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Introduction to the thesis

Understanding the determinants of students' educational trajectories is a central objective in the Economics of Education. Educational inequalities emerge through a cumulative process that begins early in life and unfolds through the interaction between skill formation, academic achievement, and educational decision-making (Heckman, 2007; Cunha and Heckman, 2007, 2008). Educational sorting constitutes one of the key mechanisms through which human capital is accumulated, and among the educational transitions students experience, the choice of the school track is particularly consequential because it determines exposure to different curricula, shapes subsequent educational opportunities, and affects labour-market prospects (Hanushek and Wößmann, 2006; Hanushek and Woessmann, 2011). Understanding the determinants of educational choices is therefore essential for explaining how inequalities develop and persist over time.

While cognitive skills are well-established predictors of educational success, a large literature shows that non-cognitive skills and related socio-emotional dimensions—such as motivation, self-perceptions, self-efficacy, and emotional responses to evaluation—also play an important role in shaping academic and later-life outcomes (Heckman et al., 2006; Almlund et al., 2011; Heckman and Kautz, 2012). More recent evidence suggests that educational choices are influenced not only by cognitive achievement but also by broader individual characteristics, including foundational cognitive skills, non-cognitive skills, competitiveness, and beliefs about one's relative academic performance (Buser et al., 2014, 2017; Lopez et al., 2024; Owen, 2023; Zhang et al., 2025). Taken together, this literature highlights that educational trajectories result from the interaction among students' skills, expectations, and the institutional environments in which educational decisions are made (Carlana and Corno, 2024; Dustmann and Schönberg, 2017).

These mechanisms are particularly relevant for understanding gender differences in education. Across educational systems, girls and boys exhibit systematic differences in academic performance, confidence, educational aspirations, competitiveness, and field-of-study choices (Else-Quest et al., 2010; Breda and Napp, 2019; Bordalo et al., 2019; Buser et al., 2014, 2017). Such disparities often emerge before major educational decisions are made and cannot be entirely accounted for by measured achievement alone. The expectancy-value framework further suggests that educational choices depend not only on prior performance but also on beliefs about competence, subjective task values, and domain-specific preferences (Eccles, 1983; Wigfield and Eccles, 2000). Understanding whether early non-cognitive characteristics contribute to the formation of educational trajectories is therefore crucial for explaining gendered educational sorting and the persistence of educational inequalities.

This dissertation investigates the relationship between non-cognitive skills, gender differences, academic achievement, and educational trajectories within the Italian educational system using longitudinal administrative data. Italy provides a particularly informative setting because students choose among differentiated upper-secondary pathways immediately after completing a common lower-secondary curriculum, with no binding admission requirements for academically oriented schools (Contini and Scagni, 2011; Angerer et al., 2023). Previous research shows that track allocation is strongly associated with family socioeconomic background and prior academic achievement, and that the organisation of secondary-school tracking contributes to the persistence of educational inequalities (Contini and Scagni, 2011; Brunello and Checchi, 2007; Dustmann and Schönberg, 2017). More recent evidence also highlights the importance of students' preferences and beliefs: experimentally elicited patience predicts enrolment in academic tracks, while experimentally activating perceived parental recommendations shifts girls' educational choices away from mathematics and towards literature (Angerer et al., 2023; Carlana and Corno, 2024). Together, this literature suggests that educational sorting reflects the joint influence of family background, academic achievement, cognitive and non-cognitive skills, beliefs, and institutional features.

The availability of administrative data collected through INVALSI assessments enables tracking students across multiple educational stages and linking early achievement, attitudes toward studying, and

test-related anxiety to later educational outcomes. At the same time, the use of such data requires careful attention to data harmonisation, measurement validity, and the integration of different administrative sources. This is particularly important when using self-reported non-cognitive measures, which may be affected by reporting bias, reference-group effects, and construct validity concerns (Duckworth and Yeager, 2015; Heckman and Kautz, 2012).

This work pursues three main objectives. First, it examines whether subject-specific attitudes and test anxiety measured during primary school are associated with academic achievement across lower- and upper-secondary education, with particular attention to gender differences. Second, it investigates whether the domain-specific attitudes are related to students' educational sorting, specifically track choices at the transition to upper-secondary education. Third, it documents the evolution of Italian educational administrative data and discusses their potential and limitations for longitudinal research. As documented in Chapter 3, the systematic collection of non-cognitive measures within INVALSI questionnaires was largely confined to the 2013/14 and 2014/15 survey waves at grade 5, which is why the analyses in Chapters 1 and 2 are based on the cohort of students observed in grade 5 in 2013/14.

The dissertation contributes to the literature along each of these lines. First, it shows that attitudes towards mathematics and literacy are already largely distinct at the end of primary school: they are almost uncorrelated with each other, unlike achievement in the two subjects, and display opposite gender gaps. These early attitudes predict later achievement in the corresponding subject, net of prior achievement and family background, and this association persists, though attenuating, through the end of upper-secondary school. Gender differences in achievement operate mainly through levels, while differences in the returns to attitudes emerge only later in adolescence; test-related anxiety, in turn, is associated with a performance penalty that is largest when the assessment carries higher stakes. Second, it contributes to the literature on educational sorting by examining whether early attitudes help explain track choices over and above the standard predictors of tracking. Third, it supports ongoing efforts to strengthen the use of administrative data for educational research in Italy.

The dissertation is organised in three chapters, each addressing one of these objectives: Chapter 1 studies achievement, Chapter 2 track choice, and Chapter 3 the underlying data infrastructure.

Taken together, these results contribute to a broader understanding of how educational trajectories are formed and how early non-cognitive characteristics are associated with educational inequality. By combining evidence on achievement formation, educational sorting, gender differences, and educational data infrastructures, the dissertation aims to advance both the substantive and methodological foundations of longitudinal research in the Economics of Education.

Chapter 1

Do Early Non-Cognitive Skills Predict Achievement? Domain-Specificity and Gender along the School Career

1.1 Introduction

Cognitive and non-cognitive skills jointly shape the accumulation of human capital and its subsequent returns in schooling and in the labour market. A large body of work documents that measured cognitive ability predicts educational attainment, wages, and labour force participation, while a more recent strand of research in the economics of skill formation shows that non-cognitive traits (motivation, self-efficacy, persistence, self-regulation, and emotional responses to evaluative environments) play an independent and quantitatively comparable role (Cunha and Heckman, 2008; Heckman et al., 2006; Heckman and Kautz, 2012). Within this framework, subject-specific self-beliefs have attracted particular attention because they are systematically gendered: girls tend to underestimate their mathematical ability relative to boys of equal objective performance, with consequences for achievement and field-of-study choice (Breda and Napp, 2019; Carlana, 2019). Whether and how these early attitudes shape subsequent academic trajectories, how their predictive content varies across domains and along the school career, and whether it differs by gender, are questions that remain relatively unexplored.

Research on academic self-concept documents a regularity that motivates the measurement choice made in this chapter. Students judge their ability in a subject partly by comparing themselves with their classmates and partly by comparing their own performance across subjects, and because the two comparisons may work in opposite directions, beliefs about ability in different domains turn out far less correlated than performance in those domains (Marsh, 1986; Möller and Marsh, 2013). Across 69 datasets and some 125,000 students, the meta-analytic estimates are 0.67 for the correlation between mathematics and verbal achievement and 0.10 for the correlation between the corresponding self-concepts (Möller et al., 2009), a pattern our data reproduce closely. The same comparisons shape not only what students believe about their ability but also the value they attach to each subject, and hence how they allocate effort between subjects (Wigfield and Eccles, 2000; Wigfield et al., 2020).

The distinction between domains matters most where gender is concerned. Girls' educational choices respond to their standing in mathematics relative to their own performance in verbal domains rather than to their absolute standing (Breda and Napp, 2019), and the gender gap in intentions to continue with mathematics widens with mathematics performance (Breda et al., 2023). Among students of equally strong mathematical ability, moreover, those who are also verbally strong, a disproportionately female group, are markedly less likely to enter a STEM occupation than those whose verbal skills are more moderate (Wang et al., 2013). Whether an early preference for one subject translates into disinvestment from the other also depends on the price of disinvesting, which is gendered where families and teachers hold stereotyped beliefs about who is suited to mathematics (Mechtenberg, 2009; Carlana, 2019; Carlana and Corno, 2024). Each of these mechanisms operates on the difference between subjects, and a measure that averages over subjects leaves no trace of it.

The battery administered at grade 5 measures motivation and self-efficacy separately for mathematics and for literacy. We use that structure to construct two domain-specific indices, each combining both components within its own domain, rather than a single general measure of non-cognitive skill.¹ De Paola and Skatova (2024) study the same cohort with general constructs and establish that non-cognitive skills predict later achievement; our design complements theirs, asking whether the variation that separates the two domains carries information a general measure cannot recover.

In this paper, we combine three ingredients that are rarely observed jointly and that together allow us to address these questions: valid measures of non-cognitive traits collected before major educational transitions, longitudinal test-score data on achievement across grades, and a sample size that allows precise estimation of heterogeneous patterns by subject and gender. We exploit longitudinal, population-level administrative records from the Italian National Institute for the Evaluation of the Education System (INVALSI), following the cohort of students observed in grade 5 during the school year 2013–14 through grade 8 in 2016–17, grade 10 in 2018–19, and grade 13 in 2021–22. Standardised mathematics and literacy test scores are available at every wave, and the grade-5 questionnaire contains an extensive battery of items on subject-specific motivation, self-efficacy, and test anxiety that is not replicated in later waves.² From this battery we construct, via principal component analysis, three validated indices: a Mathematics Attitude Index, a Literacy Attitude Index, and a Test Anxiety Index.³

We ask three related questions. First, do subject-specific non-cognitive traits measured at the end of primary school predict subsequent academic achievement, conditional on prior cognitive ability? Second,

¹The same structure, self-efficacy and intrinsic motivation measured separately for mathematics and for reading, is employed by Fan and Williams (2018) on United States data, with self-efficacy items adapted from PISA and modified to be subject-specific rather than general.

²See Chapter 3 for more details on INVALSI data availability.

³See Duckworth and Yeager (2015) and Heckman and Kautz (2013) for validation practice in the economics of skill formation.

is this predictive content domain-specific, in the sense that an attitude towards one subject predicts achievement in that subject in particular rather than reflecting a general academic disposition, and how does it evolve as students progress through lower and upper secondary school? Third, how do these relationships differ by gender?

The Italian institutional setting is well-suited to address these questions. Class composition at school entry is governed by pedagogical equivalence criteria that constrain within-school sorting (Carlana, 2019), which supports the use of primary-school class fixed effects as a meaningful control for unobserved peer and teacher inputs. Moreover, the three follow-up waves differ in their evaluative stakes: grade 8 is high-stakes, as the INVALSI score contributes to the final lower-secondary exit grade, while grades 10 and 13 can be considered low-stakes. This contrast helps interpret the role of early test anxiety (Putwain et al., 2022). Throughout the analysis, subject-specific attitudes constitute our primary object of interest. The Test Anxiety Index plays a complementary role: it captures a non-cognitive trait that is relevant in the context of standardised assessments and is therefore included to absorb a potentially confounding source of within-subject performance variation.

Our empirical strategy exploits the temporal ordering between the grade-5 measures of non-cognitive traits and the subsequent test-score outcomes. We estimate a sequence of value-added specifications in which achievement at grades 8, 10, and 13 is regressed on the grade-5 Attitude indices and the Test Anxiety Index, controlling for prior test scores at each preceding wave, for a rich set of grade-5 individual and family background characteristics (ESCS index, kindergarten attendance, immigrant status, and enrolment timing), and for primary-school class fixed effects. Gender heterogeneity is allowed for through interactions of each index with a female indicator.

The temporal gap between the measurement of non-cognitive traits in grade 5 and the realisation of outcomes in grades 8, 10, and 13 significantly mitigates concerns about reverse causality, since later achievement cannot mechanically determine attitudes recorded three to eight years earlier. The temporal ordering, however, is not sufficient on its own: grade-5 attitudes may themselves reflect cognitive ability and academic performance accumulated during the first four years of primary school, so that an unconditional association between grade-5 attitudes and later achievement could partly capture the persistence of predetermined ability rather than the predictive content of non-cognitive traits. To address this concern, we condition on the grade-5 INVALSI score in the corresponding domain, which absorbs the cognitive component of attitudes that is predetermined at the moment of measurement (De Paola and Skatova, 2024).

We adopt primary-school class fixed effects as our baseline specification, since the educational inputs most likely to confound the attitude–achievement relationship (teacher quality, peer composition, and classroom pedagogical practices) operate at the class rather than at the school level, as multilevel analyses of INVALSI data confirm (Masci et al., 2016). Following De Paola and Skatova (2024), we exclude secondary-school fixed effects, since the choice of secondary school is itself plausibly affected by grade-5 non-cognitive traits and conditioning on it would constitute a “bad control” (Angrist and Pischke, 2009).

Our research design does not deliver causal estimates in a strict sense; nevertheless, the combination of predetermined covariates, primary-school class fixed effects, and a full set of lagged cognitive controls substantially limits the scope for confounding and supports an informative description of the association between early non-cognitive dispositions and later academic performance.

Four main findings emerge from the empirical analysis. First, subject-specific attitudes at age ten are strong predictors of later achievement in the corresponding domain, net of prior test scores, individual and family background, and primary-school class fixed effects. In the preferred specification, a one-standard-deviation (SD) increase in the Mathematics Attitude Index is associated with an increase of 10.6% of a SD in mathematics achievement at grade 8, 8.4% at grade 10, and 5.4% at grade 13; the analogous estimates for literacy are 4.4%, 3.5%, and 2.2% of a SD. The predictive content is therefore systematically larger in mathematics than in literacy.

Second, the predictive content of grade-5 attitudes attenuates monotonically across grades in both subjects. This pattern is consistent with the cumulative role of subsequent learning, institutional sorting into tracks, and exposure to new peer and teacher environments along the educational trajectory (Almlund et al., 2011; Cunha and Heckman, 2008). In addition, the grade-13 wave coincides with the 2021–22 academic year, in which the cohort’s upper-secondary trajectory was disrupted by the COVID-19 pandemic. The grade-13 estimates should be interpreted with caution, given that the pandemic disrupted both teaching conditions and the institutional stakes of the assessment, while grades 8 and 10 provide a cleaner characterisation of the association (Engzell et al., 2021; Contini et al., 2022; Agostinelli et al., 2022).

Third, gender heterogeneity in the attitude–achievement relationship is small at the first follow-up in

grade 8. It emerges progressively, operating primarily through differences in levels rather than in returns. The Female indicator tracks the well-documented symmetric gender gaps: a negative and widening gap in mathematics and a positive and narrowing gap in literacy. The interaction between attitude and gender is statistically indistinguishable from zero at grade 8 in both subjects. It becomes negative and significant for literacy at grade 10 and for mathematics only at grade 13. The divergence in returns therefore appears earlier in literacy, the domain in which girls hold an average advantage in levels. The evidence is thus consistent with gendered self-concepts that are already visible at age ten and that gradually translate into differential payoffs to equivalent motivational traits during adolescence (Breda and Napp, 2019; Guiso et al., 2008; Contini et al., 2017, 2023).

Fourth, the Test Anxiety Index is associated with a performance penalty at the high-stakes grade-8 assessment that attenuates at the two low-stakes follow-ups, consistent with evidence that the activation of evaluative anxiety depends on the institutional features of the assessment environment (Putwain et al., 2022). The grade-8 penalty is smaller for girls than for boys in mathematics, with no gender differential in literacy.

Robustness checks include both alternative samples and alternative model specifications. First, because the analytical sample is itself positively selected at each transition, part of the attenuation could in principle reflect compositional change; the robustness analysis in Section 1.5 shows that estimates obtained on a balanced panel of students observed at all follow-up waves are quantitatively similar to the main results, indicating that compositional changes alone do not account for the decay. Second, we test whether results change with the inclusion of three additional non-cognitive indices (general motivation, time management, and social isolation), measured contemporaneously at grade 5 and found to be relevant predictors in recent work (De Paola and Skatova, 2024). Including these additional indices leaves the main subject-specific coefficients essentially unchanged. Third, the cross-subject test set out above shows that the literacy attitude carries essentially no predictive content for mathematics achievement, an order of magnitude below the own-domain coefficient. The reverse is not true: the mathematics attitude predicts literacy achievement about as strongly as the literacy attitude itself does, which suggests that the mathematics index also captures a general component of academic confidence.

The heterogeneity analysis examines how returns to early attitudes vary across the conditional distribution of test scores, across socio-economic quartiles, and across geographical macro-areas. In mathematics, the predictive content of grade-5 attitudes is similar across the conditional distribution at grades 8 and 13, with a mildly increasing profile at grade 10. In literacy, the cross-quantile profile changes shape across waves: it is increasing at grade 8, inverts at grade 10 with returns larger at the lower tail of the conditional distribution, and continues to decline toward the upper tail at grade 13. Gender heterogeneity in the cross-quantile profiles is more visible in literacy than in mathematics: at the low-stakes grade-10 follow-up, the predictive content of grade-5 literacy attitudes is statistically significant and roughly twice as large for boys as for girls along the entire conditional distribution, while gender differences in mathematics returns at the same wave are more localised in the tails. Returns are essentially invariant across quartiles of family socio-economic status in both domains, with the exception of a more pronounced negative interaction between attitude and gender among middle-lower ESCS students in mathematics at grade 13. Finally, our results do not suggest a clear role for geography in shaping the returns to early subject-specific attitudes. Territorial differences in these returns are limited in magnitude and do not display a systematic pattern across grades and macro-areas. This finding does not rule out the role of geography as a determinant of educational outcomes more broadly.

This paper contributes to three strands of the literature. First, it adds new evidence on the domain-specific role of non-cognitive inputs in the technology of skill formation (Cumha and Heckman, 2008; Heckman and Kautz, 2012), showing that their predictive content is neither uniform across subjects nor stable over time and that it varies with the institutional stakes of the assessment. Second, it informs the literature on gender gaps in education (Bordalo et al., 2019; Breda and Napp, 2019; Guiso et al., 2008; Else-Quest et al., 2010; Fryer and Levitt, 2010; Pope and Sydnor, 2010) by documenting that gendered subject-specific self-beliefs are visible at the end of primary school, operate primarily through differences in levels rather than in returns, and follow the asymmetric dynamics of the female advantage in literacy and disadvantage in mathematics during adolescence. Third, these findings add to the literature on the territorial and socio-economic gradients in Italian student achievement (Bratti et al., 2007; Agasisti and Cordero-Ferrera, 2013) by showing that early non-cognitive heterogeneity is associated with persistent, although attenuating, differences in achievement trajectories, and that these differences do not vary systematically with family socio-economic status or across geographic macro-areas.

This study builds most directly on papers that exploit Italian longitudinal or cohort data to relate non-cognitive traits to later achievement and choices (De Paola and Skatova, 2024; Contini et al., 2017;

Di Liberto et al., 2022), as well as international work on subject-specific self-concepts and evaluative anxiety (Else-Quest et al., 2010; Putwain et al., 2022; Fan and Williams, 2018).

The remainder of the Chapter is organised as follows. Section 1.2 describes the INVALSI data, the construction of the cohort datasets, the attrition patterns, and the psychometric procedure underlying the non-cognitive indices. Section 1.3 outlines the empirical strategy and the identifying assumptions. Section 1.4 reports the main results separately for mathematics and literacy across grades 8, 10, and 13. Section 1.5 presents robustness checks, including specifications augmented with general non-cognitive indices and a cross-subject test of domain-specificity. Section 1.6 documents heterogeneity across the conditional distribution of test scores by socio-economic background and across macro-areas. Section 1.7 concludes.

1.2 Data and descriptives

Our primary data source consists of administrative records provided by the National Institute for the Evaluation of the Italian Education System (INVALSI), which administers nationwide standardised assessments to all students enrolled in Italian primary and secondary schools. These assessments are conducted in grades 2 and 5 (primary education), grade 8 (lower secondary education), and grades 10 and 13 (upper secondary education). Each year, the tests measure students' competencies in literacy and mathematics and, in more recent years, also in English. The stakes attached to these assessments vary across grades and over time. At grades 5 and 10 the tests are low-stakes throughout the period we study. At grades 8 and 13 the regime changed over time: for our cohort, the grade-8 test sat in 2016–17 contributed to the final lower-secondary exit grade, while the grade-13 test sat in 2021–22 did not condition admission to the upper-secondary examination, and was therefore formally low-stakes. Its classification is nonetheless less clear-cut: the wave falls in the final examination year and in the immediate post-pandemic period, a context we take into account when interpreting the grade-13 estimates.

The tests are written examinations composed of multiple-choice and closed-short-answer items and are scored using a nationally standardised scoring scheme. Participation is compulsory for all Italian students enrolled in public schools and state-accredited private schools, ensuring near-universal coverage of the student population. INVALSI data include information for more than 90% of enrolled students in each tested grade. Appendix 1.A provides more detail on the Italian education system and the structure of the INVALSI assessment programme.⁴

In our analysis, we exploit a key feature of these data that allows us to track students over time along their academic trajectory. Specifically, we focus on the cohort of students observed in grade 5 during the 2013–14 school year and merge their records when they are observed in grade 8 (2016–17), grade 10 (2018–19), and grade 13 (2021–22). We exclude English test scores from the analysis as these assessments were not administered in the earlier years. This procedure yields a longitudinal dataset containing standardised test scores, along with demographic characteristics and class- and school-level information, spanning grades 5 through 13.

The INVALSI test scores are expressed on a Rasch scale calibrated separately for each grade, with no common items linking them (INVALSI, 2019). Score levels are therefore not comparable across grades. All scores then enter the analysis standardised within their own wave, so that the estimated coefficients are expressed in standard deviations of the corresponding grade.

The mode of administration also changed over the period we observe. INVALSI moved the grade-8 and grade-10 assessments to computer-based delivery in 2017–18 (INVALSI, 2019); the grade-5 assessment remained paper-based throughout (INVALSI, 2019). For our cohort, the tests at grade 5 (2013–14) and grade 8 (2016–17) were paper-based, and those at grade 10 (2018–19) and grade 13 (2021–22) were computer-based. Botta and Lasorsa (2018) compare the same grade-10 mathematics field-trial test administered in both modes and report that items are on average more difficult under computer-based delivery, while the resulting ability estimates do not differ appreciably. Within-wave standardisation addresses the difference in scales; it does not by itself ensure that the assessment measures the same construct with the same precision under the two modes. Section 1.5 examines whether the change of delivery is visible in our estimates.

In addition to test scores, INVALSI collects rich background information through questionnaires administered to students and schools, covering demographic characteristics, family background, and, in selected years, measures of non-cognitive skills and attitudes toward schooling.

⁴Further details on population coverage are reported in Table 1.A.1. See also Chapter 3, section 3.3.1, for other details on INVALSI data availability.

1.2.1 Attrition

The structure of the data implies that the analysis is restricted to students observed at each subsequent wave, excluding those who drop out or repeat a grade. To assess the extent of potential selection concerns, we examine attrition rates across three educational transitions: from grade 5 to grade 8, from grade 8 to grade 10, and from grade 10 to grade 13. Table 1.1 reports the share of students lost at each transition. Overall, approximately 39% of students observed at grade 5 are not followed through to grade 13. Attrition varies substantially across transitions, reflecting different institutional mechanisms.

The first transition, from grade 5 to grade 8, records a loss of approximately 17% of students. As noted above, at grade 8 the INVALSI test carries high-stakes implications, as results contribute to the final lower-secondary exit examination; this induces near-universal participation and limits selective absenteeism. This is not the case at grade 5: leavers at this stage are more likely to reflect test-day absenteeism than dropout or grade retention, both of which affect only a marginal share of students at the primary level.⁵ Indeed, at grade 5 no institutional consequence follows from non-participation, so that test-day absenteeism translates directly into a loss from the analytical sample. The same applies, for our cohort, to grades 10 and 13: at grade 10 the test is diagnostic, and at grade 13 the participation requirement, formally introduced by Legislative Decree 62/2017, was suspended throughout the COVID-19 emergency and remained suspended for the school year 2021–22 of our cohort.⁶ Among the four waves of our panel, institutional pressure plausibly enforces near-universal participation only in grade 8.

Attrition is most pronounced at the transition from grade 8 to grade 10 (19%). This coincides with the entry into upper secondary education, a stage characterised by increased academic demands and substantially higher rates of grade repetition and school dropout. It is also the point at which formal tracking begins, with students sorting into academic, technical, and vocational programmes.

Table 1.1: Entry and exit flows on available Invalsi scores.

	From grade 5 to 8	From grade 8 to 10	From grade 10 to grade 13
<i>Mathematics</i>			
No. of Stayers	416,526	342,785	302,928
No. of Leavers	71,043	66,135	41,831
<i>Literacy</i>			
No. of Stayers	409,382	345,614	305,966
No. of Leavers	71,160	66,170	41,897

Notes: Numbers are counted considering Invalsi scores. Stayers are students observed in both grades of a given transition; students lost to follow-up are observed in the first transition grade but not in the subsequent grade.

We then investigate whether students who exit the panel differ systematically from those who remain. Table 1.2 reports the relevant comparison: as expected, students lost to follow-up are more likely to be male, come from disadvantaged socio-economic backgrounds, and report lower grade-5 achievement and weaker motivation toward schooling. We discuss the implications of this selection pattern for the interpretation of the main estimates in both Section 1.2.3 below and Section 1.5 where we replicate the analysis on a balanced panel of students observed in all four waves. Additional details on dataset construction, cleaning procedures, merging diagnostics, and attrition checks are provided in Appendix 1.A.

⁵In Italy, the Ministry of Education makes school-level average INVALSI scores publicly available. While this transparency serves accountability purposes, it may also create incentives for schools to influence the composition of students attending on test day, contributing to selective absenteeism.

⁶See Ministerial Order n. 65 of 14 March 2022, Article 3, paragraph 1, letter (a), which explicitly admits students to the *Esame di Stato*.

Table 1.2: Descriptive statistics by Attrition Status.

Variable	From grade 5 to 8			From grade 8 to 10			From grade 10 to 13		
	Stayer	Lost	Δ	Stayer	Lost	Δ	Stayer	Lost	Δ
Main characteristics									
Literacy score G5	57.588	51.378	-6.210***	57.704	52.396	-5.308***	57.116	55.199	-1.918***
Mathematics score G5	60.331	54.393	-5.938***	60.473	55.179	-5.294***	59.863	58.219	-1.644***
Females	0.472	0.398	-0.074***	0.472	0.421	-0.052***	0.477	0.377	-0.100***
Immigrant G5 (yes=1)	0.078	0.259	0.181***	0.065	0.178	0.112***	0.086	0.207	0.121***
ESCS Index G5	0.090	-0.392	-0.482***						
Attitude: Mathematics	0.034	-0.202	-0.236***						
Attitude: Literacy	0.034	-0.200	-0.234***						
Test-anxiety Index	-0.026	0.154	0.180***						
Literacy score G8				60.981	52.531	-8.450***			
Mathematics score G8				54.669	46.362	-8.308***			
Immigrant G8 (yes=1)				0.065	0.178	0.112***			
Literacy score G10							58.073	49.405	-8.667***
Mathematics score G10							55.018	45.946	-9.073***
Immigrant G10 (yes=1)							0.086	0.207	0.121***
ESCS Index G10							0.109	-0.295	-0.404***

Notes: Stayers are students observed in both grades of a given transition; students lost to follow-up are observed in the first transition grade but not in the subsequent grade. Grade 8 ESCS index is not available.

1.2.2 Non-Cognitive Skills: Measurement and Index Construction

The 2013-14 grade 5 student questionnaire includes an extensive battery of items capturing non-cognitive dimensions, such as subject-specific self-efficacy, intrinsic motivation, and test-related anxiety.⁷ These measures form the basis of the non-cognitive indices used in the empirical analysis. Responses to each item are recorded on a four-point Likert scale ranging from 1 (strongly disagree) to 4 (strongly agree), with the two intermediate categories corresponding to "moderately disagree" (2) and "somewhat agree" (3).

The measurement of non-cognitive skills presents well-known conceptual and empirical challenges. Standardised achievement tests are not designed to capture socio-emotional traits or motivational constructs, and self-reported measures may be sensitive to reporting bias and reference-group effects. Recent work in economics and education has emphasised the importance of rigorous psychometric validation and the use of latent variable models when incorporating non-cognitive measures into production function frameworks (Duckworth and Yeager, 2015; Heckman and Kautz, 2013). Accordingly to large-scale international assessments—most notably OECD-PISA and its recent frameworks on students' attitudes and socio-emotional skills—have institutionalised this approach, combining survey instruments with validated scaling procedures (OECD, 2021, 2025). In line with these practices, INVALSI supplements standardised tests with detailed student questionnaires, allowing the integration of non-cognitive measures into models of academic achievement.

Using the grade 5 Invalsi Students' questionnaire, we construct three indices: the Mathematics Attitude Index, the Literacy Attitude Index, and the Test Anxiety Index. The first two are domain-specific, capturing intrinsic motivation and self-efficacy in each subject; the third captures students' emotional responses to evaluative environments and performance pressure. A growing empirical literature shows that achievement emotions (particularly anxiety) are systematically associated with performance through cognitive interference and reduced effective effort (Putwain et al., 2022). Moreover, gender differences in academic self-beliefs and in anxiety are well documented (Else-Quest et al., 2010), and have been linked to later subject specialisation (Breda and Napp, 2019; Wang et al., 2013). The subject-specific attitudes indexes created are grounded in contemporary self-determination theory and derived from items capturing intrinsic motivation (enjoyment and interest) and students' perceived self-efficacy within a domain. Similar constructs have been shown to predict engagement and achievement (Ryan and Deci, 2000; Sisk et al., 2018). Tables 1.3 and 1.4 report students' responses to the individual items on mathematics and literacy, respectively. The test anxiety items are used to construct the dedicated Test Anxiety Index (see Table 1.5).

⁷See Chapter 3, section 3.3.1 for more details.

Table 1.3: Students' self-perceived attitude toward Mathematics in grade 5, by gender.

Please indicate if you agree with the following statements (Mathematics) using the following scale 1-strongly disagree, 2-moderately disagree, 3-somewhat agree, 4 strongly agree	Females	Males	Δ
Q4.D - I like studying Mathematics	2.91	3.20	-0.289***
Q4.E - I learn interesting thing in this subject	3.32	3.39	-0.067***
Q4.F - This subject is boring	1.78	1.67	0.109***
Q6.D - Usually I am good at this subject	2.93	3.24	-0.303***
Q6.E - I easily learn this subject	2.91	3.17	-0.264***
Q6.F - For me, this subject is more difficult than for my peers	1.94	1.76	0.181***
Observations	243,160	251,654	

Notes: Items from the INVALSI student questionnaire in grade 5, 2013/14. Mean responses are reported separately by gender; the last column shows the male–female difference, with significance levels from a two-sample *t*-test (*, **, *** at the 10%, 5%, and 1% level, respectively).

Table 1.4: Students' self-perceived attitude toward Literacy in grade 5, by gender.

Please indicate if you agree with the following statements (Literacy) using the following scale 1-strongly disagree, 2-moderately disagree, 3-somewhat agree, 4 strongly agree	Females	Males	Δ
Q4.A - I like studying Literacy	3.02	2.68	0.345***
Q4.B - I learn interesting thing in this subject	3.32	3.11	0.210***
Q4.C - This subject is boring	1.73	2.11	-0.387***
Q6.A - Usually I am good at this subject	3.06	2.88	0.186***
Q6.B - I easily learn this subject	3.11	2.89	0.214***
Q6.C - For me, this subject is more difficult than for my peers	1.76	2.02	-0.265***
Observations	242,718	251,101	

Notes: Items from the INVALSI student questionnaire in grade 5, 2013/14. Mean responses are reported separately by gender; the last column shows the male–female difference, with significance levels from a two-sample *t*-test (*, **, *** at the 10%, 5%, and 1% level, respectively).

Table 1.5: Students' self-perceived Anxiety toward the Invalsi test in grade 5, by gender.

Please indicate if you agree with the following statements (Test Anxiety) using the following scale 1-strongly disagree, 2-moderately disagree, 3-somewhat agree, 4 strongly agree	Females	Males	Δ
Q9.A - Even before the test, I was worried about having to take it.	2.84	2.52	0.323***
Q9.B - I was so nervous that I could not find the answers.	1.79	1.74	0.050***
Q9.C - While answering the questions, I felt that I was performing poorly.	2.54	2.35	0.184***
Q9.D - While answering the questions, I felt calm.	2.33	2.64	-0.312***
Observations	241,733	248,656	

Notes: Items from the INVALSI student questionnaire in grade 5, 2013/14. Mean responses are reported separately by gender; the last column shows the male–female difference, with significance levels from a two-sample *t*-test (*, **, *** at the 10%, 5%, and 1% level, respectively).

Descriptive statistics reported in Tables 1.3, 1.4, and 1.5 reveal that gender differences in non-cognitive skills are already present at the end of primary school. Boys report higher confidence and enjoyment in mathematics, whereas girls report stronger confidence in literacy and higher levels of stress in evaluative environments.

To construct each index, we apply a Principal Component Analysis (PCA) to the survey items reported in the previous three tables. Subject-specific indexes needed a reverse-coding for negatively framed items.⁸

⁸Specifically, items Q4.F and Q6.F in Table 1.3, items Q4.C and Q6.C in Table 1.4, and item Q9.D in Table 1.5 are reverse-coded by replacing the original 4-point Likert response $x \in \{1, 2, 3, 4\}$ with $5 - x$, so that all items within each construct load in the same direction: higher values consistently denote greater intrinsic motivation and self-efficacy in the case of the attitude indices, and greater test anxiety in the case of the anxiety index.

Table 1.6: Psychometric index estimation results.

	Cronbachs' Alpha		PCA	
	Value	No. Items	Eigenvalue	AVE
Mathematics Attitude Index	0.855	6	3.5155	58.6%
Literacy Attitude Index	0.788	6	2.9863	49.8%
Test Anxiety Index	0.762	4	2.3383	58.5%

Notes: Cronbach's alpha is calculated on the original Likert-scale of Q4 and Q6 items and on Q9 items for the different indexes from grade 5 without standardisation. The coefficients exceed the standard threshold of 0.60, indicating good internal consistency. Principal Component Analysis (PCA) uses standardised items with linear scoring. The eigenvalues exceed the standard threshold of 1, indicating strong validity of the first considered component.

After that, we combine Q4 items on intrinsic motivation and enjoyment with Q6 items on self-efficacy to construct unified domain-specific attitude indices.

In each case, a single dominant component emerges: eigenvalues exceed one, and the first component explains above 49.8% of the variance, consistent with a unidimensional structure. Internal consistency is further supported by Cronbach's Alpha values above 0.60 — the conventional threshold for large-scale socio-emotional measures (Duckworth and Yeager, 2015) — as reported in Table 1.6. To assess whether the unidimensional structure is robust to the choice of method, we complement PCA with Exploratory Factor Analysis (FA). Across all specifications, a single latent factor fits the data well, confirming the unidimensionality of each construct. Alternative index constructions — including row means and separate motivation and self-efficacy sub-indices — yield nearly identical results, supporting the parsimony of the unified indices. Full details are provided in Appendix 1.C.

Given students' age, these measures are best interpreted as early-emerging non-cognitive dispositions rather than fixed adult personality traits. Developmental evidence shows that socio-emotional traits display moderate stability from late childhood onward and constitute foundational inputs in the dynamic process of skill formation (Heckman and Kautz, 2013). Within this framework, early motivational beliefs and emotional regulation plausibly influence both contemporaneous learning and the evolution of achievement gaps over time.

1.2.3 Main Descriptives

Table 1.7 reports descriptive statistics for the variables used in the regression analysis, organised into three panels corresponding to the three cross-sectional models estimated in equation (1.1): Panel (a) covers the grade-8 follow-up, Panel (b) the grade-10 follow-up, and Panel (c) the grade-13 follow-up. The outcome variables are the Rasch-scaled INVALSI scores in mathematics and literacy at grades 8, 10, and 13, respectively. These scores are calibrated to have a mean of 200 and a standard deviation of 40 in the national reference population at each grade. The lagged outcome variables (the grade-5 score and, where applicable, the grade-8 and grade-10 scores) serve as prior achievement controls in the value-added specification.

Table 1.7: Descriptive statistics.

	Panel (a): Grade 8			Panel (b): Grade 10			Panel (c): Grade 13		
	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.
Outcome Variables									
Mathematics score G8	206.88	39.64	416,525						
Literacy score G8	207.76	39.21	409,382						
Mathematics score G10				206.76	39.28	346,641			
Literacy score G10				206.76	38.46	343,946			
Mathematics score G13							196.97	38.77	317,699
Literacy score G13							192.66	39.66	314,182
Lagged Outcome Variables									
Mathematics score G5	215.57	43.86	416,950	219.09	43.50	347,043	220.20	43.48	318,058
Literacy score G5	213.25	40.52	409,382	216.98	39.67	343,946	218.30	39.47	314,182
Mathematics score G8				211.38	39.14	342,874	212.81	39.15	314,179
Literacy score G8				212.66	38.05	339,848	214.56	37.83	310,356
Mathematics score G10							209.20	38.97	302,999
Literacy score G10							209.42	37.70	301,195
Non-Cognitive Skills' Measures (Grade 5)									
Attitude Mathematics Index	0.03	0.99	416,525	0.07	0.98	346,641	0.07	0.97	317,699
Attitude Literacy Index	0.04	0.99	409,382	0.06	0.98	343,946	0.08	0.97	314,182
Test-anxiety Index	-0.03	0.99	417,803	-0.06	0.99	347,766	-0.06	0.98	318,641
Additional students' characteristics (Grade 5)									
Females	0.51	0.50	415,946	0.52	0.50	346,544	0.53	0.50	317,650
ESCS Index	0.11	0.99	416,164	0.19	0.97	346,385	0.22	0.97	317,465
Kindergarten (yes=1)	0.86	0.35	364,398	0.87	0.34	303,821	0.87	0.34	278,493
Immigrant (yes=1)	0.07	0.26	410,912	0.06	0.23	342,482	0.05	0.22	314,076
Early enrolled (yes=1)	0.01	0.12	416,483	0.01	0.12	346,612	0.01	0.12	317,676
Late enrolled (yes=1)	0.02	0.13	416,483	0.01	0.12	346,612	0.01	0.11	317,676
Motivation Index	0.02	1.01	416,096	0.05	1.01	346,330	0.06	1.02	317,432
Time Management Index	0.04	0.97	413,702	0.07	0.95	344,382	0.08	0.95	315,661
Social Isolation Index	-0.05	0.96	416,275	-0.08	0.95	346,452	-0.09	0.94	317,517

Notes: The ESCS index is constructed by INVALSI, combining parental education, parental occupation, and home cultural and economic resources, and is standardised to have a mean of zero and unit variance in the national reference population at each grade. The non-cognitive indices are standardised to mean zero and unit variance in the grade-5 cohort. For each panel, the number of observations reported for each variable reflects the presence in that specific wave.

The descriptive statistics make the compositional implications of non-random attrition immediately visible. As we move from the grade-8 panel to the grade-13 panel, the average grade-5 Rasch score of the surviving cohort rises by roughly 5 points in mathematics ($215.6 \rightarrow 220.2$) and by 5 points in literacy ($213.3 \rightarrow 218.3$), even though grade-5 measurements are mechanically identical across panels: the increase reflects pure selection, since students who remain in the panel until grade 13 had, on average, higher prior achievement than those who are lost earlier. The same pattern emerges for grade-5 non-cognitive measures: the Mathematics and Literacy Attitude Indices drift slightly upward across panels (from approximately 0.03 to 0.07, and from 0.04 to 0.08, respectively), while the Test-Anxiety Index becomes slightly more negative (from -0.03 to -0.06). Family-background characteristics shift consistently in the same direction: the average ESCS index doubles from 0.11 to 0.22 across panels, and the share of immigrant students declines from 7% to 5%, while the share of female students rises from 51% to 53%, in line with the higher dropout rates among male students documented in the attrition analysis.

To assess the sensitivity of our main results to these compositional shifts, in Section 1.5 we replicate the analysis on a balanced panel of students observed in all four INVALSI waves, from grade 5 through grade 13; descriptive statistics for this sample are reported in Table 1.E.17. The balanced design holds the student composition fixed across estimation horizons. It separates changes in estimated coefficients from compositional shifts driven by attrition.

We complement the tabular evidence by examining the full distribution of the main variables of interest, separately by gender, reported in Appendix 1.B.

Figure 1.B.1 reports kernel density estimates of INVALSI Rasch scores at grades 5 and 13. Gender differences in cognitive performance are already present at grade 5 and widen by grade 13 in opposite directions across subjects: males outperform females in mathematics, while females outperform males in literacy. Figure 1.B.2 reports the analogous kernel density estimates for the subject-specific attitude indices at grade 5. The gender gap in attitudes mirrors the one in cognitive performance: boys' mathematics-attitude distribution lies to the right of girls', while girls report higher literacy attitude than boys. Figure 1.B.3 reports the kernel density of the Test Anxiety Index at grade 5 by gender. Girls display a rightward-shifted distribution relative to boys, indicating higher self-reported test anxiety already at the end of primary school.

The two subject-specific indices are constructed from parallel item blocks of the same questionnaire, administered to the same students in the same sitting, and are standardised to mean zero and unit variance in the grade-5 cohort. Table 1.8 reports the correlation between them, alongside the correlation between the grade-5 Rasch scores in the two corresponding domains, computed on a common sample.

Table 1.8: Correlations between domains at grade 5.

	Full sample	Males	Females
Rasch scores: mathematics vs. literacy	0.67	0.69	0.67
Attitude indices: mathematics vs. literacy	0.03	0.07	0.05
Observations	446,535	222,817	223,718

Notes: Correlations computed on the sample of students with non-missing values on the four indicators and on gender. The attitude indices are standardised to mean zero and unit variance in the grade-5 cohort; achievement is measured by the grade-5 INVALSI Rasch scores.

The two sets of correlations differ by an order of magnitude. Mathematics and literacy achievement at grade 5 correlate at 0.67: performance in the two domains shares a large common component, as one would expect of measures that both reflect general ability, family background, and school and classroom inputs. The attitudes towards those same two subjects, reported by the same students at the same moment, correlate at 0.03 in the pooled sample, 0.07 among boys and 0.05 among girls. The pooled figure falls below both within-gender figures because boys and girls differ in opposite directions on the two indices, boys reporting a higher mathematics attitude and girls a higher literacy attitude (Tables 1.3 and 1.4), so that pooling the two groups adds a negative between-gender component to an association that is already negligible within each of them.

The indices are not weak measures. Each is separately validated and internally consistent, with Cronbach's α of 0.855 and 0.788 respectively (Table 1.6), so that each captures its own construct reliably. What they capture is almost entirely not shared.⁹ Section 1.1 sets out why this pattern is expected on theoretical grounds and what it implies for the use of subject-specific rather than general non-cognitive measures; Section 1.5 examines whether the distinction carries through to achievement.

Taken together, the descriptive evidence shows that students' self-beliefs and emotional responses to evaluation already differ systematically at the end of primary school, both between girls and boys and across the two domains. The empirical analysis that follows examines whether these early differences are associated with subsequent academic performance over the educational trajectory.

1.3 Empirical strategy

To estimate the association between early domain-specific non-cognitive skills and subsequent academic achievement, we estimate by OLS the following value-added specification:

$$Y_{ij(t+n)} = \alpha + \beta_1 \text{Attitude Index}_{ij} + \beta_2 \text{Test Anxiety}_{ij} + \beta_3 Y_{ijt} + \gamma X_{ij} + \delta_j + \varepsilon_{ij} \quad (1.1)$$

The dependent variable $Y_{ij(t+n)}$ is the Rasch standardised score in literacy or mathematics of student i in primary school class j , observed at grade $t + n \in \{8, 10, 13\}$. When the outcome is observed at grade 8, the prior achievement control Y_{ijt} is the grade 5 Rasch score in the corresponding subject;

⁹Möller et al. (2009) report that the internal/external pattern does not hold when self-efficacy measures replace self-concept measures, cross-domain correlations being larger in that case; they attribute the failure to items formulated at the level of the individual task rather than of the subject. The items underlying our indices refer to the subject as a whole, and the correlation reported here is of the order the model predicts for self-concept measures.

where the outcome is observed at grade 10, we additionally include the grade-8 score; and when the outcome is observed at grade 13, we additionally include the grade-8 and grade-10 scores. The key regressor Attitude Index $_{ij}$ is the subject-specific index of motivation and self-perceived academic ability constructed in Section 1.2.2, elicited at the end of primary school. Test Anxiety $_{ij}$ captures students' self-reported emotional responses to evaluative situations, measured at the same point in time. The vector X_{ij} includes predetermined individual and family background characteristics measured at grade 5: socioeconomic status (ESCS index), immigrant background, pre-primary school attendance, and early or late enrollment indicators. All specifications include primary school class fixed effects δ_j , absorbing common classroom-level inputs and peer composition at the time non-cognitive skills are measured.

All controls in X_{ij} are measured contemporaneously with the non-cognitive skill indices. Although some of these characteristics, such as gender and immigrant background, are time-invariant by nature, others, including the ESCS index and enrollment indicators, are drawn from the grade 5 wave of the data, the wave at which non-cognitive skills are measured, to avoid conditioning on post-treatment family adjustments.

All non-cognitive indices are standardised to mean zero and unit variance in the grade 5 population, so that the estimated coefficients are interpretable as standard deviation effects. Specifications are estimated separately for literacy and mathematics outcomes. Standard errors are heteroskedasticity-robust and clustered at the primary school class level, consistent with the level at which non-cognitive skills are measured, and primary school class fixed effects are defined. This accounts for within-class correlation in both the regressors of interest and the residuals arising from shared classroom inputs at the time of treatment measurement.

Our identification strategy builds on [De Paola and Skatova \(2024\)](#), who studied the same Italian cohort and adopted a similar value-added framework with temporal ordering of non-cognitive skill measurement. Relative to that paper, we introduce different domain-specific attitude indices as the central objects of inquiry, and extend the analysis to grade 13. The strategy rests on three complementary elements: the temporal ordering of measurement, the value-added specification, and the inclusion of primary school class fixed effects.

The first and most direct source of identification is the temporal ordering of measurement. Non-cognitive skills are elicited at grade 5, before the realisation of all outcomes considered in the analysis, which rules out direct reverse causality: performance at grades 8, 10, or 13 cannot influence attitudes reported three to eight years earlier. A similar strategy has been adopted by [Heckman et al. \(2006\)](#), who exploit early measures of locus of control and self-esteem from the National Longitudinal Survey of Youth to study the influence of non-cognitive traits on later-life outcomes.

The second element is the value-added structure. By conditioning on the lagged Rasch scores at every preceding wave for which they are available the specification absorbs the persistent component of cognitive ability and the cumulative contribution of all prior schooling inputs to skill formation ([Cunha and Heckman, 2007](#); [Todd and Wolpin, 2003, 2007](#); [Harris and Sass, 2011](#)).¹⁰ This serves two complementary purposes. First, it differentiates out the time-invariant unobserved heterogeneity in cognitive endowment that would otherwise confound the association between early attitudes and later achievement. Second, it blocks the indirect channel through which grade-5 attitudes may affect later performance by raising achievement at intermediate stages: because INVALSI assessments are sequentially correlated along the educational career, a positive attitude at grade 5 mechanically propagates forward through better intermediate scores, which in turn predict later ones. By holding intermediate scores fixed, our specification removes this cascade. The estimated coefficient on the attitude index thus captures only the residual, direct association—the part of attitudes' contribution that persists *net of* accumulated achievement, rather than the part that operates mechanically through better intermediate test scores. The estimated coefficient is therefore to be interpreted as the partial association between non-cognitive skills measured at the end of primary school and later academic outcomes, conditional on the full trajectory of test-score performance up to the grade preceding the outcome of interest.

A residual concern arises with respect to the inclusion of the lagged Rasch scores themselves. Because intermediate test scores are themselves outcomes potentially shaped by grade-5 attitudes and by correlated time-varying unobservables, conditioning on them may introduce post-treatment bias ([Angrist and Pischke, 2009](#)). The literature shows that value-added specifications rest on restrictive assumptions on the persistence of past inputs and unobserved endowments ([Todd and Wolpin, 2003](#)), but also that conditioning on prior achievement performs comparatively well across a wide range of settings, as the lagged score serves as a proxy for unobserved individual heterogeneity ([Guarino et al., 2015](#)). We therefore adopt the value-added specification, while acknowledging that the grade-10 and grade-13 estimates

¹⁰grade-5 scores when the outcome is at grade 8, grade-5 and grade-8 scores when the outcome is at grade 10, and grade-5, grade-8 and grade-10 scores when the outcome is at grade 13

are net of intermediate achievement and should be interpreted accordingly. Re-estimating these models without intermediate scores, and assessing the role of selection on unobservables through the bounds of Oster (2019), are left to future work.

We defer discussion of two remaining concerns, the potential evolution of non-cognitive skills over adolescence and the implications of non-random attrition to Section 1.5.

1.4 Results

This section presents the main estimation results. We report findings separately for mathematics and literacy, following the same sequential structure in both cases: outcomes at grade 8, grade 10, and grade 13 are examined in turn, allowing us to trace the persistence and evolution of the association between early non-cognitive traits and academic achievement over the full span of compulsory and upper-secondary schooling.

Each table follows a common specification sequence. Column (1) presents the most parsimonious specification, including only the relevant attitude index and class fixed effects. Column (2) adds prior achievement. Column (3) introduces student and family background characteristics (ESCS index, kindergarten attendance, immigrant status, early and late enrollment). Column (4) adds the interaction between the attitude index and gender. Column (5) adds the *Test Anxiety Index*. Column (6) adds the interaction between the *Test Anxiety Index* and gender. Column (5) is our baseline specification. It includes the full set of background controls, the gender interaction with the Attitude Index, and the Test Anxiety Index. Column (6) further allows the test anxiety penalty to vary by gender.

The number of observations falls as controls are added, because each specification is estimated on students with non-missing values on all included regressors. The main reduction occurs at column (3), when background characteristics enter, and reflects item missingness on these variables, primarily kindergarten attendance. This across-column variation is separate from the across-wave attrition documented in Section 1.2.1.

An important institutional feature distinguishes the three follow-up waves along the dimension of evaluative pressure, although this mapping is more straightforward for some waves than for others. In 2016–17 the grade-8 INVALSI assessment was mandatory and contributed to the final lower-secondary exit grade, creating binding incentives for participation and effort. The grade 10 assessment, by contrast, carries no formal consequences for students and can be unambiguously characterised as low-stakes. The grade-13 assessment is also formally low-stakes for our cohort. The wave corresponds to the 2021–22 academic year, in which INVALSI tests at the upper-secondary level had not yet been reinstated as a prerequisite for admission to the *Esame di Stato*, following their suspension during the two preceding pandemic years.¹¹ The INVALSI assessment itself was therefore administered for monitoring purposes only and carried no individual consequences. Two features of this wave nonetheless warrant caution when interpreting its estimates. First, the *Esame di Stato*, remained a high-stakes terminal examination, and the broader evaluative climate of the final upper-secondary year may have shaped how students approached any assessment activity during that period. Second, the 2021–22 cohort sat the INVALSI tests in the immediate aftermath of two academic years marked by school closures, remote instruction, and prolonged disruption, conditions that have been linked to elevated levels of school-related anxiety among adolescents. For these reasons, we treat the grade 13 estimates with greater interpretive caution than those at grades 8 and 10.

1.4.1 Mathematics test scores

Table 1.9 Model (1) presents the most parsimonious specification, in which the *Mathematics Attitude Index* enters as the only regressor alongside class fixed effects. The estimated coefficient is positive and significant (0.297***), indicating a positive within-class association between early attitudes towards mathematics and subsequent performance. Model (2) adds prior Mathematics achievement in grade 5, which absorbs a substantial share of the variation in the outcome: the coefficient on the *Mathematics Attitude Index* falls markedly, from 0.297 to 0.113, while the grade 5 score enters with a coefficient of 0.735***. This attenuation is informative: it suggests that part of the association estimated in column (1) between attitude and performance reflects dynamic complementarity with prior cognitive ability, and that controlling for predetermined achievement is essential to isolate the incremental contribution of non-cognitive skills. Model (3) adds the full set of individual and family background characteristics (ESCS

¹¹The reinstatement of INVALSI tests as a formal prerequisite for the *Esame di Stato* took effect from the 2022–23 academic year onwards.

index, kindergarten attendance, immigrant status, early and late enrollment). The coefficient on the *Attitude Index* attenuates to 0.111***, and the control variables display the expected signs: socio-economic background is positively and significantly associated with achievement; late enrollment is associated with substantially lower scores; students with immigrant backgrounds perform below their non-immigrant peers; and kindergarten attendance is positively correlated with outcomes. The coefficient on *Female* is negative and significant (−0.029***), documenting the expected gender gap in mathematics achievement. Model (4) introduces the interaction between the *Attitude Index* and gender. The interaction term is small (−0.001) and statistically indistinguishable from zero, indicating that at this stage the returns to attitude do not differ significantly between boys and girls.

Model (5), our baseline specification, adds the *Test Anxiety Index*, which enters with a negative and significant coefficient (−0.045***), consistent with the interpretation that test anxiety constitutes a distinct burden that depresses performance independently of attitudes and prior ability. The coefficient on the *Mathematics Attitude Index* attenuates to 0.106***. In this specification, a one-standard-deviation increase in the Mathematics Attitude Index is associated, for boys, with an increase of 10.6% of a standard deviation in mathematics performance. The coefficient on *Female* indicates that girls' scores are 1.9% of a standard deviation lower than boys', conditional on the full value-added specification. The *Attitude × Female* interaction is small and not statistically distinguishable from zero, so the data do not support a difference in return to mathematics attitude by gender. Model (6) further adds the interaction between the *Test Anxiety Index* and gender. The *Test Anxiety × Female* interaction in column (6) is positive and significant, indicating that girls are less penalised by test anxiety than boys in terms of mathematics performance at grade 8.

The contrasting significance of the two interaction terms deserves closer attention. The non-significance of *Attitude × Female* suggests that the estimated association between positive attitudes towards mathematics and achievement is similar for boys and girls, and that gender differences in mathematics achievement operate primarily through levels, as captured by the *Female* coefficient, rather than through differential returns to motivational traits. The significance of *Test Anxiety × Female*, by contrast, is consistent with a pattern documented in the psychology literature, whereby girls tend to report higher levels of test anxiety but experience a smaller performance penalty (Zeidner, 1998; Putwain et al., 2022). Several mechanisms could generate this asymmetry, and our reduced-form estimates do not allow us to discriminate between them. First, girls may employ more effective coping strategies that attenuate the impact of anxiety on performance. Alternatively, the asymmetry may reflect more mechanical forces: if girls start from a higher mean level of test anxiety, a marginal increase may produce diminishing effects on performance; self-reported anxiety may be measured with smaller error among girls, who tend to underreport less than boys; and girls with high anxiety may compensate through greater study effort, attenuating the observed performance penalty without any underlying difference in coping. Disentangling these channels is beyond the scope of the present analysis, but the heterogeneity by gender remains a consistent pattern across specifications.

Table 1.9: The influence of male and female attitudes towards Mathematics on Invalsi test performance in 8th grade.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Attitude: Mathematics	0.297*** (0.002)	0.113*** (0.001)	0.111*** (0.001)	0.112*** (0.002)	0.106*** (0.002)	0.105*** (0.002)
Mathematics score G05		0.735*** (0.002)	0.709*** (0.002)	0.709*** (0.002)	0.700*** (0.002)	0.700*** (0.002)
Gender (female=1)			-0.029*** (0.003)	-0.029*** (0.003)	-0.019*** (0.003)	-0.019*** (0.003)
Attitude x Female				-0.001 (0.003)	-0.003 (0.003)	-0.001 (0.003)
ESCS Index			0.100*** (0.002)	0.100*** (0.002)	0.098*** (0.002)	0.098*** (0.002)
Kindergarten (yes=1)			0.028*** (0.010)	0.028*** (0.010)	0.026*** (0.010)	0.026*** (0.010)
Immigrant (yes=1)			-0.076*** (0.005)	-0.076*** (0.005)	-0.072*** (0.005)	-0.072*** (0.005)
Early enrolled (yes=1)			0.104*** (0.013)	0.104*** (0.013)	0.104*** (0.013)	0.104*** (0.013)
Late enrolled (yes=1)			-0.125*** (0.011)	-0.125*** (0.011)	-0.123*** (0.011)	-0.123*** (0.011)
Test-anxiety Index					-0.045*** (0.001)	-0.050*** (0.002)
Test Anxiety x Female						0.010*** (0.003)
Constant	0.091*** (0.000)	0.054*** (0.000)	0.043*** (0.008)	0.042*** (0.008)	0.039*** (0.009)	0.038*** (0.009)
Observations	416,526	416,526	359,004	359,004	352,902	352,902
R-squared	0.255	0.523	0.537	0.537	0.539	0.539

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.10: The influence of male and female attitudes towards Mathematics on Invalsi test performance in 10th grade.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Attitude: Mathematics	0.302*** (0.002)	0.088*** (0.001)	0.083*** (0.002)	0.086*** (0.002)	0.084*** (0.002)	0.084*** (0.002)
Mathematics score G05		0.318*** (0.003)	0.311*** (0.003)	0.311*** (0.003)	0.309*** (0.003)	0.309*** (0.003)
Mathematics score G08		0.457*** (0.002)	0.446*** (0.002)	0.446*** (0.002)	0.445*** (0.002)	0.445*** (0.002)
Gender (female=1)			-0.056*** (0.003)	-0.056*** (0.003)	-0.054*** (0.003)	-0.054*** (0.003)
Attitude x Female				-0.004 (0.003)	-0.004 (0.003)	-0.004 (0.003)
ESCS Index			0.062*** (0.002)	0.062*** (0.002)	0.062*** (0.002)	0.062*** (0.002)
Kindergarten (yes=1)			0.007 (0.011)	0.007 (0.011)	0.009 (0.011)	0.009 (0.011)
Immigrant (yes=1)			0.009 (0.006)	0.009 (0.006)	0.010 (0.006)	0.010 (0.006)
Early enrolled (yes=1)			0.118*** (0.013)	0.118*** (0.013)	0.118*** (0.013)	0.118*** (0.013)
Late enrolled (yes=1)			-0.083*** (0.013)	-0.083*** (0.013)	-0.085*** (0.013)	-0.085*** (0.013)
Test-anxiety Index					-0.013*** (0.001)	-0.013*** (0.002)
Test Anxiety x Female						-0.000 (0.003)
Constant	0.120*** (0.000)	-0.008*** (0.000)	0.011 (0.009)	0.010 (0.009)	0.008 (0.009)	0.008 (0.010)
Observations	342,484	342,484	296,567	296,567	291,909	291,909
R-squared	0.291	0.587	0.597	0.597	0.597	0.597

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.10 reports estimates for grade 10, the second follow-up wave, when students are enrolled in the second year of upper secondary school. The *Mathematics Attitude Index* remains positive and statistically significant across all specifications. In our main specification (column 5), a one standard deviation increase in the attitude index is associated with an 8.4% of a standard deviation increase in Mathematics achievement for boys. This is only modestly smaller than the 10.6% estimate in grade 8, despite the five-year gap and the inclusion of two waves of prior achievement as controls. The stability of this association points to the independent and durable predictive content of early motivational beliefs, which persist well beyond the primary-to-lower secondary transition and into a more institutionally heterogeneous educational environment.

The coefficient on *Female* is negative and statistically significant, and its absolute magnitude has increased relative to grade 8, signalling a widening conditional gender gap in Mathematics achievement. The *Attitude × Female* interaction remains statistically insignificant (−0.004).

The widening gender gap thus continues to operate through differences in levels, as captured by the *Female* coefficient, rather than through heterogeneous returns to motivational traits.

The *Test Anxiety Index* attenuates relative to grade 8: a one standard deviation increase in anxiety is now associated with a decline of 1.3% of a standard deviation in Mathematics scores, compared to 4.5% at the previous wave. The *Test Anxiety × Female* interaction, moreover, is no longer statistically significant, indicating that the differential penalisation of anxiety observed at grade 8 does not persist in the medium run. A natural reading of these patterns points to the institutional context in which the grade 10 assessment is administered. Unlike grade 8, the grade 10 INVALSI test carries no formal consequences

for students, and a less binding evaluative environment plausibly triggers weaker affective responses during the assessment itself. Dispositional anxiety may then translate less forcefully into performance loss under low-stakes conditions.

Table 1.11: The influence of male and female attitudes towards Mathematics on the Invalsi test performance in 13th grade.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Attitude: Mathematics	0.305*** (0.002)	0.056*** (0.001)	0.050*** (0.001)	0.053*** (0.002)	0.054*** (0.002)	0.053*** (0.002)
Mathematics score G05		0.128*** (0.002)	0.125*** (0.003)	0.125*** (0.003)	0.125*** (0.003)	0.125*** (0.003)
Mathematics score G08		0.211*** (0.002)	0.207*** (0.002)	0.207*** (0.002)	0.207*** (0.002)	0.207*** (0.002)
Mathematics score G10		0.506*** (0.002)	0.499*** (0.003)	0.499*** (0.003)	0.500*** (0.003)	0.500*** (0.003)
Gender (female=1)			-0.082*** (0.003)	-0.082*** (0.003)	-0.082*** (0.003)	-0.082*** (0.003)
Attitude x Female				-0.007** (0.003)	-0.007** (0.003)	-0.006** (0.003)
ESCS Index			0.026*** (0.002)	0.026*** (0.002)	0.026*** (0.002)	0.026*** (0.002)
Kindergarten (yes=1)			0.004 (0.011)	0.005 (0.011)	0.005 (0.011)	0.005 (0.011)
Immigrant (yes=1)			0.002 (0.006)	0.002 (0.006)	0.001 (0.006)	0.001 (0.006)
Early enrolled (yes=1)			0.094*** (0.012)	0.094*** (0.012)	0.095*** (0.012)	0.095*** (0.012)
Late enrolled (yes=1)			-0.089*** (0.013)	-0.089*** (0.013)	-0.088*** (0.014)	-0.088*** (0.014)
Test-anxiety Index					0.001 (0.001)	-0.002 (0.002)
Test Anxiety x Female						0.005* (0.003)
Constant	0.154*** (0.000)	-0.007*** (0.000)	0.034*** (0.009)	0.033*** (0.009)	0.034*** (0.010)	0.033*** (0.010)
Observations	299,314	299,314	259,686	259,686	255,736	255,736
R-squared	0.302	0.669	0.675	0.675	0.675	0.675

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.11 reports estimates for grade 13, the final follow-up wave, observed at the end of upper secondary school. The *Mathematics Attitude Index* remains positive and statistically significant, though further attenuated relative to both earlier waves. Results in (column 5) indicate that a one standard deviation increase in attitude is associated with a 5.4% of a standard deviation increase in Mathematics achievement for boys, smaller than the grade-8 estimate. That a significant association persists eight years after attitudes are measured, conditional on three intervening waves of prior achievement, is consistent with the long-run predictive relevance of early motivational and self-efficacy beliefs.

By grade 13, the gender dimension of the relationship has changed qualitatively. The *Attitude × Female* interaction is negative and statistically significant (-0.007^{**}), so that the marginal effect for girls amounts to 4.7% of a standard deviation—still positive, but smaller than for boys. This gender difference in returns is absent at grades 8 and 10 and appears only at this final wave. One reading is that girls draw a smaller performance gain than boys from the same level of self-perceived competence, and that this gap widens towards the end of secondary school, when expectations tied to gender identity and stereotypes become more pronounced (Steele, 1997).

By contrast, the *Test Anxiety Index* is no longer statistically significant (-0.001). As noted above, we read the grade-13 estimates with caution, given the post-pandemic context of the 2021–22 wave.

Taken together, the dynamic pattern of coefficients across grades 8, 10, and 13 in mathematics yields three central findings. First, early domain-specific attitudes retain a statistically significant association with mathematics performance even eight years after attitudes are measured and conditional on three intervening waves of prior achievement. This persistence suggests a long-run predictive role for motivational and self-efficacy beliefs formed by the end of primary school. Second, the magnitude of this association attenuates gradually across waves, consistent with the progressive accumulation of subsequent academic inputs and environmental influences. Part of this attenuation, however, may be mechanical: because the value-added conditioning set widens across waves, the later-grade coefficients are net of more intermediate achievement—precisely the channel through which early attitudes operate—and are therefore not strictly comparable across grades. Reassuringly, the grade-10 coefficient (8.4% of a SD) remains close to the grade-8 estimate (10.6%) despite two additional waves of prior achievement, suggesting that the decline is not driven by the wider conditioning set alone. A third pattern concerns gender: a divergence in returns emerges at grade 13, with girls deriving smaller benefits from equivalent levels of early motivational beliefs. Because this wave coincided with the immediate post-pandemic period, the late-emerging gender asymmetry should be interpreted with caution: existing evidence indicates that pandemic-related learning losses differed by gender (Contini et al., 2022), and the gender pattern observed at grade 13 may partly reflect this differential exposure rather than a steady-state divergence in returns to early attitudes. Overall, these results are consistent with a framework in which early non-cognitive traits show persistent but evolving predictive relationships, shaped by cumulative achievement, possibly by the institutional features of each evaluative environment, and by gender-specific social processes that may intensify in late adolescence.

1.4.2 Literacy test scores

We now turn to literacy achievement, applying the same empirical specifications used for mathematics. Tables 1.12, 1.13, and 1.14 report OLS estimates for grades 8, 10, and 13, respectively. As in the mathematics analysis, we take column (5)—which includes the *Literacy Attitude Index*, its interaction with gender, the *Test Anxiety Index*, and the full set of additional controls—as our baseline specification, and also present column (6) results that allows the anxiety penalty to vary by gender. Overall, across all three waves, the introduction of the *Test Anxiety* $\times$ *Female* interaction in column (6) leaves the remaining estimates virtually unchanged, indicating that the main coefficients are stable to this additional flexibility.

The *Literacy Attitude Index* enters positively and significantly at every wave, with magnitudes that attenuate over time. In our baseline specification, a one standard deviation increase in literacy attitude at grade 5 is associated with a 4.4% of a standard deviation increase in literacy performance for boys at grade 8, declining to 3.5% at grade 10 and 2.2% at grade 13—a 50% reduction over the eight-year window. These magnitudes are consistently smaller than the corresponding mathematics estimates (10.6%, 8.4%, and 5.4% at the three waves). One possible explanation for this difference between the two subjects is that learning in mathematics is highly cumulative and depends on sustained effort across successive instructional stages, whereas literacy achievement may depend to a greater extent on learning opportunities outside the classroom, such as exposure to language-rich home environments. An additional explanation emerges from the cross-subject specification in Section 1.5: the mathematics index appears to capture, alongside a domain-specific component, a component of general academic confidence, which may inflate its coefficient relative to the literacy index.

As expected, the coefficient on *Female* is positive and significant throughout, documenting a female advantage in literacy that contrasts with the male advantage documented for mathematics. The conditional gap is large at grade 8 (20.1% of a standard deviation), narrows substantially by grade 10 (8.3%), and shrinks further by grade 13 (6.6%). This narrowing female advantage in literacy moves in the same direction as the widening female disadvantage in mathematics over the same interval. In both domains, girls’ relative performance deteriorates as students advance through secondary school. This common pattern could be read in light of the gender-differentiated attrition documented in Section 1.2: boys exit the panel at higher rates than girls, partly reflecting their higher probability of grade retention and early school dropout in the Italian secondary system. The cohort of boys observed at grade 10 and grade 13 is therefore positively selected on prior achievement and non-cognitive dispositions relative to the grade 5 baseline, which may improve boys’ relative standing and thereby compress the female advantage in literacy, amplify the female disadvantage in mathematics, or both. In this case, part of this improvement in boys’ relative standing would reflect compositional change rather than a substantive deterioration in girls’ relative achievement; we check this point in the robustness analysis of Section 1.5.

The *Attitude* $\times$ *Female* interaction tells a related but distinct story. It is negligible at grade 8 (-0.001 , not significant), but becomes negative and significant at grade 10 (-0.017^{***}) and remains negative and marginally significant at grade 13 (-0.005^*). The implied marginal effect of attitude for girls thus falls from approximately 4.3% at grade 8 to 1.8% and 1.7% at later waves. Notably, the gender divergence in returns emerges earlier in literacy than in mathematics, where the analogous interaction becomes significant only at grade 13.

The *Test Anxiety Index* enters negatively and significantly at all three waves, with magnitudes that likewise decline over time: -4.5% at grade 8, -2.3% at grade 10, and -1.1% at grade 13. The grade 8 estimate is comparable to the corresponding figure in mathematics (-4.5%), but a notable difference between the two subjects emerges thereafter: in mathematics the *Test Anxiety Index* becomes statistically indistinguishable from zero by grade 13, whereas in literacy it retains significance even at the end of upper secondary school. The persistence of a detectable anxiety–achievement association in literacy may reflect domain-specific dynamics in how early emotional responses to testing map onto long-run verbal outcomes, although the cautions previously outlined for Mathematics regarding the post-pandemic context of the 2021–22 wave apply equally here. The *Test Anxiety* $\times$ *Female* interaction, introduced in column (6), is small and statistically indistinguishable from zero at every wave (0.002 , -0.004 , -0.002). This is one of the clearest contrasts between the two subjects in the analysis: at grade 8, the analogous interaction in mathematics is positive and highly significant (0.010^{***}), indicating that girls bear a smaller anxiety penalty than boys in mathematics, while in literacy the gradient is gender-neutral throughout.

Overall, the literacy results are similar to those obtained for mathematics. Specifically, they confirm the existence of persistent, though gradually weakening, associations between early subject-specific attitudes and later achievement, as well as a gender divergence in these associations that emerges over the course of secondary education. At the same time, the estimates reveal several differences between the two subjects. Effect sizes are consistently smaller in literacy, while their proportional attenuation across grades is similar. Moreover, the interaction between attitudes and gender becomes statistically significant by grade 10 in literacy, whereas it does not emerge until grade 13 in mathematics, suggesting an earlier gender divergence in the domain where girls are traditionally advantaged. The anxiety channel remains gender-neutral in literacy throughout the observation period, contrasting with the gender-differentiated association observed in mathematics at grade 8. Overall, these patterns suggest that the relationship between non-cognitive traits and academic achievement may be domain-specific, with the same underlying traits operating through mechanisms influenced by gender stereotypes, institutional contexts, and the cultural salience of the subject.

Table 1.12: The influence of male and female attitudes towards Literacy on the Invalsi test performance in 8th grade.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Attitude: Literacy	0.167*** (0.002)	0.074*** (0.001)	0.047*** (0.001)	0.046*** (0.002)	0.044*** (0.002)	0.044*** (0.002)
Literacy score G05		0.701*** (0.002)	0.667*** (0.002)	0.667*** (0.002)	0.657*** (0.002)	0.657*** (0.002)
Gender (female=1)			0.186*** (0.003)	0.186*** (0.003)	0.201*** (0.003)	0.201*** (0.003)
Attitude x Female				0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
ESCS Index			0.104*** (0.002)	0.104*** (0.002)	0.101*** (0.002)	0.101*** (0.002)
Kindergarten (yes=1)			0.030*** (0.010)	0.030*** (0.010)	0.031*** (0.010)	0.031*** (0.010)
Immigrant (yes=1)			-0.057*** (0.005)	-0.057*** (0.005)	-0.056*** (0.005)	-0.056*** (0.005)
Early enrolled (yes=1)			0.086*** (0.013)	0.086*** (0.013)	0.086*** (0.013)	0.086*** (0.013)
Late enrolled (yes=1)			-0.096*** (0.011)	-0.096*** (0.011)	-0.094*** (0.011)	-0.094*** (0.011)
Test-anxiety Index					-0.045*** (0.001)	-0.046*** (0.002)
Test Anxiety x Female						0.002 (0.003)
Constant	0.122*** (0.000)	0.073*** (0.000)	-0.054*** (0.008)	-0.054*** (0.008)	-0.061*** (0.009)	-0.062*** (0.009)
Observations	409,382	409,382	353,170	353,170	347,269	347,269
R-squared	0.186	0.502	0.522	0.522	0.524	0.524

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.13: The influence of male and female attitudes towards Literacy on the Invalsi test performance in 10th grade.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Attitude: Literacy	0.156*** (0.002)	0.040*** (0.001)	0.029*** (0.002)	0.037*** (0.002)	0.035*** (0.002)	0.035*** (0.002)
Literacy score G05		0.379*** (0.002)	0.373*** (0.003)	0.374*** (0.003)	0.370*** (0.003)	0.370*** (0.003)
Literacy score G08		0.417*** (0.002)	0.404*** (0.002)	0.404*** (0.002)	0.402*** (0.002)	0.402*** (0.002)
Gender (female=1)			0.073*** (0.003)	0.074*** (0.003)	0.083*** (0.003)	0.082*** (0.003)
Attitude x Female				-0.017*** (0.003)	-0.017*** (0.003)	-0.018*** (0.003)
ESCS Index			0.060*** (0.002)	0.060*** (0.002)	0.059*** (0.002)	0.059*** (0.002)
Kindergarten (yes=1)			0.009 (0.011)	0.009 (0.011)	0.010 (0.011)	0.010 (0.011)
Immigrant (yes=1)			0.016** (0.006)	0.016** (0.006)	0.016** (0.007)	0.016** (0.007)
Early enrolled (yes=1)			0.086*** (0.012)	0.086*** (0.012)	0.087*** (0.013)	0.087*** (0.013)
Late enrolled (yes=1)			-0.069*** (0.013)	-0.069*** (0.013)	-0.069*** (0.013)	-0.069*** (0.013)
Test-anxiety Index					-0.023*** (0.002)	-0.021*** (0.002)
Test Anxiety x Female						-0.004 (0.003)
Constant	0.148*** (0.000)	-0.012*** (0.000)	-0.062*** (0.010)	-0.061*** (0.010)	-0.065*** (0.010)	-0.065*** (0.010)
Observations	339,848	339,848	294,533	294,533	289,963	289,963
R-squared	0.193	0.537	0.546	0.547	0.547	0.547

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.14: The influence of male and female attitudes towards Literacy on the Invalsi test performance in 13th grade.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Attitude: Literacy	0.156*** (0.002)	0.028*** (0.001)	0.021*** (0.002)	0.023*** (0.002)	0.022*** (0.002)	0.023*** (0.002)
Literacy score G05		0.208*** (0.002)	0.207*** (0.003)	0.207*** (0.003)	0.206*** (0.003)	0.206*** (0.003)
Literacy score G08		0.238*** (0.002)	0.231*** (0.002)	0.231*** (0.002)	0.231*** (0.002)	0.231*** (0.002)
Literacy score G10		0.432*** (0.002)	0.427*** (0.003)	0.426*** (0.003)	0.426*** (0.003)	0.426*** (0.003)
Gender (female=1)			0.062*** (0.003)	0.062*** (0.003)	0.066*** (0.003)	0.066*** (0.003)
Attitude x Female				-0.004 (0.003)	-0.005* (0.003)	-0.005* (0.003)
ESCS Index			0.032*** (0.002)	0.032*** (0.002)	0.032*** (0.002)	0.032*** (0.002)
Kindergarten (yes=1)			0.004 (0.011)	0.004 (0.011)	0.005 (0.011)	0.005 (0.011)
Immigrant (yes=1)			-0.012* (0.007)	-0.012* (0.007)	-0.013* (0.007)	-0.013* (0.007)
Early enrolled (yes=1)			0.091*** (0.012)	0.091*** (0.012)	0.091*** (0.012)	0.091*** (0.012)
Late enrolled (yes=1)			-0.070*** (0.014)	-0.070*** (0.014)	-0.067*** (0.014)	-0.067*** (0.014)
Test-anxiety Index					-0.011*** (0.001)	-0.010*** (0.002)
Test Anxiety x Female						-0.002 (0.003)
Constant	0.187*** (0.000)	-0.016*** (0.000)	-0.055*** (0.010)	-0.054*** (0.010)	-0.057*** (0.010)	-0.056*** (0.010)
Observations	297,858	297,858	258,671	258,671	254,794	254,794
R-squared	0.219	0.632	0.638	0.638	0.638	0.638

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

1.5 Robustness

A first concern relates to the measurement of non-cognitive skills: attitudes are observed at grade 5, while outcomes are realised three to eight years later. If non-cognitive skills evolve over adolescence, grade-5 attitudes are imperfect proxies of the traits operating at the time of each outcome. Under classical measurement error, this attenuates β_1 towards zero, by an amount that grows with the gap between attitude and outcome. The attenuation across grades documented in Section 1.4 could then reflect this growing measurement error rather than a real decline in predictive content. To assess this, we follow De Paola and Skatova (2024) and re-estimate the association using an outcome measured in the same school year as the attitudes, at grade 5, where the gap between attitude and outcome is minimal by construction. The outcome is the first-term teacher-assigned grade in mathematics and literacy at grade 5, obtained from school administrative records. We use the teacher-assigned grade because a grade-4 teacher grade, self-reported by students in the grade-5 questionnaire, is also available, which lets us add a prior-achievement control even at grade 5; this is not possible with the INVALSI Rasch score, which is not collected at grade 4. The teacher-assigned grade is set by the classroom teacher and recorded on a different scale, so it is not mechanically linked to the Rasch covariates of the main specifications. We standardise it to mean zero and unit standard deviation, and estimate three specifications. Results are

reported in Table 1.15.

Measurement error of this kind would make the association decline as the gap between attitude and outcome grows. We examine this separately by subject, using the column (1) estimates, which include only the attitude index and class fixed effects. All coefficients reported here are positive and significant at the 1% level. All three follow-up outcomes are INVALSI Rasch scores standardised within wave, so the coefficients of both table 1.15 and the previous set of tables 1.9-1.14 are on a common standard-deviation scale.

For mathematics, the follow-up estimates are flat across the gap: 0.297 at grade 8, 0.302 at grade 10, and 0.305 at grade 13 (column 1 of Tables 1.9, 1.10, and 1.11). The contemporaneous grade-5 estimate is 0.320, close to the follow-up values even though the outcome is the teacher-assigned grade. The association does not decline as the gap grows.

For literacy, the follow-up estimates are also flat: 0.167 at grade 8, 0.156 at grade 10, and 0.156 at grade 13 (column 1 of Tables 1.12, 1.13, and 1.14). The contemporaneous grade-5 estimate is 0.234, above the follow-up values. This step likely reflects the outcome metric (given by the teacher-assigned grade rather than the Rasch score) not the gap, since the follow-up series itself is flat.

In neither subject does the association decline as the gap widens. Measurement error from the temporal evolution of attitudes is therefore unlikely to be the main driver of the attenuation observed in the value-added specifications.

The same series speaks to a second concern. The mode of administration changes between grade 8 and grade 10: the grade-8 test was paper-based, the grade-10 and grade-13 tests were computer-based (Section 1.2). If the move to computer-based delivery had altered the relationship between early attitudes and measured achievement, the series would show a step at that point, persisting at grade 13. In mathematics, no step is visible: the coefficient moves from 0.297 to 0.302. In literacy, the coefficient declines by 0.011, from 0.167 to 0.156, and then remains at 0.156. Attributed entirely to the change in delivery, this decline amounts to about 7% of the coefficient. The attenuation continues where delivery does not change: between grade 10 and grade 13, both administered on computer, the baseline literacy estimate falls from 3.5% to 2.2% of a standard deviation and the mathematics estimate from 8.4% to 5.4%.

Table 1.15: The influence of male and female attitudes towards Mathematics and Literacy on Teachers' scores in 5th grade.

(a) Mathematics				(b) Literacy			
VARIABLES	(1)	(2)	(3)	VARIABLES	(1)	(2)	(3)
Attitude: Mathematics	0.320*** (0.002)	0.288*** (0.002)	0.045*** (0.001)	Attitude: Literacy	0.234*** (0.002)	0.176*** (0.002)	0.024*** (0.001)
Gender (female=1)		0.135*** (0.003)	0.105*** (0.002)	Gender (female=1)		0.217*** (0.003)	0.140*** (0.002)
ESCS Index		0.233*** (0.002)	0.087*** (0.001)	ESCS Index		0.261*** (0.002)	0.103*** (0.001)
Kindergarten (yes=1)		0.162*** (0.011)	0.076*** (0.009)	Kindergarten (yes=1)		0.183*** (0.011)	0.085*** (0.009)
Immigrant (yes=1)		-0.330*** (0.007)	-0.132*** (0.005)	Immigrant (yes=1)		-0.419*** (0.006)	-0.176*** (0.005)
Early enrolled (yes=1)		0.001 (0.013)	0.005 (0.010)	Early enrolled (yes=1)		0.008 (0.013)	0.006 (0.010)
Late enrolled (yes=1)		-0.285*** (0.012)	-0.138*** (0.010)	Late enrolled (yes=1)		-0.352*** (0.012)	-0.158*** (0.009)
Test-anxiety Index		-0.106*** (0.002)	-0.029*** (0.001)	Test-anxiety Index		-0.123*** (0.002)	-0.036*** (0.001)
Mathematics Teachers' score G4			0.671*** (0.002)	Literacy Teachers' score G4			0.659*** (0.002)
Constant	0.016*** (0.000)	-0.162*** (0.010)	-0.104*** (0.008)	Constant	0.015*** (0.000)	-0.214*** (0.010)	-0.127*** (0.008)
Observations	439,003	372,231	367,525	Observations	439,890	373,145	368,018
R-squared	0.316	0.397	0.662	R-squared	0.283	0.394	0.663

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The availability of a lagged outcome at grade 4 allows a complementary exercise that is not implemented in De Paola and Skatova (2024). When the grade-4 teacher-assigned grade enters as a control alongside the full set of background characteristics (column (3)), the coefficient on the attitude index falls

from 0.288 (column (2)) to 0.045 for mathematics, and from 0.176 to 0.024 for literacy. This pattern is consistent with the interpretation that early attitudes reflect, in part, the cumulative performance trajectory inherited from the first years of primary school. It supports the inclusion of a prior-achievement control in the main specifications, which isolates the incremental predictive content of non-cognitive traits.¹²

A second concern for the interpretation of the main results is sample selection across the three follow-up waves. The analytical sample shrinks progressively as students transition from grade 5 to grade 8, grade 10, and grade 13. At each wave, students who exit the panel display, on average, lower prior achievement, more disadvantaged socio-economic backgrounds, and less favourable grade-5 non-cognitive dispositions (see Section 1.2.1). If the attitude–achievement association varies systematically along these dimensions, the attenuation across grades documented in Section 1.4 could in part reflect compositional change rather than a decay in the predictive content of grade-5 attitudes.

To address this concern, we restrict the sample to students observed in all four INVALSI waves (grade 5, grade 8, grade 10, and grade 13) and replicate the analysis on this balanced panel. In our main specification (Model 5), the restriction yields a sample of 255,736 students for mathematics and 254,794 students for literacy. By construction, this sample is positively selected on the same dimensions. Holding its composition fixed isolates whether the attenuation across grades reflects compositional change. Descriptive statistics specific to both subjects for the balanced panel are reported in Table 1.E.17.

We re-estimate the value-added specification of equation 1.1 on the balanced panel, separately for mathematics and literacy and for the grade-8 and grade-10 outcomes.¹³ The set of controls and the fixed-effects structure are unchanged. Results are reported in Tables 1.E.18–1.E.21 of the Appendix 1.E.

The estimates on the balanced panel are close to those in the main analysis for the attitude and test-anxiety coefficients. The exception is the female coefficient in mathematics, which is larger in absolute value in the balanced sample. In the main analysis, the conditional male advantage in mathematics widens across grades, from 1.9% of a SD at grade 8 to 5.4% at grade 10 and 8.2% at grade 13. On the balanced panel, the advantage is larger at grades 8 and 10 (4.2% and 7.7%) and reaches the same 8.2% at grade 13. Part of the widening in the main analysis is likely to reflect the progressive exit of lower-performing boys, not a change within a fixed cohort. The female advantage in literacy moves in the opposite direction. It narrows from 20.1% of a SD at grade 8 to 6.6% at grade 13 in the main analysis, and from 19.7% to 6.6% on the balanced panel. The narrowing is almost the same in the two samples, so it is not explained by compositional change.

The coefficient on the *Mathematics Attitude Index* shows the same attenuation across grades observed in the full sample, moving from 11.1% of a SD at grade 8 to 8.3% at grade 10. The pattern for the *Literacy Attitude Index* is also preserved, with coefficients of 4.9% and 3.3% of a SD at grade 8 and grade 10, respectively. The coefficient on the *Test Anxiety Index* reproduces the reduction in magnitude between the high-stakes grade 8 and the low-stakes grade 10 documented in the main specification.

Two points follow. First, the attenuation of the attitude–achievement association across grades is not driven by the progressive selection of the analytical sample: it persists when the composition of students is held constant by construction. Second, the predictive content of grade-5 attitudes holds within the subsample of students who complete the full upper-secondary trajectory, not only in the larger sample that includes students later lost to attrition.

The remainder of this section examines the measurement choice on which the chapter rests. Section 1.2.2 constructs two domain-specific attitude indices rather than a single general non-cognitive measure, as De Paola and Skatova (2024) did on the same data. Two questions follow. Do general non-cognitive traits account for the association we attribute to subject-specific attitudes? And is that association itself domain-specific, in the sense that an attitude toward one subject predicts achievement in that subject and not in the other? We take them in turn.

The first question asks whether the subject-specific indices carry information beyond that contained in general non-cognitive traits. The economics of skill formation models non-cognitive skills — motivation, self-regulation — as inputs in the human capital production function alongside cognitive ability (Heckman et al., 2006; Cunha and Heckman, 2008; Heckman and Kautz, 2012). Models of belief formation and self-concept, by contrast, treat confidence and ability perceptions as domain-specific traits that shape task-specific effort provision (Eccles, 1983; Bordalo et al., 2019; Möller and Marsh, 2013). The two views imply different empirical predictions: if effort allocation is subject-targeted, domain-specific beliefs

¹²Being self-reported, the grade-4 teacher grade is subject to recall error.

¹³The grade-13 sample coincides by construction with the balanced panel, since being observed at grade 13 is the binding requirement for inclusion. The grade-13 estimates reported in Section 1.4 are therefore unchanged in this exercise.

should retain explanatory power for achievement in the corresponding subject once general non-cognitive traits are controlled for.

We augment model 5 with three general non-cognitive indices measured at grade 5, following [De Paola and Skatova \(2024\)](#): a general motivation index, a time management index, and a social isolation index. The three indices are constructed from the same INVALSI Student Questionnaire used to derive the subject-specific indices, and are standardised to mean zero and unit standard deviation. The stability of the coefficients on the subject-specific attitude indices across specifications provides evidence on whether domain-specific attitudes capture variation that is not accounted for by general non-cognitive traits. Results are reported in Table 1.16.

Table 1.16: Attitudes and academic performance, controlling for motivation, time management, and social isolation.

(a) Mathematics				(b) Literacy			
VARIABLES	(1) Grade 8	(2) Grade 10	(3) Grade 13	VARIABLES	(1) Grade 8	(2) Grade 10	(3) Grade 13
Attitude: Mathematics	0.108*** (0.002)	0.084*** (0.002)	0.053*** (0.002)	Attitude: Literacy	0.027*** (0.002)	0.031*** (0.002)	0.020*** (0.002)
Mathematics score G05	0.699*** (0.002)	0.309*** (0.003)	0.126*** (0.003)	Literacy score G05	0.654*** (0.002)	0.370*** (0.003)	0.207*** (0.003)
Mathematics score G08		0.445*** (0.002)	0.207*** (0.002)	Literacy score G08		0.402*** (0.002)	0.231*** (0.002)
Mathematics score G10			0.498*** (0.003)	Literacy score G10			0.424*** (0.003)
Gender (female=1)	-0.022*** (0.003)	-0.059*** (0.003)	-0.086*** (0.003)	Gender (female=1)	0.193*** (0.003)	0.077*** (0.003)	0.061*** (0.003)
Attitude x Female	-0.004 (0.003)	-0.005* (0.003)	-0.008*** (0.003)	Attitude x Female	-0.001 (0.003)	-0.017*** (0.003)	-0.005* (0.003)
ESCS Index	0.099*** (0.002)	0.063*** (0.002)	0.027*** (0.002)	ESCS Index	0.099*** (0.002)	0.060*** (0.002)	0.032*** (0.002)
Kindergarten (yes=1)	0.028*** (0.010)	0.011 (0.011)	0.005 (0.011)	Kindergarten (yes=1)	0.031*** (0.010)	0.012 (0.011)	0.008 (0.011)
Immigrant (yes=1)	-0.074*** (0.005)	0.004 (0.006)	-0.004 (0.006)	Immigrant (yes=1)	-0.060*** (0.005)	0.008 (0.007)	-0.020*** (0.007)
Early enrolled (yes=1)	0.101*** (0.013)	0.117*** (0.013)	0.095*** (0.012)	Early enrolled (yes=1)	0.086*** (0.013)	0.084*** (0.013)	0.091*** (0.012)
Late enrolled (yes=1)	-0.126*** (0.011)	-0.088*** (0.013)	-0.091*** (0.014)	Late enrolled (yes=1)	-0.094*** (0.011)	-0.074*** (0.013)	-0.070*** (0.014)
Test-anxiety Index	-0.045*** (0.001)	-0.012*** (0.002)	0.001 (0.001)	Test-anxiety Index	-0.041*** (0.001)	-0.021*** (0.002)	-0.010*** (0.001)
Motivation Index	0.014*** (0.001)	0.019*** (0.002)	0.014*** (0.001)	Motivation Index	0.025*** (0.001)	0.025*** (0.002)	0.022*** (0.002)
Time Management Index	-0.016*** (0.001)	-0.003* (0.002)	0.001 (0.002)	Time Management Index	0.019*** (0.001)	0.003 (0.002)	0.000 (0.002)
Social Isolation Index	0.005*** (0.001)	0.023*** (0.002)	0.016*** (0.002)	Social Isolation Index	-0.020*** (0.001)	0.027*** (0.002)	0.022*** (0.002)
Constant	0.039*** (0.009)	0.011 (0.010)	0.037*** (0.010)	Constant	-0.058*** (0.009)	-0.061*** (0.010)	-0.055*** (0.010)
Observations	350,120	289,720	253,865	Observations	344,522	287,780	252,911
R-squared	0.540	0.598	0.676	R-squared	0.526	0.549	0.639

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The coefficient on the *Mathematics Attitude Index* remains largely unchanged in both magnitude and statistical significance across all three follow-up waves once the general indices are included. For literacy, the coefficient on the *Literacy Attitude Index* is virtually unchanged at grades 10 and 13. At grade 8, it declines from 0.044 to 0.027 standard deviations of the outcome, but remains statistically significant at the 1% level. Overall, these results suggest that subject-specific attitudes retain predictive power beyond that captured by broader non-cognitive traits. This pattern is consistent with a framework in which general traits contribute to achievement across domains, while subject-specific attitudes provide additional information about performance in the corresponding subject.

The coefficients on the three additional indices do not reproduce in full those reported by [De Paola and Skatova \(2024\)](#) on the same data, but go in the same direction in most cells of Table 1.16. The comparison refers to the columns of [De Paola and Skatova \(2024\)](#) that use the Rasch test scores as the dependent variable and include the full set of controls (their Tables 5–8, last column for grade-8 outcomes

and the corresponding fully-saturated column for grade-10 outcomes). The *Motivation Index* is positive and significant at the 1% level in all four cells, in line with their estimates, with smaller magnitudes in our specifications. The *Social Isolation Index* reproduces the sign reversal between grade 8 and grade 10 documented by De Paola and Skatova (2024), who interpret the positive sign at grade 10 as a consequence of positive selection into upper-secondary school. The *Time Management Index* is positive and significant for literacy at grade 8, in line with their estimates, while the divergence is more pronounced at grade 10 in both subjects and at grade 8 in mathematics.

Two factors are likely to contribute to this divergence. First, the specifications are not directly parallel: our preferred model includes the subject-specific attitude index and the test-anxiety index alongside the three general indices, whereas De Paola and Skatova (2024) estimates the partial association of the three general indices alone. The pairwise correlations between general and subject-specific indices at grade 5 are non-negligible, in particular between Time Management and the Literacy Attitude Index (0.41) and between Time Management and the Mathematics Attitude Index (0.29). Part of the variation that loads on the general indices in their specification is therefore reallocated to the subject-specific term in ours. The coefficients on the three general indices in Table 1.16 should accordingly be read as the residual association between general traits and achievement, net of the subject-specific channel. Second, the set of controls and the fixed-effects structure differ: we condition on primary-school class fixed effects and on the full sequence of lagged outcomes from grade 5 to the wave preceding the outcome, while De Paola and Skatova (2024) use primary-school fixed effects and grade-5 Rasch scores. The richer sequence of prior outcomes absorbs part of the cumulative learning trajectory that, in their specification, loads on the general indices.

This exercise supplies the benchmark that a comparison against a single general measure would provide, and supplies it using general constructs built by other authors on the same cohort rather than an aggregate of our own items. The subject-specific coefficients are essentially unchanged by their inclusion. General non-cognitive measures do not, therefore, substitute for domain-specific ones: they are not the same construct captured more parsimoniously, but a different one, and the near-orthogonality of the two attitude indices documented in Section 1.2.3 indicates why. Whether the domain-specific content they capture is genuinely tied to its own domain is a separate question, which the next exercise addresses directly.

The second question is whether the estimated associations are genuinely domain-specific rather than reflecting a general disposition that happens to be elicited with subject-specific wording. We address it directly through a cross-subject specification. We re-estimate equation (1.1) replacing the own-domain attitude index with the index constructed for the other domain, so that mathematics achievement is regressed on the Literacy Attitude Index and literacy achievement on the Mathematics Attitude Index. We then estimate a joint specification in which both indices enter simultaneously, which allows the own- and cross-domain coefficients to be compared within a single equation. Results are reported in Table 1.F.23 Panels A and B.

Two points of interpretation should be stated before the results. First, this is not a placebo test against a null of zero. A disposition toward one subject may plausibly bear on achievement in the other, through spillovers of effort, general academic confidence, or study habits common to both domains, and a non-zero cross-domain coefficient is therefore not by itself evidence against domain-specificity. The hypothesis under examination concerns relative magnitude: whether the own-domain association is substantially larger than the cross-domain one. Second, because the two indices are almost uncorrelated (a correlation of 0.02 in the pooled sample; Section 1.2.3), the own- and cross-domain coefficients are separately identified and the joint specification raises no collinearity concern. The same near-orthogonality implies that omitting the other domain's attitude from the baseline specification introduces negligible omitted-variable bias, which the joint estimates confirm: the own-domain coefficients are unchanged to the third decimal.

The evidence is asymmetric, and we report it as such. In the literacy-to-mathematics direction the test succeeds cleanly. The Literacy Attitude Index carries essentially no predictive content for mathematics achievement: -0.010 , 0.019 and 0.005 of a standard deviation at grades 8, 10 and 13, against own-domain coefficients of 0.106 , 0.084 and 0.054 in the corresponding specifications. The cross-domain estimates are not merely an order of magnitude smaller; they change sign across waves, which is what one expects of a channel carrying no systematic content. The joint specification, in which both indices enter the same equation, gives the same picture: 0.106 for the own-domain index against -0.012 for the cross-domain one at grade 8. We draw the comparison in terms of magnitude rather than statistical significance: with samples in excess of 300,000 observations, a formal test of equality between the two coefficients would be rejected for differences of no economic consequence, and would therefore not be informative.

In the mathematics-to-literacy direction it does not. The Mathematics Attitude Index predicts literacy

achievement with coefficients of 0.053, 0.025 and 0.009 of a standard deviation, exceeding at grade 8 the own-domain coefficient of the Literacy Attitude Index (0.044); the joint specification gives 0.052 against 0.044. The most plausible reading is that the mathematics index captures, alongside a domain-specific component, a component of general academic confidence that the literacy index does not. [Fan and Williams \(2018\)](#) report the same asymmetry on United States data: mathematics self-efficacy relates to achievement in both domains, reading self-efficacy only to achievement in its own. If so, the mathematics estimates should be read as an upper bound on the strictly domain-specific association.

One feature of the cross-domain channel is worth recording, because the own-domain specification cannot reveal it. The interaction between the Literacy Attitude Index and gender in the mathematics equation is large and negative at grade 10 (-0.032): the small positive association estimated for boys (0.019) is absent, and if anything reversed, among girls (-0.013). Whether the reversal reflects a gendered substitution of effort across subjects ([Möller and Marsh, 2013](#); [Mechtenberg, 2009](#)) is beyond what these data can establish, and we leave it to future work.

1.6 Heterogeneity

The baseline estimates summarise the average association between grade-5 subject-specific non-cognitive skills and subsequent academic achievement. We focus the heterogeneity analysis on the variable of primary interest of the paper, namely the subject-specific Attitude Index. The returns to non-cognitive inputs need not be uniform across students. The skill-formation framework of [Cunha and Heckman \(2008\)](#) predicts that the productivity of early inputs depends on the stock of skills already accumulated and on the institutional context of subsequent learning; [Almlund et al. \(2011\)](#) and [Heckman and Kautz \(2012\)](#) report that the predictive content of personality traits varies with family resources, local environment, and gender norms.

We examine three dimensions of heterogeneity. First, we estimate quantile regressions to assess whether returns differ across the conditional distribution of achievement. Second, we partition the sample by quartile of the family socio-economic status index (ESCS), which addresses the role of household resources as a moderator of the attitude–achievement association. Third, we estimate the model separately by geographic macro-area, given the territorial disparities documented for the Italian system (Section 1.6.3). Each of the three margins is further interacted with student gender, in light of the gender gaps in achievement and academic self-concept reported for Italy.

The analysis is conducted separately for mathematics and literacy. Unless stated otherwise, all specifications retain the controls of the preferred model (column 5 of Tables 1.9 and 1.12): prior cognitive achievement, individual and family characteristics, and primary-school class fixed effects. Standard errors are clustered at the primary-school class level. The following figures 1.2–1.8 report the estimated coefficient on the Attitude Index for each subgroup; the corresponding full regression output is reported in the Appendix 1.D.

Figures that report estimates by gender adopt a common visual convention throughout the section. Orange markers refer to female students and green markers to male students. A filled marker denotes that the difference between the male and female coefficients at the corresponding bin is statistically significant at the 5% level; an empty marker indicates that the male–female difference is not statistically distinguishable from zero. Figures that pool the two genders use a single colour and adopt the convention specified in the corresponding caption.

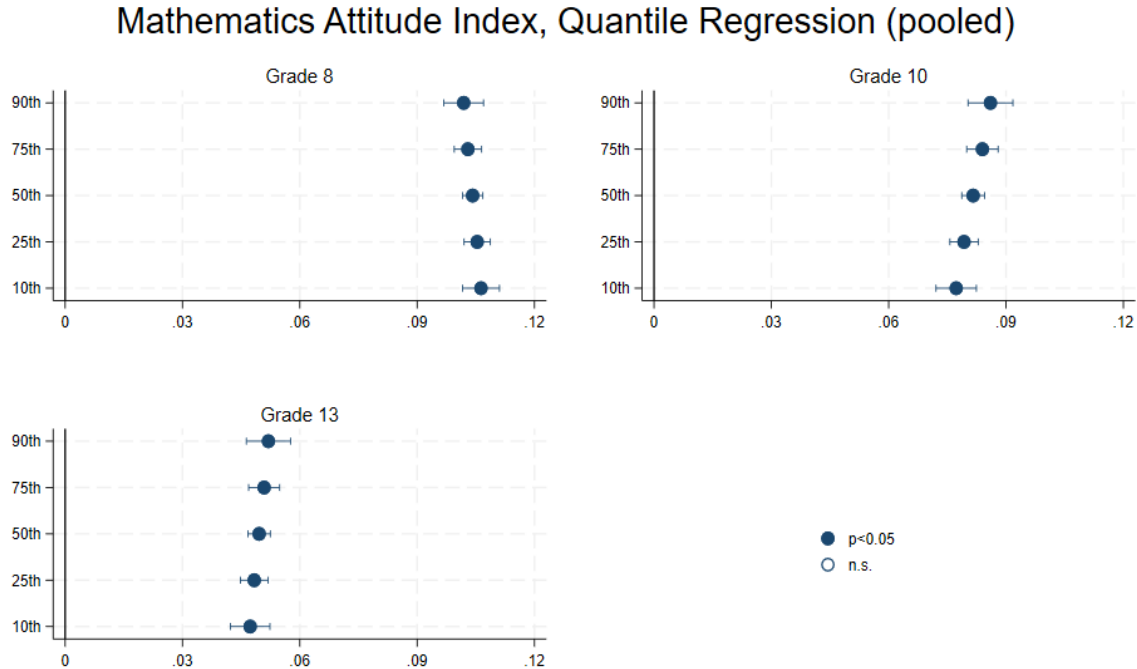
1.6.1 Quantile regressions

The OLS estimates discussed in Section 1.4 summarise the average association between grade-5 attitudes and subsequent achievement at the conditional mean. Quantile regression generalises this analysis by estimating the same relationship at different points of the conditional distribution of the outcome, allowing the predictive content of the index to differ across students who, given the same set of observable characteristics, end up with low or high test scores. The lower tail describes students who, given prior achievement and background, are weaker performers; the upper tail describes stronger performers within the same conditioning set. The skill-formation framework of [Cunha and Heckman \(2008\)](#) suggests two distinct margins. On one side, non-cognitive traits can substitute for limited cognitive resources, so that students at the lower tail of the conditional distribution may benefit relatively more from a positive disposition towards the subject. On the other side, the same framework features possible complementarities between cognitive and non-cognitive skills, by which a higher stock of one input raises the productivity of the other; under this margin, returns to attitudes are amplified for students at the upper tail, where

the cognitive endowment is higher. Quantile regression makes it possible to characterise both margins jointly, rather than summarising the relationship at the conditional mean.

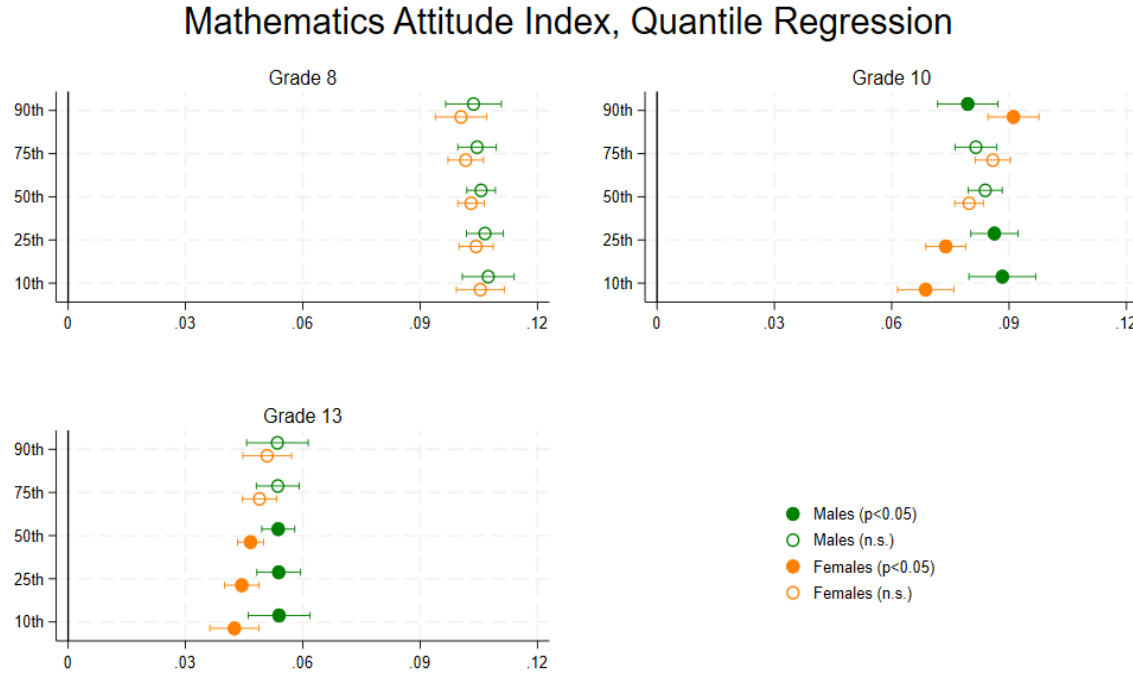
We estimate the model at the 10th, 25th, 50th, 75th, and 90th percentiles using the method-of-moments estimator of [Machado and Santos Silva \(2019\)](#). For each subject we first report the pooled estimates, which omit the interaction with the female indicator, and then re-estimate the model separately by gender.

Figure 1.1: Quantile regression coefficients of the Mathematics Attitude Index, grades 8, 10, and 13.



Notes: Each marker reports the estimated coefficient on the Mathematics Attitude Index at the 10th, 25th, 50th, 75th, and 90th percentiles of the conditional outcome distribution, estimated using the method-of-moments quantile regression of [Machado and Santos Silva \(2019\)](#). The dependent variable is the standardised INVALSI mathematics Rasch score measured at grades 8, 10, and 13. The specification corresponds to column 5 of Table 1.9 without the interaction between the index and the female indicator. Lines represent 95% confidence intervals; filled markers denote statistical significance at the 5% level. Standard errors are clustered at the primary-school class level.

Figure 1.1 presents one panel per grade. Each marker is the estimated coefficient on the Mathematics Attitude Index at the corresponding percentile, and the horizontal line is its 95% confidence interval; filled markers denote significance at the 5% level. The coefficient is positive and significant at every quantile in every grade. As expected from the OLS results, magnitudes decline along the educational trajectory: estimates cluster around 0.10–0.11 SD in grade 8, 0.075–0.09 SD in grade 10, and 0.045–0.055 SD in grade 13. The profile across the conditional distribution is close to flat in grades 8 and 13, and mildly increasing in grade 10, where the coefficient rises from about 0.075 SD at the 10th percentile to about 0.09 SD at the 90th percentile. In terms of the two margins outlined above, this near-flat shape indicates that neither substitution nor complementarity dominates in mathematics: a one-standard-deviation increase in the index is therefore associated with a similar gain in subsequent mathematics achievement for weaker and stronger performers within the conditioning set, with point estimates that decline by roughly half between grade 8 and grade 13. The slight upward slope at grade 10 is the only sign of a complementarity-type pattern, but given its small magnitude—about 0.015 SD across the entire distribution—we do not read it as evidence of a systematic increase across quantiles.

Figure 1.2: Quantile regression coefficients of the Mathematics Attitude Index by gender, grades 8, 10, and 13.

Notes: Each marker reports the estimated coefficient on the Mathematics Attitude Index at the 10th, 25th, 50th, 75th, and 90th percentiles of the conditional outcome distribution, estimated separately by gender using the method-of-moments quantile regression of Machado and Santos Silva (2019). orange markers refer to female students; green markers to male students. The dependent variable is the standardised INVALSI mathematics Rasch score measured at grades 8, 10, and 13. The specification corresponds to column 5 of Table 1.9 estimated separately on the male and female subsamples. Lines represent 95% confidence intervals. Filled markers denote that the difference between the male and female coefficients at that quantile is statistically significant at the 5% level. Standard errors are clustered at the primary-school class level.

Figure 1.2 reports the corresponding estimates separately for male and female students. Here a filled marker denotes a significant male–female difference at that quantile, not a significant coefficient as in the pooled figure. The decline in magnitude across grades documented for the pooled estimates is preserved within each gender.

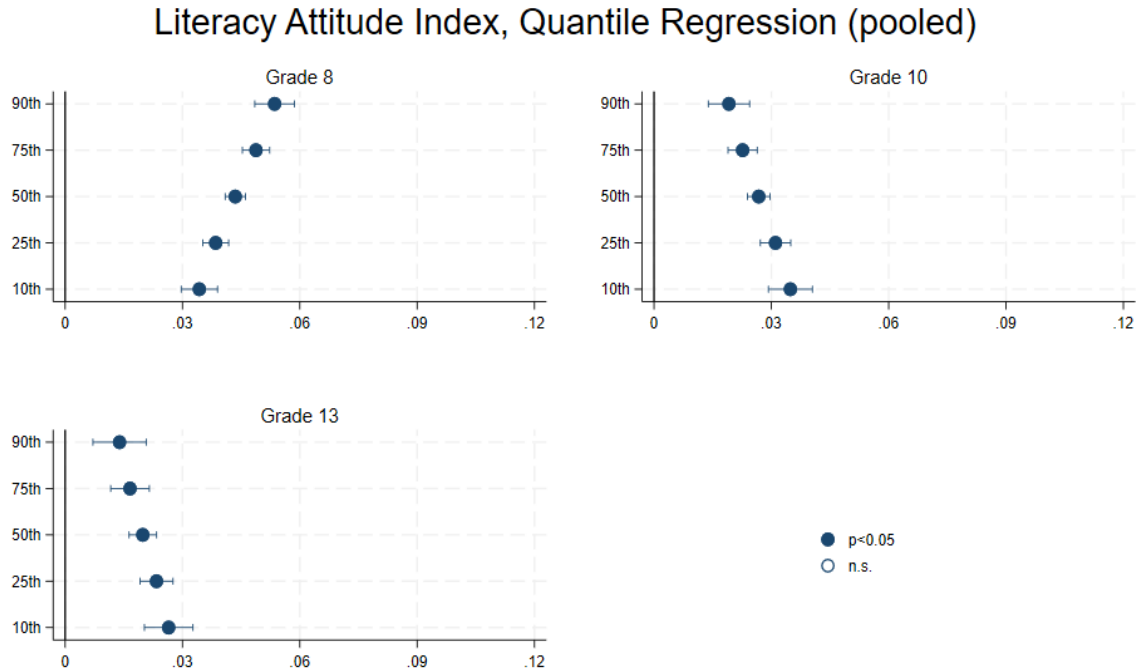
In grade 8, male and female coefficients are close to one another at every quantile, with point estimates around 0.10–0.11 SD, and none of the gender differences is significant at the 5% level. In grade 10, the two profiles diverge along the conditional distribution: male coefficients exceed female coefficients in the lower half by about 0.01–0.02 SD, with the largest gap at the 10th percentile (approximately 0.09 SD for males against 0.07 SD for females), while the ordering reverses at the 90th percentile, where the female estimate (about 0.09 SD) exceeds the male one (about 0.08 SD); the difference is significant at the 5% level at the lower and upper quantiles. In grade 13, the gender difference is instead confined to the lower and lower-central part of the distribution: male coefficients exceed female ones by about 0.01 SD at the 10th, 25th, and 50th percentiles, where the gap is significant, while at the 75th and 90th percentiles the two estimates essentially overlap (both around 0.05–0.055 SD) and the difference is not significant. These gender gaps are small in magnitude throughout, so the grade-10 crossover is best read as a mild asymmetry rather than a reversal of who benefits most from early attitudes.

Three patterns emerge. First, the predictive content of grade-5 mathematics attitudes is similar across the conditional distribution and declines monotonically across grades for both boys and girls; at grade 8 it carries essentially no gender information, either at the mean or along the distribution. Second, gender differences emerge only from grade 10 onwards—the point at which students enter upper-secondary education and sort into different tracks—consistent with the widening conditional gender gap found in the OLS estimates (Section 1.4) and with the gendered track choices as documented in the analysis of Chapter 2. Third, read together, grades 10 and 13 reveal a consistent and localized pattern: the male advantage in returns is concentrated among weaker performers—students who, conditional on prior achievement and background, fall in the lower part of the outcome distribution—and recurs with the same sign and location across both waves. These differences are small but stable, whereas the female

advantage at the upper tail is confined to grade 10 and does not persist. A reading consistent with this configuration is that, among weaker performers, early dispositions towards the subject translate into later achievement more strongly for boys than for girls, for whom other factors appear to override the signal of initial attitudes.

We now turn to literacy. Figures 1.3 and 1.4 replicate the previous exercise on the standardised INVALSI literacy Rasch score, with the Literacy Attitude Index in place of its mathematics counterpart and the regressors of column 5 of Table 1.12.

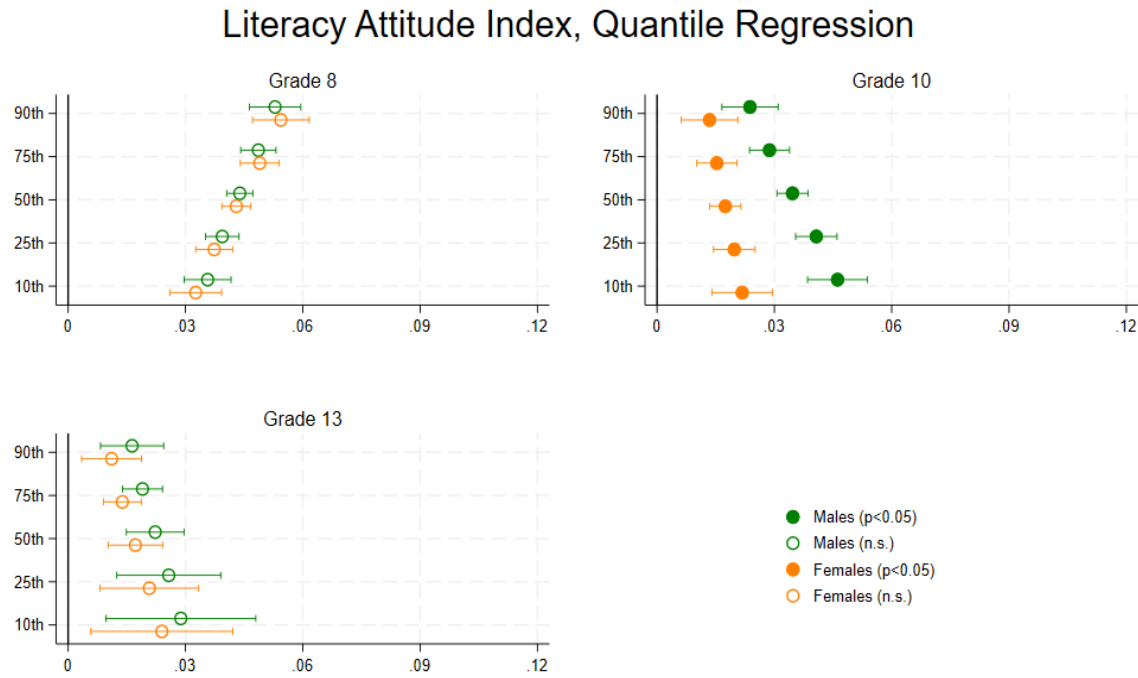
Figure 1.3: Quantile regression coefficients of the Literacy Attitude Index, grades 8, 10, and 13.



Notes: Each marker reports the estimated coefficient on the Literacy Attitude Index at the 10th, 25th, 50th, 75th, and 90th percentiles of the conditional outcome distribution, estimated using the method-of-moments quantile regression of Machado and Santos Silva (2019). The dependent variable is the standardised INVALSI literacy Rasch score measured at grades 8, 10, and 13. The specification corresponds to column 5 of Table 1.12 without the interaction between the index and the female indicator. Lines represent 95% confidence intervals; filled markers denote statistical significance at the 5% level. Standard errors are clustered at the primary-school class level.

In contrast to the broadly flat cross-quantile profile found for mathematics, the literacy estimates—positive and significant at every quantile and grade—change shape across grades. In grade 8, the coefficient increases mildly from about 0.035 SD at the 10th percentile to about 0.055 SD at the 90th: early literacy attitudes are more rewarding for stronger performers within the conditioning set, the pattern one would expect under cognitive–non-cognitive complementarity. In grade 10, the profile flattens and slightly inverts, with a small premium at the lower tail. By grade 13, the inversion is clearer: the coefficient is largest at the 10th percentile and declines to about 0.015 SD at the 90th, so that early literacy attitudes retain predictive content mainly for weaker performers—the pattern consistent with substitution, whereby a positive disposition compensates for scarcer resources.

Read across waves, then, the role of early literacy attitudes appears to shift from amplifying the achievement of stronger students to supporting that of weaker ones as students progress through secondary school. We are cautious, however, about reading this changing shape through the lens of skill formation. While the move from an upper-tail to a lower-tail premium could loosely be described as a shift from complementarity to substitution in the sense of Cunha and Heckman (2008), the conditional quantiles are an imperfect proxy for students' latent resources, the cross-quantile differences are modest, and the same profile may simply reflect the progressive sorting of students into upper-secondary tracks of differing curricular intensity. We therefore treat the Cunha–Heckman reading as one interpretation among others, and leave the separation of these channels to future work.

Figure 1.4: Quantile regression coefficients of the Literacy Attitude Index by gender, grades 8, 10, and 13.

Notes: Each marker reports the estimated coefficient on the Literacy Attitude Index at the 10th, 25th, 50th, 75th, and 90th percentiles of the conditional outcome distribution, estimated separately by gender using the method-of-moments quantile regression of Machado and Santos Silva (2019). Orange markers refer to female students; green markers to male students. The dependent variable is the standardised INVALSI literacy Rasch score measured at grades 8, 10, and 13. The specification corresponds to column 5 of Table 1.12, estimated separately on the male and female subsamples. Lines represent 95% confidence intervals. Filled markers denote that the difference between the male and female coefficients at that quantile is statistically significant at the 5% level. Standard errors are clustered at the primary-school class level.

Splitting the sample by gender (Figure 1.4) reveals a pattern that, relative to mathematics, is more uniform across the distribution but confined to a single wave. In grades 8 and 13, the male and female profiles overlap at every quantile, with no significant gender difference. In grade 10, by contrast, male coefficients lie clearly above female coefficients throughout the distribution: returns range from 0.024 to 0.046 SD for boys and from 0.014 to 0.022 SD for girls, so that the predictive content of grade-5 literacy attitudes for grade-10 literacy achievement is roughly twice as large for boys as for girls. The gender difference is statistically significant at all quantiles.

The grade-10 gap indicates that, at this follow-up and low-stakes stage, early Literacy attitudes carry predictive content for boys but much less for girls. This might be, at first sight, counterintuitive: as documented in Chapter 2, girls are over-represented in the most literacy-intensive upper-secondary tracks, such as the *liceo classico* and other academic licei, where one might expect early dispositions towards reading and writing to matter most. A possible reading consistent with the broader evidence in this chapter is that, precisely because girls sort into curricula with heavy and relatively uniform literacy content, track exposure comes to dominate the signal carried by their initial attitudes, compressing the role of early dispositions; boys, who enter such tracks far less often, retain a tighter link between early attitudes and later literacy achievement. However, a comparable gap is absent at both grade 8 and grade 13, which cautions against reading the grade-10 result as a persistent gender-specific pattern.

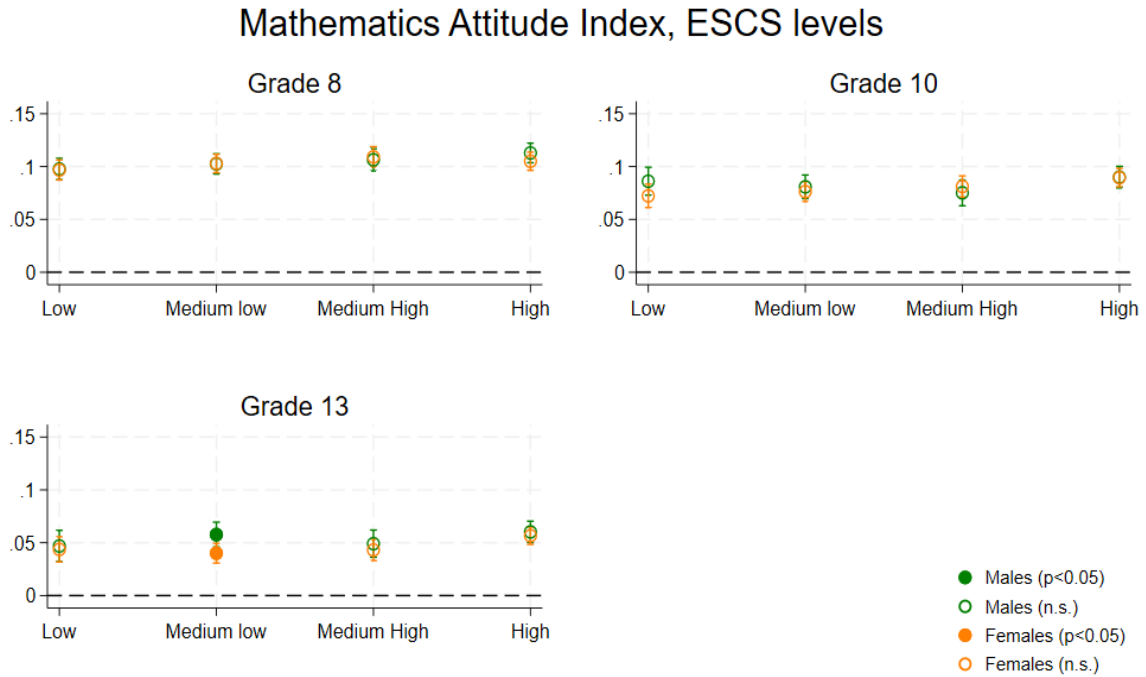
1.6.2 Heterogeneity by ESCS

We partition the sample by quartile of the ESCS index and estimate the model separately by gender within each quartile, retaining the controls of the preferred specification (column 5 of Tables 1.9 and 1.12). The exercise is informative about two competing predictions. Under complementarity between non-cognitive inputs and family resources, the returns to grade-5 attitudes should rise with ESCS, since household resources, parental expectations, and out-of-school inputs reinforce the productivity of a positive disposition towards the subject. Under substitution, attitudes should produce larger returns among disadvantaged

students, for whom they compensate for the limited availability of family inputs. Evidence for Italy indicates that disadvantaged students can attain high levels of achievement, and that school-level inputs contribute to this outcome alongside individual characteristics (Agasisti and Longobardi, 2014). A flat profile across quartiles is informative against both predictions and suggests that, conditional on prior achievement and primary-school class fixed effects, the association between attitudes and subsequent achievement is independent of household economic resources.

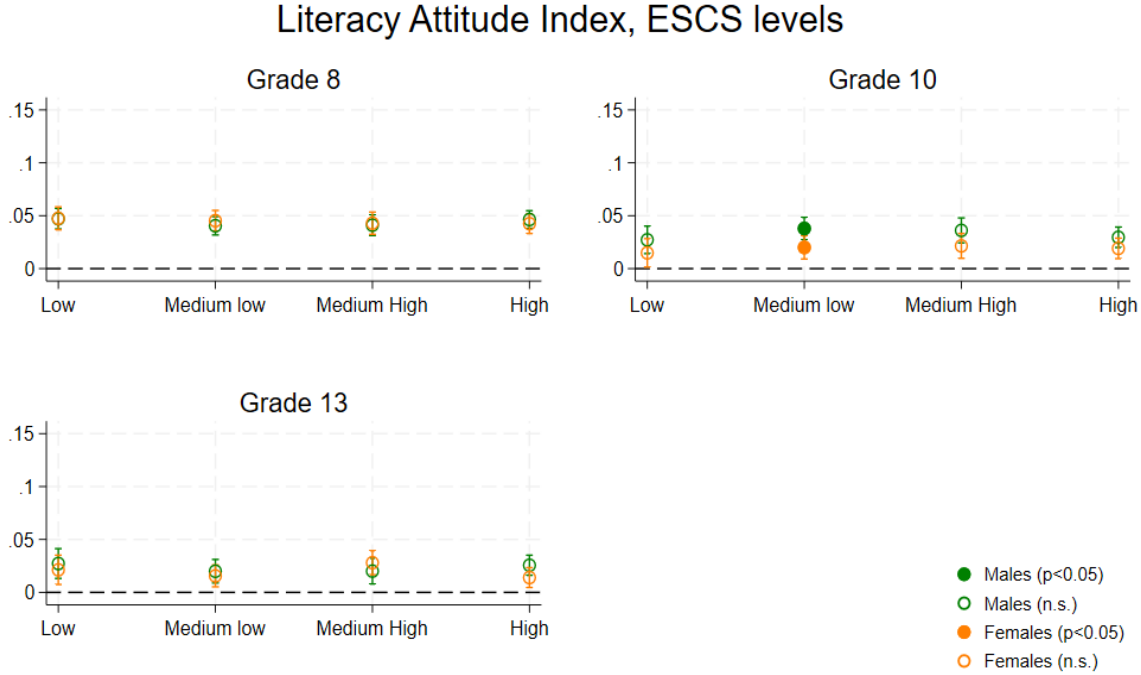
As in Figure 1.2, Figures 1.5 and 1.6, orange markers refer to female students and green markers to male students. A filled/empty marker denotes that the difference between the male and female coefficients at the corresponding ESCS quartile is statistically significant/not significant at the 5% level at that quartile.

Figure 1.5: Coefficients of the Mathematics Attitude Index by ESCS quartile, grades 8, 10, and 13.



Notes: Each marker reports the estimated coefficient on the Mathematics Attitude Index from a separate OLS regression estimated by gender and ESCS quartile (low, medium-low, medium-high, and high). Orange markers refer to female students; green markers to male students. The dependent variable is the standardised INVALSI mathematics Rasch score measured at grades 8, 10, and 13, respectively. The Mathematics Attitude Index is a composite measure standardised to mean zero and unit standard deviation. All specifications include prior cognitive achievement, individual and family characteristics, and primary-school class fixed effects, following the full set of controls of the preferred specification in column 5 of Table 1.9. Lines represent 95% confidence intervals. Filled markers denote that the difference between the male and female coefficients at the corresponding ESCS quartile is statistically significant at the 5% level. Standard errors are clustered at the primary-school class level.

Figure 1.5 reports the estimated coefficient of the Mathematics Attitude Index by gender and ESCS quartile. A one-standard-deviation (SD) increase in the index is associated with approximately 0.10 SD of subsequent achievement in grade 8, 0.08 SD in grade 10, and 0.05 SD in grade 13. Point estimates are flat across quartiles within each grade. The confidence intervals are similar, and the male–female difference is not statistically significant at the 5% level at any quartile in those grades. Significant gender differences emerge only in grade 13, where they concentrate in the middle-to-lower part of the ESCS distribution. Conditional on prior achievement and primary-school class fixed effects, the predictive content of mathematics attitudes does not vary across ESCS quartiles and shows no systematic gender asymmetry within quartiles in grades 8 and 10. The pattern is consistent with attitudes operating independently of household economic resources, once prior achievement and class composition are accounted for.

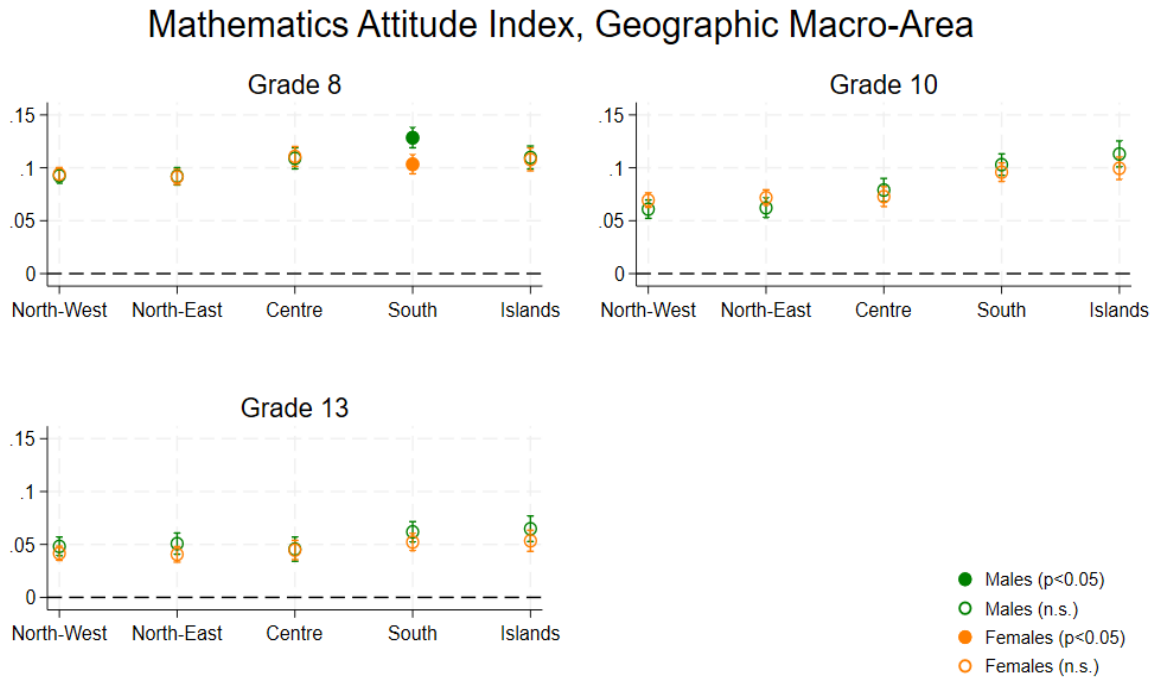
Figure 1.6: Coefficients of the Literacy Attitude Index by ESCS quartile, grades 8, 10, and 13.

Notes: Each marker reports the estimated coefficient on the Literacy Attitude Index from a separate OLS regression estimated by gender and ESCS quartile (low, medium-low, medium-high, and high). Orange markers refer to female students; green markers to male students. The dependent variable is the standardised INVALSI Literacy Rasch score measured at grades 8, 10, and 13, respectively. The Literacy Attitude Index is a composite measure standardised to mean zero and unit standard deviation. All specifications include prior cognitive achievement, individual and family characteristics, and primary-school class fixed effects, following the full set of controls of the preferred specification in column 5 of Table 1.12. Lines represent 95% confidence intervals. Filled markers denote that the difference between the male and female coefficients at the corresponding ESCS quartile is statistically significant at the 5% level. Standard errors are clustered at the primary-school class level.

Figure 1.6 reports the corresponding estimates for literacy. The specification mirrors that of mathematics: separate OLS regressions by gender and ESCS quartile, retaining the same set of controls and fixed effects. Returns to the Literacy Attitude Index are approximately 0.040–0.047 SD in grade 8, 0.027–0.038 SD in grade 10, and 0.020–0.027 SD in grade 13, smaller than the corresponding mathematics estimates across all three grades. Point estimates are flat across ESCS quartiles within each grade. The male–female difference is not statistically significant at the 5% level at any quartile in grades 8 and 13, with the sole exception of the middle-to-lower part of the ESCS distribution in grade 10. As for mathematics, the predictive content of literacy attitudes does not vary with household economic resources and shows no systematic gender asymmetry within quartiles in the first two follow-up waves.

1.6.3 Macro areas

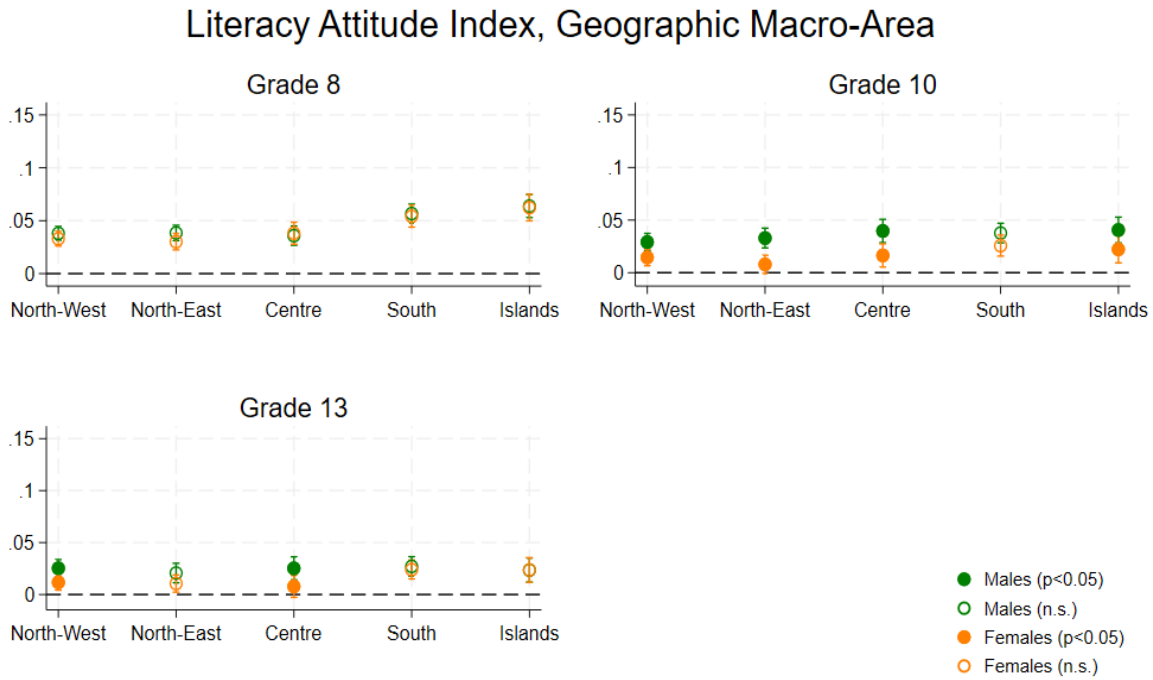
We finally re-estimate the model separately by gender and geographic macro-area (North-West, North-East, Centre, South, and Islands), retaining the controls of the preferred specification. The exercise is motivated by the persistent territorial disparities documented for the Italian education system (Agasisti and Cordero-Ferrera, 2013; Bratti et al., 2007) and by the gendered patterns in achievement and academic self-concept observed across regions (Contini et al., 2017; Guiso et al., 2008).

Figure 1.7: Coefficients of the Mathematics Attitude Index by geographic macro-area, grades 8, 10, and 13.

Notes: Each marker reports the estimated coefficient on the Mathematics Attitude Index from a separate OLS regression estimated by gender and geographic macro-area (North-West, North-East, Centre, South, and Islands). Orange markers refer to female students; green markers to male students. The dependent variable is the standardized INVALSI Mathematics Rasch score measured at grades 8, 10, and 13, respectively. The Mathematics Attitude Index is a composite measure standardized to mean zero and unit standard deviation. All specifications include prior cognitive achievement, individual and family characteristics, and primary-school class fixed effects, following the full set of controls of the preferred specification in column 5 of Table 1.9. Lines represent 95% confidence intervals. Filled markers denote that the difference between the male and female coefficients in the corresponding macro-area is statistically significant at the 5% level. Standard errors are clustered at the primary-school class level.

Figure 1.7 reports the estimated coefficients of the Mathematics Attitude Index by gender and macro-area. Estimates range from 0.09 to 0.13 SD in grade 8, from 0.06 to 0.11 SD in grade 10, and from 0.04 to 0.06 SD in grade 13. The dispersion across macro-areas within each grade is small relative to the width of the confidence intervals. Significant male–female differences are sparse across macro-areas and grades and do not concentrate in any specific area or wave. The figure does not display a stable territorial or gender pattern that survives across the three follow-up waves.

Figure 1.8 reports the corresponding estimates for literacy. Coefficients range from 0.036 to 0.064 SD in grade 8, and decline at the two subsequent waves, in line with the overall attenuation of the literacy estimates documented in Section 1.4. While statistically significant male–female differences emerge in most macro-areas at grade 10, they are not replicated in grades 8 or 13. As for mathematics, the figure does not display a stable territorial or gender pattern across the three follow-up waves.

Figure 1.8: Coefficients of the Literacy Attitude Index by geographic macro-area, grades 8, 10, and 13.

Notes: Each marker reports the estimated coefficient on the Literacy Attitude Index from a separate OLS regression estimated by gender and geographic macro-area (North-West, North-East, Centre, South, and Islands). Orange markers refer to female students; green markers to male students. The dependent variable is the standardised INVALSI literacy Rasch score measured at grades 8, 10, and 13, respectively. The Literacy Attitude Index is a composite measure standardised to mean zero and unit standard deviation. All specifications include prior cognitive achievement, individual and family characteristics, and primary-school class fixed effects, following the full set of controls of the preferred specification in column 5 of Table 1.12. Lines represent 95% confidence intervals. Filled markers denote that the difference between the male and female coefficients in the corresponding macro-area is statistically significant at the 5% level. Standard errors are clustered at the primary-school class level.

1.7 Conclusions

This chapter has examined whether subject-specific attitudes and test anxiety measured at the end of primary school predict later academic achievement, following the Italian cohort observed in grade 5 in 2013–14 through grade 13.

Four main findings emerge. First, attitudes towards mathematics and literacy are already largely distinct at age ten: the two indices are almost uncorrelated, whereas achievement in the two subjects is strongly correlated, and they display opposite gender gaps. Second, these attitudes predict later achievement in the corresponding subject, net of prior achievement, family background, and class fixed effects. A one-standard-deviation increase in the Mathematics Attitude Index is associated with 10.6% of a standard deviation in mathematics achievement at grade 8; the corresponding estimate for literacy is 4.4%. The association is largely tied to its own domain, although the mathematics index also partly captures general academic confidence. Third, the predictive content persists up to the end of upper-secondary school but attenuates, by about half between grade 8 and grade 13 in both subjects. Fourth, gender gaps in achievement operate mainly through levels rather than through differences in the returns to attitudes, which emerge only later, in literacy at grade 10 and in mathematics at grade 13. Test anxiety is associated with a performance penalty that is largest in the high-stakes grade-8 assessment and fades in the subsequent low-stakes waves.

These patterns are robust to restricting the sample to students observed in all waves and to controlling for general non-cognitive traits, and they do not vary systematically with family socio-economic status or across macro-areas.

The results are conditional associations rather than causal effects. The measures are self-reported, the sample is positively selected by attrition, and the grade-10 and grade-13 estimates are net of intermediate achievement, with the last wave falling in the immediate post-pandemic period. Future work will re-

estimate the later-grade models without intermediate achievement, assess selection on unobservables through bounding approaches, and investigate the channels behind the gender differences documented here. Whether these early attitudes are also associated with educational choices is the question addressed in Chapter 2.

Chapter 1: Appendix

1.A Institutional Setting and Data

This appendix describes the institutional setting in which our cohort is observed, the structure of the INVALSI standardised assessment programme, and the construction of the analytical sample. The Italian education system is organised into two main educational cycles, articulated across four schooling levels. Pre-primary education (*scuola dell’infanzia*) is available to children aged 3 to 6. Compulsory education begins with primary school (*scuola primaria*), which spans grades 1 to 5 and serves children aged 6 to 11. This is followed by lower secondary school (*scuola secondaria di I grado*), lasting three years from grades 6 to 8, for students aged 11 to 14. Upper secondary school (*scuola secondaria di II grado*) extends from grades 9 to 13 and typically lasts five years, enrolling students aged 14 to 19. At this stage, students are tracked into different educational pathways, including academic, technical, and vocational programs. Primary and lower secondary schools differ in their organisational structure and teaching practices. In primary school, students may have two main reference teachers: one responsible for humanities-related subjects and one for scientific subjects. These teachers often follow the same cohort of students throughout the entire primary cycle, facilitating the development of stable and close teacher–student relationships. In contrast, lower secondary school students are taught by multiple teachers, usually one per subject, and are expected to acquire competencies across a broader and more specialised curriculum.

Since the 2009-10 school year, Italian students at selected grades have been monitored through standardised tests in mathematics and literacy administered by INVALSI (*Istituto Nazionale per la Valutazione del Sistema Educativo di Istruzione e Formazione*). INVALSI conducts annual nationwide assessments of student achievement in Mathematics and literacy, and, for selected grades, in English reading and listening. The assessment system is based on standardised tests and accompanying questionnaires. Participation is nearly universal, covering almost all Italian schools and students, both public and private. To preserve test standardisation, the Invalsi guidelines also retain discretion over the participation of students with disabilities or specific learning disorders. Students’ special educational needs were flagged for internal use, allowing INVALSI to handle data confidentiality appropriately, but such sensitive information is excluded from our analytical dataset.¹⁴

INVALSI assessments are administered at specific grade levels throughout compulsory and upper-secondary education.¹⁵ The grades involved in the testing programme are grade 2 (early stage of primary education), grade 5 (end of primary school), grade 8 (end of lower-secondary education and transition to upper-secondary school), grade 10 (second year of upper-secondary school and end of compulsory education), and grade 13 (final year of upper-secondary education). Grade 2 is excluded from the analysis, as it cannot be longitudinally linked to subsequent grades.

In addition to test scores, INVALSI collects a rich set of individual-level information from multiple sources. These include: (i) students’ demographic and administrative information, compiled by school administrative staff and reported on students’ answer sheets; (ii) family background information collected through a Family Questionnaire administered shortly before the tests; (iii) additional information on family, school, and environmental characteristics collected through the Student Questionnaire completed by each student; and (iv) teacher characteristics, collected through a Teacher Questionnaire administered only in sample classes.

Mathematics and literacy tests are typically administered on two or three separate days, usually during the month of May, with one session per subject. Test scores are constructed based on grade- and subject-specific sets of items. The Student Questionnaire is administered on the same day as one of the standardised tests. The standardised tests are presented to students as ability assessments and consist of written instruments, including multiple-choice and closed-format questions. Table 1.A.1 reports the number of total and registered students, the registration rate, and the number of classes at each wave of our analytical cohort.

¹⁴See “Nota sullo svolgimento delle prove INVALSI 2013-2014 per gli allievi con bisogni educativi speciali”, INVALSI, April 7, 2014.

¹⁵Mathematics and literacy tests for grade 6 were discontinued after the 2012-13 school year, while grade 13 assessments were introduced in 2018-19. English reading and listening tests have been administered in grades 5, 8, and 13 since 2017-18, and only in grade 13 in 2018-19. See Chapter 3 for more details.

Table 1.A.1: INVALSI test coverage and Italian student population, by grade.

	Grade 5	Grade 8	Grade 10	Grade 13
No. Total students	561,183	574,525	541,147	n.a.
No. Registered students	549,756	531,623	501,224	n.a.
% Registered students	98%	93%	93%	> 90%
No. Total classes	29,685	31,092	26,845	n.a.

Notes: Figures from the INVALSI *Rapporto Integrale* of each survey year. Exact grade-13 participation counts are not published; participation rates are reported as above 90%.

The construction of the longitudinal dataset required merging several INVALSI files and harmonising variable definitions across waves. We summarise the procedure briefly.

INVALSI provides the data in separate files, one for each subject (mathematics and literacy) and each questionnaire (the standardised test answer sheet and the student background questionnaire), at each grade level. Files referring to the same student in the same grade were merged using an anonymous student identifier. Files across different grades were linked through the SIDI code, a unique identifier assigned by the Italian Ministry of Education to each student in the National Student Register, which allows individual records to be linked across waves and students to be followed longitudinally.

Variable labels were harmonised across waves, and string-based missing codes (*Not available*, *Missing*, *Not applicable*) were recoded as true missing values.

We then checked for longitudinal coherence in time-invariant characteristics. Some individual-level variables (sex, place of birth, month and year of birth) occasionally take different values across waves for the same student. We treat these characteristics as invariant by construction and recover the consistent value as the modal value across all records of the student. The procedure recovers approximately 2,500 observations that would otherwise be lost to within-student inconsistencies. Replicating the main regressions on the dataset without this step yields identical results. Further details are available upon request.

1.B Kernel density estimates by gender

This section reports kernel density estimates of the main variables of interest, separately by gender. Figure 1.B.1 plots INVALSI Rasch scores in mathematics and literacy at grades 5 and 13. Figure 1.B.2 plots the subject-specific attitude indices at grade 5. Figure 1.B.3 plots the Test Anxiety Index at grade 5. The three figures are commented in Section 1.2.3 of the main text.

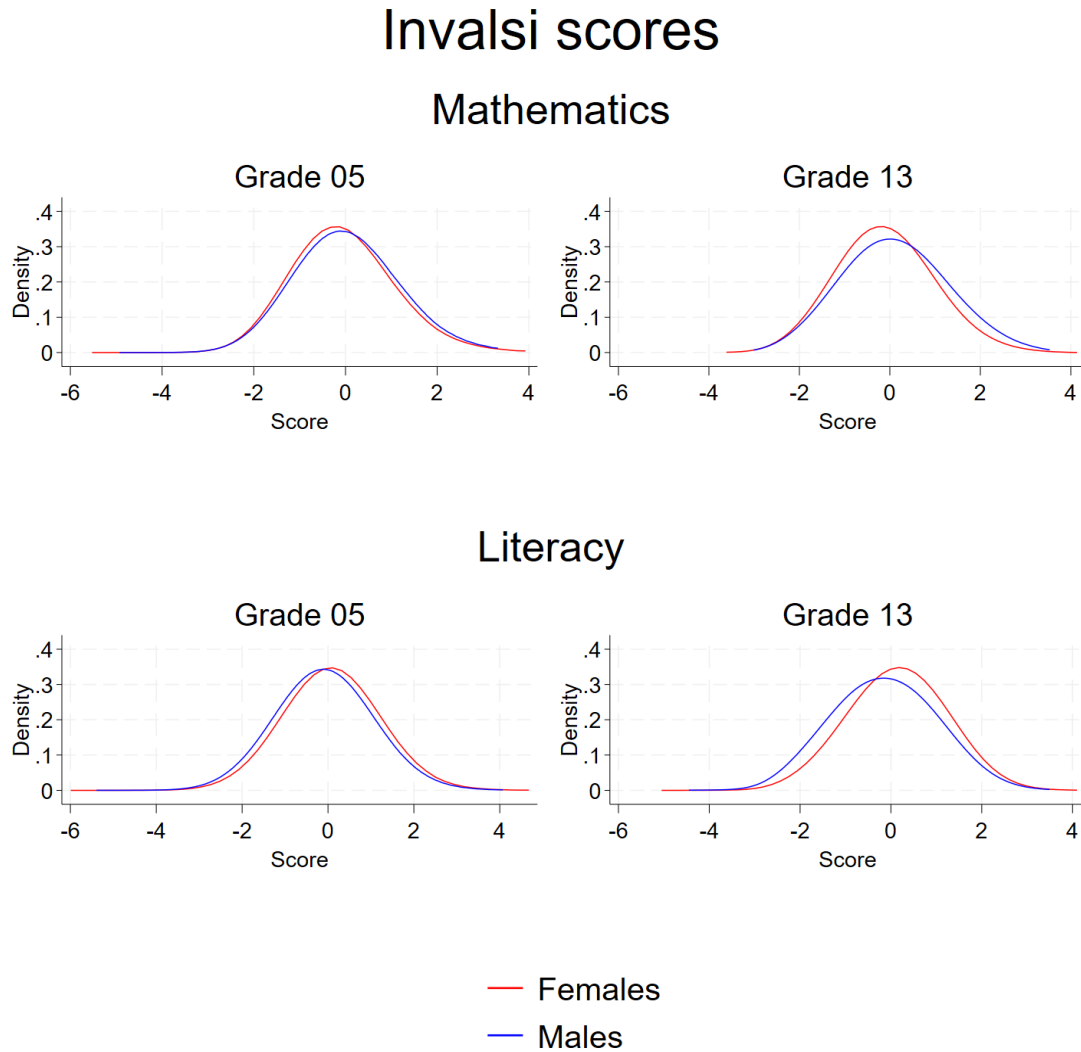


Figure 1.B.1: Kernel density of INVALSI scores by gender, grades 5 and 13.

Notes: Each panel reports the kernel density of INVALSI Rasch scores, separately by gender, in mathematics and literacy at grades 5 and 13. Two-sample Kolmogorov-Smirnov tests reject equality of the male and female distributions at every wave (all $p < 0.001$). The D statistic, which measures the maximum vertical distance between the two cumulative distributions, approximately doubles over time in mathematics ($D = 0.050$ at grade 5; $D = 0.102$ at grade 13) and increases by roughly 80% in literacy ($D = 0.071$ at grade 5; $D = 0.125$ at grade 13), indicating that the gender gap widens in both subjects between grade 5 and grade 13.

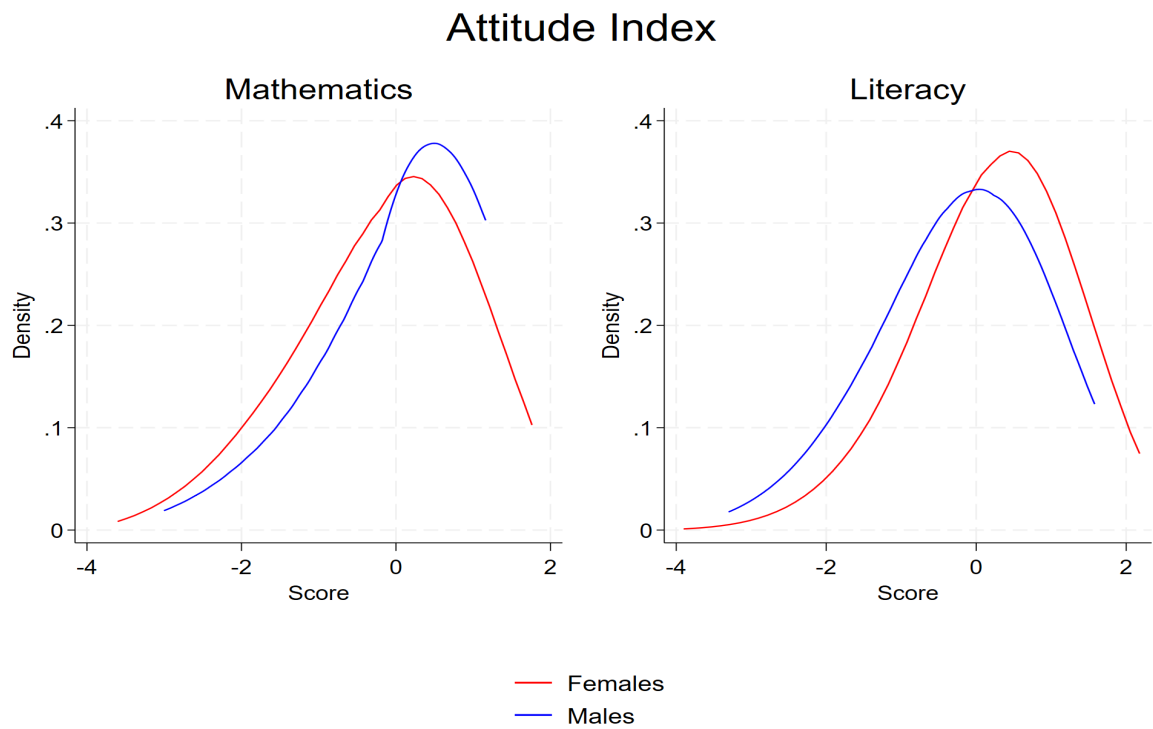


Figure 1.B.2: Kernel density of the subject-specific attitude indices at grade 5, by gender.

Notes: Sample of students observed in grade 5 in school year 2013–14. Attitude indices are constructed via PCA from the items reported in Tables 1.3 and 1.4 and standardised to mean zero and unit variance.

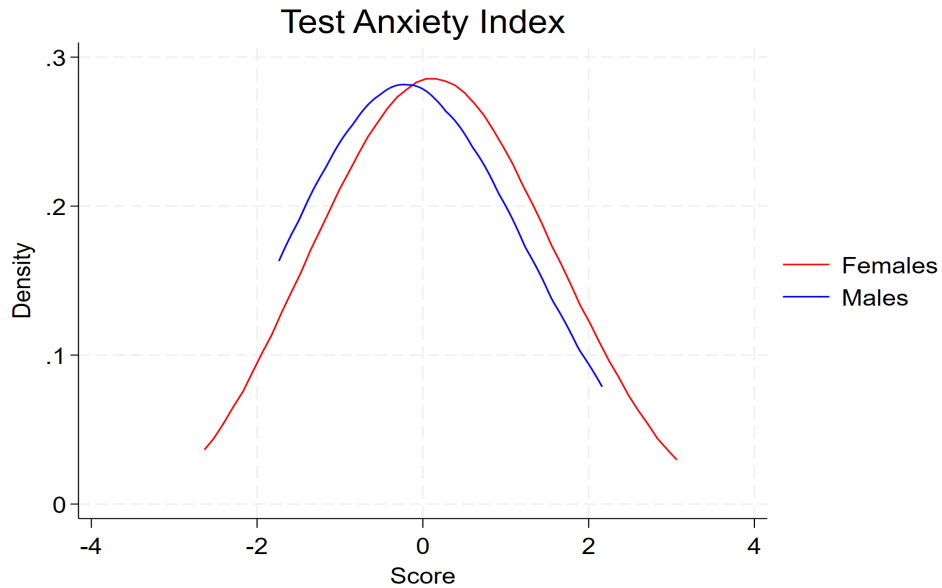


Figure 1.B.3: Kernel distribution comparison by gender of the Test Anxiety Index calculated in grade 5.

Notes: Italian students observed in grade 5 in school year 2013–14. The Test Anxiety Index is constructed via Principal Component Analysis from the items reported in Table 1.5 and standardised to mean zero and unit variance in the grade-5 population. Higher values denote greater self-reported test anxiety.

1.C Construction and Validation of the Non-Cognitive Skill Indices

We construct three non-cognitive measures—two subject-specific measures, the Mathematics Attitude Index and the Literacy Attitude Index, and the Test Anxiety Index—from items in the INVALSI student questionnaire. To build the indices, we adopt the factor-model approach to skill formation widely used in the economics of education, which treats latent skills as imperfectly measured by multiple noisy indicators and recovers them through a dedicated measurement system.

The validation procedure consists of four sequential steps. First, we assess internal consistency through Cronbach’s α . Second, we evaluate dimensionality using Principal Component Analysis (PCA). Third, we supplement the dimensionality assessment with exploratory Factor Analysis (FA). Fourth, we cross-validate the resulting scores by computing pairwise Pearson correlations across three alternative constructions: row mean, PCA, and FA.

For the attitude indices, we examine alternative specifications by estimating the validation procedure on both a unified index and two separate sub-indices.¹⁶ Across all approaches, the evidence supports a unidimensional latent structure, indicating that the selected items capture a common underlying construct.

For each final index, we retain the first principal component from the PCA, standardised to mean zero and unit variance, as the headline measure. We adopt PCA over FA and row-mean indices on two grounds: (i) near-equivalence with model-based alternatives, as documented by Pearson correlations of at least 0.99 between the PCA score and the FA and row-mean indices (Tables 1.C.4, 1.C.7, and 1.C.10); and (ii) transparency and replicability—PCA loadings depend only on the observed correlation matrix and require no auxiliary distributional assumptions.

Throughout, we report internal consistency on the original Likert items (Cronbach’s α) and the eigenvalue structure of the PCA and FA. The analysis sample is described in Section 1.2 of the main text.

The construction items are reproduced in Tables 1.3, 1.4, and 1.5 of the main text, and refer to questions Q4 (motivation), Q6 (academic self-efficacy), and Q9 (test anxiety) of the INVALSI grade-5 student questionnaire (school year 2013/14).

1.C.1 Mathematics Attitude Index

The Mathematics Attitude Index combines six items: three motivation items (Q4) and three self-efficacy items (Q6) reproduced in Table 1.3 of the main text.

Internal consistency. Cronbach’s α for the unified six-item scale equals 0.855, comfortably exceeding the 0.70 threshold for exploratory research and the 0.80 threshold for established constructs. The motivation (Q4) and self-efficacy (Q6) sub-scales display α of 0.805 and 0.772, respectively—values consistent with two reliable but related sub-dimensions (Table 1.C.2).

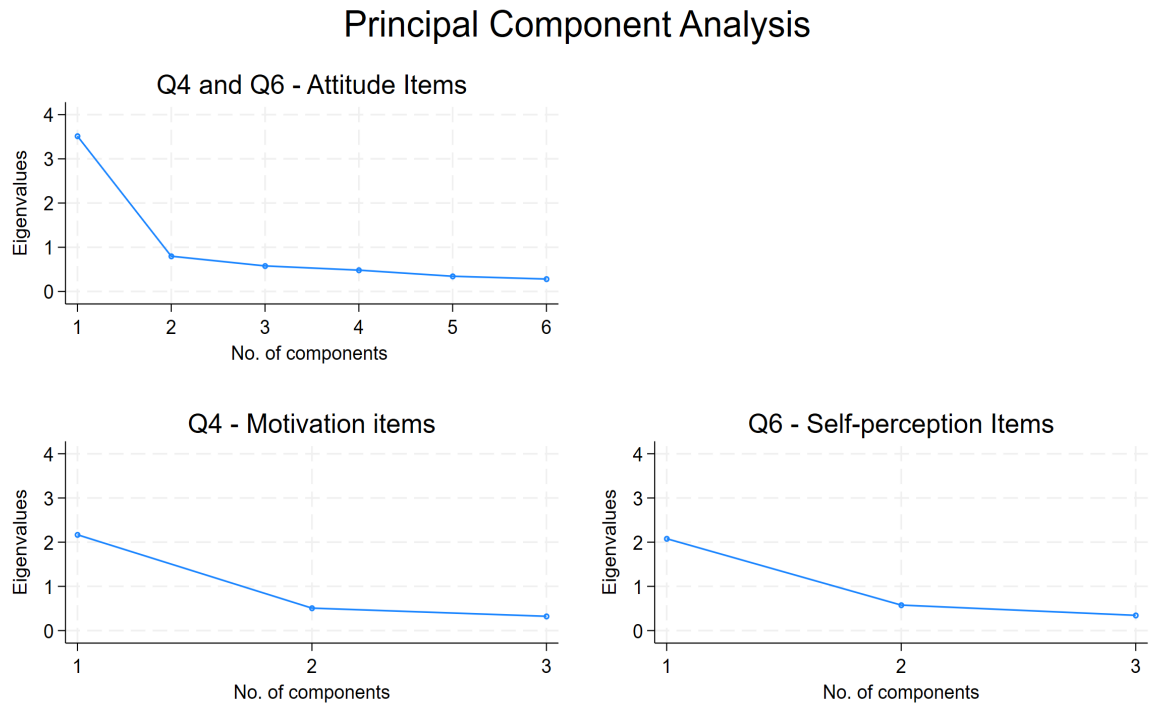
Table 1.C.2: Internal Consistency of the Mathematics Attitude items.

Statistic	Item-unified Index	Item-separated Index	
	Q4 & Q6 items	Q4 items	Q6 items
Number of items in the scale	6	3	3
Average inter-item covariance	0.444	0.531	0.465
Cronbach’s alpha	0.855	0.805	0.772

Notes: Cronbach’s alpha is computed on the original Likert-scale items without standardisation. The 0.80 threshold is conventionally used for established constructs; the 0.70 threshold is conventionally used for exploratory research.

Dimensionality. The first principal component of the unified scale has eigenvalue 3.516 and explains 58.6% of the total variance; the second eigenvalue (0.797) falls below the Kaiser threshold of 1 (Table 1.C.3), corroborating the unidimensional structure.

¹⁶Items used in the analysis are described in the main text; see Section 1.2.2.

Figure 1.C.4: Principal Component Analysis (PCA) of the Mathematics Attitude Index.

Notes: The figure compares the eigenvalue structure of a unified index (Q4+Q6 items) with two separate indices constructed from Q4 and Q6 items, respectively. Eigenvalues are computed using (i) separate indices based on Q4 and Q6 items from the INVALSI student questionnaire, and (ii) a unified index combining both sets of items. The reference threshold is 1: eigenvalues above this value indicate that the corresponding component explains a non-negligible share of the total variance, supporting its retention, whereas values below 1 suggest limited explanatory relevance.

Figure 1.C.4 displays the eigenvalue structure of the unified scale and of the two sub-scales. The top panel, based on the pooled Q4 and Q6 items, exhibits a pronounced elbow: the first eigenvalue lies well above 3.5, while the second already falls below the Kaiser reference line at unity. The two lower panels, computed separately on the Q4 motivation items and on the Q6 self-efficacy items, mirror this pattern. The leading eigenvalues equal approximately 2.17 for Q4 and 2.08 for Q6, while all subsequent components lie below the threshold. The convergent evidence across the pooled and item-separated specifications supports the interpretation of a single dominant latent construct underlying both motivational and self-evaluative responses in mathematics.

Table 1.C.3: Alternative latent index constructions for the Mathematics Attitude Index

(a) Item-unified Index			
Method	Comp.	Eigenvalue	Exp. Var.
PCA	1	3.516	58.6
	2	0.797	13.2
FA	1	3.010	50.1
	2	0.230	3.8

(b) Item-separated Index			
(b1) Q4 Motivation items		(b2) Q6 Self-perception items	
Method	Comp.	Eigenvalue	Exp. Var.
PCA	1	2.168	72.3
	2	0.508	16.9
FA	1	1.625	54.2
	2	-0.104	-3.5

Notes: Indices are constructed from six Likert items capturing Q4 (motivation) and Q6 (academic self-efficacy). PCA and FA use standardised items with linear scoring; component retention follows the Kaiser criterion (eigenvalue ≥ 1). The PCA-based unified specification is retained as the headline measure; the unidimensional structure is supported by the dominance of the first eigenvalue (item-separated specifications are reported as robustness).

Table 1.C.3 confirms that the information conveyed by the Q4 and Q6 items can be summarised through a single component under all three specifications: the dominant eigenvalue of the unified PCA (3.516) implies that nearly 60% of the variance in the six-item scale is captured by one linear combination—a strong result for a scale of this length, while the second component is 0.79, below the unit threshold.

Following the same comparison logic, we estimate an Exploratory Factor Analysis on the pooled set of items. The first factor has eigenvalue 3.010 (50.1% of the variance), confirming the unidimensional structure already obtained via PCA.

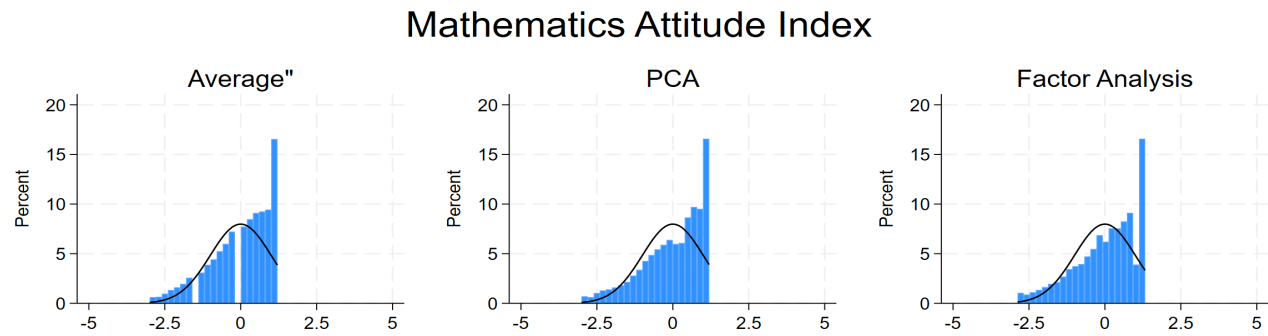
Cross-method robustness. Pairwise Pearson correlations among the three candidate scores (Table 1.C.4) all exceed 0.99, indicating that the headline PCA index is empirically interchangeable with the alternatives. We retain the PCA score as the Mathematics Attitude Index.

Table 1.C.4: Correlation matrix of alternative Mathematics Attitude Indices.

	Average	PCA	Factor Analysis
Average	1.0000		
PCA	0.9990	1.0000	
Factor Analysis	0.9935	0.9963	1.0000

Notes: The table reports pairwise correlation coefficients across alternative constructions of the unified Mathematics Attitude Index. Results for the separated index specifications are available upon request.

Figure 1.C.5: Distribution of alternative Mathematics Attitude Indices.



Notes: Unified Mathematics Attitude Indices are constructed using row means (Average), Principal Component Analysis (PCA) and Factor Analysis (FA). Results for the separated index specifications are available upon request.

Figure 1.C.5 plots the empirical distributions of the three alternative indices. All three constructions produce visually equivalent profiles: a left-skewed distribution concentrated between -2.5 and $+1.5$, with a clear mass-point at the upper tail driven by the Likert ceiling on the most favourable response category. The PCA and FA panels are essentially indistinguishable; the row-mean panel reveals slightly more discretisation, reflecting the limited number of distinct combinations admissible on a six-item ordinal scale. The visual evidence confirms the substantive equivalence of the three constructions and supports the use of the PCA index as a continuous, standardised measure of mathematics attitude.

1.C.2 Literacy Attitude Index

The Literacy Attitude Index follows the same construction logic as the Mathematics Attitude Index.

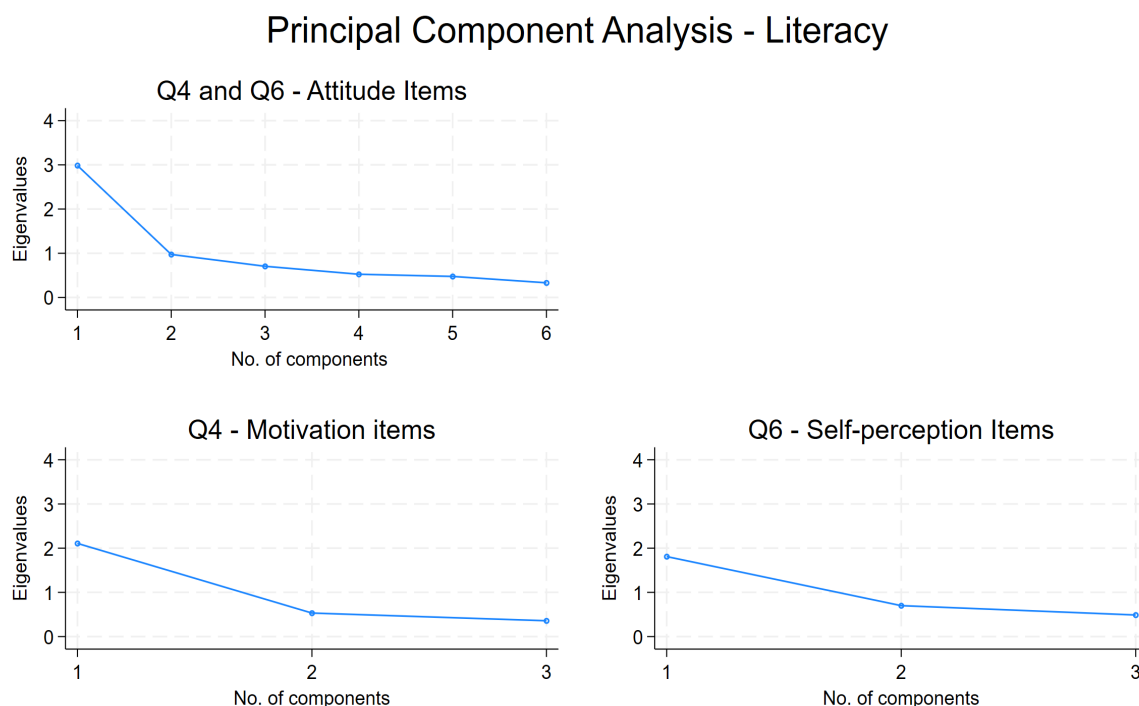
Internal consistency. The unified six-item scale yields $\alpha = 0.788$, narrowly below the 0.80 benchmark but well above the 0.70 threshold for exploratory research. The Q4 motivation sub-scale ($\alpha = 0.786$) is internally consistent; the Q6 self-efficacy sub-scale ($\alpha = 0.653$) falls below 0.70, reflecting greater heterogeneity in self-efficacy assessments for verbal tasks. Together, these patterns favour the unified specification reported in Table 1.C.5.

Table 1.C.5: Internal consistency of the Literacy Attitude items.

Statistic	Item-unified Index	Item-separated Index	
	Q4 and Q6 items	Q4 items	Q6 items
Number of items in the scale	6	3	3
Average inter-item covariance	0.301	0.476	0.273
Cronbach’s alpha	0.788	0.786	0.653

Notes: Cronbach’s alpha is computed on the original Likert-scale items without standardisation. The 0.80 threshold is conventionally used for established constructs; the 0.70 threshold is conventionally used for exploratory research.

Dimensionality. PCA and FA are estimated on standardised items with linear scoring; component retention follows the Kaiser criterion (eigenvalue ≥ 1). The first principal component of the unified scale has eigenvalue 2.99 (49.8% of the variance); the second eigenvalue (0.97) falls just below the Kaiser cutoff (Table 1.C.6). FA returns a leading eigenvalue of 2.38 and a second of 0.31, consistent with a single common factor. The PCA-based unified specification is therefore retained as the headline measure.

Figure 1.C.6: Principal Component Analysis (PCA) of the Literacy Attitude Index.

Notes: The figure compares the eigenvalue structure of a unified index (Q4+Q6 items) with two separate indices constructed from Q4 and Q6 items, respectively. Eigenvalues are computed using (i) separate indices based on Q4 and Q6 items from the INVALSI student questionnaire, and (ii) a unified index combining both sets of items. The reference threshold is 1: eigenvalues above this value indicate that the corresponding component explains a non-negligible share of the total variance, supporting its retention, whereas values below 1 suggest limited explanatory relevance.

Figure 1.C.6 reports the eigenvalue structure for the literacy items. The top panel, based on the pooled Q4 and Q6 items, displays an elbow at the second component, although the gap between the first and second eigenvalues is smaller than the one observed for mathematics. Specifically, the second eigenvalue stands at 0.97, narrowly below the Kaiser threshold; the inference of a single dominant component therefore relies on the combined evidence from Cronbach's Alpha, PCA and FA, rather than on PCA alone. The two lower panels confirm the unidimensional structure of each sub-scale: the leading eigenvalues equal 2.11 for Q4 and 1.81 for Q6, while all subsequent eigenvalues lie below one. The somewhat weaker dominance of the first component for literacy—relative to mathematics—is consistent with the lower reliability of self-efficacy responses on verbal tasks already documented through Cronbach's α .

Table 1.C.6: Alternative latent index constructions for the Literacy Attitude Index

(a) Item-unified Index			
Method	Comp.	Eigenvalue	Exp. Var.
PCA	1	2.99	49.8
	2	0.97	16.2
FA	1	2.38	39.7
	2	0.31	5.2

(b) Item-separated Index			
(b1) Q4 Motivation items			
Method	Comp.	Eigenvalue	Exp. Var.
PCA	1	2.11	70.3
	2	0.53	17.7
FA	1	1.53	50.9
	2	-0.11	-3.7
(b2) Q6 Self-perception items			
Method	Comp.	Eigenvalue	Exp. Var.
PCA	1	1.81	60.3
	2	0.70	23.3
FA	1	1.07	35.7
	2	-0.10	-3.4

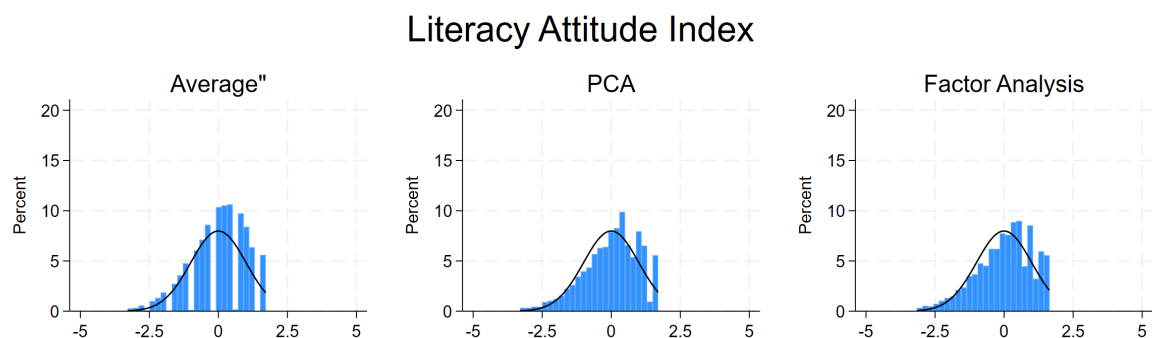
Notes: All indices are constructed from the same set of Likert-scale items capturing Q4 (motivation) and Q6 (self-efficacy) dimensions. PCA and FA are estimated on standardised items with linear scoring; component retention follows the Kaiser criterion (eigenvalue ≥ 1). The Exp. Variance estimates the average proportion of variance in the indicators that is explained by the latent factor (rule-of-thumb: AVE ≥ 0.50). The PCA-based unified index is selected as the preferred specification.

Cross-method robustness. Pairwise correlation coefficients across alternative constructions of the unified Literacy Attitude Index (Table 1.C.7) range from 0.989 to 0.996, implying that the headline PCA index is empirically interchangeable with the row-mean and FA alternatives. The three constructions overlap almost perfectly in informational content; we retain the PCA score as the Literacy Attitude Index.

Table 1.C.7: Correlation matrix of alternative Literacy Attitude Indices.

	Average	PCA	Factor Analysis
Average	1.0000		
PCA	0.9962	1.0000	
Factor Analysis	0.9891	0.9959	1.0000

Notes: The table reports pairwise correlation coefficients across alternative constructions of the unified Literacy Attitude Index. Results for the separated index specifications are available upon request.

Figure 1.C.7: Distribution of alternative Literacy Attitude Indices.

Notes: Unified Literacy Attitude Indices are constructed using row means (Average), Principal Component Analysis (PCA), and Factor Analysis (FA). Results for the separated index specifications are available upon request.

Figure 1.C.7 plots the empirical distributions of the three alternative literacy indices. Compared with the mathematics counterpart, the literacy distributions are less left-skewed and more symmetric, with the bulk of mass falling between -2 and $+1.5$ and a milder right-tail truncation near $+2$. The three constructions track each other closely throughout the support: the PCA and FA densities are practically superimposed, and the row-mean panel differs only by a slightly coarser discretisation. The visual evidence is consistent with the high pairwise correlations reported in Table 1.C.7 and confirms that the PCA index provides a continuous, well-behaved measure of literacy attitude.

1.C.3 Test Anxiety Index

The Test Anxiety Index is constructed from the four Q9 items administered to grade-5 students in the 2013/14 school year. These items capture feelings of anxiety before the test, nervousness during the test, fear of poor performance, and (reverse-coded) calmness during the test, in both literacy and mathematics. Because Q9 contains a single set of theoretically homogeneous items, no item-separated specification is estimated (see table 1.5 in the main text.).

Internal consistency. The four-item scale yields $\alpha = 0.762$ (Table 1.C.8), exceeding the 0.70 threshold appropriate for short scales. All items load meaningfully on the latent construct capturing students' test anxiety.

Table 1.C.8: Internal Consistency of the Test Anxiety items.

Statistic	Value
Number of items in the scale	4
Average inter-item covariance	0.452
Cronbach's alpha	0.762

Notes: Cronbach's alpha is computed using the original Likert-scale items (without standardisation). The value exceeds the 0.70 threshold conventional for short scales.

Dimensionality. The first principal component has eigenvalue 2.34, explaining 58.5% of the total variance; the second eigenvalue drops to 0.64 (Table 1.C.9). Subsequent components (PC2–PC4) account for 15.8%, 14.5%, and 11.1% of the variance, respectively, and none exceeds the Kaiser threshold of 1. All items load positively and substantially on the leading component, providing strong empirical support for the unidimensionality of the test-anxiety construct.

Table 1.C.9: Alternative latent index constructions for the Test Anxiety Index.

Model	Components	Eigenvalue	AVE
PCA	No. 1	2.34	58.5%
	No. 2	0.64	15.9 %
Factor Analysis (FA)	No. 1	1.67	41.7 %
	No. 2	-0.06	-1.4 %

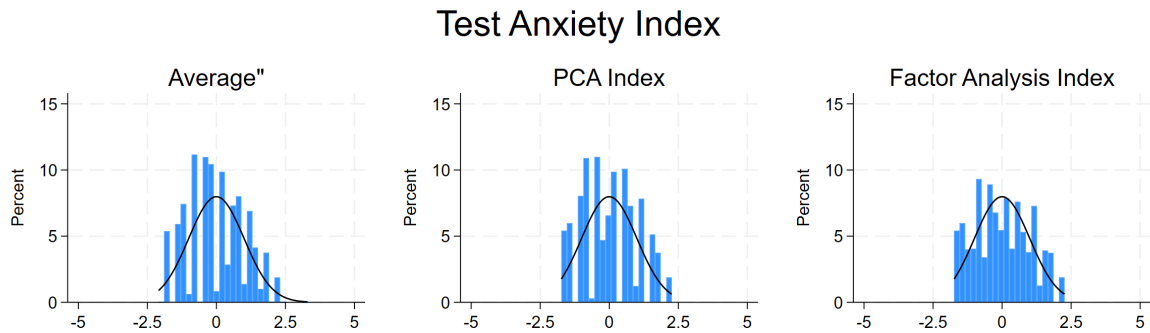
Notes: PCA and FA are estimated using standardised items with linear scoring; component retention follows the Kaiser criterion (eigenvalue ≥ 1). The PCA-based index is selected as the most representative specification.

Cross-method robustness. Pairwise Pearson correlations among the three candidate scores (Table 1.C.10) range from 0.997 to 0.999, indicating that the headline PCA index is empirically interchangeable with the model-based alternatives. We retain the PCA score as the Test Anxiety Index.

Table 1.C.10: Correlation matrix of alternative Test Anxiety Index.

	Average	PCA	Factor Analysis
Average	1.0000		
PCA	0.9998	1.0000	
Factor Analysis	0.9975	0.9986	1.0000

Notes: The table reports pairwise correlation coefficients across alternative constructions of the unified Test Anxiety Index.

Figure 1.C.8: Distribution of alternative Test Anxiety Indices.

Notes: Test Anxiety Indices are constructed using row means (Average), Principal Component Analysis (PCA) and Factor Analysis (FA).

Figure 1.C.8 plots the empirical distributions of the three alternative test-anxiety indices. The distributions are approximately symmetric and broadly bell-shaped over the interval $[-2.5, +2.5]$, in line with the more balanced response pattern observed on the four Q9 items relative to the attitude scales. The row-mean panel exhibits visible discreteness arising from the limited number of distinct row-mean values available on a four-item ordinal scale; the PCA and FA panels, by contrast, are essentially continuous and almost indistinguishable from each other. The visual evidence is fully consistent with the pairwise correlations reported in Table 1.C.10 and supports the interchangeability of the three constructions.

Summary. Across the three indices, the four validation steps converge on the same conclusion: each set of INVALSI items captures a single dominant latent construct that is well measured by the first principal component, internally consistent in terms of Cronbach's α , empirically equivalent to row-mean and factor-analytic alternatives. The PCA score is therefore retained as the headline measure for each of the three non-cognitive constructs used throughout the paper.

1.D Heterogeneity tables

Tables from 1.D.11 to 1.D.16 report the estimation results for Mathematics corresponding to Figures in Section 1.6.

Table 1.D.11: The influence of male and female attitudes towards Mathematics on the Invalsi test performance in 8th, 10th and 13th grades: quantile regression.

Grade 8	10th	25th	50th	75th	90th
Attitude: Mathematics	0.107*** (0.003)	0.107*** (0.002)	0.106*** (0.002)	0.105*** (0.003)	0.104*** (0.004)
Gender (female=1)	-0.021*** (0.004)	-0.020*** (0.003)	-0.019*** (0.002)	-0.018*** (0.003)	-0.017*** (0.005)
Attitude x Female	-0.002 (0.004)	-0.002 (0.003)	-0.003 (0.002)	-0.003 (0.003)	-0.003 (0.005)
Test-anxiety Index	-0.043*** (0.002)	-0.044*** (0.002)	-0.045*** (0.001)	-0.047*** (0.002)	-0.048*** (0.003)
Observations	352,902	352,902	352,902	352,902	352,902
Grade 10	10th	25th	50th	75th	90th
Attitude: Mathematics	0.088*** (0.004)	0.086*** (0.003)	0.084*** (0.002)	0.082*** (0.003)	0.079*** (0.004)
Gender (female=1)	-0.015*** (0.005)	-0.033*** (0.004)	-0.054*** (0.003)	-0.075*** (0.003)	-0.093*** (0.005)
Attitude x Female	-0.020*** (0.005)	-0.012*** (0.004)	-0.004 (0.003)	0.004 (0.003)	0.012** (0.005)
Test-anxiety Index	-0.014*** (0.003)	-0.013*** (0.002)	-0.013*** (0.001)	-0.012*** (0.002)	-0.011*** (0.003)
Observations	291,909	291,909	291,909	291,909	291,909
Grade 13	10th	25th	50th	75th	90th
Attitude: Mathematics	0.054*** (0.004)	0.054*** (0.003)	0.054*** (0.002)	0.054*** (0.003)	0.054*** (0.004)
Gender (female=1)	-0.011** (0.005)	-0.043*** (0.003)	-0.082*** (0.003)	-0.121*** (0.003)	-0.154*** (0.005)
Attitude x Female	-0.011** (0.005)	-0.009*** (0.003)	-0.007*** (0.003)	-0.005 (0.003)	-0.003 (0.005)
Test-anxiety Index	0.001 (0.003)	0.001 (0.002)	0.001 (0.001)	0.001 (0.002)	0.001 (0.003)
Observations	255,736	255,736	255,736	255,736	255,736
<i>Controls</i>					
Prev. academic performance	Yes	Yes	Yes	Yes	Yes
Stud. charact.	Yes	Yes	Yes	Yes	Yes
Other indexes	No	No	No	No	No
Class FE	Yes	Yes	Yes	Yes	Yes

Notes: Quantile Regression estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.D.12: The influence of male and female attitudes towards Literacy on the Invalsi test performance in 8th, 10th and 13th grades: quantile regression.

Grade 8	10th	25th	50th	75th	90th
Attitude: Literacy	0.036*** (0.003)	0.039*** (0.002)	0.044*** (0.002)	0.049*** (0.002)	0.053*** (0.003)
Gender (female=1)	0.202*** (0.004)	0.202*** (0.003)	0.201*** (0.002)	0.201*** (0.003)	0.201*** (0.005)
Attitude x Female	-0.003 (0.004)	-0.002 (0.003)	-0.001 (0.002)	0.000 (0.003)	0.001 (0.005)
Test-anxiety Index	-0.043*** (0.002)	-0.044*** (0.002)	-0.045*** (0.001)	-0.046*** (0.002)	-0.047*** (0.002)
Observations	347,269	347,269	347,269	347,269	347,269
Grade 10	10th	25th	50th	75th	90th
Attitude: Literacy	0.046*** (0.004)	0.041*** (0.003)	0.035*** (0.002)	0.029*** (0.003)	0.024*** (0.004)
Gender (female=1)	0.157*** (0.005)	0.121*** (0.004)	0.081*** (0.003)	0.043*** (0.004)	0.011** (0.005)
Attitude x Female	-0.024*** (0.005)	-0.021*** (0.004)	-0.017*** (0.003)	-0.013*** (0.004)	-0.010** (0.005)
Test-anxiety Index	-0.022*** (0.003)	-0.022*** (0.002)	-0.023*** (0.001)	-0.024*** (0.002)	-0.025*** (0.003)
Observations	289,963	289,963	289,963	289,963	289,963
Grade 13	10th	25th	50th	75th	90th
Attitude: Literacy	0.029*** (0.010)	0.026*** (0.007)	0.022*** (0.004)	0.019*** (0.003)	0.016*** (0.004)
Gender (female=1)	0.158*** (0.013)	0.113*** (0.009)	0.063*** (0.005)	0.017*** (0.003)	-0.022*** (0.005)
Attitude x Female	-0.005 (0.013)	-0.005 (0.009)	-0.005 (0.005)	-0.005 (0.003)	-0.005 (0.005)
Test-anxiety Index	-0.007 (0.007)	-0.009* (0.005)	-0.011*** (0.003)	-0.013*** (0.002)	-0.015*** (0.003)
Observations	254,794	254,794	254,794	254,794	254,794
<i>Controls</i>					
Prev. academic performance	Yes	Yes	Yes	Yes	Yes
Stud. charact.	Yes	Yes	Yes	Yes	Yes
Other indexes	No	No	No	No	No
Class FE	Yes	Yes	Yes	Yes	Yes

Notes: Quantile Regression estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.D.13: The influence of male and female attitudes towards Mathematics on the Invalsi test performance in 8th, 10th and 13th grades: by ESCS levels.

Grade 8	All SES levels	Low	Med-low	Med-high	High
Attitude: Mathematics	0.106*** (0.002)	0.098*** (0.005)	0.102*** (0.005)	0.106*** (0.005)	0.113*** (0.005)
Gender (female=1)	-0.019*** (0.003)	-0.018** (0.007)	-0.014** (0.006)	-0.014** (0.007)	-0.029*** (0.006)
Attitude x Female	-0.003 (0.003)	-0.001 (0.007)	0.000 (0.006)	0.003 (0.007)	-0.008 (0.006)
Test-anxiety Index	-0.045*** (0.001)	-0.041*** (0.004)	-0.047*** (0.003)	-0.044*** (0.004)	-0.045*** (0.003)
Constant	0.039*** (0.009)	-0.056*** (0.022)	0.052*** (0.019)	0.018 (0.025)	0.047* (0.026)
Observations	352,902	81,815	93,131	81,111	96,845
R-squared	0.539	0.580	0.607	0.631	0.603
<hr/>					
Grade 10	All SES levels	Low	Med-low	Med-high	High
Attitude: Mathematics	0.084*** (0.002)	0.086*** (0.007)	0.081*** (0.006)	0.075*** (0.006)	0.090*** (0.005)
Gender (female=1)	-0.054*** (0.003)	-0.077*** (0.008)	-0.054*** (0.007)	-0.039*** (0.008)	-0.045*** (0.006)
Attitude x Female	-0.004 (0.003)	-0.014* (0.008)	-0.005 (0.007)	0.006 (0.008)	-0.000 (0.006)
Test-anxiety Index	-0.013*** (0.001)	-0.022*** (0.004)	-0.023*** (0.004)	-0.006 (0.004)	-0.001 (0.003)
Constant	0.008 (0.009)	-0.044 (0.029)	0.032 (0.022)	-0.030 (0.028)	0.027 (0.029)
Observations	291,909	58,666	76,814	69,346	87,083
R-squared	0.597	0.672	0.669	0.685	0.644
<hr/>					
Grade 13	All SES levels	Low	Med-low	Med-high	High
Attitude: Mathematics	0.054*** (0.002)	0.047*** (0.008)	0.058*** (0.006)	0.049*** (0.007)	0.060*** (0.005)
Gender (female=1)	-0.082*** (0.003)	-0.093*** (0.009)	-0.088*** (0.007)	-0.078*** (0.008)	-0.076*** (0.006)
Attitude x Female	-0.007** (0.003)	-0.003 (0.009)	-0.018** (0.007)	-0.006 (0.008)	-0.004 (0.006)
Test-anxiety Index	0.001 (0.001)	-0.002 (0.005)	0.004 (0.004)	0.000 (0.004)	0.002 (0.003)
Constant	0.034*** (0.010)	-0.013 (0.030)	0.033 (0.024)	0.054* (0.029)	0.026 (0.026)
Observations	255,736	48,007	66,985	61,470	79,274
R-squared	0.675	0.754	0.746	0.756	0.721
<hr/>					
<i>Controls</i>					
Prev. academic performance	Yes	Yes	Yes	Yes	Yes
Stud. charact.	Yes	Yes	Yes	Yes	Yes
Other indexes	No	No	No	No	No
Class FE	Yes	Yes	Yes	Yes	Yes

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.D.14: The influence of male and female attitudes towards Literacy on the Invalsi test performance in 8th, 10th and 13th grades: by ESCS levels.

Grade 8	All SES levels	Low	Med-low	Med-high	High
Attitude: Literacy	0.044*** (0.002)	0.047*** (0.005)	0.040*** (0.004)	0.041*** (0.005)	0.046*** (0.004)
Gender (female=1)	0.201*** (0.003)	0.199*** (0.007)	0.201*** (0.006)	0.206*** (0.007)	0.199*** (0.006)
Attitude x Female	-0.001 (0.003)	0.000 (0.007)	0.005 (0.006)	0.002 (0.007)	-0.004 (0.006)
Test-anxiety Index	-0.045*** (0.001)	-0.041*** (0.004)	-0.047*** (0.003)	-0.047*** (0.004)	-0.042*** (0.003)
Constant	-0.061*** (0.009)	-0.073*** (0.022)	-0.052*** (0.019)	-0.103*** (0.028)	-0.038 (0.025)
Observations	347,269	79,908	91,730	79,922	95,709
R-squared	0.524	0.578	0.593	0.613	0.571
Grade 10	All SES levels	Low	Med-low	Med-high	High
Attitude: Literacy	0.035*** (0.002)	0.027*** (0.007)	0.038*** (0.005)	0.036*** (0.006)	0.030*** (0.005)
Gender (female=1)	0.083*** (0.003)	0.095*** (0.009)	0.081*** (0.007)	0.097*** (0.008)	0.069*** (0.007)
Attitude x Female	-0.017*** (0.003)	-0.012 (0.009)	-0.018** (0.007)	-0.015* (0.008)	-0.010 (0.007)
Test-anxiety Index	-0.023*** (0.002)	-0.035*** (0.005)	-0.021*** (0.004)	-0.016*** (0.004)	-0.019*** (0.003)
Constant	-0.065*** (0.010)	-0.152*** (0.030)	-0.049** (0.024)	-0.025 (0.030)	-0.089*** (0.029)
Observations	289,963	58,218	76,233	68,911	86,601
R-squared	0.547	0.646	0.632	0.642	0.589
Grade 13	All SES levels	Low	Med-low	Med-high	High
Attitude: Literacy	0.022*** (0.002)	0.027*** (0.007)	0.020*** (0.006)	0.020*** (0.006)	0.026*** (0.005)
Gender (female=1)	0.066*** (0.003)	0.073*** (0.010)	0.084*** (0.007)	0.071*** (0.008)	0.042*** (0.006)
Attitude x Female	-0.005* (0.003)	-0.006 (0.010)	-0.004 (0.007)	0.008 (0.008)	-0.012* (0.006)
Test-anxiety Index	-0.011*** (0.001)	-0.017*** (0.005)	-0.009** (0.004)	-0.009** (0.004)	-0.008** (0.003)
Constant	-0.057*** (0.010)	-0.110*** (0.031)	-0.086*** (0.025)	-0.067** (0.031)	-0.038 (0.027)
Observations	254,794	47,873	66,687	61,215	79,019
R-squared	0.638	0.739	0.719	0.727	0.669
<i>Controls</i>					
Prev. academic performance	Yes	Yes	Yes	Yes	Yes
Stud. charact.	Yes	Yes	Yes	Yes	Yes
Other indexes	No	No	No	No	No
Class FE	Yes	Yes	Yes	Yes	Yes

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.D.15: The influence of male and female attitudes towards Mathematics on the Invalsi test performance in 8th, 10th and 13th grades: by geographic areas.

Grade 8	All areas	North-West	North-East	Centre	South	Islands
Attitude: Mathematics	0.106*** (0.002)	0.093*** (0.004)	0.092*** (0.004)	0.109*** (0.005)	0.128*** (0.005)	0.110*** (0.006)
Gender (female=1)	-0.019*** (0.003)	-0.029*** (0.005)	-0.039*** (0.006)	-0.056*** (0.007)	0.019*** (0.006)	0.037*** (0.008)
Attitude x Female	-0.003 (0.003)	0.001 (0.005)	-0.001 (0.005)	0.002 (0.007)	-0.025*** (0.006)	-0.002 (0.007)
Test-anxiety Index	-0.045*** (0.001)	-0.042*** (0.002)	-0.043*** (0.003)	-0.048*** (0.004)	-0.049*** (0.003)	-0.039*** (0.004)
Constant	0.039*** (0.009)	0.184*** (0.015)	0.202*** (0.017)	0.065*** (0.024)	-0.157*** (0.021)	-0.097*** (0.019)
Observations	352,902	91,903	69,804	53,906	80,646	56,643
R-squared	0.539	0.603	0.615	0.542	0.460	0.468
Grade 10	All areas	North-West	North-East	Centre	South	Islands
Attitude: Mathematics	0.084*** (0.002)	0.061*** (0.004)	0.062*** (0.005)	0.079*** (0.006)	0.103*** (0.005)	0.113*** (0.006)
Gender (female=1)	-0.054*** (0.003)	-0.012** (0.006)	-0.019*** (0.006)	-0.033*** (0.007)	-0.083*** (0.006)	-0.127*** (0.007)
Attitude x Female	-0.004 (0.003)	0.008 (0.005)	0.010* (0.006)	-0.006 (0.007)	-0.007 (0.006)	-0.014* (0.008)
Test-anxiety Index	-0.013*** (0.001)	0.003 (0.003)	-0.001 (0.003)	-0.007* (0.004)	-0.027*** (0.003)	-0.032*** (0.004)
Constant	0.008 (0.009)	0.212*** (0.018)	0.276*** (0.019)	-0.011 (0.026)	-0.186*** (0.022)	-0.364*** (0.021)
Observations	291,909	72,948	57,023	46,108	68,938	46,892
R-squared	0.597	0.592	0.611	0.563	0.507	0.484
Grade 13	All areas	North-West	North-East	Centre	South	Islands
Attitude: Mathematics	0.054*** (0.002)	0.048*** (0.005)	0.051*** (0.005)	0.046*** (0.006)	0.062*** (0.005)	0.065*** (0.006)
Gender (female=1)	-0.082*** (0.003)	-0.099*** (0.005)	-0.099*** (0.006)	-0.078*** (0.007)	-0.056*** (0.006)	-0.074*** (0.007)
Attitude x Female	-0.007** (0.003)	-0.007 (0.005)	-0.010* (0.006)	-0.001 (0.007)	-0.010 (0.006)	-0.011 (0.007)
Test-anxiety Index	0.001 (0.001)	0.006** (0.003)	0.008** (0.003)	0.000 (0.004)	-0.004 (0.003)	-0.007* (0.004)
Constant	0.034*** (0.010)	0.193*** (0.019)	0.210*** (0.021)	0.011 (0.028)	-0.116*** (0.023)	-0.183*** (0.019)
Observations	255,736	63,665	50,015	40,867	60,537	40,652
R-squared	0.675	0.671	0.658	0.650	0.603	0.602
<i>Controls</i>						
Prev. academic performance	Yes	Yes	Yes	Yes	Yes	Yes
Stud. charact.	Yes	Yes	Yes	Yes	Yes	Yes
Other indexes	No	No	No	No	No	No
Class FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.D.16: The influence of male and female attitudes towards Literacy on the Invalsi test performance in 8th, 10th and 13th grades: by geographic areas.

Grade 8	All areas	North-West	North-East	Centre	South	Islands
Attitude: Literacy	0.044*** (0.002)	0.038*** (0.003)	0.038*** (0.004)	0.036*** (0.005)	0.057*** (0.005)	0.064*** (0.006)
Gender (female=1)	0.201*** (0.003)	0.190*** (0.005)	0.183*** (0.005)	0.182*** (0.007)	0.219*** (0.007)	0.232*** (0.008)
Attitude x Female	-0.001 (0.003)	-0.005 (0.005)	-0.008 (0.005)	0.002 (0.007)	-0.003 (0.007)	-0.001 (0.008)
Test-anxiety Index	-0.045*** (0.001)	-0.039*** (0.002)	-0.039*** (0.003)	-0.049*** (0.003)	-0.053*** (0.003)	-0.043*** (0.004)
Constant	-0.061*** (0.009)	0.013 (0.015)	-0.032* (0.017)	-0.034 (0.025)	-0.136*** (0.022)	-0.111*** (0.021)
Observations	347,269	90,795	68,783	52,895	79,503	55,293
R-squared	0.524	0.567	0.567	0.527	0.480	0.493

Grade 10	All areas	North-West	North-East	Centre	South	Islands
Attitude: Literacy	0.035*** (0.002)	0.029*** (0.004)	0.033*** (0.005)	0.040*** (0.006)	0.038*** (0.005)	0.041*** (0.006)
Gender (female=1)	0.083*** (0.003)	0.064*** (0.006)	0.062*** (0.006)	0.093*** (0.008)	0.092*** (0.007)	0.103*** (0.008)
Attitude x Female	-0.017*** (0.003)	-0.015*** (0.006)	-0.025*** (0.006)	-0.023*** (0.008)	-0.012* (0.007)	-0.018** (0.009)
Test-anxiety Index	-0.023*** (0.002)	-0.010*** (0.003)	-0.015*** (0.003)	-0.021*** (0.004)	-0.036*** (0.003)	-0.034*** (0.004)
Constant	-0.065*** (0.010)	0.098*** (0.019)	0.198*** (0.022)	-0.049* (0.027)	-0.259*** (0.024)	-0.363*** (0.022)
Observations	289,963	72,516	56,487	45,541	68,788	46,631
R-squared	0.547	0.539	0.553	0.512	0.505	0.496

Grade 13	All areas	North-West	North-East	Centre	South	Islands
Attitude: Literacy	0.022*** (0.002)	0.025*** (0.004)	0.021*** (0.005)	0.025*** (0.006)	0.027*** (0.005)	0.023*** (0.006)
Gender (female=1)	0.066*** (0.003)	0.034*** (0.006)	0.052*** (0.006)	0.071*** (0.007)	0.086*** (0.006)	0.090*** (0.008)
Attitude x Female	-0.005* (0.003)	-0.013** (0.006)	-0.010 (0.006)	-0.017** (0.007)	-0.003 (0.006)	0.000 (0.008)
Test-anxiety Index	-0.011*** (0.001)	-0.008*** (0.003)	-0.003 (0.003)	-0.010*** (0.004)	-0.016*** (0.003)	-0.012*** (0.004)
Constant	-0.057*** (0.010)	0.125*** (0.019)	0.120*** (0.021)	-0.069** (0.028)	-0.218*** (0.021)	-0.253*** (0.022)
Observations	254,794	63,361	49,622	40,482	60,724	40,605
R-squared	0.638	0.617	0.621	0.605	0.599	0.607

<i>Controls</i>						
Prev. academic performance	Yes	Yes	Yes	Yes	Yes	Yes
Stud. charact.	Yes	Yes	Yes	Yes	Yes	Yes
Other indexes	No	No	No	No	No	No
Class FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Ordinary Least Squares (OLS) estimates. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

1.E Balanced Panel Estimations

This appendix replicates the regression analysis on the balanced panel. The balanced sample includes students observed in all four INVALSI waves, from grade 5 through grade 13. Being observed at grade 13 is the binding requirement, so the balanced sample is the same set of students for every outcome wave. The number of students therefore equals the grade-13 sample of the main analysis, and does not change across the grade-8, grade-10, and grade-13 regressions. The sample is subject-specific, conditioning on a non-missing score in the relevant subject, so it is slightly smaller for literacy than for mathematics. Within each table, the number of observations still falls as controls are added, because each specification is estimated on students with non-missing values on the included regressors, as in the main tables. Table 1.E.17 reports descriptive statistics for the balanced samples. Tables 1.E.18 and 1.E.19 report the mathematics estimates at grades 8 and 10. Tables 1.E.20 and 1.E.21 report the literacy estimates at the same grades. Grade-13 tables are not reproduced, because they coincide by construction with the main analysis. Grade-5 estimates are reported in Table 1.E.22, panel (a) for mathematics and panel (b) for literacy. The estimates on the balanced panel are close to those in the main analysis. We discuss them in Section 1.5.

Table 1.E.17: Descriptive statistics from balanced subject-specific data.

Dataset: Mathematics	Panel (a): Grade 8			Panel (b): Grade 10			Panel (c): Grade 13		
	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.
Outcome Measures:									
Mathematics score G8	213.37	39.13	299,314						
Mathematics score G10				209.36	38.92	299,314			
Mathematics score G13							197.96	38.61	299,314
Lagged Outcome Variables									
Mathematics score G5	220.71	43.31	299,314	220.71	43.31	299,314	220.71	43.31	299,314
Mathematics score G8	213.37	39.13	299,314	213.37	39.13	299,314	213.37	39.13	299,314
Mathematics score G10				209.36	38.92	299,314	209.36	38.92	299,314
Non-Cognitive Skills' Measures (Grade 5)									
Attitude Mathematics Index	0.00	1.00	299,314	0.00	1.00	299,314	0.00	1.00	299,314
Test-anxiety Index	-0.00	1.00	294,716	-0.00	1.00	294,716	-0.00	1.00	294,716
Additional Students' Characteristics (Grade 5)									
Females	0.54	0.50	299,313	0.54	0.50	299,313	0.54	0.50	299,313
ESCS Index	0.23	0.96	299,104	0.23	0.96	299,104	0.23	0.96	299,104
Kindergarten (yes=1)	0.87	0.34	262,739	0.87	0.34	262,739	0.87	0.34	262,739
Immigrant (yes=1)	0.05	0.22	295,911	0.05	0.22	295,911	0.05	0.22	295,911
Early enrolled (yes=1)	0.02	0.12	299,295	0.02	0.12	299,295	0.02	0.12	299,295
Late enrolled (yes=1)	0.01	0.11	299,295	0.01	0.11	299,295	0.01	0.11	299,295
Motivation Index	0.00	1.00	299,065	0.00	1.00	299,065	0.00	1.00	299,065
Time Management Index	0.00	1.00	297,403	0.00	1.00	297,403	0.00	1.00	297,403
Social Isolation Index	-0.00	1.00	299,153	-0.00	1.00	299,153	-0.00	1.00	299,153
Dataset: Literacy	Panel (a): Grade 8			Panel (b): Grade 10			Panel (c): Grade 13		
	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.
Outcome Measures:									
Literacy score G8	215.07	37.72	297,858						
Literacy score G10				209.59	37.64	297,858			
Literacy score G13							193.58	39.40	297,858
Lagged Outcome Variables									
Literacy score G5	218.85	39.24	297,858	218.85	39.24	297,858	218.85	39.24	297,858
Literacy score G8	215.07	37.72	297,858	215.07	37.72	297,858	215.07	37.72	297,858
Literacy score G10				209.59	37.64	297,858	209.59	37.64	297,858
Non-Cognitive Skills' Measures (Grade 5)									
Attitude Literacy Index	0.00	1.00	297,858	0.00	1.00	297,858	0.00	1.00	297,858
Test-anxiety Index	-0.00	1.00	293,352	-0.00	1.00	293,352	-0.00	1.00	293,352
Additional Students' Characteristics (Grade 5)									
Females	0.54	0.50	297,857	0.54	0.50	297,857	0.54	0.50	297,857
ESCS Index	0.23	0.96	297,657	0.23	0.96	297,657	0.23	0.96	297,657
Kindergarten (yes=1)	0.87	0.34	261,717	0.87	0.34	261,717	0.87	0.34	261,717
Immigrant (yes=1)	0.05	0.22	294,459	0.05	0.22	294,459	0.05	0.22	294,459
Early enrolled (yes=1)	0.02	0.12	297,839	0.02	0.12	297,839	0.02	0.12	297,839
Late enrolled (yes=1)	0.01	0.10	297,839	0.01	0.10	297,839	0.01	0.10	297,839
Motivation Index	0.00	1.00	297,607	0.00	1.00	297,607	0.00	1.00	297,607
Time Management Index	0.00	1.00	295,939	0.00	1.00	295,939	0.00	1.00	295,939
Social Isolation Index	-0.00	1.00	297,693	-0.00	1.00	297,693	-0.00	1.00	297,693

Notes: Descriptive statistics for the variables used in the analysis. The sample is restricted to the balanced panel.

Table 1.E.18: The influence of male and female attitudes towards Mathematics on Invalsi test performance in 8th grade with balanced panel.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Attitude: Mathematics	0.300*** (0.002)	0.120*** (0.002)	0.116*** (0.002)	0.117*** (0.003)	0.111*** (0.003)	0.110*** (0.003)
Mathematics score G05		0.718*** (0.003)	0.699*** (0.003)	0.699*** (0.003)	0.690*** (0.003)	0.690*** (0.003)
Gender (female=1)			-0.052*** (0.003)	-0.052*** (0.003)	-0.042*** (0.003)	-0.042*** (0.003)
Attitude x Female				-0.003 (0.003)	-0.004 (0.003)	-0.002 (0.003)
ESCS Index			0.089*** (0.002)	0.089*** (0.002)	0.086*** (0.002)	0.086*** (0.002)
Kindergarten (yes=1)			0.024* (0.013)	0.024* (0.013)	0.022* (0.013)	0.022* (0.013)
Immigrant (yes=1)			-0.065*** (0.008)	-0.065*** (0.008)	-0.061*** (0.008)	-0.061*** (0.008)
Early enrolled (yes=1)			0.104*** (0.015)	0.104*** (0.015)	0.105*** (0.015)	0.105*** (0.015)
Late enrolled (yes=1)			-0.112*** (0.017)	-0.112*** (0.017)	-0.112*** (0.017)	-0.112*** (0.017)
Test-anxiety Index					-0.047*** (0.002)	-0.054*** (0.002)
Test Anxiety x Females						0.012*** (0.003)
Constant	0.016*** (0.000)	0.009*** (0.000)	-0.001 (0.011)	-0.002 (0.011)	-0.004 (0.012)	-0.005 (0.012)
Observations	299,314	299,314	259,686	259,686	255,736	255,736
R-squared	0.278	0.528	0.539	0.539	0.542	0.542

Notes: Ordinary Least Squares (OLS) estimates. The sample is restricted to the balanced panel. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.E.19: The influence of male and female attitudes towards Mathematics on Invalsi test performance in 10th grade with balanced panel.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Attitude: Mathematics	0.302*** (0.002)	0.089*** (0.002)	0.083*** (0.002)	0.085*** (0.002)	0.083*** (0.003)	0.083*** (0.003)
Mathematics score G05		0.311*** (0.003)	0.304*** (0.003)	0.304*** (0.003)	0.302*** (0.003)	0.302*** (0.003)
Mathematics score G08		0.451*** (0.002)	0.440*** (0.002)	0.440*** (0.002)	0.439*** (0.002)	0.439*** (0.002)
Gender (female=1)			-0.079*** (0.003)	-0.079*** (0.003)	-0.077*** (0.003)	-0.077*** (0.003)
Attitude x Female				-0.004 (0.003)	-0.003 (0.003)	-0.004 (0.003)
ESCS Index			0.060*** (0.002)	0.060*** (0.002)	0.059*** (0.002)	0.059*** (0.002)
Kindergarten (yes=1)			0.007 (0.012)	0.007 (0.012)	0.008 (0.012)	0.008 (0.012)
Immigrant (yes=1)			0.024*** (0.007)	0.024*** (0.007)	0.024*** (0.007)	0.024*** (0.007)
Early enrolled (yes=1)			0.111*** (0.014)	0.111*** (0.014)	0.112*** (0.014)	0.112*** (0.014)
Late enrolled (yes=1)			-0.084*** (0.015)	-0.084*** (0.015)	-0.084*** (0.015)	-0.084*** (0.015)
Test-anxiety Index					-0.013*** (0.002)	-0.012*** (0.002)
Test Anxiety x Females						-0.001 (0.003)
Constant	0.014*** (0.000)	0.003*** (0.000)	0.029*** (0.011)	0.028*** (0.011)	0.027** (0.011)	0.027** (0.011)
Observations	299,314	299,314	259,686	259,686	255,736	255,736
R-squared	0.302	0.593	0.603	0.603	0.603	0.603

Notes: Ordinary Least Squares (OLS) estimates. The sample is restricted to the balanced panel. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.E.20: The influence of male and female attitudes towards Literacy on Invalsi test performance in 8th grade with balanced panel.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Attitude: Literacy	0.167*** (0.002)	0.078*** (0.002)	0.052*** (0.002)	0.051*** (0.002)	0.049*** (0.002)	0.048*** (0.002)
Literacy score G05		0.682*** (0.002)	0.659*** (0.002)	0.659*** (0.002)	0.649*** (0.002)	0.649*** (0.002)
Gender (female=1)			0.181*** (0.003)	0.181*** (0.003)	0.197*** (0.004)	0.197*** (0.004)
Attitude x Female				0.002 (0.003)	0.001 (0.003)	0.001 (0.003)
ESCS Index			0.096*** (0.002)	0.096*** (0.002)	0.094*** (0.002)	0.094*** (0.002)
Kindergarten (yes=1)			0.013 (0.013)	0.013 (0.013)	0.014 (0.013)	0.014 (0.013)
Immigrant (yes=1)			-0.043*** (0.008)	-0.043*** (0.008)	-0.044*** (0.008)	-0.044*** (0.008)
Early enrolled (yes=1)			0.081*** (0.016)	0.081*** (0.016)	0.080*** (0.016)	0.080*** (0.016)
Late enrolled (yes=1)			-0.092*** (0.017)	-0.092*** (0.017)	-0.091*** (0.018)	-0.091*** (0.018)
Test-anxiety Index					-0.046*** (0.002)	-0.049*** (0.002)
Test Anxiety x Females						0.004 (0.003)
Constant	0.016*** (0.000)	0.007*** (0.000)	-0.125*** (0.012)	-0.125*** (0.012)	-0.133*** (0.012)	-0.134*** (0.012)
Observations	297,858	297,858	258,671	258,671	254,794	254,794
R-squared	0.204	0.489	0.506	0.506	0.508	0.508

Notes: Ordinary Least Squares (OLS) estimates. The sample is restricted to the balanced panel. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.E.21: The influence of male and female attitudes towards Literacy on Invalsi test performance in 10th grade with balanced panel.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Attitude: Literacy	0.154*** (0.002)	0.038*** (0.002)	0.028*** (0.002)	0.035*** (0.002)	0.033*** (0.002)	0.034*** (0.002)
Literacy score G05		0.377*** (0.003)	0.372*** (0.003)	0.372*** (0.003)	0.368*** (0.003)	0.368*** (0.003)
Literacy score G08		0.397*** (0.002)	0.386*** (0.002)	0.386*** (0.002)	0.384*** (0.003)	0.384*** (0.003)
Gender (female=1)			0.061*** (0.003)	0.061*** (0.003)	0.070*** (0.003)	0.069*** (0.003)
Attitude x Female				-0.014*** (0.003)	-0.014*** (0.003)	-0.015*** (0.003)
ESCS Index			0.061*** (0.002)	0.061*** (0.002)	0.060*** (0.002)	0.060*** (0.002)
Kindergarten (yes=1)			0.022* (0.013)	0.022* (0.013)	0.022* (0.013)	0.022* (0.013)
Immigrant (yes=1)			0.030*** (0.008)	0.029*** (0.008)	0.030*** (0.008)	0.030*** (0.008)
Early enrolled (yes=1)			0.083*** (0.014)	0.083*** (0.014)	0.085*** (0.014)	0.085*** (0.014)
Late enrolled (yes=1)			-0.065*** (0.016)	-0.065*** (0.016)	-0.063*** (0.016)	-0.063*** (0.016)
Test-anxiety Index					-0.024*** (0.002)	-0.022*** (0.002)
Test Anxiety x Females						-0.004 (0.003)
Constant	0.014*** (0.000)	0.003*** (0.000)	-0.060*** (0.011)	-0.059*** (0.011)	-0.063*** (0.012)	-0.062*** (0.012)
Observations	297,858	297,858	258,671	258,671	254,794	254,794
R-squared	0.202	0.540	0.548	0.548	0.549	0.549

Notes: Ordinary Least Squares (OLS) estimates. The sample is restricted to the balanced panel. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1.E.22: The influence of male and female attitudes towards Mathematics and Literacy on Teachers' scores in 5th grade with Balanced Panel.

(a) Mathematics				(b) Literacy			
VARIABLES	(1)	(2)	(3)	VARIABLES	(1)	(2)	(3)
Attitude: Mathematics	0.299*** (0.002)	0.273*** (0.002)	0.047*** (0.002)	Attitude: Literacy	0.226*** (0.002)	0.184*** (0.002)	0.033*** (0.002)
Gender (female=1)		0.067*** (0.004)	0.068*** (0.003)	Gender (female=1)		0.161*** (0.004)	0.111*** (0.003)
ESCS Index		0.181*** (0.002)	0.066*** (0.002)	ESCS Index		0.212*** (0.002)	0.083*** (0.002)
Kindergarten (yes=1)		0.099*** (0.018)	0.038*** (0.014)	Kindergarten (yes=1)		0.101*** (0.017)	0.033*** (0.014)
Immigrant (yes=1)		-0.280*** (0.010)	-0.114*** (0.008)	Immigrant (yes=1)		-0.391*** (0.010)	-0.161*** (0.008)
Early enrolled (yes=1)		-0.010 (0.016)	0.004 (0.013)	Early enrolled (yes=1)		-0.014 (0.016)	-0.005 (0.013)
Late enrolled (yes=1)		-0.140*** (0.022)	-0.046*** (0.016)	Late enrolled (yes=1)		-0.225*** (0.022)	-0.087*** (0.017)
Test-anxiety Index		-0.098*** (0.002)	-0.026*** (0.002)	Test-anxiety Index		-0.112*** (0.002)	-0.031*** (0.002)
Mathematics Teachers' score G4			0.641*** (0.002)	Literacy Teachers' score G4			0.636*** (0.002)
Constant	0.016*** (0.000)	-0.129*** (0.016)	-0.060*** (0.012)	Constant	0.017*** (0.000)	-0.183*** (0.015)	-0.079*** (0.012)
Observations	283,239	245,137	242,874	Observations	282,283	244,649	242,176
R-squared	0.359	0.404	0.648	R-squared	0.336	0.399	0.654

Notes: Ordinary Least Squares (OLS) estimates. The sample is restricted to the balanced panel. Robust standard errors, adjusted for clustering at the class level, are reported in parentheses. All regressions include class fixed effects. Test scores and self-reported non-cognitive skill indices are standardised (mean = 0, standard deviation = 1). A detailed description of all variables is provided in the Appendix. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

1.F Cross-subject and Joint Attitude Specifications

Table 1.F.23 reports a domain-specificity robustness check. The table is organised into two panels by outcome domain—Panel A for mathematics achievement and Panel B for literacy achievement. Within each panel, two stacked blocks report alternative specifications of the attitude regressors, each estimated separately for grades 8, 10, and 13.

The *cross-subject specification* replaces the own-subject attitude index with the attitude index for the other subject (e.g., mathematics achievement and the literacy attitude index), while holding the remaining controls unchanged. This specification assesses whether the association between attitudes and achievement extends across subject domains. The *joint specification* includes both attitude indices simultaneously, allowing the own-subject and cross-subject associations to be estimated conditional on one another. The mathematics and literacy attitude indices are essentially uncorrelated (correlation coefficient of approximately 0.03; see Section 1.2.3), suggesting that multicollinearity between the two attitude regressors is unlikely to materially affect the estimates in the joint specification.

Both specifications include the full set of controls used in the main-text models: prior academic performance, student characteristics, the remaining attitude and socio-emotional indices (including the anxiety index), the corresponding interactions with gender, and class fixed effects, as indicated in the “Controls” block at the bottom of each panel.¹⁷ Given the large sample size ($N > 300,000$), comparisons across specifications focus primarily on the magnitude and stability of the estimated coefficients rather than on differences in statistical significance, consistent with the interpretive approach adopted throughout the paper. Regressors that do not enter a given specification are denoted accordingly in the corresponding table cells rather than assigned a coefficient of zero.

¹⁷See sections 1.1 and 1.4 for more details on the model and the results.

Table 1.F.23: Own-Subject, Cross-Subject, and Joint Attitude Specifications — Mathematics and Literacy

Mathematics				Literacy			
Cross-subject model	Grade 8	Grade 10	Grade 13	Cross-subject model	Grade 8	Grade 10	Grade 13
Attitude: Literacy	-0.010*** (0.002)	0.019*** (0.002)	0.005** (0.002)	Attitude: Mathematics	0.053*** (0.002)	0.025*** (0.002)	0.009*** (0.002)
Attitude Lit. x females	0.001 (0.003)	-0.032*** (0.003)	-0.006** (0.003)	Attitude Math x females	-0.003 (0.003)	-0.003 (0.003)	0.001 (0.003)
Females	-0.041*** (0.003)	-0.074*** (0.003)	-0.096*** (0.003)	Females	0.235*** (0.003)	0.100*** (0.003)	0.077*** (0.003)
Observations	353,240	292,217	255,991	Observations	346,938	289,674	254,568
<hr/>				<hr/>			
Joint model	Grade 8	Grade 10	Grade 13	Joint model	Grade 8	Grade 10	Grade 13
Attitude: Mathematics	0.106*** (0.002)	0.083*** (0.002)	0.054*** (0.002)	Attitude: Mathematics	0.052*** (0.002)	0.024*** (0.002)	0.009*** (0.002)
Attitude: Literacy	-0.012*** (0.002)	0.018*** (0.002)	0.004** (0.002)	Attitude: Literacy	0.044*** (0.002)	0.035*** (0.002)	0.022*** (0.002)
Attitude Math x females	-0.003 (0.003)	-0.002 (0.003)	-0.007** (0.003)	Attitude Math x females	-0.002 (0.003)	-0.001 (0.003)	0.001 (0.003)
Attitude Lit. x females	0.002 (0.003)	-0.031*** (0.003)	-0.005* (0.003)	Attitude Lit. x females	-0.000 (0.003)	-0.017*** (0.003)	-0.004 (0.003)
Females	-0.015*** (0.003)	-0.054*** (0.003)	-0.083*** (0.003)	Females	0.216*** (0.003)	0.090*** (0.003)	0.069*** (0.003)
Observations	348,835	288,789	253,090	Observations	342,970	286,583	251,922
<hr/>				<hr/>			
<i>Controls</i>				<i>Controls</i>			
Prev. academic performance	Yes	Yes	Yes	Prev. academic performance	Yes	Yes	Yes
Stud. character.	Yes	Yes	Yes	Stud. character.	Yes	Yes	Yes
Test Anxiety index	Yes	Yes	Yes	Test Anxiety index	Yes	Yes	Yes
Other indexes	No	No	No	Other indexes	No	No	No
Class FE	Yes	Yes	Yes	Class FE	Yes	Yes	Yes

Chapter 2

Early Attitudes and Educational Sorting at the Upper-Secondary Transition

2.1 Introduction

Educational sorting is a key mechanism in the accumulation of human capital. Among the transitions students face, the choice of school track is likely to be consequential: it determines exposure to different curricula, shapes subsequent educational opportunities, and affects labour-market prospects (Hanushek and Wößmann, 2006; Hanushek and Woessmann, 2011). Understanding what drives these choices is therefore a central question in the economics of education.

A large literature shows that educational choices arise from the interaction between students' individual characteristics and the institutional environment. On the individual side, track selection has been linked to competitiveness (Buser et al., 2014, 2017), foundational cognitive skills acquired in childhood (Lopez et al., 2024), broader cognitive and non-cognitive abilities (Zhang et al., 2025), and beliefs about relative academic performance (Owen, 2023). Institutional features, in turn, shape both how students are allocated across pathways and the long-term consequences of these decisions (Dustmann and Schönberg, 2017).

The Italian educational system offers a particularly informative setting. After a common lower-secondary curriculum, students choose, at grade 9, among differentiated upper-secondary pathways without facing binding admission requirements for academically oriented schools. The literature finds that track allocation is strongly associated with family socioeconomic background, and the way tracking is organised contributes to the persistence of educational inequalities (Contini and Scagni, 2011; Brunello and Checchi, 2007). Preferences and beliefs also matter: experimental evidence shows that elicited patience predicts enrolment in academic tracks, while activating perceived parental recommendations shifts girls' choices away from mathematics and towards literature (Angerer et al., 2023; Carlana and Corno, 2024). Overall, both the international and Italian literature identify institutional design, family background, cognitive skills, beliefs, and individual preferences as key determinants of educational choices.

This chapter addresses a less explored dimension of these mechanisms: students' attitudes towards specific school subjects. If such orientations emerge early, they may contribute to educational sorting by shaping students' preferences for curricula with different academic profiles, as expectancy-value models of achievement-related choices suggest (Wigfield and Eccles, 2000). Using data on Italian students, we exploit two indices measured at Grade 5, Attitude towards Mathematics and Attitude towards Literacy, several years before students choose an upper-secondary school. We then examine whether attitudes formed at the end of primary school are associated with later educational sorting.

We first examine whether these subject-specific attitudes are associated with non-persistence along the educational path. We do so by analysing students who are no longer observed in the regular cohort by Grade 10. We cannot observe the reason for non-observation, and this outcome may reflect grade repetition, dropout, migration, or absence from the assessment. As one might expect, non-persistence declines across the distribution of both attitude indices: students with stronger early attitudes are more likely to remain in the cohort through Grade 10.

The second outcome is students' track choice, which constitutes the main focus of the analysis. We identify which upper-secondary track Italian students enter among five possibilities: *Liceo classico*, *Liceo scientifico*, *Altri Licei*, *Tecnici*, and *Professionali*. We estimate multinomial logit models of track choice controlling for prior achievement, family socioeconomic background, demographic characteristics, and province fixed effects.

The results show that early subject-specific attitudes predict track choice along subject lines: a stronger early Attitude towards Mathematics is associated with enrolment in *Liceo scientifico* and *Tecnici*, while a stronger Attitude towards Literacy is associated with *Liceo classico* and *Altri Licei*. The two indices are not a single measure of general motivation but distinct predictors, each sorting students towards the track built around its own subject. More importantly, these associations are sizeable, especially for mathematics. A one-standard-deviation increase in the Attitude towards Mathematics raises the probability of enrolling in *Liceo scientifico* by 5.2 percentage points, of the same order as family socioeconomic background (6.7), larger than prior achievement at Grade 5 (1.8) and smaller than at Grade 8 (9.3). Symmetrically, a one-standard-deviation increase in the Attitude towards Literacy raises the probability of *Liceo classico* by 1.9 percentage points, equal to the effect of Grade-5 literacy achievement and below that of socioeconomic background (3.4). Note that these estimates condition on Grade-8 achievement, measured after the attitudes, so they capture predictive content beyond students' intermediate achievement trajectory. The subject-specific pattern is robust to measuring prior achievement with teacher-assigned grades rather than standardised test scores (Section 2.3.2).

Overall, these patterns reveal a substantial yet under-explored association between early subject-specific attitudes and educational sorting. While the analysis is predictive rather than causal, this evidence calls for further research into whether these attitudes shape educational choices and into the

mechanisms through which subject-specific attitudes form already during primary school, a process in which early schooling and teachers' beliefs appear to play a role (Carlana, 2019; Martinot et al., 2025).

The remainder of the chapter is organised as follows. Section 2.2 describes the data and the descriptive evidence. Section 2.3 presents the empirical framework, the main results, and a robustness check using teacher grades. Section 2.4 explores heterogeneity in the estimated associations by gender. Section 2.5 concludes.

2.2 Data and Descriptives

This study exploits the longitudinal INVALSI dataset described in Section 1.2 of Chapter 1. We follow a cohort of students observed in Grade 5 in the 2013–14 school year through Grade 8 (2016–17) and Grade 10 (2018–19), combining standardised achievement measures with rich information on students' socioeconomic background and non-cognitive skills. The longitudinal structure of the data allows us to observe students' characteristics before the transition to upper-secondary education and relate them to subsequent track allocation.¹

Table 2.1 summarises the sample selection process. The initial sample consists of 436,889 students successfully linked between Grades 5 and 8. Extending the linkage to Grade 10 yields information for 366,139 students (83.81%), hereafter referred to as the *Grade 5–10 sample* or *Track-choice sample*. The remaining 70,750 students (16.19%) are not observed in Grade 10. Since administrative records do not report the reasons for non-observation, this group may include students who dropped out, repeated a grade, migrated abroad, or were absent on the assessment day. Given the nationwide coverage of the INVALSI data and the use of unique student identifiers, non-observation is unlikely to be driven by transfers across schools within Italy.

Our main outcome is the upper-secondary track attended in Grade 10. Track information is reconstructed from questionnaire data collected during the Italian and Mathematics assessments, allowing us to identify five educational tracks: *Liceo classico*, *Liceo scientifico*, other *Licei*, technical institutes *Tecnici*, and vocational institutes *Professional*. A small number of observations (3,722 students, approximately 1% of those with observed track information) cannot be assigned unambiguously to this classification and are excluded from the analysis. Details on the construction of the track variable and the characteristics of excluded observations are reported in Appendix 2.A.

The final estimation sample further excludes observations with missing values in the covariates used in the empirical analysis, resulting in an *analytical sample* of 331,843 students. This sample forms the basis for all subsequent analyses.

The empirical analysis exploits pre-transition measures of academic achievement, personal and family characteristics, and non-cognitive skills. Covariates include Mathematics and Literacy achievement measured by INVALSI scores in Grades 5 and 8, the ESCS index, kindergarten attendance, indicators for early and late enrolment in primary school, gender, immigrant status, and PCA-based indices capturing attitudes towards Mathematics and Literacy. Descriptive analyses additionally consider a Test Anxiety index. Unless otherwise noted, all explanatory variables are measured in Grade 5, while Grade 8 achievement scores capture students' academic performance immediately prior to track choice.²

Table 2.2 reports descriptive statistics for the Grade 5–8 sample and for the subset of students who remain observable in Grade 10, the track-choice sample. The comparison reveals clear evidence of non-random attrition. Students retained in the panel exhibit higher achievement in both Mathematics and Literacy already in Grade 5, and these differences become even more pronounced by Grade 8. The Grade 10 sample also displays more favourable non-cognitive skills, including higher attitudes towards Mathematics and Literacy and lower levels of test anxiety.

Differences also emerge in terms of socioeconomic background and demographic characteristics. Students observed through Grade 10 have substantially higher ESCS levels, are less likely to have an immigrant background, and are slightly more likely to be female. By contrast, only limited differences are observed in kindergarten attendance and early or late school enrolment. Overall, these patterns suggest that the observable sample is non-randomly selected, underrepresenting academically and socioeconomically vulnerable students.

The bottom panel of Table 2.2 reports the distribution of students across upper-secondary tracks in the Grade 10 sample. Academic tracks account for the majority of enrolments, with *Tecnici* representing the largest single track (29.1%), followed by *Liceo scientifico* (27.9%) and other *Licei* (23.6%). *Professional*

¹ See also Chapter 3, section 3.3.1 for more details.

² See chapter 1 for more details on indexes and other variables' creation.

enrol approximately 11% of students, while *Liceo classico* accounts for about 7%. These figures highlight the substantial heterogeneity in educational pathways available after lower-secondary school and motivate the analysis of the determinants of track allocation developed in the following sections.

Section 2.2.1 examines the extent of attrition between Grades 8 and 10. The evidence indicates that persistence in the panel is non-random: students observed in Grade 10 exhibit higher prior achievement, more favourable non-cognitive skills, and higher socioeconomic status than those who are no longer observed. They are also more likely to be female and less likely to have an immigrant background. The section 2.2.2 then describes the distribution of students across upper-secondary tracks. Academic tracks – *Liceo classico*, *Liceo scientifico*, and *Altri Licei* – account for approximately 58.9% of enrolments in the *analytical sample*, while the remaining students attend technical or vocational institutes.

Table 2.1: Sample selection

	Obs.	Percent
Observed at G5 and G8	436,889	100.00
Persistent at G10	366,139	83.81
Non-persistent at G10	70,750	16.19

Table 2.2: Descriptive statistics for the Grade 5–8 sample and the Grade 5–10 sample.

	Non-persistence sample			Track-choice sample		
	Mean	SD	Obs.	Mean	SD	Obs.
Outcome Variable						
Non-persistence by G10 (yes=1)	0.162	0.368	436,889			
Non-Cognitive Skills' Measures (Grade 5)						
Attitude: Mathematics	0.034	0.988	417,333	0.068	0.976	351,198
Attitude: Literacy	0.034	0.986	417,755	0.060	0.976	351,585
Test-anxiety Index	-0.026	0.995	418,619	-0.055	0.986	352,342
Lagged Outcome Variables						
Mathematics score G05	0.051	0.984	427,663	0.132	0.974	359,295
Literacy score G05	0.061	0.972	428,335	0.155	0.949	359,851
Mathematics score G08	0.089	0.986	436,473	0.197	0.973	365,794
Literacy score G08	0.110	0.962	436,495	0.232	0.932	365,804
Additional Students' Characteristics (Grade 5)						
Gender (female=1)	0.506	0.500	436,272	0.518	0.500	366,045
ESCS Index	0.090	0.998	434,623	0.172	0.980	364,506
Kindergarten (yes=1)	0.979	0.142	431,083	0.992	0.091	365,167
Immigrant (yes=1)	0.070	0.256	430,940	0.056	0.231	361,631
Early enrolled (yes=1)	0.013	0.115	436,842	0.015	0.120	366,107
Late enrolled (yes=1)	0.019	0.136	436,842	0.014	0.116	366,107
Upper-Secondary School Tracks						
Liceo scientifico (yes=1)	0.234	0.423	436,889	0.279	0.449	366,139
Liceo classico (yes=1)	0.062	0.241	436,889	0.074	0.262	366,139
Altri licei (yes=1)	0.198	0.398	436,889	0.236	0.425	366,139
Tecnici (yes=1)	0.244	0.429	436,889	0.291	0.454	366,139
Professionali (yes=1)	0.092	0.289	436,889	0.110	0.312	366,139

Notes: The table reports means, standard deviations and the number of observations for the non-persistence and track-choice samples. The ESCS index is constructed by INVALSI and combines parental education, parental occupation and home cultural and economic resources. Non-cognitive indices are standardised to have mean of zero and unit variance in the Grade-5 reference population.

2.2.1 Non-persistence analysis

To assess whether attrition between Grade 8 and Grade 10 is systematically related to students' characteristics, Table 2.3 compares students who remain in the sample through Grade 10 with those who do not.

As expected, the differences are substantial and consistent across all dimensions. Students retained in the sample exhibit higher prior achievement already in Grade 5, with positive average Mathematics and Literacy scores relative to the reference population (0.132 and 0.155 standard deviations), whereas those lost before Grade 10 perform well below average (-0.374 and -0.431 standard deviations).

A similar pattern emerges for non-cognitive skills: retained students report more favourable attitudes towards Mathematics and Literacy and lower levels of test anxiety. Attrition is also strongly associated with family background. Students who remain in the sample have higher socioeconomic status (average ESCS of 0.172 versus -0.335), are less likely to have an immigrant background (5.6% versus 14.3%), and are more likely to have attended kindergarten and enrolled on time in primary school. Female students are slightly overrepresented among those retained.

Table 2.3: Attrition analysis between students observed and not observed at Grade 10.

	Observed at G10		Not observed at G10	
	Mean	SD	Mean	SD
Non-Cognitive Skills' Measures (Grade 5)				
Attitude: Mathematics	0.068	0.976	-0.145	1.036
Attitude: Literacy	0.060	0.976	-0.106	1.026
Test-anxiety Index	-0.055	0.986	0.128	1.025
Lagged Outcome Variables (Grade 5)				
Mathematics score G05	0.132	0.974	-0.374	0.922
Literacy score G05	0.155	0.949	-0.431	0.946
Additional Students' Characteristics (Grade 5)				
Gender (female=1)	0.518	0.500	0.447	0.497
ESCS Index	0.172	0.980	-0.335	0.978
Kindergarten (yes=1)	0.992	0.091	0.911	0.284
Immigrant (yes=1)	0.056	0.231	0.143	0.350
Early enrolled (yes=1)	0.015	0.120	0.008	0.088
Late enrolled (yes=1)	0.014	0.116	0.045	0.208

Notes: The table reports means and standard deviations of Grade-5 characteristics separately for students observed and not observed at Grade 10. The ESCS index is constructed by INVALSI and combines parental education, parental occupation, and home cultural and economic resources. Non-cognitive indices are standardised to have mean of zero and unit variance in the Grade-5 reference population.

Overall, the evidence indicates non-random attrition. Students observed through Grade 10 are positively selected in terms of prior achievement, non-cognitive skills, and socioeconomic background, implying that the track-choice sample represents a more advantaged subset of the original cohort.

Tables 2.4–2.5 further document heterogeneity in non-persistence between Grades 8 and 10. Non-persistence is higher among boys than among girls (18.0% versus 14.2%), although the gender gradient is smaller than the differences observed by socioeconomic status and prior achievement.

In Tables 2.4 and 2.5, rows correspond to quartiles of the conditioning variable (Q1 collects the bottom 25% of the distribution, Q4 the top 25%), and the Mean column reports the share of non-persistent students within each quartile.

The socioeconomic gradient is pronounced. The probability of not being observed in Grade 10 decreases monotonically across the Grade-5 ESCS distribution, from 26.8% in the bottom quartile to 8.7% in the top quartile.

Table 2.5 reports the same monotonic pattern for quartiles of prior cognitive achievement at G5. In Mathematics, non-persistence falls from 27.0% among students in the bottom quartile of Grade-5 achievement to 8.3% among those in the top quartile. The pattern is even slightly steeper in Literacy, where the corresponding rates are 28.7% and 7.2%. These differences show that students lost before Grade 10 are disproportionately low-achieving students already in Grade 5.

Table 2.4: Non-persistence by gender (left panel) and by ESCS quartile at G5 (right panel).

	Mean	Obs.		Mean	Obs.
Male	0.180	215,321	Q1 (0–25%)	0.268	104,102
Female	0.142	220,951	Q2 (25–50%)	0.163	120,608
Total	0.161	436,272	Q3 (50–75%)	0.131	98,823
			Q4 (75–100%)	0.087	111,090
			Total	0.161	434,623

Notes: The table reports means and the number of observations of Grade-5 characteristics for students not observed at Grade 10, the non-persistence sample. The ESCS index is constructed by INVALSI and combines parental education, parental occupation, and home cultural and economic resources.

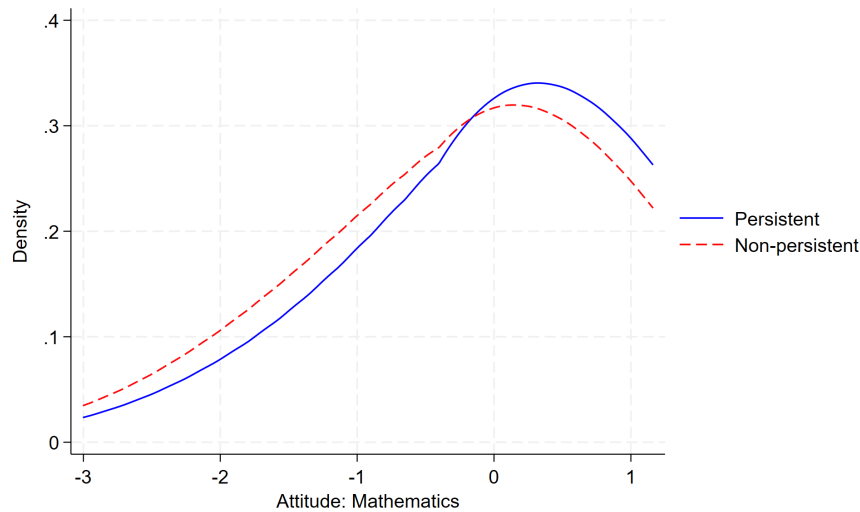
Table 2.5: Non-persistence by quartile of prior achievement (G5), by subject

Panel A: Mathematics			Panel B: Literacy		
	Mean	Obs.		Mean	Obs.
Q1 (0–25%)	0.270	108,287	Q1 (0–25%)	0.287	106,357
Q2 (25–50%)	0.164	114,096	Q2 (25–50%)	0.169	106,083
Q3 (50–75%)	0.117	99,063	Q3 (50–75%)	0.110	119,467
Q4 (75–100%)	0.083	106,217	Q4 (75–100%)	0.072	96,428
Total	0.160	427,663	Total	0.160	428,335

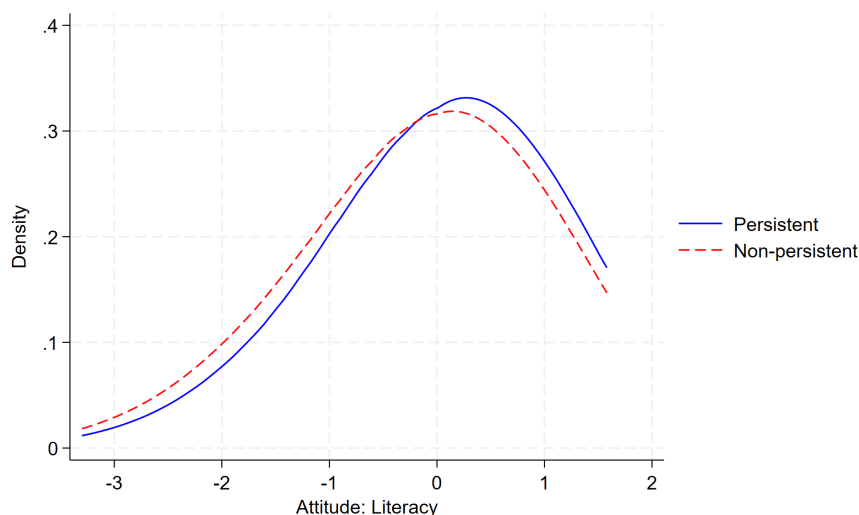
Notes: The table reports means and the number of observations of Grade-5 characteristics for students not observed at Grade 10, the non-persistence sample.

Following the heterogeneity analysis on the non-persistent sample, we explore the relationship with non-cognitive skills measured in Grade 5. Figures 2.1 and 2.2 present kernel density estimates of the Mathematics and Literacy Attitude indices for persistent (solid blue) and non-persistent (dashed red) students.

In both cases, the distribution for non-persistent students is shifted to the left, indicating lower attitude scores already in Grade 5. The difference is particularly pronounced in the lower tail of the distributions. These patterns are consistent with the descriptive evidence reported in Table 2.2, suggesting that students who later leave the sample exhibit less favourable attitudes towards both subjects well before Grade 10.

Figure 2.1: Attitude Mathematics at G5, by non-persistence status

Notes: Smoothing bandwidth: 0.7.

Figure 2.2: Attitude Literacy at G5, by non-persistence status

Notes: Smoothing bandwidth: 0.7.

Table 2.6: Non-persistence by quartile of Attitude (G5), by subject**Panel A: Attitude in Mathematics**

	Mean	Obs.
Q1 (0–25%)	0.199	99,886
Q2 (25–50%)	0.167	103,666
Q3 (50–75%)	0.147	111,893
Q4 (75–100%)	0.122	101,888
Total	0.158	417,333

Panel B: Attitude in Literacy

	Mean	Obs.
Q1 (0–25%)	0.190	100,621
Q2 (25–50%)	0.158	109,398
Q3 (50–75%)	0.151	99,972
Q4 (75–100%)	0.136	107,764
Total	0.158	417,755

Notes: The table reports means and the number of observations of Grade-5 characteristics for students not observed at Grade 10, the non-persistence sample.

Table 2.6 shows that non-persistence declines monotonically across quartiles of both attitude indices. The rate falls from 19.9% to 12.2% for Mathematics and from 19.0% to 13.6% for Literacy. While smaller than the corresponding gradient for prior achievement (Table 2.5), these differences suggest that students with more positive attitudes in Grade 5 are more likely to remain in the sample through Grade 10.

A regression analysis of non-persistence is left to future work; the remainder of the chapter focuses on the track-choice analysis.

2.2.2 Track-choice analysis

We now turn to the track-choice analysis. The Mathematics and Literacy Attitude indices are measured in Grade 5, three years before students choose their upper-secondary track at the end of Grade 8. We expect early subject-specific attitudes to be associated with subsequent track allocation in a subject-consistent direction. The descriptive evidence below documents these patterns, while Section 2.3 examines them within a multivariate framework.

As discussed in Section 2.2, the analysis focuses on the five main upper-secondary tracks. Students belonging to the residual *Licei* categories that cannot be classified unambiguously are excluded from the main sample. Appendix 2.A compares these excluded students with those retained in the analytical sample.

The comparison indicates that excluded students differ systematically from those assigned to the five main track categories. In particular, they exhibit higher literacy achievement and socioeconomic background and are more likely to be female. This pattern is consistent with the fact that both residual categories belong to the broader *Licei* group.

The tables below report the distribution of track choice across the five main upper-secondary tracks in the analytical sample.

Table 2.7: Descriptive statistics of the track-choice analysis sample.

Track	Liceo scientifico		Liceo classico		Tecnici		Altriicei		Professionali	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Non-Cognitive Skills' Measures										
Attitude: Mathematics	0.383	0.823	-0.047	0.981	0.120	0.953	-0.227	1.022	-0.168	1.028
Attitude: Literacy	0.056	0.957	0.458	0.874	-0.129	1.001	0.220	0.920	-0.054	0.998
Test-anxiety Index	-0.253	0.951	-0.142	0.950	-0.046	0.994	0.078	0.973	0.209	0.999
Lagged Outcome Variables										
Mathematics score G05	0.524	0.949	0.378	0.969	0.006	0.917	-0.032	0.906	-0.365	0.932
Literacy score G05	0.494	0.875	0.675	0.904	-0.081	0.880	0.152	0.891	-0.457	0.929
Additional students' characteristics										
Gender (female=1)	0.432	0.495	0.702	0.457	0.327	0.469	0.809	0.393	0.481	0.500
ESCS Index	0.531	0.943	0.740	0.965	-0.084	0.882	0.159	0.927	-0.442	0.874
Kindergarten (yes=1)	0.996	0.066	0.996	0.065	0.990	0.099	0.992	0.087	0.983	0.129
Immigrant (yes=1)	0.041	0.198	0.019	0.137	0.074	0.262	0.052	0.222	0.086	0.280
Early enrolled (yes=1)	0.021	0.143	0.036	0.185	0.008	0.089	0.011	0.106	0.008	0.090
Late enrolled (yes=1)	0.008	0.089	0.005	0.073	0.017	0.128	0.013	0.112	0.027	0.163

Notes: Track-choice analysis sample restricted to the five main track categories. The two residual licei categories (approximately 1% of the Grade 5–10 sample) are presented in the Appendix 2.A.

Table 2.7 reports means and standard deviations of the student-level variables by track at grade 10.³

Prior cognitive achievement and ESCS are highest among students enrolling in *Liceo scientifico* and *Liceo classico*, lowest among students in *Professionali*, with *Tecnici* and *Altri Licei* in between. The subject-specific Attitude indices already show a subject-coherent pattern: the Mathematics attitude is highest in *Liceo scientifico* (0.38) and *Tecnici* (0.12), the two tracks with stronger mathematical content, and lowest in *Altri Licei* (−0.23) and *Professionali* (−0.17); the Literacy attitude is highest in *Liceo classico* (0.46) and *Altri Licei* (0.22), the two tracks with stronger humanities content.

Professionali is the only track where both Attitude indices fall below zero: −0.17 for Mathematics attitudes and −0.05 for Literacy attitudes.

Liceo classico is the only track where the Attitude index and the INVALSI score have opposite signs within the same subject. Its Mathematics attitude is slightly below zero (−0.05) while its Mathematics score is positive and substantial (0.38): students enrolling in *Liceo classico* declare a low Mathematics attitude but perform well on the Mathematics test at grade 5. In the other four tracks, the Attitude index and the INVALSI score align in sign within each subject.

The three tables that follow reverse the perspective, examining how track choice is distributed within the same subgroups considered in the previous non-persistence heterogeneity analysis (section 2.2.1): gender, socioeconomic background (ESCS), and prior achievement.

Each table reports the same cross-tabulation under two complementary normalisations that provide different information. In the row-percentage panel, each row sums to 100% across the five columns, and each cell reports the within-subgroup percentage of students choosing that track at G10. By contrast, in the column-percentage panel, each cell reports the within-track percentage of students belonging to that subgroup.

³The corresponding means across the seven categories of `track5`, including the two residual licei categories not distinguishable from their candidate sub-tracks, are reported in Table 2.A.1, Appendix 2.A.

Table 2.8: Track choice by gender

Panel A: row percentages						
	Liceo scientifico	Liceo classico	Altriicei	Tecnici	Professionali	Total
Male	33.17	4.62	9.43	40.89	11.89	100.00
Female	23.56	10.18	37.34	18.60	10.32	100.00
Total	28.20	7.50	23.86	29.36	11.08	100.00

Panel B: column percentages						
	Liceo scientifico	Liceo classico	Altriicei	Tecnici	Professionali	Total
Male	56.81	29.75	19.10	67.26	51.86	48.30
Female	43.19	70.25	80.90	32.74	48.14	51.70
Total	100.00	100.00	100.00	100.00	100.00	100.00

Notes: Track-choice analysis sample restricted to the five main track categories. Panel A reports row percentages: within each gender group, the percentage of students enrolled in each track (rows sum to 100%). Panel B reports column percentages: within each track, the percentage of male and female students (columns sum to 100%).

Table 2.8 highlights substantial gender segregation in track choice. The column-percentage panel shows the gender composition within each track. Females are overrepresented in *Liceo classico* (70%) and *Altri Licei* (81%), while males are concentrated in *Tecnici* (67%). In contrast, *Liceo scientifico* and *Professional* exhibit a more balanced gender composition. These patterns closely mirror the well-established gender stratification of Italian upper-secondary education.

Table 2.9: Track choice by ESCS quartile (G5)

Panel A: row percentages						
	Liceo scientifico	Liceo classico	Altriicei	Tecnici	Professionali	Total
Q1(0-25%)	14.46	2.93	22.25	37.69	22.66	100.00
Q2(25-50%)	24.22	5.21	25.18	33.70	11.69	100.00
Q3(50-75%)	29.00	6.84	25.41	30.05	8.70	100.00
Q4(75-100%)	41.95	13.78	22.47	18.17	3.63	100.00
Total	28.22	7.49	23.87	29.37	11.05	100.00

Panel B: column percentages						
	Liceo scientifico	Liceo classico	Altriicei	Tecnici	Professionali	Total
Q1(0-25%)	10.75	8.22	19.56	26.91	43.01	20.98
Q2(25-50%)	23.82	19.29	29.27	31.84	29.35	27.75
Q3(50-75%)	24.20	21.51	25.07	24.09	18.53	23.55
Q4(75-100%)	41.22	50.99	26.10	17.15	9.11	27.72
Total	100.00	100.00	100.00	100.00	100.00	100.00

Notes: Track-choice analysis sample restricted to the five main track categories. Panel A reports row percentages: within each gender group, the percentage of students enrolled in each track (rows sum to 100%). Panel B reports column percentages: within each track, the percentage of male and female students (columns sum to 100%).

Table 2.9 reveals substantial socioeconomic sorting in track choice. Students from more advantaged families are disproportionately represented in academic tracks, particularly *Liceo classico* and *Liceo scientifico*, whereas those from disadvantaged backgrounds are more likely to enrol in *Tecnici* and Profes-

sionali. The contrast is especially marked at the extremes of the ESCS distribution, highlighting the strong association between family background and educational pathways.

Table 2.10: Track choice by quartile of prior achievement (G5), by subject

Panel A: Mathematics, row percentages						
	Liceo scientifico	Liceo classico	Altri licei	Tecnici	Professionalisti	Total
Q1(0-25%)	12.48	4.69	28.31	33.14	21.39	100.00
Q2(25-50%)	22.23	6.84	27.11	32.48	11.34	100.00
Q3(50-75%)	32.43	8.31	22.97	28.86	7.43	100.00
Q4(75-100%)	43.47	9.78	17.76	23.59	5.39	100.00
Total	28.32	7.52	23.84	29.34	10.99	100.00

Panel B: Mathematics, column percentages						
	Liceo scientifico	Liceo classico	Altri licei	Tecnici	Professionalisti	Total
Q1(0-25%)	9.71	13.72	26.15	24.88	42.87	22.02
Q2(25-50%)	20.85	24.15	30.21	29.40	27.41	26.56
Q3(50-75%)	27.88	26.91	23.46	23.94	16.45	24.34
Q4(75-100%)	41.57	35.22	20.18	21.77	13.28	27.08
Total	100.00	100.00	100.00	100.00	100.00	100.00

Panel C: Literacy, row percentages						
	Liceo scientifico	Liceo classico	Altri licei	Tecnici	Professionalisti	Total
Q1(0-25%)	12.99	2.58	21.91	38.54	23.98	100.00
Q2(25-50%)	23.02	4.84	25.38	34.83	11.93	100.00
Q3(50-75%)	32.59	8.35	25.37	27.13	6.57	100.00
Q4(75-100%)	41.34	13.41	22.29	18.65	4.31	100.00
Total	28.27	7.52	23.88	29.33	11.00	100.00

Panel D: Literacy, column percentages						
	Liceo scientifico	Liceo classico	Altri licei	Tecnici	Professionalisti	Total
Q1(0-25%)	9.72	7.24	19.40	27.78	46.07	21.14
Q2(25-50%)	19.98	15.78	26.08	29.14	26.60	24.53
Q3(50-75%)	34.03	32.76	31.37	27.31	17.62	29.52
Q4(75-100%)	36.27	44.23	23.15	15.77	9.72	24.80
Total	100.00	100.00	100.00	100.00	100.00	100.00

Notes: Track-choice analysis sample restricted to the five main track categories. Panel A reports row percentages: within each gender group, the percentage of students enrolled in each track (rows sum to 100%). Panel B reports column percentages: within each track, the percentage of male and female students (columns sum to 100%).

As expected, table 2.10 reveals substantial achievement-based sorting in track choice. In both Mathematics and Literacy, students with higher Grade-5 achievement are increasingly likely to enrol in academic tracks and less likely to enter vocational education. This gradient is evident across the entire achievement distribution and is particularly strong for *Liceo scientifico*. The column percentages show that high-achieving students are disproportionately represented in the academic licei, especially *Liceo scientifico* and *Liceo classico*, while low-achieving students are concentrated in technical and vocational tracks. Overall, the results point to a strong alignment between prior academic performance and subsequent educational pathways.

NCS indices by track

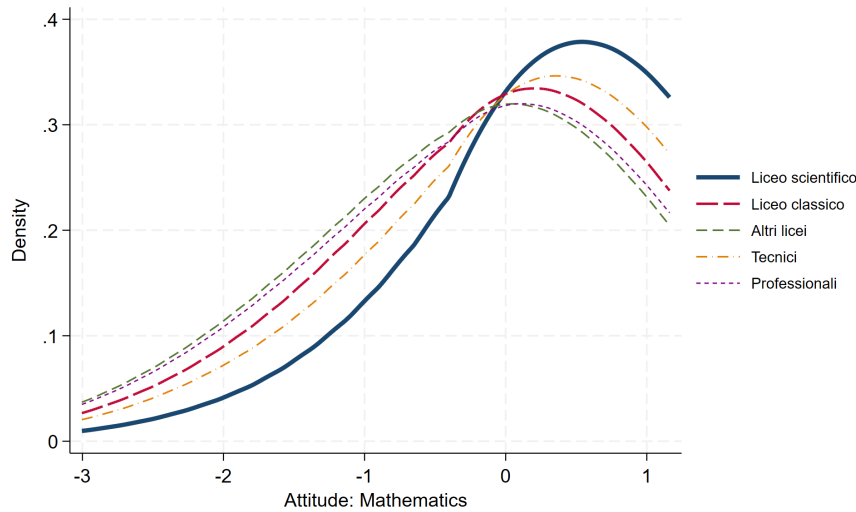
We complement the cross-tabulations of the previous tables with kernel density estimates of the two Attitude indices at grade 5, by track at grade 10. Each figure plots one curve per track: horizontal shifts between curves capture differences in central tendency across tracks, while differences in spread and shape capture within-track heterogeneity in the index.

The two figures display the subject-coherent pattern visually. The Mathematics attitude density (Figure 2.3) is shifted furthest to the right for *Liceo scientifico*, followed by *Tecnici*; the Literacy attitude density (Figure 2.4) is shifted furthest to the right for *Liceo classico*, followed by *Altri licei*. The tracks with the highest attitude at grade 5 are those whose content at grade 10 is most aligned with the corresponding subject.

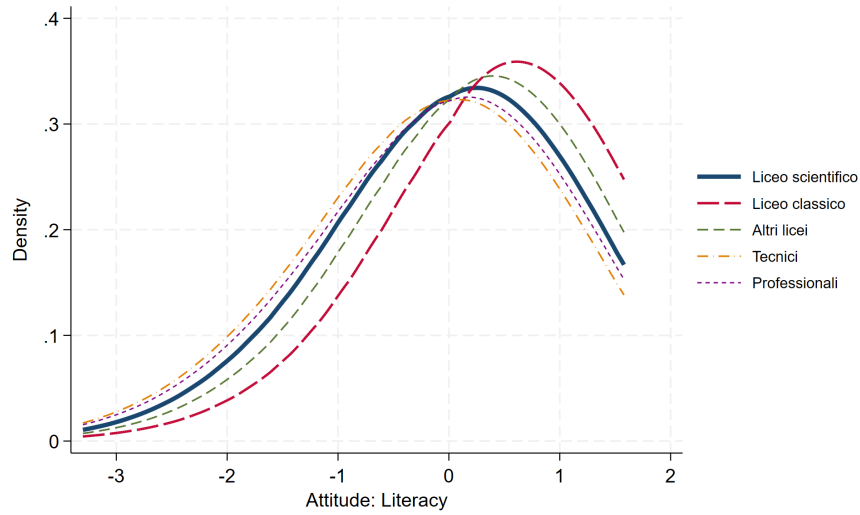
Table 2.11 reports the distribution of track choice at grade 10 by quartile of the Attitude index, by subject. Students with stronger attitudes towards Mathematics are increasingly likely to enrol in *Liceo scientifico*, while those with stronger attitudes towards Literacy are increasingly likely to enrol in *Liceo classico*. These gradients are monotonic across the attitude distribution.

The column percentages show that students in the upper tail of the relevant attitude distribution are disproportionately concentrated in the corresponding academic track, whereas technical and vocational tracks recruit more evenly across attitude levels. Together with the density estimates, these results suggest that subject-specific attitudes are an important correlate of subsequent track choice.

Figure 2.3: Attitude Mathematics at G5, by track



Notes: Kernel density estimates of the Mathematics Attitude Index at G5 on the track-choice analysis sample, by track at G10 in five main categories. The *Liceo scientifico* density is shifted to the right of the other tracks, with a modal value at approximately +0.5. The *Tecnici* density has a modal value at approximately +0.3, followed by *Liceo classico* at approximately +0.2; the *Altri licei* and *Professionali* densities have modal values near zero. Higher values of the Mathematics attitude at G5 are associated with enrolment at G10 in tracks with a stronger mathematical content. Smoothing bandwidth: 0.7.

Figure 2.4: Attitude Literacy at G5, by track

Notes: Kernel density estimates of the Literacy Attitude Index at G5 on the track-choice analysis sample, by track at G10 in five main categories. The *Liceo classico* density is shifted to the right of the other tracks, with a modal value at approximately +0.6. The *Altri Licei* density follows at approximately +0.3, then *Liceo scientifico* with a modal value near zero; the *Tecnici* and *Professionali* densities have modal values at approximately -0.2 and -0.1, respectively. Higher values of the Literacy attitude at G5 are associated with enrolment at G10 in tracks with a stronger humanities content. Smoothing bandwidth: 0.7.

Table 2.11: Track choice by quartile of Attitude (G5), by subject

Panel A: Attitude in Mathematics, row percentages						
	Liceo scientifico	Liceo classico	Altri licei	Tecnici	Professionalisti	Total
Q1(0-25%)	15.59	8.64	34.11	26.99	14.67	100.00
Q2(25-50%)	23.82	8.37	27.01	28.84	11.96	100.00
Q3(50-75%)	31.37	7.33	21.52	29.83	9.94	100.00
Q4(75-100%)	41.11	5.93	14.13	31.26	7.58	100.00
Total	28.40	7.53	23.85	29.30	10.91	100.00

Panel B: Attitude in Mathematics, column percentages						
	Liceo scientifico	Liceo classico	Altri licei	Tecnici	Professionalisti	Total
Q1(0-25%)	12.52	26.15	32.59	20.99	30.64	22.79
Q2(25-50%)	20.62	27.33	27.83	24.19	26.94	24.58
Q3(50-75%)	30.00	26.45	24.50	27.65	24.74	27.16
Q4(75-100%)	36.86	20.06	15.08	27.16	17.68	25.47
Total	100.00	100.00	100.00	100.00	100.00	100.00

Panel C: Attitude in Literacy, row percentages						
	Liceo scientifico	Liceo classico	Altri licei	Tecnici	Professionalisti	Total
Q1(0-25%)	28.17	3.95	18.34	36.92	12.62	100.00
Q2(25-50%)	29.46	5.81	22.67	31.14	10.93	100.00
Q3(50-75%)	28.60	7.80	25.17	27.61	10.82	100.00
Q4(75-100%)	27.37	12.16	28.67	22.34	9.46	100.00
Total	28.40	7.54	23.85	29.30	10.91	100.00

Panel D: Attitude in Literacy, column percentages						
	Liceo scientifico	Liceo classico	Altri licei	Tecnici	Professionalisti	Total
Q1(0-25%)	23.02	12.16	17.84	29.24	26.86	23.20
Q2(25-50%)	27.19	20.20	24.91	27.85	26.26	26.21
Q3(50-75%)	24.31	24.98	25.47	22.75	23.95	24.14
Q4(75-100%)	25.49	42.65	31.78	20.16	22.93	26.44
Total	100.00	100.00	100.00	100.00	100.00	100.00

Notes: Track-choice analysis sample restricted to the five main track categories. Panel A reports row percentages: within each gender group, the percentage of students enrolled in each track (rows sum to 100%). Panel B reports column percentages: within each track, the percentage of male and female students (columns sum to 100%).

2.3 Empirical model and Results

We model students' track choice at grade 10 using a multinomial logit with the five main tracks as alternatives. The coefficients describe the association between the predictors and the track chosen relative to the baseline given by the Liceo scientifico. The model is estimated on the track-choice analysis sample (students observed at grades 5, 8 and 10; $N = 331,843$). Formally, the probability that student i enrolls in track j , conditional on the covariates x_i , is given by

$$\Pr(y_i = j \mid x_i) = \frac{\exp(x_i' \beta_j)}{\sum_{k=1}^5 \exp(x_i' \beta_k)}, \quad j = 1, \dots, 5 \quad (2.1)$$

where y_i is the track of enrolment, β_j the coefficients for track j . We report two specifications:

- Specification (a): prior cognitive achievement at grade 5 and at grade 8 in Mathematics and Literacy (standardised Rasch scores), individual and family controls (gender, ESCS, kindergarten attendance, immigrant background, early and late enrolment in primary school), and province dummies.
- Specification (b): the regressors of column (a) plus the two subject-specific Attitude indices in Mathematics and Literacy, measured at grade 5.

Prior achievement enters as standardised Rasch scores in Mathematics and Literacy at grades 5 and 8; because grade-8 achievement is observed after the attitudes, conditioning on it gives the estimates a value-added reading. Moreover, since Italian student outcomes display large and persistent territorial disparities (Agasisti and Cordero-Ferrera, 2013; Bratti et al., 2007), geographic differences are controlled for using province (NUTS3) dummies. These absorb variation between provinces but not the within-province supply of school types: the tracks locally available differ across municipalities, and the data do not record the municipality of the school. Therefore, associations with variables that are sorted within provinces partly reflect the local opportunity set rather than individual propensity. Standard errors are clustered at the primary-school class level. In sum, column (a) documents the contribution of the standard predictors, while column (b) adds the two Attitude indices; comparing the two isolates the contribution of the attitudes over and above the standard predictors.

Results are read from the average marginal effects (AMEs) rather than the raw log-odds, which are reported in the appendix (see Appendix 2.B). AMEs measures how the probability of choosing a track j changes with a one-standard-deviation increase in the predictor x . Accordingly, the AMEs reported in the tables are defined as

$$\text{AME}_{x,j} = \frac{1}{N} \sum_{i=1}^N \frac{\partial \Pr(y_i = j \mid x_i)}{\partial x_i}. \quad (2.2)$$

Because the Attitude indices, the four Rasch scores and the ESCS index are all standardised, their marginal effects can be read on a common one-standard-deviation scale. The incremental contribution of the attitude indices is assessed in three complementary ways. First, we report the AMEs from both specifications and examine how estimated track-choice probabilities change after the inclusion of the attitude measures. Second, we use a cluster-robust Wald test to evaluate the null hypothesis that the coefficients associated with the mathematics and Literacy attitude indices are jointly equal to zero across all non-reference track equations in the multinomial logit model. Third, for each track, we test whether the AME associated with the mathematics attitude index equals the AME associated with the Literacy attitude index, thereby assessing the extent to which attitudes operate in a subject-specific manner.

As a complementary measure, we report the change in McFadden's pseudo- (R^2) between the baseline specification and the model augmented with the attitude indices, computed on the same estimation sample. The change in pseudo- (R^2) provides a descriptive likelihood-based measure of the improvement in model fit after adding the attitude variables.

The multinomial logit model relies on the Independence of Irrelevant Alternatives (IIA) assumption (McFadden, 1974). For any pair of tracks j and k , the model-implied ratio of choice probabilities $\frac{\Pr(y_i=j|X_i)}{\Pr(y_i=k|X_i)}$ depends only on the difference in their systematic utilities. This property follows from the i.i.d. extreme-value errors of the multinomial logit, and is restrictive when two tracks are close substitutes. We argue that, conditional on the covariates and given the Italian institutional context, this assumption is unlikely to be a binding restriction. Relaxing it with a nested logit would, in any case, require a nesting of the tracks that matches their substitution patterns, and no obvious grouping of the five tracks into nests is evident. The relevant margins do not run along the liceo / non-liceo boundary: a student strong in Mathematics plausibly weighs *Liceo scientifico* against *Tecnici* as much as against *Liceo*

classico, so substitution crosses the academic–vocational divide along subject lines. The choice between *Liceo scientifico* and *Liceo classico* is concentrated among students of high socio-economic background and is associated with gender, rather than reflecting a generic substitution within the licei; *Altri Licei* is a heterogeneous residual rather than a single substitute pool; and the choice of *Professionali* is associated with the family’s socio-economic level. These patterns operate through achievement, family background and gender, which enter the model as covariates, so the assumption restricts only the residual, unobserved component. We therefore estimate a multinomial logit, which imposes no nesting, rather than adopt a nesting that the setting does not support. Moreover, given that our primary goal is to estimate how individual attributes relate to choice probabilities rather than to investigate choice elasticities or substitution patterns, the IIA assumption is less restrictive in our context. As noted by Train (2009), the consequences of violating logit assumptions are typically far less severe when the researcher’s focus is on estimating average preferences rather than predicting shifts in market shares resulting from changes in the choice set.

2.3.1 Main results

Table 2.12 presents the track-choice results as AMEs, placing the specification without the Attitude indices (column (a)) next to the one that adds them (column (b)); the underlying results in terms of log-odds are in Appendix 2.B. We read the estimates from column (b).

The two Attitude indices predict the enrolment track along subject lines. A one-standard-deviation increase in the Mathematics attitude raises the predicted probability of *Liceo scientifico* by 5.2 percentage points and by 0.9 for *Tecnici*, but lowers the probability of every other destination, most of all *Altri Licei* (−3.7). The Literacy attitude moves in the opposite direction at the two ends of the distribution: a one-standard-deviation increase raises the probability of *Liceo classico* by 1.9 points and of *Altri Licei* by 1.5, and lowers that of *Liceo scientifico* (−1.0), *Tecnici* (−1.7) and *Professionali* (−0.7). All ten marginal effects are significant at the 1% level. A stronger orientation toward mathematics predicts sorting into the scientific track, and a stronger orientation toward literacy predicts sorting into the humanistic licei, such as *Liceo classico* and *Altri Licei*.

These associations are precisely estimated, and their sizes are comparable to those of the variables the literature treats as the main predictors of tracking. The 5.2-point effect of the Mathematics attitude on *Liceo scientifico* is of the same order as that of family socio-economic status (6.7), larger than that of prior achievement at grade 5 (Mathematics 1.8, Literacy 0.7), and smaller than that of achievement at grade 8 (Mathematics 9.3, Literacy 5.3). The Literacy attitude is smaller: its 1.9-point effect on *Liceo classico* equals that of grade-5 Literacy achievement, falls below that of socio-economic status (3.4) and grade-8 Literacy achievement (3.9), and exceeds that of Mathematics achievement at both grades. Set against the standard determinants of tracking, the predictive weight of early subject-specific attitudes is of the same order as that of socio-economic background and of cognitive achievement at the end of primary school.

Table 2.12: Average marginal effects on track-choice probabilities, multinomial logit.

	Liceo scientifico		Liceo classico		Altriicei		Tecnici		Professionali	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Attitude: Mathematics		0.052*** (0.001)		-0.015*** (0.000)		-0.037*** (0.001)		0.009*** (0.001)		-0.010*** (0.001)
Attitude: Literacy		-0.010*** (0.001)		0.019*** (0.001)		0.015*** (0.001)		-0.017*** (0.001)		-0.007*** (0.001)
Mathematics score G05	0.029*** (0.001)	0.018*** (0.001)	-0.011*** (0.001)	-0.007*** (0.001)	-0.023*** (0.001)	-0.015*** (0.001)	0.011*** (0.001)	0.007*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)
Mathematics score G08	0.104*** (0.001)	0.093*** (0.001)	-0.006*** (0.001)	-0.002*** (0.001)	-0.053*** (0.001)	-0.042*** (0.001)	-0.011*** (0.001)	-0.016*** (0.001)	-0.034*** (0.001)	-0.033*** (0.001)
Literacy score G05	0.001 (0.001)	0.007*** (0.001)	0.023*** (0.001)	0.019*** (0.001)	0.020*** (0.001)	0.014*** (0.001)	-0.025*** (0.001)	-0.022*** (0.001)	-0.019*** (0.001)	-0.019*** (0.001)
Literacy score G08	0.051*** (0.001)	0.053*** (0.001)	0.041*** (0.001)	0.039*** (0.001)	0.021*** (0.001)	0.017*** (0.001)	-0.060*** (0.001)	-0.056*** (0.001)	-0.053*** (0.001)	-0.053*** (0.001)
Gender (female=1)	-0.080*** (0.001)	-0.065*** (0.001)	0.033*** (0.001)	0.024*** (0.001)	0.250*** (0.001)	0.236*** (0.002)	-0.195*** (0.001)	-0.187*** (0.001)	-0.008*** (0.001)	-0.008*** (0.001)
ESCS Index	0.067*** (0.001)	0.067*** (0.001)	0.034*** (0.001)	0.034*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	-0.061*** (0.001)	-0.061*** (0.001)	-0.045*** (0.001)	-0.045*** (0.001)
Kindergarten (yes=1)	0.042*** (0.010)	0.043*** (0.010)	-0.005 (0.007)	-0.005 (0.007)	-0.017*** (0.008)	-0.017*** (0.008)	-0.003 (0.008)	-0.004 (0.008)	-0.017*** (0.005)	-0.017*** (0.005)
Immigrant (yes=1)	0.045*** (0.004)	0.034*** (0.004)	-0.027*** (0.003)	-0.025*** (0.003)	-0.029*** (0.003)	-0.021*** (0.003)	0.018*** (0.003)	0.017*** (0.003)	-0.007*** (0.002)	-0.004*** (0.002)
Early enrolled (yes=1)	0.060*** (0.006)	0.058*** (0.006)	0.032*** (0.003)	0.033*** (0.003)	-0.026*** (0.006)	-0.025*** (0.006)	-0.045*** (0.008)	-0.046*** (0.008)	-0.021*** (0.005)	-0.021*** (0.005)
Late enrolled (yes=1)	-0.037*** (0.008)	-0.036*** (0.008)	-0.012* (0.006)	-0.012* (0.006)	0.029*** (0.007)	0.029*** (0.007)	-0.005 (0.007)	-0.006 (0.007)	0.025*** (0.004)	0.024*** (0.004)
Observations	331843	331843	331843	331843	331843	331843	331843	331843	331843	331843

Notes: Average marginal effects computed from the multinomial logit of Equation (2.1). Province dummies are included in the model, but their marginal effects are not reported. Delta-method standard errors clustered at the primary-school class level (`codice_classe_05`; 28,239 clusters) in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Within each destination, the two attitudes carry marginal effects of different sizes, and the gap between them is itself informative. We test directly, for each track j , whether the two indices have the same effect ($AME_{\text{Math},j} = AME_{\text{Lit},j}$). The difference $AME_{\text{Math},j} - AME_{\text{Lit},j}$, its cluster-robust standard error and the χ^2_1 statistic are reported in Table 2.B.5 in Appendix 2.B. The equality is rejected in every track (all $p < 0.001$). The gap is widest on *Liceo scientifico*, where the Mathematics attitude exceeds the Literacy attitude by 6.2 percentage points, and on *Tecnici* (2.7 points); it reverses on the humanistic licei, where the Literacy attitude is the stronger predictor (by 3.4 points on *Liceo classico* and 5.1 on *Altri licei*); and it all but disappears on *Professionalisti* (0.3 points). Each attitude predicts entry into the track built around its own subject.

The analysis thus delivers two results. First, early subject-specific attitudes predict track choice with a weight of the same order as socio-economic background and prior achievement at the end of primary school. Second, that predictive weight is organised along subject lines: the two indices are not a single measure of general motivation, but distinct predictors, each sorting students toward the track built around its own subject. We read this as students sorting into tracks aligned with their subject-specific orientation, while noting that the data cannot separate the channels through which the sorting operates: the preferences of students, the influence of families and teachers, or unobserved factors correlated with the attitudes.

Adding the attitudes also shifts the achievement estimates in an interpretable way. The effect of grade-8 Mathematics on *Liceo scientifico* falls from 10.4 to 9.3 points when the attitudes enter, and that of grade-5 Mathematics from 2.9 to 1.8. Grade-8 achievement is measured after the grade-5 attitudes and is itself predicted by them, so the specification carries a value-added reading: the attitude effects in column (b) capture predictive content beyond the intermediate achievement trajectory. The part of the early attitude that reappears later as higher measured achievement is absorbed by including the grade-8 scores. For Literacy the adjustment runs the other way on *Liceo scientifico*, where the Literacy attitude is a negative predictor: once that negative association is held fixed, the grade-8 Literacy effect edges up from 5.1 to 5.3 points, and the grade-5 Literacy effect turns from a non-significant 0.1 to a significant 0.7.

The remaining predictors behave as expected, even accounting for the attitude indices. Prior achievement is the dominant predictor: grade-8 Mathematics carries the largest single positive effect on *Liceo scientifico* (+9.3 points), and grade-8 Literacy separates the academic from the vocational tracks, raising the probability of the licei and lowering that of *Tecnici* (−5.6) and *Professionalisti* (−5.3); the grade-5 scores keep predictive content of their own once the grade-8 scores are included. Gender produces the two largest effects in the table: relative to comparable boys, girls are 23.6 points more likely to enter *Altri Licei* and 18.7 points less likely to enter *Tecnici*, with smaller effects on the other three tracks. The stability of the Socio-economic status coefficient across specifications suggests that attitudinal measures capture an independent dimension of heterogeneity rather than mediating the relationship between socioeconomic background and the outcome. The remaining controls follow the expected pattern and are left to the table. The immigrant estimate is probably the most exposed to the within-province school-supply limitation noted above: immigrant residence tends to be more concentrated within provinces than that of other groups, so that the immigrant association may reflect local opportunity rather than a difference in track propensity between immigrant- and native-origin students.

Finally, results suggest that the contribution of the attitudes to the overall fit of the model is not large. With prior achievement at grades 5 and 8 in the model, McFadden’s pseudo- R^2 rises from 0.196 to 0.205 when the two indices are added, a gain of 0.009, and a joint Wald test rejects the hypothesis that their coefficients are all zero ($\chi^2(8) = 7,028$, $p < 0.001$; Table 2.B.4 in Appendix 2.B). The Wald statistic reflects the precision afforded by the sample rather than predictive size.

This gain is a value-added figure: grade-8 achievement is measured after grade-5 attitudes and is partly predicted by them, so conditioning on it nets out the share of the attitudes’ predictive content that passes through intermediate achievement.

The small gain in fit does not qualify the two findings of this section, which concern the size of the attitude effects and their organisation along subject lines rather than the overall explanatory power of the model.

2.3.2 Teacher grades and track choice: a robustness check

The main specification measures prior achievement with INVALSI test scores. Teacher-assigned grades are an alternative measure, but not an equivalent one. INVALSI tests are nationally set and administered under a protocol that limits teachers’ discretion, and can be considered quasi-blind assessments (Burgess and Greaves, 2013; Di Liberto et al., 2022). Teacher grades, by contrast, are an overall assessment formed

by the class teacher over several months and, besides performance and knowledge, may also reflect participation, behaviour in class, and motivation (Stobart et al., 1992; Mechtenberg, 2009). Gender differences therefore tend to be more favourable to girls in teacher grades than in blind assessments (Lavy, 2008; Falch and Naper, 2013; Terrier, 2020). For Italy, Di Liberto et al. (2022) document a grading differential against boys in both mathematics and language that persists after controlling for self-reported self-efficacy and intrinsic motivation, and US evidence shows that the gender gap between test scores and teacher assessments is substantially reduced once non-cognitive skills reported by teachers are accounted for (Cornwell et al., 2013).

Teacher grades are also likely to be an important signal of achievement for students and families when choosing the upper-secondary track. We therefore re-estimate the model replacing INVALSI scores with teacher-assigned grades in Mathematics and Literacy at grades 5 and 8. At both grades we use first-term grades from school administrative records: at grade 8, they reflect teachers' assessment in the period in which the upper-secondary track is chosen; at grade 5, the same source and timing ensure consistency and avoid the recall error affecting grades self-reported by students. Because grades may reflect effort, motivation, and classroom behaviour, they may be correlated with the attitudes more strongly than INVALSI scores. Controlling for teacher grades may therefore absorb part of the information carried by the attitudes, so that somewhat smaller attitude estimates should be expected. The exercise tests whether the subject-specific pattern survives this more demanding control.

Teacher grades have more missing values than INVALSI scores, so the comparison is carried out on the 277,389 students of the track-choice analysis sample with non-missing grades in both subjects and at both grades (the teacher-grade subsample). Appendix 2.4 shows that this subsample is only slightly positively selected. Table 2.13 reports the average marginal effects from two specifications, both estimated on this subsample and both including the covariates of column (b) of Table 2.12. Column (1) replicates the main specification, with INVALSI scores at grades 5 and 8; column (2) replaces them with teacher grades at the same grades. Column (1) also shows that the selection does not drive the results: the average marginal effects of the attitudes are virtually identical to those obtained on the full track-choice analysis sample, for instance 5.2 percentage points for the Mathematics attitude on *Liceo scientifico* and 1.9 for the Literacy attitude on *Liceo classico* in both cases. Differences between the two columns can therefore be attributed to the change in the achievement measure rather than to the change in sample.

Table 2.13: Average marginal effects on track-choice probabilities with INVALSI scores and teacher grades as measures of prior achievement, teacher-grade subsample, multinomial logit.

	Liceo scientifico		Liceo classico		Altri licei		Tecnici		Professional	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Attitude: Mathematics	0.052*** (0.001)	0.042*** (0.001)	-0.015*** (0.001)	-0.016*** (0.001)	-0.037*** (0.001)	-0.034*** (0.001)	0.010*** (0.001)	0.012*** (0.001)	-0.010*** (0.001)	-0.004*** (0.001)
Attitude: Literacy	-0.009*** (0.001)	-0.018*** (0.001)	0.019*** (0.001)	0.016*** (0.001)	0.015*** (0.001)	0.015*** (0.001)	-0.018*** (0.001)	-0.011*** (0.001)	-0.007*** (0.001)	-0.001* (0.001)
Mathematics score G05	0.017*** (0.001)		-0.007*** (0.001)		-0.014*** (0.001)		0.008*** (0.001)		-0.004*** (0.001)	
Mathematics score G08	0.093*** (0.001)		-0.002** (0.001)		-0.041*** (0.001)		-0.017*** (0.001)		-0.033*** (0.001)	
Literacy score G05	0.008*** (0.001)		0.019*** (0.001)		0.013*** (0.001)		-0.022*** (0.001)		-0.018*** (0.001)	
Literacy score G08	0.054*** (0.001)		0.038*** (0.001)		0.017*** (0.001)		-0.056*** (0.001)		-0.053*** (0.001)	
Mathematics Teachers' score G5		0.034*** (0.002)		-0.001 (0.001)		-0.015*** (0.001)		0.000 (0.002)		-0.018*** (0.001)
Mathematics Teachers' score G8		0.132*** (0.001)		-0.017*** (0.001)		-0.063*** (0.001)		-0.013*** (0.001)		-0.040*** (0.001)
Literacy Teachers' score G5		0.013*** (0.002)		0.016*** (0.001)		0.019*** (0.001)		-0.022*** (0.002)		-0.025*** (0.001)
Literacy Teachers' score G8		0.017*** (0.001)		0.056*** (0.001)		0.035*** (0.001)		-0.062*** (0.001)		-0.046*** (0.001)
Gender (female=1)	-0.063*** (0.002)	-0.101*** (0.002)	0.023*** (0.001)	0.015*** (0.001)	0.237*** (0.002)	0.245*** (0.002)	-0.189*** (0.002)	-0.169*** (0.002)	-0.009*** (0.001)	0.009*** (0.001)
ESCS Index	0.068*** (0.001)	0.061*** (0.001)	0.033*** (0.001)	0.031*** (0.001)	0.005*** (0.001)	0.003*** (0.001)	-0.060*** (0.001)	-0.058*** (0.001)	-0.046*** (0.001)	-0.037*** (0.001)
Kindergarten (yes=1)	0.036*** (0.011)	0.031*** (0.011)	-0.003 (0.008)	-0.002 (0.008)	-0.018** (0.009)	-0.018** (0.009)	0.001 (0.009)	0.004 (0.009)	-0.017*** (0.005)	-0.015*** (0.005)
Immigrant (yes=1)	0.034*** (0.004)	0.043*** (0.004)	-0.025*** (0.003)	-0.021*** (0.003)	-0.021*** (0.004)	-0.018*** (0.004)	0.016*** (0.004)	0.012*** (0.004)	-0.005** (0.002)	-0.017*** (0.002)
Early enrolled (yes=1)	0.056*** (0.006)	0.052*** (0.006)	0.031*** (0.003)	0.031*** (0.003)	-0.023*** (0.007)	-0.023*** (0.007)	-0.044*** (0.008)	-0.042*** (0.008)	-0.020*** (0.006)	-0.018*** (0.006)
Late enrolled (yes=1)	-0.035*** (0.009)	-0.044*** (0.008)	-0.013* (0.007)	-0.016** (0.007)	0.026*** (0.007)	0.026*** (0.007)	-0.002 (0.007)	0.006 (0.007)	0.023*** (0.004)	0.028*** (0.004)
Observations	277389	277389	277389	277389	277389	277389	277389	277389	277389	277389

Notes: Average marginal effects computed from the multinomial logit of Equation (2.1); base outcome = Liceo scientifico. Estimated on the teacher-grade subsample ($N = 277,389$; students in the track-choice analysis sample with non-missing teacher grades in both subjects and at both grades; see Table 2.9 in Appendix 2.4). Achievement is measured with INVALSI (Rasch) test scores in column (1) and with teacher-assigned grades in column (2). Delta-method standard errors clustered at the primary-school-class level in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Replacing INVALSI scores with teacher grades, in column (2), leaves the main result unchanged: each attitude still predicts enrolment in the track built around its own subject, and all signs are preserved. The effects on these tracks are somewhat smaller, as anticipated: the effect of the Mathematics attitude on *Liceo scientifico* falls from 5.2 to 4.2 percentage points, and that of the Literacy attitude on *Liceo classico* from 1.9 to 1.6. Effects on the other tracks change in both directions, without altering their sign. Among the other covariates, the gender coefficient changes most, with the female effect on *Liceo scientifico* moving from -6.3 to -10.1 percentage points, consistent with the grading differential against boys documented for Italy. The subject-specific sorting documented in Section 2.3.1 is therefore not an artefact of measuring prior achievement with standardised tests. We retain INVALSI scores in the main specification because teacher grades may partly overlap with the attitudes themselves.

2.4 Heterogeneity

This section investigates whether the predictive structure of the pooled track-choice analysis differs by gender. The analysis is exploratory: tracking in Italy is gendered, so the pooled estimates may average over distinct male and female patterns. We re-estimate the track-choice analysis separately for boys and girls, and compare across genders the incremental fit of the attitude block, the AMEs of the two attitude indices, and their subject-specificity; we then test whether the attitude coefficients differ across genders.

The split yields $N_m = 159,422$ males and $N_f = 172,421$ females; within each gender, the specification is identical to column (b) of the pooled analysis: prior achievement at grade 5 and grade 8 (standardised Rasch scores in Mathematics and Literacy), the two Attitude indices, individual and family controls, and province dummies. Standard errors are clustered at the primary-school class level.

The two within-gender samples are selected to different degrees on persistence: boys are over-represented among non-persistent students (55% against 48% among the persistent; Table 2.3), so the male track-choice sample excludes a larger, and on average more disadvantaged, share of its base population. Because non-persistent students have lower attitude indices, the male estimates rest on a sample more truncated on the low-attitude tail than the female estimates; cross-gender differences may therefore reflect this differential selection as well as genuine differences in the attitude-track relationship. This is one reason for caution in reading the comparison.

Consider first the incremental contribution of the attitude block within each gender. The joint null that the two Attitude indices provide no additional in-sample explanatory content, conditional on the included covariates, is rejected for both genders: the cluster-robust Wald test yields $\chi^2(8) = 3,034.8$ for males and $\chi^2(8) = 4,325.7$ for females (both $p < 0.001$). The McFadden pseudo- R^2 rises from 0.167 to 0.175 for males and from 0.145 to 0.155 for females, increments of 0.008 and 0.010 that are similar in size across gender (Table 2.6).

Turning to the AMEs reported in Table 2.14, we can see that the sign structure of the pooled analysis replicates within each gender: in both, Mathematics attitude is positively associated with *Liceo scientifico* and *Tecnici*, the Literacy attitude with *Liceo classico* and *Altri licei*. The effects are somewhat larger for girls on the academic licei: the Mathematics attitude raises the probability of *Liceo scientifico* by 6.2 percentage points for girls against 4.1 for boys, while the Literacy attitude raises the probability of *Liceo classico* by 2.5 percentage points for girls against 1.4 for boys. They are close to identical on the two vocational tracks, where the Mathematics and Literacy attitudes move the probability of *Tecnici* by +1.0 and -1.7 percentage points respectively, for both genders.

Table 2.14: Average marginal effects of the attitude indices by gender, across the five tracks (specification with attitudes).

	Liceo scientifico		Liceo classico		Altriicei		Tecnici		Professionali	
	M	F	M	F	M	F	M	F	M	F
Attitude: Mathematics	0.041*** (0.001)	0.062*** (0.001)	-0.014*** (0.001)	-0.016*** (0.001)	-0.024*** (0.001)	-0.048*** (0.001)	0.010*** (0.001)	0.010*** (0.001)	-0.013*** (0.001)	-0.008*** (0.001)
Attitude: Literacy	-0.001 (0.001)	-0.018*** (0.001)	0.014*** (0.001)	0.025*** (0.001)	0.011*** (0.001)	0.018*** (0.001)	-0.017*** (0.001)	-0.017*** (0.001)	-0.006*** (0.001)	-0.007*** (0.001)
Mathematics score G05	0.015*** (0.002)	0.022*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.012*** (0.001)	-0.017*** (0.002)	0.009*** (0.002)	0.005*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)
Mathematics score G08	0.099*** (0.002)	0.088*** (0.001)	-0.005*** (0.001)	0.002 (0.001)	-0.029*** (0.001)	-0.054*** (0.002)	-0.025*** (0.002)	-0.008*** (0.001)	-0.039*** (0.001)	-0.027*** (0.001)
Literacy score G05	0.017*** (0.002)	-0.002 (0.002)	0.014*** (0.001)	0.025*** (0.001)	0.013*** (0.001)	0.016*** (0.002)	-0.025*** (0.002)	-0.020*** (0.002)	-0.018*** (0.001)	-0.019*** (0.001)
Literacy score G08	0.073*** (0.002)	0.036*** (0.001)	0.029*** (0.001)	0.047*** (0.001)	0.018*** (0.001)	0.017*** (0.002)	-0.071*** (0.002)	-0.044*** (0.002)	-0.049*** (0.001)	-0.056*** (0.001)
ESCS Index	0.084*** (0.001)	0.051*** (0.001)	0.025*** (0.001)	0.042*** (0.001)	0.011*** (0.001)	-0.001 (0.001)	-0.075*** (0.001)	-0.048*** (0.001)	-0.045*** (0.001)	-0.045*** (0.001)
Kindergarten (yes=1)	0.057*** (0.014)	0.026* (0.015)	-0.011 (0.007)	0.002 (0.012)	-0.016** (0.007)	-0.015 (0.015)	-0.015 (0.013)	0.008 (0.011)	-0.015** (0.007)	-0.021*** (0.006)
Immigrant (yes=1)	0.015** (0.006)	0.050*** (0.005)	-0.019*** (0.004)	-0.031*** (0.005)	-0.010*** (0.004)	-0.031*** (0.005)	0.012** (0.006)	0.020*** (0.004)	0.002 (0.003)	-0.008*** (0.003)
Early enrolled (yes=1)	0.075*** (0.009)	0.043*** (0.007)	0.024*** (0.003)	0.041*** (0.004)	-0.006 (0.007)	-0.045*** (0.010)	-0.064*** (0.012)	-0.026*** (0.009)	-0.030*** (0.008)	-0.014** (0.007)
Late enrolled (yes=1)	-0.032*** (0.011)	-0.038*** (0.011)	-0.006 (0.006)	-0.017* (0.010)	0.024*** (0.006)	0.031*** (0.012)	-0.004 (0.010)	-0.006 (0.008)	0.018*** (0.005)	0.029*** (0.005)

Notes: Average marginal effects from the gender-specific multinomial logit with the two Attitude indices (Liceo scientifico is the reference outcome of the underlying model). M = males ($N = 159,422$); F = females ($N = 172,421$). Province dummies are included; their marginal effects are not reported. Delta-method standard errors clustered at the primary-school class level in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

We then examine subject-specificity separately by gender (Table 2.7). The restriction $AME_{\text{Math},j} = AME_{\text{Lit},j}$ is rejected at the 1% level for every track in both genders, with one exception: *Professional* among girls, where the two effects are indistinguishable ($p = 0.745$). The differentiation is again wider for girls on the academic licei: on *Liceo scientifico* the difference between the two attitude AMEs is +8.0 percentage points for girls against +4.2 for boys, while it is the same across genders on *Tecnici* (+2.7).

Finally, we test whether the attitude coefficients themselves differ across genders, stacking the two within-gender models with **suest** on the log-odds scale (Table 2.8). The joint null of equal attitude coefficients is rejected overall ($\chi^2(8) = 172.6$), but the rejection is concentrated in the two vocational tracks and is driven by the Mathematics attitude: the male–female difference in the log-odds coefficient is 0.134 on *Tecnici* and 0.129 on *Professional*, whereas for the academic licei the null is not rejected. These log-odds differences do not translate into relevant differences in terms of AMEs.

The comparison calls for further caution. The cross-gender test is conducted on the multinomial-logit coefficients, whereas the magnitudes reported throughout are AMEs, which average predicted-probability changes across the gender-specific distribution of covariates. As a result, differences in AMEs need not mirror differences in the underlying coefficients. In principle, a gender gap in AMEs may reflect both a *coefficient* channel, whereby boys and girls differ in their response to the same attitude, and a *composition* channel, whereby identical coefficients map into different probability changes because the distribution of covariates and baseline track probabilities differs across genders. The present results illustrate this distinction: statistically significant differences in the log-odds coefficients emerge for the vocational tracks, yet the corresponding AMEs remain very similar. However, the relative contribution of coefficient and composition effects cannot be identified from the current analysis alone. A formal decomposition on the AME scale is therefore left to future work.

2.5 Conclusions

Using the INVALSI longitudinal panel for the cohort observed at grade 5 in 2013–14, the chapter documents that both non-persistence and track choice are associated with subject-specific attitudes measured at the end of primary school. The share of students who leave the regular cohort by grade 10 falls across quartiles of both Attitude indices — from about 20% in the lowest quartile to 12–14% in the highest — though less steeply than across quartiles of prior achievement. And the grade-5 distribution of each index shifts across grade-10 tracks along subject lines, with the two indices peaking in different academic tracks: Mathematics attitude is highest among students who later enter *Liceo scientifico*, and Literacy attitude among those who enter *Liceo classico*. The two indices therefore separate the academic licei from one another (scientifico from classico) and not merely the academic from the vocational tracks.

The regression analysis concentrates on the track-choice transition. The two Attitude indices predict the track of enrolment at grade 10 with a weight of the same order as the standard predictors of tracking (prior achievement and family socio-economic status), and this predictive content is organised along subject lines: the Mathematics attitude predicts the scientific and technical tracks, the Literacy attitude the humanistic licei, with the two indices distinguishable on every track. The pattern holds within each gender and when prior achievement is measured with teacher-assigned grades. The reading is predictive: attitudes are measured years before the transition, which rules out reverse causality from track choice to attitudes, but not the influence of unobserved factors correlated with both.

Two features qualify the interpretation of the track-choice estimates: they rest on the students who persist to grade 10, who differ from those who do not, and geography is controlled only at the province level, so part of the association with geographically sorted characteristics reflects the local supply of schools rather than individual propensity.

The predictive content of early attitudes, alongside the standard predictors already in administrative records, could inform educational monitoring well before the transition, provided that such measures are collected systematically (see Chapter 3). Future work will deepen the analysis along several lines: estimating the non-persistence regression on the full sample, following the cohort to upper-secondary outcomes at grade 13, and decomposing the gender differences on the average-marginal-effect scale. Beyond these extensions, the main open question is whether early subject-specific attitudes shape these transitions rather than only predicting them, which requires a causal research design.

Chapter 2: Appendix

2.A Sample composition and descriptive statistics

The educational-track variable is constructed by combining the track information collected in the grade-10 Italian and Mathematics questionnaires. At grade 10, the track of attendance is recorded in two INVALSI questionnaire variables: one in the Italian questionnaire and one in the Mathematics. The two aggregate the *Licei* differently. The Italian questionnaire variable groups *Liceo classico* with *Liceo scientifico* in a single code and identifies *Altri Licei* separately. The Mathematics-questionnaire variable isolates *Liceo scientifico* and groups *Liceo classico* with *altri licei*. *Tecnici* and *Professionalisti* are coded identically in both. We exploit the intersection of the two codings to identify five tracks unambiguously when both variables are observed: *Liceo scientifico*, *Liceo classico*, *Altri Licei*, *Tecnici* and *professionalisti*. Cross-macro inconsistencies between the two questionnaires are not observed in the data: for every student who completed both questionnaires, the two variables agree on the macro-track.

When only one of the two questionnaires is available, the intersection cannot be exploited, and the exact liceo type cannot be recovered. These observations therefore fall into two residual categories: students recorded only as attending either *Liceo classico* or *Liceo scientifico*, and students recorded only as attending either *Liceo classico* or *Altri licei*. Together, these residual categories account for approximately 1% of the track-choice analysis sample. Since their exact educational track cannot be identified, they are excluded from the regression analysis and from the descriptive tables reported in the main text.

Table 2.A.1 reports descriptive statistics for the complete seven-category classification, including the two residual categories. This table extends the descriptive statistics presented in the main text by documenting the observable characteristics of the excluded observations.

To assess whether excluding these observations may affect the empirical analysis, Table 2.A.2 compares students in the two residual categories with those belonging to the five identified tracks. Group 1–5 comprises students enrolled in the five main track categories (*Liceo scientifico*, *Liceo classico*, *Altri licei*, *Tecnici*, *Professionalisti*). Group 6–7 comprises students in the two residual *licei* categories: track 6, recorded as *Liceo classico* or *Liceo scientifico* in only one of the two grade-10 questionnaires and not further distinguishable; and track 7, recorded as *Liceo classico* or *Altri licei* in only one questionnaire. For each covariate, the table reports the group means, their difference (residual minus main group), cluster-robust standard errors at the primary-school class level (`codice_classe_05`), the corresponding *p*-value, and the Imbens–Rubin standardized difference. Following Imbens and Rubin (2015), absolute standardised differences larger than 0.25 are interpreted as indicating a substantively meaningful imbalance independently of statistical significance. The last row reports the chi-squared statistic from a joint probit model of residual-category membership estimated on the full set of student characteristics with cluster-robust standard errors.

The balance test indicates that the residual categories are not randomly selected from the analysis sample. The joint test rejects equality of observable characteristics between the two groups ($\chi^2 = 612.57$, $p < 0.001$). Only two variables exceed the conventional Imbens–Rubin threshold for substantive imbalance (0.25): the grade-8 Literacy score (standardised difference = 0.28) and the ESCS index (standardised difference = 0.27), while the grade-5 Literacy score lies just below the threshold (standardised difference = 0.21). Students in the residual categories also exhibit a moderately higher female share (standardised difference = 0.16). Overall, the residual categories display higher socioeconomic status and stronger prior academic achievement than students in the five identified tracks, a pattern consistent with the fact that both residual groups consist exclusively of students attending *licei*.

Table 2.A.1: Descriptive statistics by track (7 categories), Grade 5–10 sample.

Track	Liceo scientifico		Liceo classico		Altriicei		Tecnici	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Non-Cognitive Skills' Measures								
Attitude: Mathematics	0.383	0.823	-0.047	0.981	-0.227	1.022	0.120	0.953
Attitude: Literacy	0.056	0.957	0.458	0.874	0.220	0.920	-0.129	1.001
Test-anxiety Index	-0.253	0.951	-0.142	0.950	0.078	0.973	-0.046	0.994
Lagged Outcome Variables								
Mathematics score G05	0.524	0.949	0.378	0.969	-0.032	0.906	0.006	0.917
Literacy score G05	0.494	0.875	0.675	0.904	0.152	0.891	-0.081	0.880
Additional students' characteristics								
Gender (female=1)	0.432	0.495	0.702	0.457	0.809	0.393	0.327	0.469
ESCS Index	0.531	0.943	0.740	0.965	0.159	0.927	-0.084	0.882
Kindergarten (yes=1)	0.996	0.066	0.996	0.065	0.992	0.087	0.990	0.099
Immigrant (yes=1)	0.041	0.198	0.019	0.137	0.052	0.222	0.074	0.262
Early enrolled (yes=1)	0.021	0.143	0.036	0.185	0.011	0.106	0.008	0.089
Late enrolled (yes=1)	0.008	0.089	0.005	0.073	0.013	0.112	0.017	0.128

Track	Professional		Licei cl./sc. n.d.		Licei cl./altri n.d.	
	Mean	SD	Mean	SD	Mean	SD
Non-Cognitive Skills' Measures						
Attitude: Mathematics	-0.168	1.028	0.288	0.884	-0.169	1.022
Attitude: Literacy	-0.054	0.998	0.102	0.977	0.281	0.925
Test-anxiety Index	0.209	0.999	-0.211	0.964	-0.007	0.990
Lagged Outcome Variables						
Mathematics score G05	-0.365	0.932	0.417	0.959	-0.022	0.934
Literacy score G05	-0.457	0.929	0.486	0.896	0.156	0.937
Additional students' characteristics						
Gender (female=1)	0.481	0.500	0.478	0.500	0.770	0.421
ESCS Index	-0.442	0.874	0.562	0.968	0.246	0.977
Kindergarten (yes=1)	0.983	0.129	0.975	0.157	0.992	0.089
Immigrant (yes=1)	0.086	0.280	0.041	0.198	0.042	0.201
Early enrolled (yes=1)	0.008	0.090	0.027	0.161	0.018	0.132
Late enrolled (yes=1)	0.027	0.163	0.011	0.106	0.012	0.108

Notes: Grade 5–10 sample: students observed at grades 5, 8, and 10. Columns report means and standard deviations of student-level variables within each category of **track5**. Tracks 1–5 are the five main categories retained in the regression analysis (Liceo scientifico, Liceo classico, Altriicei, Tecnici, Professional). Track 6 comprises students recorded in only one of the two grade-10 questionnaires as attending either Liceo classico or Liceo scientifico (not further distinguishable); track 7 comprises students recorded as attending either Liceo classico or Altriicei. Tracks 6 and 7 together account for approximately 1% of the track-choice analysis sample and are excluded from the main-text cross-tabulations and from the regression analysis.

Table 2.A.2: Balance test on observable characteristics: residual licei categories vs main categories, track-choice analysis sample

	Group 1–5	Group 6–7	Mean diff.	SE	p-value	Std. diff.
Attitude: Mathematics	0.068	0.104	0.036	0.016	0.027	0.037
Attitude: Literacy	0.059	0.174	0.115	0.016	0.000	0.118
Test-anxiety Index	-0.055	-0.129	-0.074	0.016	0.000	-0.075
Mathematics score G05	0.131	0.240	0.109	0.017	0.000	0.112
Literacy score G05	0.153	0.352	0.199	0.016	0.000	0.213
Mathematics score G08	0.196	0.339	0.143	0.016	0.000	0.149
Literacy score G08	0.229	0.483	0.254	0.015	0.000	0.277
Gender (female=1)	0.517	0.597	0.080	0.008	0.000	0.161
ESCS Index	0.170	0.434	0.264	0.017	0.000	0.269
Kindergarten (yes=1)	0.992	0.982	-0.010	0.002	0.000	-0.088
Immigrant (yes=1)	0.057	0.041	-0.015	0.003	0.000	-0.071
Early enrolled (yes=1)	0.014	0.023	0.009	0.003	0.001	0.063
Late enrolled (yes=1)	0.014	0.012	-0.002	0.002	0.241	-0.018
Observations	362,417	3,722				
<i>Joint probit test:</i> $\chi^2 = 612.57$, $p < 0.001$.						

Notes: Track-choice analysis sample ($N = 366,139$: 362,417 students in tracks 1–5; 3,722 in tracks 6–7). Group 1–5 comprises students enrolled in the five main track categories (Liceo scientifico, Liceo classico, Altri licei, Tecnici, Professionali). Group 6–7 comprises students in the two residual licei categories: track 6 (recorded as Liceo classico or Liceo scientifico in only one of the two grade-10 questionnaires, not further distinguishable) and track 7 (recorded as Liceo classico or Altri licei in only one questionnaire). “Mean diff.” is the difference in sample means between group 6–7 and group 1–5; SE is its standard error. The p -value refers to a two-sided test of the null of equal means. “Std. diff.” is the standardised mean difference: the raw difference divided by the square root of the average within-group variance. The joint probit test regresses a binary indicator for group 6–7 membership on all listed student-level variables simultaneously; the χ^2 statistic and p -value are from a cluster-robust Wald test, with standard errors clustered at the primary-school class level (`codice_classe_05`).

2.B Multinomial logit estimates and specification tests

This appendix reports the multinomial logit coefficients (log-odds scale) underlying the average marginal effects of the track-choice analysis, together with a set of specification tests on the role of the attitudes. The base outcome is *Liceo scientifico*; each pair of columns refers to one of the four remaining track categories, and columns (a) and (b) report the specifications without and with the two Attitude indices. Standard errors, in parentheses, are clustered at the primary-school class level. Province dummies are included in both specifications and not reported.

The Wald test evaluates the null hypothesis that the coefficients associated with the attitude measures are jointly equal to zero across all five choice equations (or outcome categories) of the multinomial logit model. A large χ^2 statistic and a p -value below conventional significance levels lead to the rejection of the null hypothesis, indicating that attitudes possess statistically significant joint predictive content. Inference is based on standard errors clustered at the classroom level.

The change in McFadden’s pseudo- R^2 , computed as $r2p_{mb} - r2p_{ma}$, quantifies the improvement in model fit obtained by adding the attitude measures to the baseline specification. Unlike the Wald test, this statistic should be interpreted as a measure of predictive gain rather than statistical significance.

Subject-specificity tests evaluate whether the predictive effect of an attitude is stronger for educational tracks more closely related to its subject domain. These tests are implemented as equality restrictions on the multinomial logit coefficients across outcome categories.

The multinomial logit coefficients are reported first, followed by the test of the incremental predictive content of the attitudes and the subject-specificity test, all for the principal specification.

Table 2.B.3: Track-choice analysis: multinomial logit coefficients (log-odds), specifications (a) and (b).

	Liceo classico		Altriicei		Tecnici		Professionali	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Attitude: Mathematics		-0.434 *** (0.009)		-0.426 *** (0.006)		-0.195 *** (0.006)		-0.365 *** (0.008)
Attitude: Literacy		0.336 *** (0.010)		0.108 *** (0.006)		-0.062 *** (0.006)		-0.075 *** (0.008)
Mathematics score G05	-0.275 *** (0.012)	-0.180 *** (0.012)	-0.245 *** (0.009)	-0.158 *** (0.009)	-0.079 *** (0.008)	-0.052 *** (0.009)	-0.187 *** (0.012)	-0.124 *** (0.012)
Mathematics score G08	-0.477 *** (0.011)	-0.375 *** (0.011)	-0.753 *** (0.009)	-0.659 *** (0.009)	-0.558 *** (0.008)	-0.536 *** (0.009)	-0.944 *** (0.012)	-0.884 *** (0.012)
Literacy score G05	0.348 *** (0.012)	0.277 *** (0.012)	0.067 *** (0.009)	0.017 * (0.009)	-0.170 *** (0.009)	-0.177 *** (0.009)	-0.289 *** (0.013)	-0.311 *** (0.013)
Literacy score G08	0.450 *** (0.011)	0.406 *** (0.011)	-0.182 *** (0.009)	-0.213 *** (0.009)	-0.610 *** (0.009)	-0.607 *** (0.009)	-1.005 *** (0.013)	-1.013 *** (0.013)
Gender (female=1)	0.936 *** (0.017)	0.770 *** (0.017)	1.574 *** (0.013)	1.470 *** (0.013)	-0.526 *** (0.012)	-0.542 *** (0.012)	0.120 *** (0.016)	0.082 *** (0.016)
ESCS Index	0.285 *** (0.010)	0.280 *** (0.010)	-0.327 *** (0.006)	-0.328 *** (0.007)	-0.671 *** (0.007)	-0.671 *** (0.007)	-0.986 *** (0.009)	-0.985 *** (0.009)
Kindergarten (yes=1)	-0.222 * (0.117)	-0.233 ** (0.118)	-0.283 *** (0.074)	-0.291 *** (0.074)	-0.223 *** (0.070)	-0.228 *** (0.070)	-0.418 *** (0.081)	-0.422 *** (0.082)
Immigrant (yes=1)	-0.570 *** (0.053)	-0.504 *** (0.053)	-0.339 *** (0.027)	-0.256 *** (0.028)	-0.102 *** (0.025)	-0.058 ** (0.025)	-0.254 *** (0.032)	-0.172 *** (0.032)
Early enrolled (yes=1)	0.262 *** (0.047)	0.282 *** (0.047)	-0.430 *** (0.045)	-0.418 *** (0.045)	-0.532 *** (0.049)	-0.530 *** (0.049)	-0.649 *** (0.074)	-0.640 *** (0.074)
Late enrolled (yes=1)	-0.026 (0.102)	-0.025 (0.102)	0.332 *** (0.057)	0.332 *** (0.058)	0.193 *** (0.054)	0.187 *** (0.054)	0.498 *** (0.063)	0.490 *** (0.064)
Observations	331,843							
Clusters	28,239							

Notes: Multinomial logit estimates: log-odds relative to the baseline category *Liceo scientifico*. Track-choice analysis sample restricted to the five main track categories. This specification came from Equation (2.1); the coefficients on the attitude indices in column (b) therefore reflect the total predictive content of attitudes net of grade-5 and grade-8 achievements. Column (a): grade-5 Rasch scores (Mathematics and Literacy), individual and family controls, and province dummies. Column (b): column (a) plus Attitude: Mathematics and Attitude: Literacy. Province dummies are included in all specifications but not reported. Standard errors, clustered at the primary-school class level (`codice_classe_05`), in parentheses.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 2.B.4: Test on the incremental predictive content of the attitudes.

	(a)	(b)
Attitude indices	No	Yes
Province dummies	Yes	Yes
McFadden pseudo- R^2	0.1960	0.2046
Log-pseudolikelihood	-398690.3	-394447.8
Δ pseudo- R^2 (b – a)	0.0086	
Wald $\chi^2(8)$, attitude block	7028.28	
p -value	<0.001	
Observations	331,843	
Clusters	28,239	

Notes: McFadden pseudo- R^2 and log-pseudolikelihood for the two specifications; Δ pseudo- R^2 and Wald $\chi^2(8)$ test of the joint contribution of the two Attitude indices. Standard errors clustered at the primary-school-class level (`codice_classe_05`; 28,239 clusters). * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 2.B.5: Subject-specificity test table.

$H_0: AME(\text{Attitude in Mathematics}) = AME(\text{Attitude in Literacy}), \text{specification (b)}$					
	Liceo scientifico	Liceo classico	Altriicei	Tecnici	Professionali
Attitude in Mathematics	0.052*** (0.001)	-0.015*** (0.000)	-0.037*** (0.001)	0.009*** (0.001)	-0.010*** (0.001)
Attitude in Literacy	-0.010*** (0.001)	0.019*** (0.001)	0.015*** (0.001)	-0.017*** (0.001)	-0.007*** (0.001)
Difference (Mathematics – Literacy)	0.062*** (0.001)	-0.034*** (0.001)	-0.051*** (0.001)	0.027*** (0.001)	-0.003*** (0.001)
Wald $\chi^2(1)$	2724.30	1976.35	2165.11	507.42	17.35
p -value	0.000	0.000	0.000	0.000	0.000

Notes: subject-specificity restriction $H_0: AME_{\text{Mathematics}} = AME_{\text{Literacy}}$ tested via a Wald restriction on the AMEs of column (b), for each track. Standard errors clustered at the primary-school-class level (`codice_classe_05`; 28,239 clusters). * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

2.3 Gender heterogeneity tests

Cross-gender heterogeneity is assessed by estimating separate multinomial logit models for males and females and combining them through `suest`, which provides a joint covariance matrix with standard errors clustered at the classroom level. Tests are conducted on the multinomial logit coefficients (log-odds scale) rather than on average marginal effects (AMEs). The first column of Table 2.8 reports a joint Wald test of the null hypothesis that all Mathematics and Literacy attitude coefficients are equal across genders in all estimated outcome equations. The second and third columns report separate tests for the equality of the Mathematics and Literacy attitude coefficients, respectively. Rejection of the null hypothesis indicates gender heterogeneity in the relationship between attitudes and educational choices. Because the tests are performed on log-odds coefficients, they should not be interpreted as tests of equality of AMEs.

Table 2.6: Incremental in-sample contribution of the attitude block, by gender: Wald test and McFadden pseudo- R^2 .

	Wald test (attitudes)		McFadden pseudo- R^2		
	$\chi^2(8)$	p -value	Without att.	With att.	Δ
Males	3,034.8	< 0.001	0.167	0.175	0.008
Females	4,325.7	< 0.001	0.145	0.155	0.010

Notes: The Wald statistic tests the joint null $H_0: \beta_{\text{Math},j} = \beta_{\text{Lit},j} = 0$ for $j = 2, \dots, 5$, with eight degrees of freedom. Standard errors are clustered at the primary-school class level. Both specifications are estimated on the same complete-case sample. Δ denotes the difference in pseudo- R^2 between the specification with and without the attitude block.

Table 2.7: Subject-specificity test ($H_0: AME_{\text{Math},j} = AME_{\text{Lit},j}$), by gender and track outcome.

Track	Males		Females	
	$AME_{\text{Math}} - AME_{\text{Lit}}$	p -value	$AME_{\text{Math}} - AME_{\text{Lit}}$	p -value
Liceo scientifico	0.042	< 0.001	0.080	< 0.001
Liceo classico	-0.028	< 0.001	-0.041	< 0.001
Altriicei	-0.035	< 0.001	-0.066	< 0.001
Tecnici	0.027	< 0.001	0.027	< 0.001
Professionalisti	-0.006	< 0.001	-0.000	0.745

Notes: The difference $AME_{\text{Math},j} - AME_{\text{Lit},j}$ is computed from the within-gender specification with attitudes (Table 2.14). The p -value is from a cluster-robust Wald test (χ^2_1) of the equality restriction. Standard errors are clustered at the primary-school class level.

Table 2.8: Cross-gender equality of the attitude coefficients (log-odds scale): **suest** test.

Track	Joint test		Attitude: Mathematics		Attitude: Literacy	
	$\chi^2(2)$	p -value	δ_{Math}	p -value	δ_{Lit}	p -value
Liceo classico	0.635	0.728	-0.007	0.694	-0.013	0.509
Altriicei	3.265	0.195	0.024	0.073	-0.004	0.757
Tecnici	111.569	< 0.001	0.134	< 0.001	-0.024	0.045
Professionalisti	75.075	< 0.001	0.129	< 0.001	-0.060	< 0.001

Notes: The joint test (χ^2_2) tests the null that the Mathematics and Literacy attitude coefficients are equal across gender for each non-base track equation. δ_{Math} and δ_{Lit} are the male minus female differences in the multinomial logit log-odds coefficients on the Attitude in Mathematics and Literacy indices, respectively. Estimates are obtained by stacking the two within-gender models via **suest**. Standard errors are clustered at the primary-school class level. *Liceo scientifico* is the base outcome and does not appear in the table.

2.4 The teacher-grade subsample: sample composition

This appendix complements Section 2.3.2 by documenting the composition of the teacher-grade subsample.

Teacher grades have more missing values than INVALSI scores. Requiring non-missing grades in both subjects and at both grades restricts the track-choice analysis sample ($N = 331,843$) to a teacher-grade subsample of 277,389 students, and excludes 54,454 students with missing teacher grades. This restriction may raise a selection issue: if the teacher-grade subsample differed substantially from the track-choice analysis sample, differences between the estimates could reflect the change in sample rather than the change in achievement measure. Table 2.9 therefore compares the characteristics of the two groups and tests whether their differences are statistically significant.

Table 2.9: Balance test on observable characteristics: teacher-grade subsample vs students with missing teacher grades.

	Missing teacher grades		Teacher-grade subsample		Difference
	Mean	SD	Mean	SD	
Gender (female=1)	0.519	0.500	0.520	0.500	0.001
ESCS Index	0.203	0.948	0.192	0.975	-0.011
Kindergarten (yes=1)	0.990	0.101	0.993	0.084	0.003***
Immigrant (yes=1)	0.057	0.233	0.055	0.229	-0.002
Early enrolled (yes=1)	0.015	0.120	0.015	0.120	-0.000
Late enrolled (yes=1)	0.013	0.113	0.012	0.111	-0.000
Mathematics score G05	0.141	0.964	0.150	0.974	0.009
Mathematics score G08	0.218	0.966	0.214	0.973	-0.004
Literacy score G05	0.168	0.935	0.171	0.945	0.002
Literacy score G08	0.260	0.928	0.246	0.929	-0.014**
Attitude: Mathematics	0.057	0.981	0.074	0.975	0.018***
Attitude: Literacy	0.035	0.980	0.070	0.974	0.034***
Observations	54,454		277,389		

Notes: The table reports means and standard deviations of student characteristics for students with missing teacher grades and for the teacher-grade subsample used in Table 2.13. The difference is the mean in the teacher-grade subsample minus the mean among students with missing teacher grades. Significance stars refer to a test of equality of means between the two groups, with standard errors clustered at the primary-school class level. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Differences between the two groups are small. Across gender, socio-economic status, kindergarten attendance, immigrant background, early and late enrolment, and the four Rasch achievement scores, they do not exceed 0.014 in absolute value; only those for kindergarten attendance and grade-8 Literacy achievement are statistically significant, which reflects the size of the samples rather than economically relevant gaps. The two Attitude indices differ somewhat more: students in the teacher-grade subsample score 0.018 standard deviations higher in Attitude: Mathematics and 0.034 higher in Attitude: Literacy (both $p < 0.01$). The teacher-grade subsample is therefore slightly positively selected on the variables of primary interest. As shown in Section 2.3.2, this mild selection does not affect the estimates.

Chapter 3

Mapping Administrative Data for a Longitudinal Study of Italian University Students^{*}

^{*}The work described in this chapter was carried out within Work Package 3.2 (Spoke 3) of the GRINS project, as a collective undertaking of the six partner universities. The results of that collective effort are presented in [Bello et al. \(2026\)](#), co-authored by the present author.

3.1 Introduction

This chapter documents the work carried out within the GRINS Project (Growing Resilient, Inclusive and Sustainable Extended Partnership), financed by the Italian National Recovery and Resilience Plan (PNRR), whose first phase was devoted to building a database on Italian university students. Alongside the research presented in Chapters 1 and 2, I took part in the design and construction of the integrated longitudinal data infrastructure developed within Work Package 3.2 (Human Capital) of Spoke 3, dedicated to households' sustainability. WP 3.2 focuses on the economic, institutional and social factors that shape investment in human capital, and on the efficiency of the educational process.

The purpose of this part of the project is to overcome the long-standing fragmentation of the Italian information system on tertiary education. Its long-term goal is to link university administrative records with the National Student Registry of the Ministry of Education and Merit (MIM), the standardised assessments collected by INVALSI, and the graduate surveys conducted by AlmaLaurea. The resulting panel is designed to follow students across compulsory schooling, upper-secondary education, higher education and entry into the labour market, providing an empirical foundation for research in the economics of education and for evidence-based policy evaluation.

The design of the Database on University Students was a collective undertaking of Spoke 3 under WP 3.2: the common codebook, the harmonisation rules applied to the administrative records and the architecture of the dashboard of monitoring indicators were defined jointly by the project team, each partner university then extracting and converting its own institutional data. Within this framework, my own contribution took two forms. As part of the Cagliari unit, I worked on the dashboard indicators on access to university, and specifically on those measuring geographical mobility and the attractiveness of degree programmes in the school-to-university transition (Section 3.2). Individually, I carried out the mapping and monitoring of the INVALSI data infrastructure presented in Section 3.3. This involved the systematic review of test availability by grade and year, and the reconstruction of the student and teacher questionnaires question by question: each individual item was tracked across grades and survey waves and classified into thematic domains, so that the non-cognitive and socio-emotional measures could be located precisely in the years in which they were surveyed. It is this exercise that identified the 2013/14 grade-5 cohort, surveyed with the most comprehensive non-cognitive battery and observable without interruption through grade 13, as the empirical basis of Chapters 1 and 2.

Once linked to MIM and INVALSI records, the GRINS panel would constitute, to the best of my knowledge, the first Italian data infrastructure to integrate administrative records on tertiary education, national standardised assessments and post-graduation surveys within a single harmonised framework available to researchers. It would bring the country closer to mature European infrastructures such as the Dutch National Cohort Study on Education (NCO), the Estonian Education Information System (EHIS), the German National Educational Panel Study (NEPS) and the United Kingdom's Longitudinal Education Outcomes (LEO), and would complement ongoing Italian initiatives such as MOBYSU.IT (Bello et al., 2026). At the time of writing, the project has not yet been finalised.

The chapter is organised as follows. Section 3.2 describes the database on university students: its objectives, the partner universities involved, the administrative codebook, the monitoring indicators and the integration of external data sources. Section 3.3 turns to the INVALSI data infrastructure, documenting the structure and availability of student-level information and of the student and teacher questionnaires.

3.2 The Database on University Students

The Database on University Students is the longitudinal data infrastructure developed within WP 3.2, Spoke 3 of the GRINS project. Its primary aim is to build a panel dataset that follows the academic careers and labour-market outcomes of Italian university students, by mapping and integrating the administrative records held by the partner universities¹ with the graduate surveys collected by AlmaLaurea (GRINS Spoke 3, WP 3.2, 2024). The administrative records cover students enrolled between 2012 and 2022 (from 2015 for some institutions), while AlmaLaurea provides information on students' socio-economic background and post-graduation occupational status. Today these data exist in isolation and have never been linked across different institutions. One goal of the project is to make this connection possible (Bello et al., 2026).

Integrating student-level data from universities that differ in the format and availability of their records required a preliminary harmonisation step. The team therefore defined a common codebook, which specifies the variables that each university extracts from its administrative records, their format and metric, and the harmonisation rules that make the records comparable across institutions. The variables are organised into seven macro-areas: demographic data; enrolled-students data (including the ISEE indicator of economic condition); AlmaLaurea graduate profiles; AlmaLaurea occupational condition; course offerings; student careers (exams and degrees); and pre-selection (TOLC) test results (GRINS Spoke 3, WP 3.2, 2024). Each partner checked the availability and format of every variable in its own system and, where needed, converted it to the shared schema through a dedicated Stata routine.

Building on the codebook, the project's second component is a dashboard of monitoring indicators that summarise key information on each partner university. Computed from the administrative data and the AlmaLaurea surveys, the indicators are organised into three macro thematic areas that follow the higher-education life cycle: access to university (e.g. the post-secondary transition rate and geographical mobility at the school-to-university transition), academic careers (graduation rates, time-to-degree, dropout, grades, and the students' performance gap by socio-economic status, gender, and degree type), and exit, from dropout to employability (the share of students at risk and post-graduation labour-market outcomes linked through AlmaLaurea) (Bello et al., 2026). Within the access area, the Cagliari unit worked on attractiveness and geographical mobility in the school-to-university transition, developing indicators on the geographical distribution of enrolled students, the applications and acceptances to each degree programme, and the share of first-year students relative to upper-secondary graduates in the same area. The full set of indicators identified as most important is reported in Tables 3.A.1, 3.A.2 and 3.A.3 in Appendix.

The administrative records form the core of the panel. A further step, still under development, aims to enhance their analytical value by linking them with external sources, the two main ones being MIM and INVALSI. This linkage remains a working hypothesis: through a cooperation agreement currently under negotiation, the partner universities aim to link their records with the National Student Registry (ANS) of MIM for students in grades 8 and 13 from the school year 2011/12, and with INVALSI standardised test scores for grades 2, 5, 8, 10, and 13 from the same year.² The planned integration would cover 2011/12–2023/24 and would allow the reconstruction of complete educational trajectories, from compulsory schooling to entry into the labour market. At the time of writing, the codebook includes only the administrative data of the partner universities and AlmaLaurea, while the MIM and INVALSI linkage is still under negotiation (GRINS Spoke 3, WP 3.2, 2024).

¹This part of the project was carried out jointly by six Extended Partnership universities: the Alma Mater Studiorum University of Bologna, the University of Bari, the University of Bergamo, the University of Cagliari, the University of Naples Federico II, and the University of Rome Tor Vergata.

²The cooperation agreement with MIM and INVALSI involves five of the six partner universities, namely all those listed above except the University of Bari.

3.3 Monitoring the INVALSI Data

In preparation for the prospective linkage with MIM and INVALSI data, a preliminary mapping exercise was undertaken to identify the student-level variables collected by these institutions over time and assess their potential integration with the data already available from the participating universities.³ INVALSI (the National Institute for the Evaluation of the Italian Education System) administers annual nationwide assessments of student achievement in Italian and Mathematics and, for selected grades, in English reading and listening. These assessments are designed to monitor both the quality and equity of the Italian education system.⁴ Almost all Italian schools, public and private, take part. Alongside the census collection, INVALSI separately gathers data for a representative sample of classes — the *sample classes* — drawn to be representative of the student population in each grade. These classes follow a different protocol that enables better control of possible cheating or teacher manipulation: the test is administered by a teacher other than the class’s own, transcribed onto a single official sheet under the principal’s supervision, and scored externally. This makes the sample-class scores comparable and reliable across schools. For this stage of the project, I analysed the INVALSI data covering the school years 2011/12–2023/24. The data provided by the university partners currently span the period 2011/12–2022/23. Future work will extend the dataset to incorporate all subsequent school years as they become available. (INVALSI, 2011)

The tests are administered at five grade levels: grade 2 (early primary), grade 5 (end of primary), grade 8 (end of lower-secondary), grade 10 (end of compulsory education), and grade 13 (final year of upper-secondary) (INDIRE, 2014). Monitoring began by surveying the years and grades for which INVALSI collected the subject-test results, producing tables that show, grade by grade and year by year, which instruments are available, and that flag the instruments used only in the sample classes and the years skipped because of the pandemic. The availability of the tests and of the student and teacher questionnaires is reported in Tables 3.1, 3.2, and 3.5, respectively.

The tests cover Italian and Mathematics in all grades and English reading and listening in grades 5, 8, and 13. Table 3.1 reports, for each subject, the grades and school years in which the test was administered. INVALSI scores are reported both on a normalised 0–100 scale and on a Rasch scale; comparability across cohorts is ensured by an anchoring procedure introduced in 2011/12, the same year from which the longitudinal SIDI–INVALSI identifier allows each student to be followed across grades and years. In grade 2, the language assessment is, in some years, supplemented by an Italian reading test (*Prova di lettura*).⁵

³This mapping exercise was conducted using the INVALSI Open Data portal for the most recent school years, available at <https://serviziostatistico.invalsi.it/catalogo-dati/>, and the *Catalogo dati* file for earlier years, available at <https://www.invalsi.it/trasparenza/altri-contenuti/accessibilita-catalogo-dati/>.

⁴See the INVALSI website: <https://www.invalsi.it/istituto/>.

⁵Since 2018, the reading test has been administered only to sample classes, in accordance with Legislative Decree 62/2017, and its results do not contribute to students’ overall scores. For further information on the legal framework governing INVALSI assessments, see: <https://www.invalsi.it/trasparenza/disposizioni-general/atti-general/riferimenti-normativi-organizzazione-attivita/>.

Table 3.1: INVALSI standardised tests for (a) Italian, Mathematics and Reading and (b) English, by school year and grade.

(a) Italian, Mathematics and Reading.

Grades:	2	5	8	10	13
2011/12	✓	✓	✓	✓	-
2012/13	✓●	✓	✓	✓	-
2013/14	✓●	✓	✓	✓	-
2014/15	✓●	✓	✓	✓	-
2015/16	✓●	✓	✓	✓	-
2016/17	✓●	✓	✓	✓	-
2017/18	✓	✓	✓	✓	-
2018/19	✓	✓	✓	✓	✓
2019/20	×	×	×	×	×
2020/21	✓	✓	✓	×	✓
2021/22	✓	✓	✓	✓	✓
2022/23	✓	✓	✓	✓	✓
2023/24	✓	✓	✓	✓	✓

(b) English: Reading and Listening.

Grades:	2	5	8	10	13
2011/12	-	-	-	-	-
2012/13	-	-	-	-	-
2013/14	-	-	-	-	-
2014/15	-	-	-	-	-
2015/16	-	-	-	-	-
2016/17	-	-	-	-	-
2017/18	-	✓	✓	-	-
2018/19	-	✓	✓	-	✓
2019/20	-	×	×	-	×
2020/21	-	✓	✓	-	✓
2021/22	-	✓	✓	-	✓
2022/23	-	✓	✓	-	✓
2023/24	-	✓	✓	-	✓

Legend:

- ✓ : Assessment administered
- : Assessment not administered
- ×
- : Assessment suspended owing to the COVID-19 pandemic
- : Additional Reading assessment administered only in Grade 2

Over the years, INVALSI has administered various questionnaires that accompany the student assessments. Together with the standardised subject tests, here I report only the monitoring of the student and teacher questionnaires.

3.3.1 Student questionnaire

The INVALSI student questionnaire is administered to students in grades 5, 8, 10, and 13 (see Table 3.2), and both its structure and the information it collects have changed considerably over the years. Although its content varies across grades and survey waves, a common set of variables can be consistently identified throughout the period.⁶

These changes in questionnaire design are reflected in the number of variables available across grades and survey years. Table 3.3 shows that the greatest variability occurs in grades 5 and 10, which also offer the longest longitudinal coverage, starting in the 2011/12 school year. The questionnaires administered in 2013/14 and 2014/15 stand out from all other waves, as they include a larger number of variables, among them an extensive battery of measures on non-cognitive, socio-emotional, and contextual factors.

⁶For grade 10 students, although the standardised tests were not carried out in the 2020/21 school year, the student questionnaire was nonetheless administered.

Table 3.2: INVALSI questionnaires for students, by school year and grade.

Grades:	2	5	8	10	13
2011/12	-	✓	-	✓	-
2012/13	-	✓	-	✓	-
2013/14	-	✓	-	✓	-
2014/15	-	✓	-	✓	-
2015/16	-	✓	-	✓	-
2016/17	-	✓	-	✓	-
2017/18	-	✓	✓	✓	-
2018/19	-	✓	✓	✓	-
2019/20	-	×	×	×	-
2020/21	-	✓	✓	✓	-
2021/22	-	✓	✓	✓	✓
2022/23	-	✓	✓	✓	✓
2023/24	-	✓	✓	✓	✓

Legend:

✓ : Assessment administered

- : Assessment not administered

× : Assessment suspended owing to the COVID-19 pandemic

Table 3.3: Variable availability in the INVALSI Student Questionnaire by grade and academic year

Grade	Academic year												
	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	19-20	20-21	21-22	22-23	23-24
Grade 5	56	40	97	101	30	30	41	16	×	15	12	22	22
Grade 8	-	-	-	-	-	-	49	18	×	23	34	34	40
Grade 10	62	49	110	136	33	33	51	25	×	33	35	34	41
Grade 13	-	-	-	-	-	-	-	-	-	-	34	34	41

Notes. Each cell reports the number of variables available in the released dataset for that grade and year. — : questionnaire not administered in that year. × : survey not conducted (COVID-19 pandemic). Grade 8 student questionnaire starts from a.a. 2017–18. Grade 13 student questionnaire starts from a.a. 2021–22. Grade 2 is excluded: no student questionnaire at that grade.

Table 3.B.4 in Appendix gives an overview of the information the grade 5 student questionnaire has gathered over the years.⁷ Although a handful of items that appear only in certain waves were moved to the subject questionnaires, most measures of non-cognitive, socio-emotional, contextual, and family-background aspects were recorded for just a short period and then discontinued.

Monitoring these indicators has been especially useful for the analyses in Chapters 1 and 2. Table 3.4 shows where they were surveyed: mainly in the 2013/14 and 2014/15 waves, covering test anxiety, motivation, goal orientation, self-efficacy and self-concept, peer relations and classroom climate, school well-being, bullying, dropout intentions, and learning strategies. With the exception of test anxiety, in recent years these dimensions have been captured for the whole population through only a few variables, even though the literature on students' educational outcomes regards them as important. It is precisely this two-year window of otherwise discontinued measures that Chapters 1 and 2 exploit to study the role of non-cognitive skills in students' educational outcomes. Of the two waves, only the 2013/14 cohort can be followed through the full sequence of assessments: the 2014/15 cohort reaches grade 10 in 2019/20, the school year in which the INVALSI tests were not administered because of the pandemic, so that its longitudinal path is broken at that wave. The 2013/14 cohort is therefore the last one for which both a comprehensive non-cognitive-skills battery and a complete set of assessments from grade 5 to grade 13 are available, although its grade-13 wave falls in 2021/22, in the immediate aftermath of the pandemic, a circumstance taken into account when interpreting the estimates in Chapter 1.

⁷The same analysis has been done for the other grades.

Table 3.4: Non-cognitive skill (NCS) constructs collected in the INVALSI student questionnaire, by grade and academic year (2011/12–2017/18).

Grade	11–12	12–13	13–14	14–15	15–16	16–17	17–18
Gr. 5	Test anxiety	Test anxiety; motivation	Test anxiety; motivation; goal orientation (mastery, perf.-approach); subject interest; self-efficacy; academic self-concept; peer relations; classroom climate; school well-being; bullying	Same as 13–14	Test anxiety	Test anxiety	Test anxiety (by subject); motivation
Gr. 8	—	—	—	—	—	—	Test anxiety (by subject); motivation; educational aspirations
Gr. 10	Test anxiety (by subject); utility value	Test anxiety (by subject); utility value	Test anxiety (by subject); goal orientation (mastery, perf.-approach, perf.-avoidance); motivation; self-efficacy; peer relations; dropout intentions; school well-being; bullying	Same as 13–14 + learning strategies; classroom climate	—	—	Test anxiety (by subject); motivation
Gr. 13	—	—	—	—	—	—	—

Legend:

— : absence of NCS items.

Notes. From 2018/19, the questionnaire reverts to a lean format with no dedicated NCS modules across all grades.

3.3.2 Teacher questionnaire

The INVALSI Teacher Questionnaire is administered to teachers of Italian, Mathematics, and English in sampled classes. It collects information on teaching practices, instructional resources, professional experience, working conditions, attitudes toward the INVALSI assessment system, and teachers' personal characteristics. The present mapping exercise focuses exclusively on the Italian and Mathematics teacher questionnaires, as the English Teacher Questionnaire was introduced in the 2020/21 school year and administered only in grades 5, 8, and 13.

The Italian and Mathematics teacher questionnaires are available for grades 2, 5, 8, and 10 from the 2013/14 school year onward, while grade 13 was included starting in 2020/21. No teacher questionnaire data were collected in the 2019/20 school year due to the COVID-19 pandemic. In addition, no data are available for grade 10 in 2020/21. Table 3.5 reports the availability of teacher questionnaire data by school year and grade.⁸

⁸At the time the mapping exercise was conducted, teacher questionnaire data for the 2023/24 school year were not yet publicly available.

Table 3.5: INVALSI questionnaires for teachers, by school year and grade.

Grades:	2	5	8	10	13
2011/12	-	-	-	-	-
2012/13	-	-	-	-	-
2013/14	✓	✓	✓	✓	-
2014/15	✓	✓	✓	✓	-
2015/16	✓	✓	✓	✓	-
2016/17	✓	✓	✓	✓	-
2017/18	✓	✓	✓	✓	-
2018/19	✓	✓	✓	✓	-
2019/20	×	×	×	×	-
2020/21	✓	✓	✓	×	✓
2021/22	✓	✓	✓	✓	✓
2022/23	✓	✓	✓	✓	✓

Legend:

✓ : Assessment administered

- : Assessment not administered

× : Assessment suspended owing to the COVID-19 pandemic

As with the student questionnaire, the GRINS project made it necessary to check which variables were collected, and for which years and grades. The teacher questionnaires are long and cover many aspects of teachers' work. The questionnaire items were first classified according to their substantive content, with individual questions grouped into thematic macro-categories: school identifiers; INVALSI test-related questions; teaching practices; instructional tools and resources; professional experience, contractual status, and school roles; professional relationships; participation in projects and initiatives; motivational dimensions; personal characteristics; and territorial indicators. The availability of these domains varies across grades and survey waves. In particular, the sections on participation in projects and motivational dimensions were introduced only in the most recent questionnaire versions, starting from the 2022/23 school year.

The analysis below is limited to illustrating the variation observed across grades and years. Table 3.6 reports the similarities and differences between the questions asked in a selection of grades and years. The comparison is made at the macro-category level rather than item by item: a set of grade-year versions is compared against a common baseline (grade 2, 2013/14), and each macro-category is classified as either unchanged or changed.

Table 3.6: Macro-category variation in the INVALSI Teacher Questionnaire.

	Grade 2 2013–14	Grade 5 2013–14	Grade 5 2015–16	Grade 8 2015–16	Grade 10 2015–16	Grade 10 2022–23	Grade 13 2022–23
School identifiers	✓	✓	✓	✓	✓	≠	≠
INVALSI tests-related questions	✓	✓	≠	≠	≠	≠	≠
Teaching practices	✓	≠	≠	≠	≠	≠	≠
Teaching tools and resources	✓	✓	≠	≠	≠	≠	≠
Work: experience, contract, roles	✓	✓	≠	≠	≠	-	-
Working relationships	✓	✓	✓	✓	✓	-	-
Projects	-	-	-	-	-	✓	✓
Motivation	-	-	-	-	-	✓	✓
Personal characteristics	✓	✓	≠	≠	≠	≠	≠
Territorial indicators	✓	✓	✓	✓	✓	≠	≠

Legend:

✓ : No variation relative to the reference version

≠ : Variation relative to the reference version

- : Macro-category not available

Notes. the survey was not administered in a.a. 2019–20 owing to the COVID-19 pandemic.

3.4 Conclusions

This chapter has provided a brief overview of the work carried out within the GRINS project dedicated to designing a database on university students. Alongside the collective effort required to build this dataset, which follows students from school to the labour market, the Cagliari unit focused in particular on the construction of some of the dashboard indicators and on monitoring the availability of INVALSI variables, both for the student population and for teachers.

This work highlighted the challenges associated with integrating data from different administrative sources. Generating robust evidence capable of informing educational policies requires access to detailed microdata; therefore, mechanisms enabling researchers to use these data under controlled and secure conditions should be strengthened. It also emerged that, over the years, the collection of important information on non-cognitive, socio-emotional, and contextual aspects was discontinued. It would be desirable for such information to be collected again, systematically, in the future.

Chapter 3: Appendix

3.A Dashboard indicators

Table 3.A.1: University of Cagliari — Thematic area: Attractiveness and geographical mobility in the school-to-university transition

Indicator	Proposed indicator	Indicator description	Data source
Geographical distribution and school-to-university transition with contextual indicators	Share of first-time entrants* per cohort relative to upper secondary graduates	Number of first-time entrants over the total number of upper secondary graduates in the same region/province/municipality (average across cohorts, ages 18–20); * = first-time enrolment	Administrative data / Register of upper secondary graduates / Register of university graduates — Spoke data
	Share of first-time entrants per cohort relative to the population	Number of first-time entrants over the total population aged 18–20 in the same region/province/municipality	Administrative data / Register of upper secondary graduates / Register of university graduates — Spoke data
	Share of first-time university entrants per cohort by type of upper secondary school of origin (technical institute, lyceum, vocational institute)	Number of first-time entrants per cohort by type of upper secondary school of origin (technical institute, lyceum, vocational institute)	Administrative data / Register of upper secondary graduates / Register of university graduates — Spoke data
	Share of first-time university entrants per cohort by gender (male/female)	Number of first-time entrants per cohort by gender (male/female)	Administrative data / Register of upper secondary graduates / Register of university graduates — Spoke data
	Share of first-time university entrants per cohort by the distribution of ISEE household income at the province/municipality level	Number of first-time entrants per cohort by the distribution of ISEE household income at the province/municipality level	Administrative data / Register of university graduates — Spoke data / ISEE data
	Share of first-time university entrants per cohort by upper secondary final grade, normalised at the regional level (top 10%, top 20%, ...)	Number of first-time entrants per cohort by upper secondary final grade, normalised at the regional level (top 10%, top 20%, ...)	Administrative data / Register of upper secondary graduates

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Indicator	Proposed indicator	Indicator description	Data source
	Share of first-time university entrants per cohort by characteristics of the school of origin	Number of first-time entrants per cohort by characteristics of the school of origin	Administrative data / Register of upper secondary graduates / Register of university graduates — Spoke data / “Scuola in chiaro” portal
	Explicit early school leaving rate (by region or province)	Share of young people aged 18–24 holding at most a lower secondary qualification, or a vocational qualification lasting no more than two years, and no longer in education or training in the reference geographical area	Administrative data

Table 3.A.2: University of Cagliari — Thematic area: Attractiveness and geographical mobility in the school-to-university transition (university-level mobility, attractiveness, and retention)

Indicator	Proposed indicator	Indicator description	Data source
University-level mobility and attractiveness / University-level retention	Share of first-time entrants residing within X km	Number of first-time entrants at the university residing in a municipality located within <30, <90, or >90 km, over total first-time entrants	Administrative data
	Share of first-time entrants who did not choose their local university	Number of first-time entrants at the university residing in a municipality whose nearest university is not the university under consideration, over the university's total first-time entrants	Administrative data
	Share of first-time entrants residing outside the region	Number of first-time entrants at the university residing in a region other than that of the university, over the university's total first-time entrants	Administrative data
	Share of first-time entrants without Italian citizenship	Number of first-time entrants at the university without Italian citizenship, over the university's total first-time entrants	Administrative data
	Share of first-time entrants residing abroad or holding a secondary school diploma obtained abroad	Number of first-time entrants at the university residing abroad or holding a secondary school diploma, over the university's total first-time entrants	Administrative data
	University attractiveness in the reference geographical area: municipality/province/region	Number of first-time entrants at the university originating from the reference geographical area, over the total number of upper secondary graduates in the reference geographical area (same province/region as the university)	Administrative data / Register of upper secondary graduates / Register of university graduates or Spoke data
	University attractiveness by type of upper secondary school of origin (technical institute, lyceum, vocational institute)	Number of first-time entrants by type of upper secondary school of origin (technical institute, lyceum, vocational institute), over the total number of upper secondary graduates in the reference geographical area with the same characteristic	Administrative data / Register of upper secondary graduates / Register of university graduates or Spoke data
	University attractiveness by gender (male/female)	Number of first-time entrants by gender (male/female), over the total number of upper secondary graduates in the reference geographical area with the same characteristic	Administrative data / Register of upper secondary graduates / Register of university graduates or Spoke data
	University attractiveness by the distribution of ISEE household income at the province/municipality level	Number of first-time entrants by the distribution of ISEE household income at the province/municipality level, over the total number of upper secondary graduates in the reference geographical area with the same characteristic	Administrative data / Register of upper secondary graduates / Register of university graduates or Spoke data
	University attractiveness by upper secondary final grade, normalised at the regional level (top 10%, top 20%, ...)	Number of first-time entrants by upper secondary final grade, normalised at the regional level (top 10%, top 20%, ...), over the total number of upper secondary graduates in the reference geographical area with the same characteristic	Administrative data / Register of upper secondary graduates / Register of university graduates or Spoke data
	University attractiveness by characteristics of the school of origin	Number of first-time entrants by characteristics of the school of origin, over the total number of upper secondary graduates in the reference geographical area with the same characteristic	Administrative data / Register of upper secondary graduates / Register of university graduates or Spoke data

Table 3.A.3: University of Cagliari — Thematic area: Geographical distribution of enrolled students, number of applications and admissions to each degree programme

Indicator	Proposed indicator	Indicator description	Data source
Entry barriers and selectivity	Restricted educational supply	Share of restricted-admission (numerus clausus) programmes over the total number of degree programmes offered by the university	Administrative data
	Rejection rate	Percentage of applications scoring below the admission threshold over total applications, restricted to numerus clausus programmes	Administrative data
	Admission rate	Ratio of first-time entrants to applications (restricted to numerus clausus programmes)	Administrative data
	University selectivity	Number of first-time entrants who sat a selective admission test, over total first-time entrants (at the university)	Administrative data
	Preference for the university	Percentage of first-time entrants at each university who had ranked that university as their first choice (restricted to programmes under national numerus clausus)	Administrative data
Composition of first-time entrants	Students sitting an admission test	Percentage of students who sat a selective admission test, over total first-time entrants	Administrative data
	Composition of first-time entrants at the university by gender	Number of first-time entrants by gender, over total first-time entrants	Administrative data
	Composition of first-time entrants at the university by ISEE thresholds	Number of first-time entrants by ISEE thresholds, over total first-time entrants	Administrative data
	Composition of first-time entrants at the university by upper secondary final grade	Number of first-time entrants by upper secondary final grade, over total first-time entrants	Administrative data
	Composition of first-time entrants at the university by type of upper secondary school of origin	Number of first-time entrants by type of upper secondary school of origin, over total first-time entrants	Administrative data
	Composition of first-time entrants in a given disciplinary area (STEM, ELSS, Health, Human) by gender	Number of first-time entrants in a given disciplinary area (STEM, ELSS, Health, Human) by gender	Administrative data
	Composition of first-time entrants in a given disciplinary area (STEM, ELSS, Health, Human) by ISEE thresholds	Number of first-time entrants in a given disciplinary area (STEM, ELSS, Health, Human) by ISEE thresholds	Administrative data
	Composition of first-time entrants in a given disciplinary area (STEM, ELSS, Health, Human) by upper secondary final grade	Number of first-time entrants in a given disciplinary area (STEM, ELSS, Health, Human) by upper secondary final grade	Administrative data
	Composition of first-time entrants in a given disciplinary area (STEM, ELSS, Health, Human) by type of upper secondary school of origin	Number of first-time entrants in a given disciplinary area (STEM, ELSS, Health, Human) by type of upper secondary school of origin	Administrative data

Notes: STEM includes engineering and computational approaches for cell culturing, genomic sequencing, and gene therapies. ELSS covers Life Sciences, including developmental and evolutionary biology. Health refers to translational research, clinical trials, and regenerative medicine. Human addresses ethical, legal, regulatory, and public health aspects of scientific innovation.

3.B Detailed variable check

Table 3.B.4: Variables in the INVALSI Student Questionnaire, Grade 5 (a.a. 2011–12 to a.a. 2023–24)

Variable	Description	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	20-21	21-22	22-23	23-24
CODICE_SCUOLA	Codice scuola	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
CODICE_CLASSE	Codice classe	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
CODICE_STUDENTE	Codice studente	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Q1A_MAT	Quanti fratelli hai?	✓*	✓*	-	-	-	-	-	-	-	✓	✓	✓
Q1B_MAT	Quante sorelle hai?	-	-	-	-	-	-	-	-	-	✓	✓	✓
Q2A_MAT	A casa hai: un posto tranquillo per studiare?	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Q2B_MAT	A casa hai: un computer che puoi usare per lo studio?	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Q2C_MAT	A casa hai: una scrivania per fare i compiti	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Q2D_MAT	A casa hai: software didattici (ad esempio GeoGebra, Matlab, MindMapper, ecc.)?	-	-	-	-	-	-	-	-	-	-	✓	✓
Q2E_MAT	A casa hai: una rete fissa per collegarti a internet (es. modem)?	✓*	✓*	✓*	✓*	✓*	✓*	✓*	✓*	✓*	✓*	✓	✓
Q2F_MAT	A casa hai: una camera tutta tua?	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Q2G_MAT	A casa hai: libri di letteratura classica (ad esempio Dante, Manzoni, Tolstoj, ecc.)?	-	-	-	-	-	-	-	-	-	-	✓	✓
Q2H_MAT	A casa hai: opere d'arte (ad esempio quadri, sculture, ecc.)?	-	-	-	-	-	-	-	-	-	-	✓	✓
Q2I_MAT	A casa hai: manuali tecnici (ad esempio manuali di utilizzo di un software, ecc.)?	-	-	-	-	-	-	-	-	-	-	✓	✓
Q2J_MAT	A casa hai: un dizionario (di italiano o altre lingue)?	✓*	✓*	✓*	✓*	✓*	✓*	✓*	✓*	✓*	✓*	✓	✓
Q2K_MAT	A casa hai: un tablet tutto tuo?	-	-	-	-	-	-	-	-	-	-	✓	✓
Q2L_MAT	A casa hai: uno smartphone tutto tuo	-	-	-	-	-	-	-	-	-	-	✓	✓
Q3_MAT	Quanti libri ci sono all'incirca a casa tua (esclusi i libri di scuola)?	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✓
Q1_ITA	Sei andato/a alla scuola dell'infanzia (scuola materna)?	✓*	-	-	✓	✓	✓	✓	✓	✓	-	✓	✓
Q2_ITA	A casa, quale lingua parli la maggior parte del tempo?	✓	-	-	✓	✓	✓	✓	✓	✓	-	✓	✓
Q3_ITA	Oltre alla lingua indicata sopra, a casa parli frequentemente anche un dialetto (siciliano, veneto, ecc.)	✓	-	-	✓	✓	✓	✓	✓	✓	-	✓	✓
Q4_ITA	Con gli amici e nel tempo libero, quale lingua parli la maggior parte del tempo?	-	-	-	-	-	-	-	-	-	✓	✓	✓
Q1_MAT	Qual è stato, alla fine dello scorso anno scolastico, il tuo voto in Matematica?	-	-	✓	✓	✓	✓	✓	✓	✓	-	-	-
Q1_ITA	Qual è stato, alla fine dello scorso anno scolastico, il tuo voto in Italiano	-	-	✓	✓	✓	✓	✓	✓	✓	-	-	-
CODICE_PLESSO	Codice plesso	-	✓	✓	✓	✓	✓	✓	✓	-	-	-	-
macrotipologia	Macrotipologia di istituto	-	✓	✓	✓	✓	✓	✓	-	-	-	-	-
livello	Grado indagato	✓*	✓*	✓*	✓*	✓*	✓*	✓	-	-	-	-	-
prog	Progressivo studente	-	✓	✓	✓	✓	✓	✓	-	-	-	-	-
campione	Classe campione	✓*	-	-	-	✓	✓	-	-	-	-	-	-
Q1A_ITA	Pensando alla prova INVALSI di Italiano... Già da prima ero preoccupato/a di dover fare la prova	-	-	-	-	-	-	✓	-	-	-	-	-
Q1B_ITA	Pensando alla prova INVALSI di Italiano... Ero così nervoso/a che non riuscivo a trovare le risposte	-	-	-	-	-	-	✓	-	-	-	-	-
Q1C_ITA	Pensando alla prova INVALSI di Italiano... Mentre rispondevo avevo l'impressione di andare male	-	-	-	-	-	-	✓	-	-	-	-	-

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(Student Questionnaire. Continued from previous page)

Variable	Description	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	20-21	21-22	22-23	23-24
Q1D_ITA	Pensando alla prova INVALSI di Italiano... Mentre rispondevo mi sentivo tranquillo/a	-	-	-	-	-	-	✓	-	-	-	-	-
Q1E_ITA	Pensando alla prova INVALSI di Italiano... Le domande di riflessione sulla lingua erano più facili degli esercizi che facciamo di solito	-	-	-	-	-	-	✓	-	-	-	-	-
Q1F_ITA	Pensando alla prova INVALSI di Italiano... I testi in Italiano erano più facili di quelli che abbiamo letto durante l'anno	-	-	-	-	-	-	✓	-	-	-	-	-
Q2A_ITA	Parliamo della materia Italiano... In generale, mi diverto a imparare gli argomenti di Italiano	-	-	-	-	-	-	✓	-	-	-	-	-
Q2B_ITA	Parliamo della materia Italiano... sono felice di studiare Italiano	-	-	-	-	-	-	✓	-	-	-	-	-
Q2C_ITA	Parliamo della materia Italiano... mi interessa imparare bene la materia Italiano	-	-	-	-	-	-	✓	-	-	-	-	-
Q2D_ITA	Parliamo della materia Italiano... mi piace imparare nuovi argomenti di Italiano	-	-	-	-	-	-	✓	-	-	-	-	-
Q2E_ITA	Parliamo della materia Italiano... non vedo l'ora di fare lezione di Italiano	-	-	-	-	-	-	✓	-	-	-	-	-
Q1A_MAT	Pensando alla prova INVALSI di Matematica... Già da prima ero preoccupato/a di dover fare le prove	-	-	-	-	-	-	✓	-	-	-	-	-
Q1B_MAT	Pensando alla prova INVALSI di Matematica... Ero così nervoso/a che non riuscivo a trovare le risposte	-	-	-	-	-	-	✓	-	-	-	-	-
Q1C_MAT	Pensando alla prova INVALSI di Matematica... Mentre rispondevo avevo l'impressione di andare male	-	-	-	-	-	-	✓	-	-	-	-	-
Q1D_MAT	Pensando alla prova INVALSI di Matematica... Mentre rispondevo mi sentivo tranquillo/a	-	-	-	-	-	-	✓	-	-	-	-	-
Q1E_MAT	Pensando alla prova INVALSI di Matematica... Le domande di Matematica erano più facili degli esercizi che facciamo di solito	-	-	-	-	-	-	✓	-	-	-	-	-
Q2A_MAT	Parliamo della materia Matematica... In generale, mi diverto a imparare gli argomenti di Matematica	-	-	-	-	-	-	✓	-	-	-	-	-
Q2B_MAT	Parliamo della materia Matematica... mi piace leggere libri di Matematica	-	-	-	-	-	-	✓	-	-	-	-	-
Q2C_MAT	Parliamo della materia Matematica... sono felice di studiare la Matematica	-	-	-	-	-	-	✓	-	-	-	-	-
Q2D_MAT	Parliamo della materia Matematica... mi piace imparare bene la Matematica	-	-	-	-	-	-	✓	-	-	-	-	-
Q2E_MAT	Parliamo della materia Matematica... mi piace imparare nuovi argomenti di Matematica	-	-	-	-	-	-	✓	-	-	-	-	-
Q2F_MAT	Parliamo della materia Matematica... non vedo l'ora di fare lezione di Matematica	-	-	-	-	-	-	✓	-	-	-	-	-
Q3	In che mese sei nato/a?	✓	✓	✓	✓	✓	✓	-	-	-	-	-	-
Q4	In che anno sei nato/a?	✓	✓	✓	✓	✓	✓	-	-	-	-	-	-
Q5	Sei femmina o maschio?	✓	✓	✓	✓	✓	✓	-	-	-	-	-	-
Q11_A	Pensando alle prove INVALSI ... con queste affermazioni? - Già da prima ero preoccupato/a di dover fare le prove	✓	✓	✓	✓	✓	✓	-	-	-	-	-	-
Q11_B	Pensando alle prove INVALSI ... con queste affermazioni? - Ero così nervoso/a che non riuscivo a trovare le risposte	✓	✓	✓	✓	✓	✓	-	-	-	-	-	-
Q11_C	Pensando alle prove INVALSI ... con queste affermazioni? - Mentre rispondevo avevo l'impressione di andare male	✓	✓	✓	✓	✓	✓	-	-	-	-	-	-

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(Student Questionnaire. Continued from previous page)

Variable	Description	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	20-21	21-22	22-23	23-24
Q11_D	Pensando alle proveINVALSI ... con queste affermazioni? - Mentre rispondevo mi sentivo tranquillo/a	✓	✓	✓	✓	✓	✓	-	-	-	-	-	-
Q11_E	Pensando alle proveINVALSI ... con queste affermazioni? - Le domande di Matematica erano più facili degli esercizi che facciamo di solito	✓	✓	✓	✓	✓	✓	-	-	-	-	-	-
Q11_F	Pensando alle proveINVALSI ... con queste affermazioni? - Le domande di grammatica erano più facili degli esercizi che facciamo di solito	✓	✓	✓	✓	✓	✓	-	-	-	-	-	-
Q11_G	Pensando alle proveINVALSI ... con queste affermazioni? - I testi di Italiano erano più facili di quelli che abbiamo letto durante l'anno	✓	✓	✓	✓	✓	✓	-	-	-	-	-	-
Q1	Pensa a che cosa significa per te studiare. Quale paragone faresti?	-	-	-	✓	-	-	-	-	-	-	-	-
Q2_A	Pensa al perché dovresti andare bene a scuola...seguenti affermazioni? - Perché se vado bene a scuola potrei ricevere in premio qualcosa che mi piace	-	-	▲	✓	-	-	-	-	-	-	-	-
Q2_B	Pensa al perché dovresti andare bene a scuola...seguenti affermazioni? - Perché mi sento in colpa se vado male a scuola	-	-	▲	✓	-	-	-	-	-	-	-	-
Q2_C	Pensa al perché dovresti andare bene a scuola...seguenti affermazioni? - Perché andare bene a scuola è importante per capire meglio le cose	-	-	▲	✓	-	-	-	-	-	-	-	-
Q2_D	Pensa al perché dovresti andare bene a scuola...seguenti affermazioni? - Perché impegnarmi a scuola, in fondo, mi piace	-	-	▲	✓	-	-	-	-	-	-	-	-
Q2_E	Pensa al perché dovresti andare bene a scuola...seguenti affermazioni? - Perché se vado bene a scuola, poi mi lasciano fare le cose che mi piacciono	-	-	▲	✓	-	-	-	-	-	-	-	-
Q2_F	Pensa al perché dovresti andare bene a scuola...seguenti affermazioni? - Perché mi vergogno se vado male a scuola	-	-	▲	✓	-	-	-	-	-	-	-	-
Q2_G	Pensa al perché dovresti andare bene a scuola...seguenti affermazioni? - Perché andare bene a scuola è importante per me stesso/a	-	-	▲	✓	-	-	-	-	-	-	-	-
Q2_H	Pensa al perché dovresti andare bene a scuola...seguenti affermazioni? - Perché impegnarmi a scuola, in fondo, è divertente	-	-	▲	✓	-	-	-	-	-	-	-	-
Q2_I	Pensa al perché dovresti andare bene a scuola...seguenti affermazioni? - Perché se vado male a scuola potrei ricevere una punizione	-	-	▲	✓	-	-	-	-	-	-	-	-
Q3_A	Pensa al perché dovresti fare i compiti... seguenti affermazioni? - Perché se faccio i compiti, poi mi lasciano fare le cose che mi piacciono	-	-	▲	✓	-	-	-	-	-	-	-	-
Q3_B	Pensa al perché dovresti fare i compiti... seguenti affermazioni? - Perché mi sento in colpa se non ho fatto i compiti	-	-	▲	✓	-	-	-	-	-	-	-	-
Q3_C	Pensa al perché dovresti fare i compiti... seguenti affermazioni? - Perché fare i compiti è importante per me stesso/a	-	-	▲	✓	-	-	-	-	-	-	-	-
Q3_D	Pensa al perché dovresti fare i compiti... seguenti affermazioni? - Perché, in fondo, fare i compiti è divertente	-	-	▲	✓	-	-	-	-	-	-	-	-
Q3_E	Pensa al perché dovresti fare i compiti... seguenti affermazioni? - Perché se non faccio i compiti potrei ricevere una punizione	-	-	▲	✓	-	-	-	-	-	-	-	-

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(Student Questionnaire. Continued from previous page)

Variable	Description	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	20-21	21-22	22-23	23-24
Q3_F	Pensa al perché dovresti fare i compiti... seguenti affermazioni? - Perché mi vergogno se non ho fatto i compiti	-	-	▲	✓	-	-	-	-	-	-	-	-
Q3_G	Pensa al perché dovresti fare i compiti... seguenti affermazioni? - Perché fare i compiti è importante per riuscire a capire meglio	-	-	▲	✓	-	-	-	-	-	-	-	-
Q3_H	Pensa al perché dovresti fare i compiti... seguenti affermazioni? - Perché, in fondo, fare i compiti mi piace	-	-	▲	✓	-	-	-	-	-	-	-	-
Q3_I	Pensa al perché dovresti fare i compiti... seguenti affermazioni? - Perché mi sento agitato/a e nervoso/a se non ho fatto i compiti	-	-	▲	✓	-	-	-	-	-	-	-	-
Q4_A	Pensa a te e allo studio, quanto sei d'accordo con le seguenti affermazioni? - Per me, l'importante a scuola è imparare cose nuove	-	-	▲	✓	-	-	-	-	-	-	-	-
Q4_B	Pensa a te e allo studio, quanto sei d'accordo con le seguenti affermazioni? - Far vedere agli altri che sono bravo/a a scuola è una cosa importante per me	-	-	▲	✓	-	-	-	-	-	-	-	-
Q4_C	Pensa a te e allo studio, quanto sei d'accordo con le seguenti affermazioni? - Per me, l'importante a scuola è imparare il più possibile	-	-	▲	✓	-	-	-	-	-	-	-	-
Q4_D	Pensa a te e allo studio, quanto sei d'accordo con le seguenti affermazioni? - Una cosa importante, per me, è far vedere agli altri che vado bene nelle interrogazioni	-	-	▲	✓	-	-	-	-	-	-	-	-
Q4_E	Pensa a te e allo studio, quanto sei d'accordo con le seguenti affermazioni? - L'importante, per me, è capire bene quello che studio	-	-	▲	✓	-	-	-	-	-	-	-	-
Q4_F	Pensa a te e allo studio, quanto sei d'accordo con le seguenti affermazioni? - Una cosa importante, per me, è far vedere agli altri che vado bene nelle verifiche	-	-	▲	✓	-	-	-	-	-	-	-	-
Q4_G	Pensa a te e allo studio, quanto sei d'accordo con le seguenti affermazioni? - Per me, l'importante a scuola è migliorare nel corso dell'anno	-	-	▲	✓	-	-	-	-	-	-	-	-
Q4_H	Pensa a te e allo studio, quanto sei d'accordo con le seguenti affermazioni? - Una cosa importante, per me, è apparire più intelligente dei/delle miei/mie compagni/e	-	-	▲	✓	-	-	-	-	-	-	-	-
Q5_A	Quanto sei d'accordo con le seguenti affermazioni? - Mi piace studiare la Matematica	-	-	✓	✓	-	-	-	-	-	-	-	-
Q5_B	Quanto sei d'accordo con le seguenti affermazioni? - Imparo molte cose interessanti durante le lezioni di Matematica	-	-	✓	✓	-	-	-	-	-	-	-	-
Q5_C	Quanto sei d'accordo con le seguenti affermazioni? - La Matematica è noiosa	-	-	✓	✓	-	-	-	-	-	-	-	-
Q5_D	Quanto sei d'accordo con le seguenti affermazioni? - Mi piace studiare l'Italiano	-	-	✓	✓	-	-	-	-	-	-	-	-
Q5_E	Quanto sei d'accordo con le seguenti affermazioni? - Imparo molte cose interessanti durante le lezioni di Italiano	-	-	✓	✓	-	-	-	-	-	-	-	-
Q5_F	Quanto sei d'accordo con le seguenti affermazioni? - L'Italiano è noioso	-	-	✓	✓	-	-	-	-	-	-	-	-
Q6_A	Quanto sei capace di... - finire in tempo i compiti che ti sono stati assegnati	-	-	▲	✓	-	-	-	-	-	-	-	-
Q6_B	Quanto sei capace di... - impegnarti nello studio quando hai altre cose interessanti da fare	-	-	▲	✓	-	-	-	-	-	-	-	-

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(Student Questionnaire. Continued from previous page)

Variable	Description	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	20-21	21-22	22-23	23-24
Q6_C	Quanto sei capace di...- concentrarti nello studio senza farti distrarre	-	-	▲	✓	-	-	-	-	-	-	-	-
Q6_D	Quanto sei capace di...- ricordare ciò che l'insegnante ha spiegato in classe	-	-	▲	✓	-	-	-	-	-	-	-	-
Q7_A	Quanto sei d'accordo con le seguenti affermazioni? - Di solito sono bravo/a in Matematica	-	-	▲	✓	-	-	-	-	-	-	-	-
Q7_B	Quanto sei d'accordo con le seguenti affermazioni? - Imparo la Matematica facilmente	-	-	▲	✓	-	-	-	-	-	-	-	-
Q7_C	Quanto sei d'accordo con le seguenti affermazioni? - La Matematica è più difficile per me che per molti miei compagni	-	-	▲	✓	-	-	-	-	-	-	-	-
Q7_D	Quanto sei d'accordo con le seguenti affermazioni? - Di solito sono bravo/a in Italiano	-	-	▲	✓	-	-	-	-	-	-	-	-
Q7_E	Quanto sei d'accordo con le seguenti affermazioni? - Imparo l'Italiano facilmente	-	-	▲	✓	-	-	-	-	-	-	-	-
Q7_F	Quanto sei d'accordo con le seguenti affermazioni? - L'Italiano è più difficile per me che per molti miei compagni	-	-	▲	✓	-	-	-	-	-	-	-	-
Q8_A	I tuoi compagni di classe. - Quanti dei tuoi compagni/e di classe parlano con te?	-	-	▲	✓	-	-	-	-	-	-	-	-
Q8_B	I tuoi compagni di classe. - Con quanti dei tuoi compagni/e di classe ti trovi bene?	-	-	▲	✓	-	-	-	-	-	-	-	-
Q8_C	I tuoi compagni di classe. - Quanti dei tuoi compagni/e di classe aiutaresti se fossero in difficoltà?	-	-	▲	✓	-	-	-	-	-	-	-	-
Q8_D	I tuoi compagni di classe. - Quanti dei tuoi compagni/e di classe consideri "amici" o "amiche"?	-	-	▲	✓	-	-	-	-	-	-	-	-
Q9_A	Pensa a quello che succede nella tua classe, quanto ... Nella mia classe, l'importante è migliorare nel corso dell'anno	-	-	▲	✓	-	-	-	-	-	-	-	-
Q9_B	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, ottenere buoni voti è una cosa importante	-	-	▲	✓	-	-	-	-	-	-	-	-
Q9_C	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, l'importante è capire veramente quello che si studia	-	-	▲	✓	-	-	-	-	-	-	-	-
Q9_D	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, dare le risposte giuste è una cosa importante	-	-	▲	✓	-	-	-	-	-	-	-	-
Q9_E	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, l'importante è capire un argomento, non impararlo semplicemente a memoria	-	-	▲	✓	-	-	-	-	-	-	-	-
Q9_F	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, ottenere dei punteggi alti ai test e alle verifiche è una cosa importante	-	-	▲	✓	-	-	-	-	-	-	-	-
Q9_G	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, l'importante è imparare cose nuove	-	-	▲	✓	-	-	-	-	-	-	-	-
Q9_H	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, prendere voti alti nelle interrogazioni è una cosa importante	-	-	▲	✓	-	-	-	-	-	-	-	-
Q10_A	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, siamo incoraggiati a fare domande durante la lezione	-	-	▲	✓	-	-	-	-	-	-	-	-
Q10_B	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, è considerato normale fare errori durante le esercitazioni	-	-	▲	✓	-	-	-	-	-	-	-	-

Continued on next page

(Student Questionnaire. Continued from previous page)

Variable	Description	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	20-21	21-22	22-23	23-24
Q10_C	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, siamo ascoltati con attenzione quando interveniamo durante la lezione	-	-	▲	✓	-	-	-	-	-	-	-	-
Q10_D	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, possiamo scegliere tra modi diversi di studiare un argomento	-	-	▲	✓	-	-	-	-	-	-	-	-
Q10_E	Pensa a quello che succede nella tua classe, quanto ... affermazioni? - Nella mia classe, quando abbiamo un problema, veniamo ascoltati	-	-	▲	✓	-	-	-	-	-	-	-	-
Q11_A	Se pensi a come ti sei sentito/a a scuola negli ultimi mesi... nei seguenti modi? - Mi sono sentito/a bene	-	-	▲	✓	-	-	-	-	-	-	-	-
Q11_B	Se pensi a come ti sei sentito/a a scuola negli ultimi mesi... nei seguenti modi? - Mi sono sentito/a tranquillo/a	-	-	▲	✓	-	-	-	-	-	-	-	-
Q11_C	Se pensi a come ti sei sentito/a a scuola negli ultimi mesi... nei seguenti modi? - Mi sono sentito/a contento/a	-	-	▲	✓	-	-	-	-	-	-	-	-
Q11_D	Se pensi a come ti sei sentito/a a scuola negli ultimi mesi... nei seguenti modi? - Mi sono sentito/a felice	-	-	▲	✓	-	-	-	-	-	-	-	-
Q13_A	Durante questo anno scolastico, quanto spesso a scuola: ti è capitato di prendere in giro altri studenti?	-	-	✓	✓	-	-	-	-	-	-	-	-
Q13_B	Durante questo anno scolastico, quanto spesso a scuola: ti è capitato di insultare altri studenti?	-	-	✓	✓	-	-	-	-	-	-	-	-
Q13_C	Durante questo anno scolastico, quanto spesso a scuola: ti è capitato di isolare o escludere altri studenti?	-	-	✓	✓	-	-	-	-	-	-	-	-
Q13_D	Durante questo anno scolastico, quanto spesso a scuola: ti è capitato di picchiare altri studenti?	-	-	✓	✓	-	-	-	-	-	-	-	-
Q13_E	Durante questo anno scolastico, quanto spesso a scuola: sei stato/a preso/a in giro da altri studenti?	-	-	✓	✓	-	-	-	-	-	-	-	-
Q13_F	Durante questo anno scolastico, quanto spesso a scuola: sei stato/a insultato/a da altri studenti?	-	-	✓	✓	-	-	-	-	-	-	-	-
Q13_G	Durante questo anno scolastico, quanto spesso a scuola: sei stato/a isolato/a o escluso/a da altri studenti?	-	-	✓	✓	-	-	-	-	-	-	-	-
Q13_H	Durante questo anno scolastico, quanto spesso a scuola: sei stato/a picchiato/a da altri studenti?	-	-	✓	✓	-	-	-	-	-	-	-	-
Q3_A	Indica quanto sei d'accordo con le seguenti frasi. Studio per accontentare i miei genitori	-	✓	-	-	-	-	-	-	-	-	-	-
Q3_B	Indica quanto sei d'accordo con le seguenti frasi. Quando un argomento è difficile lo lascio perdere	-	✓	-	-	-	-	-	-	-	-	-	-
Q3_C	Indica quanto sei d'accordo con le seguenti frasi. Studio per fare contenti i miei insegnanti	-	✓	-	-	-	-	-	-	-	-	-	-
Q3_D	Indica quanto sei d'accordo con le seguenti frasi. Quando studio molto raggiungo buoni risultati	-	✓	-	-	-	-	-	-	-	-	-	-
Q3_E	Indica quanto sei d'accordo con le seguenti frasi. Studio così a casa mi fanno dei regali	-	✓	-	-	-	-	-	-	-	-	-	-
Q3_F	Indica quanto sei d'accordo con le seguenti frasi. Quando studio mi impegno anche se l'argomento è noioso	-	✓	-	-	-	-	-	-	-	-	-	-
Q3_G	Indica quanto sei d'accordo con le seguenti frasi. Studio per non fare brutta figura con i miei compagni	-	✓	-	-	-	-	-	-	-	-	-	-

Continued on next page

(Student Questionnaire. Continued from previous page)

Variable	Description	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	20-21	21-22	22-23	23-24
Q5_A	Durante una normale giornata, attività fuori dalla scuola? - Guardare la televisione	✓	✓	-	-	-	-	-	-	-	-	-	-
Q5_B	Durante una normale giornata, attività fuori dalla scuola? - Usare il computer o i videogiochi	✓	✓	-	-	-	-	-	-	-	-	-	-
Q5_C	Durante una normale giornata, attività fuori dalla scuola? - Giocare con gli amici	✓	✓	-	-	-	-	-	-	-	-	-	-
Q5_D	Durante una normale giornata, attività fuori dalla scuola? - Dare un aiuto in casa	✓	✓	-	-	-	-	-	-	-	-	-	-
Q5_E	Durante una normale giornata, attività fuori dalla scuola? - Leggere un libro o un giornale come passatempo	✓	✓	-	-	-	-	-	-	-	-	-	-
Q6_A	Con quale frequenza fai queste cose fuori dal normale orario scolastico? - I compiti per casa	✓	✓	-	-	-	-	-	-	-	-	-	-
Q6_B	Con quale frequenza fai queste cose fuori dal normale orario scolastico? - Sport	✓	✓	-	-	-	-	-	-	-	-	-	-
Q6_C	Con quale frequenza fai queste cose fuori dal normale orario scolastico? - Altre attività	✓	✓	-	-	-	-	-	-	-	-	-	-
regolarità	regolarità nel percorso di studi	✓	-	-	-	-	-	-	-	-	-	-	-
cittadinanza	cittadinanza dello studente	✓	-	-	-	-	-	-	-	-	-	-	-
cod_provincia_istat	Provincia	✓	-	-	-	-	-	-	-	-	-	-	-
nome_reg	Regione	✓	-	-	-	-	-	-	-	-	-	-	-
cod_reg	Codice Regione	✓	-	-	-	-	-	-	-	-	-	-	-
areageo_3	Area Geografica a 3 aree	✓	-	-	-	-	-	-	-	-	-	-	-
areageo_4	Area Geografica a 4 aree	✓	-	-	-	-	-	-	-	-	-	-	-
areageo_5	Area Geografica a 5 aree	✓	-	-	-	-	-	-	-	-	-	-	-
areageo_5_istat	Area Geografica a 5 aree Istat	✓	-	-	-	-	-	-	-	-	-	-	-
pon	Area Geografica Pon	✓	-	-	-	-	-	-	-	-	-	-	-
luogo_padre	Luogo di nascita del padre dello studente	✓	-	-	-	-	-	-	-	-	-	-	-
titolo_padre	Titolo di studio del padre dello studente	✓	-	-	-	-	-	-	-	-	-	-	-
professione_padre	Professione del padre dello studente	✓	-	-	-	-	-	-	-	-	-	-	-
luogo_madre	Luogo di nascita della madre dello studente	✓	-	-	-	-	-	-	-	-	-	-	-
titolo_madre	Titolo di studio della madre dello studente	✓	-	-	-	-	-	-	-	-	-	-	-
professione_madre	Professione della madre dello studente	✓	-	-	-	-	-	-	-	-	-	-	-
luogo_nascita	Luogo di nascita dello studente	✓	-	-	-	-	-	-	-	-	-	-	-
voto_scritto_italia	Voto in Italiano scritto	✓	-	-	-	-	-	-	-	-	-	-	-
voto_orale_italiano	Voto in Italiano orale	✓	-	-	-	-	-	-	-	-	-	-	-
voto_scritto_matema	Voto in Matematica scritto	✓	-	-	-	-	-	-	-	-	-	-	-
voto_orale_matemati	Voto in Matematica orale	✓	-	-	-	-	-	-	-	-	-	-	-
codice_orario	codice_orario	✓	-	-	-	-	-	-	-	-	-	-	-

Legend:

✓ : Variable available

* : Variation in the variable name and/or definition

▲ : Similar questions identified, but not verified at the item level

— : Variable not available

Notes. The survey was not conducted in a.a. 2019–20 (COVID-19 pandemic).

Variable-specific notes: Q1A_MAT: * hai fratelli o sorelle?; Q2E_MAT: * un collegamento ad internet; Q2J_MAT: * A casa hai: enciclopedie; Q1_ITA: * domande separate per asilo nido e scuola materna; livello: * Livello indagato; campione: * Scuola campione.

Concluding Remarks

This dissertation examined the role of early domain-specific attitudes toward learning and test anxiety in shaping educational trajectories within the Italian educational system. Drawing on longitudinal administrative data from INVALSI, it pursued three objectives: investigating whether these early non-cognitive characteristics predict subsequent academic achievement, with particular attention to gender differences; examining their association with students' educational sorting at the transition to upper-secondary school; and assessing the evolution of the Italian educational administrative data infrastructure and its potential for longitudinal research.

Taken together, the findings show that educational trajectories emerge from the interaction between cognitive achievement, non-cognitive characteristics, educational choices, and the family and institutional environments in which students progress through school. Domain-specific attitudes measured at the end of primary school predict later achievement in the corresponding domain and are also associated with students' sorting into different upper-secondary tracks, as well as with differential attrition from the administrative panel prior to that transition. Although these relationships cannot be interpreted causally, they consistently indicate that early attitudes and test anxiety retain predictive content beyond prior achievement and family background, suggesting that they may contribute to the processes through which educational inequalities develop over time.

Beyond these empirical findings, the dissertation highlights the importance of longitudinal administrative data for understanding educational trajectories. Linking students' attitudes, socio-emotional characteristics, and contextual information to later educational outcomes substantially expands the range of research questions that can be addressed. At the same time, the analysis of the INVALSI data infrastructure shows that several of these measures have gradually disappeared from student questionnaires. Preserving this information would therefore represent a valuable investment for both research and policy, enabling the identification of early signals of educational disadvantage and a deeper understanding of the mechanisms underlying students' educational pathways.

Several limitations should nevertheless be acknowledged. The analyses rely on observational data and therefore identify predictive associations rather than causal effects. Moreover, the non-cognitive measures are self-reported and capture only a subset of the broader socio-emotional dimensions that may influence educational trajectories. Finally, although INVALSI data provide near-population coverage of the Italian school system, longitudinal analyses are affected by selective non-persistence, implying that the results describe the trajectories of students who remain observable over time.

These limitations also point to important directions for future research. Future studies could investigate the mechanisms underlying the gender differences documented in this dissertation, examine whether the predictive role of early attitudes extends to university and labour-market outcomes, and identify the institutional conditions under which these attitudes become more or less relevant. More fundamentally, an open question remains whether interventions capable of changing students' attitudes would also modify their educational trajectories, rather than simply anticipate them.

Overall, this dissertation confirms that educational trajectories cannot be fully understood through cognitive achievement alone. Specifically, early domain-specific attitudes and test anxiety provide meaningful information about students' future educational pathways beyond prior achievement and family background, while the ability to study these processes depends critically on the availability of longitudinal administrative data that preserve such information over time. Strengthening these data infrastructures, therefore, represents not only a methodological advance for educational research but also an essential prerequisite for producing evidence capable of informing educational policy and identifying educational disadvantage before it becomes entrenched.

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