences during secondary education: apart from non-random attrition (those who enrol in shorter courses or drop-out are negatively selected), "surviving" students in vocational schools lose positions in the distribution of ability vis a vis students in high schools who gain ranks. We argue that, other things constant, differences in tracks (in terms of teaching contents and teacher selection) are detrimental for students who are already weaker on learning grounds.

Since INVALSI data do not provide information on students' intentions to proceed further to tertiary education, we resort to another source of information, which is the PISA survey conducted in 2018 among 15-year-old Italian students. In this case, we possess analogue information on student competences (literacy, numeracy, and science) and family background, but we can also measure aspirations to college from students and separately from their parents. Even though the intersection of college aspirations between students and their families may represent a rough proxy for future decisions, we can study the role of measured ability and family background in forming these aspirations. We show that tracks affect college aspirations since students in vocational tracks, other things constant (including ability net of family background), are less likely to apply for college. By studying the distribution of intention to apply across tracks over the percentiles of ability, we can also simulate what could be the likely effect of setting a threshold of ability in college admission. Consequently, we provide evidence that the existence of admission tests to college makes the life of vocational students even harder since they lose positions in the ability distribution and have lower aspirations but are admitted on an equal basis of test scores.

In a partial equilibrium analysis, the choice of selective admissions by universities pays back in terms of signalling in the tertiary education market since it makes them more attractive for high-ability students who aim to self-select with similar peers. Bratti et al. (2024) study the switch from open access to selective admissions (19.2% of programs undertake this change in the period 2010-2022) and from selective admissions to open access (15.7% undertake this change over the same period). They conclude that selective access reduces the number of students, improves average student quality at entrance, and also students' university performance. However, they do not consider the aggregate consequences of these transitions. Admission tests, when adopted by universities intended to switch to selective admissions, either set a very low threshold or hinder the ability of the country to make the Lisbon 2030 target of reaching 40% of the young population with tertiary education.

Finally, we focus on the usefulness of admission tests as predictors of academic career. We make use of selective admissions in one large university in Milan to study the correlation of three outcomes (probability of drop-out during the first year, number of ECTS obtained, and GPA, both at the end of the first year). We find that the admission score is correlated to these outcomes. However, the admission score has a weaker correlation for students from vocational schools than those from other tracks, possibly because students from vocational schools have other interior strengths that help them navigate the system despite discouragement and lack of information. So even when admitted to selective courses, the small minority of students from vocational schools does not obtain recognition for their actual efforts. Once they succeed in graduating from college, they still suffer the "scar" of vocational education, as already found in the literature. Agarwal et al. (2021) estimate the returns to college by secondary school type attended in Italy, finding that returns are lower for vocational than for academic high school graduates in terms of employment probability (−4%), hourly wages (−3.1%), and the probability of finding the first job less than 1 year after graduation (−9.2%).[24]

We have provided additional new evidence that students attending vocational schools are in a disadvantaged position, even when they start with the same level of potential as students attending high schools: their competences grow less, their aspirations are contained, and they end up underrepresented among the students admitted to universities, especially under selective admissions. If we were to improve the equity in accessing tertiary education[25] we cannot abstract from students attending vocational education. There are different policy options that are not mutually exclusive, even though they require different time horizons. The most radical one would be de-tracking secondary education (following the comprehensive movement that crossed Europe fifty years ago), replacing current curricula with optional majors and minors, such that students can compose their portfolio of skills according to their inclinations and not according to the school orientation chosen by their parents and children when they were 14-year-old. A less radical reform, undertaken in the 90's, would be to extend the comprehensive junior high school until grade 10, postponing the track choice by two years and ensuring the same teaching contents to everyone. However, these choices are hotly debated since different political orientations support different alternatives. A third alternative would be revising the vocational education teaching curricula, giving more space to theoretical approaches and thus making students more adaptable to a changing world.
If previous options require Ministerial involvement and parliamentary actions, universities could undertake actions at the local level to encourage applications from students in vocational tracks. They could design orientation modules stressing the complementarities of some university programs with subjects taught in this track. But if universities intend to attract the best students from vocational tracks who are discouraged by their lower level in admission tests, they could either introduce different admission thresholds by track of origin or adopt compensatory scores in admission for students from vocational schools in recognition of the cumulated disadvantage associated with such attendance. These solutions raise equity issues, and universities adopting one of these compensatory measures would likely encounter the opposition of students (and their voicey families) who would end up excluded despite a higher admission score.
Another alternative would be the replacement of admission tests with the graduation marks obtained at the exit of secondary education, or the test score measured by INVALSI during 13th grade. Both

[24] The wage penalty associated with high school vocational education is lower when they consider college majors such as engineering and economics and business, for which the complementarity with the vocational skills developed in high school is presumably higher.
[25] Let us remind that SDG 4 (Sustainable Development Goals proposed by United Nations) calls for "*Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all*".

measures have analogous predictive power on future careers but have the advantage of being universally available, thus removing the informational (and economic) barrier of test taking. Thus, a student interested in tertiary education could observe the admission mark (or score) for each selective admission program in the previous year and decide whether to apply or not, without the uncertainty (and the cost) of test taking.[26]

A related policy action involves investing resources in non-academic tertiary education as a pathway for career progression for students enrolled in secondary vocational education. Available evidence (Turri 2023) suggests that this option is predominantly pursued by students from technical tracks, indicating that students from vocational education do not receive equal opportunities in this area either.

The crucial social issue is whether students in vocational tracks voluntarily chose a simpler (and often shorter) path based on their fully informed preferences (e.g., higher costs of academic effort or a stronger preference for leisure), or if they were willingly or unwillingly directed into this track by external factors such as family financial constraints, misguided guidance from teachers, school proximity, or similar influences. While it is undisputed that these students tend to be academically weaker, our results suggest that their prospects might have been different if the segregation into vocational education had not been so detrimental and/or if university admission policies had been less selective toward them. The social composition of this student group—where non-citizen students make up nearly half of the attendees—raises concerns that targeted actions are necessary to address and balance social disadvantages.

[26] Just to give an idea of the business of test administration, if we multiply the number of tests undertaken at CISIA last year (329.274) by the individual cost (30 euros), we obtain almost 10 million euros that are disbursed by applicants to colleges.

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Appendix

Table A.1 – Population, graduates and enrolled in universities – Italy – year 2022

population aged 19 in year 2022	568 972
secondary school graduates - regular students - aged 19 in 2022	383 099
secondary school graduates - repeating students - older than 19 in 2022	125 375
secondary school graduates - in 2022	508 474
university enrolment (1st year) - 19-year old in 2022	225 819
university enrolment (1st year) - older tan 19 in 2022	76 693
university enrolment (1st year) in 2022	302 512
secondary school graduates - high schools (licei) - in 2022	255 458
secondary school graduates - technical schools (ist.tecnici) - in 2022	161 264
secondary school graduates - vocational schools (ist.professionali) - in 2022	91 752
secondary school graduates - in 2022	508 474
university enrolment (1st year) - graduate from high schools - in 2022	195 595
university enrolment (1st year) - graduate from technical schools - in 2022	74 557
university enrolment (1st year) - graduate from vocational schools - in 2022	22 602
university enrolment (1st year) - graduate from not available - in 2022	9 758
university enrolment (1st year) - in 2022	302 512

Source: ANVUR 2023, figures 1.2.11-1.2.12

Table A.2 – Probability of absence of matching – linear probability model

dependent variable:	1 not matched in grade 8	2 not matched in grade 8	3 not matched in grade 13	4 not matched in grade 13	5 not matched in grade 13
female	-0.088***	-0.052***	-0.029***	-0.024***	-0.019***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
birth year < 1997	0.126***	0.177***	0.830***	0.978***	0.978***
	[0.047]	[0.049]	[0.023]	[0.009]	[0.010]
birth year = 1998	0.097**	0.142***	0.943***	0.958***	0.956***
	[0.046]	[0.049]	[0.023]	[0.008]	[0.009]
birth year = 1999	0.03	0.074	0.926***	0.863***	0.861***
	[0.046]	[0.048]	[0.023]	[0.008]	[0.009]
birth year = 2000	-0.250***	-0.159***	0.187***	0.100***	0.101***
	[0.046]	[0.048]	[0.023]	[0.008]	[0.009]
birth year = 2001	-0.261***	-0.170***	0.176***	0.101***	0.101***
	[0.046]	[0.048]	[0.023]	[0.008]	[0.009]
birth year > 2001	-0.144**	-0.012	0.574***	0.611***	0.608***
	[0.066]	[0.069]	[0.053]	[0.060]	[0.064]
highest parental education=primary	0.158***	0.127***			
	[0.006]	[0.006]			
highest parental education=lower secondary	0.058***	0.034***			
	[0.002]	[0.002]			
highest parental education=vocational	0.002	-0.011***			
	[0.003]	[0.003]			
highest parental education=high school	-0.066***	-0.061***			
	[0.002]	[0.002]			
highest parental education=non academic tertiary	-0.054***	-0.052***			
	[0.004]	[0.004]			
highest parental education=BA or MA	-0.087***	-0.064***			
	[0.002]	[0.002]			
ESCS (cultural-socio-economic conditions)				0.004***	0.004***
				[0.001]	[0.001]
native	-0.081***	-0.085***	-0.305***	-0.117***	-0.124***
	[0.016]	[0.018]	[0.003]	[0.010]	[0.011]
foreign born to foreign parents	0.006	0.011	-0.475***	-0.293***	-0.302***
	[0.017]	[0.018]	[0.005]	[0.011]	[0.011]
born inland to foreign parents	0.043***	0.030*	-0.316***	-0.126***	-0.135***
	[0.017]	[0.018]	[0.004]	[0.010]	[0.011]
macroregion: North-East	-0.034***	-0.030***	-0.025***	-0.022***	-0.022***
	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
macroregion: Center	-0.069***	-0.080***	-0.031***	-0.025***	-0.024***
	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]
macroregion: South	-0.088***	-0.096***	-0.063***	-0.053***	-0.052***
	[0.002]	[0.002]	[0.001]	[0.001]	[0.002]
macroregion: Islands	-0.010***	-0.027***	-0.073***	-0.064***	-0.063***
	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]
Literacy test score	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Numeracy test score	-0.002***	-0.001***	-0.001***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Grade in Italian (oral)		-0.059***			-0.005***
		[0.001]			[0.001]
Grade in Mathematics (oral)		-0.056***			-0.002***
		[0.001]			[0.000]
Constant	1.504***	1.714***	0.494***	0.355***	0.387***
	[0.046]	[0.048]	[0.023]	[0.013]	[0.014]
Observations	512 876	451 572	454 265	317 450	295 947
R^2	0.226	0.271	0.584	0.567	0.567

Robust standard errors in parentheses - *** p<0.01, ** p<0.05, * p<0.1 –
Except than in the case of macro-regions, the excluded case is given by the missing observation case

Table A.3 – Probability of track allocation – ordered probit model

	1	2	3	4
dependent variable: track allocation (%)				
1.high schools (classico/scientifico)	*29.54*	*29.40*	*29.40*	*29.40*
2.other high schools	*30.28*	*30.22*	*30.22*	*30.22*
3.technical schools	*29.02*	*29.14*	*29.14*	*29.14*
4.vocational schools	*11.17*	*11.23*	*11.23*	*11.23*
female	-0.106***	-0.008	-0.054***	-0.056***
	[0.004]	[0.005]	[0.005]	[0.005]
birth year < 1997	0.364	0.255	0.193	0.213
	[0.260]	[0.292]	[0.292]	[0.292]
birth year = 1998	0.344	0.226	0.181	0.189
	[0.215]	[0.248]	[0.247]	[0.248]
birth year = 1999	0.169	0.069	0.056	0.064
	[0.211]	[0.243]	[0.243]	[0.244]
birth year = 2000	-0.463**	-0.303	-0.287	-0.288
	[0.211]	[0.243]	[0.243]	[0.243]
birth year = 2001	-0.534**	-0.399	-0.382	-0.364
	[0.211]	[0.243]	[0.243]	[0.243]
birth year > 2001	-0.27	-0.051	-0.06	-0.063
	[0.292]	[0.326]	[0.326]	[0.327]
native	-0.113	0.012	0.022	0.015
	[0.078]	[0.087]	[0.087]	[0.087]
foreign born to foreign parents	-0.02	0.07	0.042	0.033
	[0.079]	[0.088]	[0.088]	[0.088]
born inland to foreign parents	-0.028	-0.008	-0.02	-0.048
	[0.079]	[0.088]	[0.088]	[0.088]
highest parental education=primary	0.588***	0.443***	0.422***	0.388***
	[0.030]	[0.033]	[0.033]	[0.033]
highest parental education=lower secondary	0.390***	0.297***	0.286***	0.230***
	[0.008]	[0.009]	[0.009]	[0.009]
highest parental education=vocational	0.314***	0.245***	0.233***	0.175***
	[0.010]	[0.011]	[0.011]	[0.011]
highest parental education=high school	0.033***	0.043***	0.044***	0.005
	[0.006]	[0.007]	[0.007]	[0.007]
highest parental education=non academic tertiary	-0.074***	-0.077***	-0.073***	-0.117***
	[0.016]	[0.017]	[0.017]	[0.017]
highest parental education=BA or MA	-0.339***	-0.262***	-0.240***	-0.270***
	[0.008]	[0.009]	[0.009]	[0.009]
ESCS (cultural-socio-economic conditions)	-0.253***	-0.206***	-0.197***	-0.195***
	[0.003]	[0.003]	[0.003]	[0.003]
macroregion: North-East	0.112***	0.116***	0.109***	-0.176***
	[0.006]	[0.007]	[0.007]	[0.003]
macroregion: Center	-0.086***	-0.185***	-0.196***	-0.204***
	[0.007]	[0.007]	[0.007]	[0.003]
macroregion: South	-0.098***	-0.185***	-0.197***	-0.003***
	[0.006]	[0.007]	[0.007]	[0.000]
macroregion: Islands	-0.080***	-0.132***	-0.126***	-0.004***
	[0.009]	[0.010]	[0.010]	[0.000]
Marks in Italian (oral)		-0.227***	-0.171***	-5.206***
		[0.003]	[0.003]	[0.245]
Marks in Mathematics (oral)		-0.262***	-0.201***	-4.195***
		[0.003]	[0.003]	[0.245]
Literacy test score			-0.003***	-2.938***
			[0.000]	[0.245]
Numeracy test score			-0.004***	-0.176***
			[0.000]	[0.003]
/cut1	-1.243***	-4.611***	-5.201***	-0.204***
	[0.207]	[0.243]	[0.243]	[0.003]
/cut2	-0.374*	-3.625***	-4.200***	-0.003***
	[0.207]	[0.243]	[0.243]	[0.000]
/cut3	0.712***	-2.393***	-2.952***	-0.004***
	[0.207]	[0.243]	[0.243]	[0.000]
Observations	253786	224138	224138	224138
Pseudo R^2	0.064	0.142	0.151	0.156

Except than in the case of macro-regions, the excluded case is given by the missing observation case

Figure A.1 – Cumulative effect of tracking, by competences

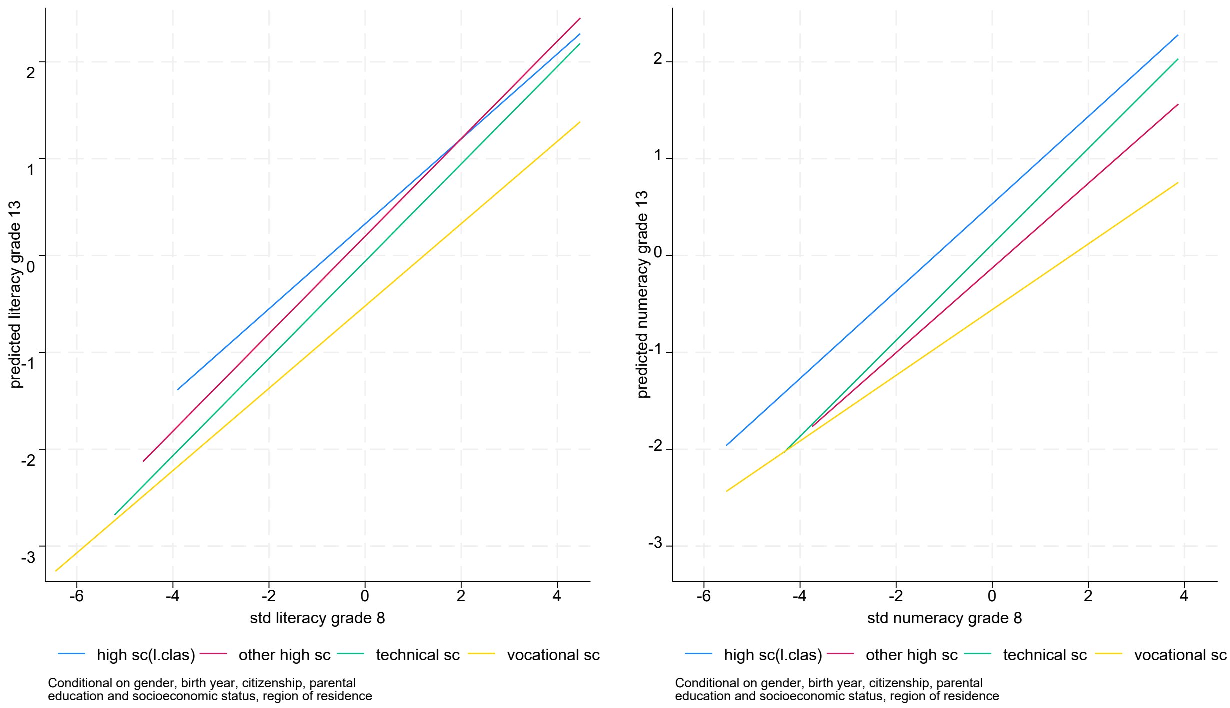

Table A.4 – Additional descriptive statistics – Italy – PISA 2018

citizenship	high school	technical schools	vocational schools	Total	# cases
Native	93.99	88.57	84.25	90.47	10207
First-Generation	2.50	4.73	7.75	4.19	473
Second-Generation	3.52	6.70	7.99	5.34	602
Total	100.00	100.00	100.00	100.00	11282
books at home	**high school**	**technical schools**	**vocational schools**	**Total**	**# cases**
0-10	5.04	14.31	27.07	12.17	1385
11-25	12.72	24.79	23.86	18.52	2108
26-100	28.69	31.13	26.31	28.94	3295
101-200	22.63	17.07	12.11	18.89	2151
201-500	20.08	8.46	5.84	13.80	1572
More than 500	10.84	4.23	4.81	7.68	874
Total	100.00	100.00	100.00	100.00	11385
highest parental education	**high school**	**technical schools**	**vocational schools**	**Total**	**# cases**
None	0.00	0.18	0.40	0.14	16
ISCED 1	0.25	0.35	1.29	0.48	55
ISCED 2	9.16	19.80	25.10	15.49	1761
ISCED 3B-3C	3.41	4.13	3.86	3.71	422
ISCED 3A-4	35.83	39.10	35.70	36.77	4179
ISCED 5B	5.89	7.34	8.75	6.89	783
ISCED 5A-6	45.47	29.11	24.90	36.52	4150
Total	100.00	100.00	100.00	100.00	11366

Table A.5 – Correlates of ability (average of numeracy/literacy/science) – Italy – PISA 2018

female	-0.033
	[0.017]*
age	0.192
	[0.030]***
First generation immigrant	-0.143
	[0.045]***
Second generation immigrant	-0.036
	[0.041]
Index of economic, social and cultural status	0.207
	[0.032]***
11-25 books at home	0.254
	[0.035]***
26-100 books at home	0.524
	[0.033]***
101-200 books at home	0.685
	[0.036]***
201-500 books at home	0.817
	[0.039]***
more than 500 books at home	0.765
	[0.045]***
Index highest parental occupational status (HISEI)	0.006
	[0.001]***
1. Highest Education of parents: ISCED 1	-0.068
	[0.272]
2. Highest Education of parents: ISCED 2	0.14
	[0.241]
3. Highest Education of parents: ISCED 3B-3C	0.254
	[0.247]
4. Highest Education of parents: ISCED 3A-4	0.257
	[0.244]
5. Highest Education of parents: ISCED 5B	-0.217
	[0.249]
6. Highest Education of parents: ISCED 5A-6	-0.101
	[0.249]
Constant	-3.781
	[0.540]***
Observations	10779
R^2	0.19

Standard errors in brackets - * significant at 10%; ** significant at 5%; *** significant at 1%

Table A.6 – Probability of enrolling in HE (probit model) – Italy – PISA 2018

Dependent variable: child and parent expect enrolment in HE	0.520	0.520
	(1)	(2)
female	0.367	0.407
	[0.026]***	[0.027]***
age	0.086	0.012
	[0.045]*	[0.046]
First generation immigrant	-0.024	0.039
	[0.070]	[0.072]
Second generation immigrant	0.08	0.109
	[0.062]	[0.064]*
Index of economic, social and cultural status	0.624	0.598
	[0.050]***	[0.051]***
11-25 books at home	0.214	0.126
	[0.054]***	[0.055]**
26-100 books at home	0.356	0.163
	[0.051]***	[0.052]***
101-200 books at home	0.441	0.192
	[0.056]***	[0.058]***
201-500 books at home	0.507	0.204
	[0.061]***	[0.063]***
more than 500 books at home	0.479	0.199
	[0.069]***	[0.072]***
Index highest parental occupational status (HISEI)	-0.003	-0.006
	[0.001]**	[0.001]***
1. Highest Education of parents: ISCED 1	-0.794	-0.854
	[0.464]*	[0.482]*
2. Highest Education of parents: ISCED 2	-1.106	-1.235
	[0.408]***	[0.424]***
3. Highest Education of parents: ISCED 3B-3C	-1.413	-1.616
	[0.416]***	[0.432]***
4. Highest Education of parents: ISCED 3A-4	-1.297	-1.489
	[0.412]***	[0.428]***
5. Highest Education of parents: ISCED 5B	-1.688	-1.72
	[0.418]***	[0.435]***
6. Highest Education of parents: ISCED 5A-6	-1.629	-1.711
	[0.420]***	[0.436]***
standardised ability (mean of literacy+numeracy+science)		0.399
		[0.016]***
Constant	-0.151	1.419
	[0.840]	[0.865]
Observations	10284	10284
Pseudo R^2	0.097	0.145

Standard errors in brackets - * significant at 10%; ** significant at 5%; *** significant at 1%

Table A.7 – Share of students that would be admitted to college by different level of **residual ability** (weighed) – Italy – PISA 2018

	cross-sectional frequency distribution					cumulated from bottom (highest ventile in ability)			
ventile in the distribution of actual ability	child and parents not expecting application to college – all schools (1)	child expecting application to college - high school (2)	child expecting application to college - technical school (3)	child expecting application to college - vocational school (4)	Total (5)	child and parents expecting application to college – all schools (6)	child expecting application to college - high school - incidence among applicants (7)	child expecting application to college - technical school - incidence among applicants (8)	child expecting application to college - vocational school - incidence among applicants (9)
1	69.6	13.1	7.8	9.6	100.0	56.4	70.5	22.5	7.0
2	62.9	19.4	11.2	6.5	100.0	57.8	71.3	22.4	6.3
3	52.9	29.9	12.7	4.5	100.0	59.0	72.0	22.1	5.9
4	53.1	26.9	12.5	7.5	100.0	59.7	72.3	21.9	5.8
5	55.0	26.2	12.4	6.3	100.0	60.5	73.1	21.6	5.3
6	53.0	28.7	14.6	3.8	100.0	61.5	73.8	21.4	4.9
7	46.7	37.2	11.6	4.6	100.0	62.5	74.5	20.8	4.7
8	46.4	37.5	9.9	6.3	100.0	63.2	74.8	20.8	4.4
9	49.4	35.1	11.6	4.0	100.0	64.0	75.1	20.9	3.9
10	51.3	31.7	14.9	2.1	100.0	65.2	75.5	20.8	3.7
11	41.7	40.3	15.6	2.5	100.0	**66.9**	**76.3**	**20.1**	**3.6**
12	39.6	43.5	12.1	4.8	100.0	67.8	77.0	19.5	3.6
13	38.0	45.7	10.8	5.6	100.0	68.8	77.5	19.4	3.1
14	34.3	46.9	16.0	2.8	100.0	69.8	78.0	19.6	2.3
15	35.2	47.7	13.6	3.6	100.0	70.4	79.1	18.9	2.0
16	32.8	53.1	13.3	0.9	100.0	71.5	80.1	18.5	1.4
17	32.7	52.1	14.6	0.7	100.0	72.6	80.3	18.2	1.4
18	31.1	55.1	12.6	1.3	100.0	74.4	81.2	17.2	1.6
19	27.6	57.0	13.8	1.6	100.0	77.1	81.8	16.7	1.4
20	18.1	69.3	12.0	0.6	100.0	81.9	84.6	14.7	0.7
Total	43.98	39.36	12.64	4.03	100				