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Italian Students Standardised Test Results: A Question of Income?

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Abstract

This study investigates the relationship between family income and student performance in standardised tests within the Italian education system. Drawing on data from INVALSI assessments in Italian language and mathematics over a five-year period, it examines whether income is correlated with academic outcomes and how this effect varies across school grades. The analysis is motivated by the limited research on this topic in Italy and by the need for reliable measures of achievement unaffected by regional grading disparities. Using multivariate regression models with fixed effects and robust standard errors, the study finds that the correlation between income and test scores increases with student age, with the strongest effects observed in Grades 10 and 13. The effect is consistently higher in mathematics than in Italian, and more pronounced in poorer regions. These results suggest that educational inequality deepens over the education path, with significant implications for dropout rates and long-term social mobility. A comparative review of policy measures from other OECD countries highlights targeted financial support for disadvantaged students, particularly in upper-secondary education, as a potentially effective intervention. Nevertheless, the findings underscore the limitations of relying solely on public spending increases and suggest that structural differences in learning time and home resources play a critical role in shaping outcomes. This research contributes to the literature on educational inequality in Italy and calls for more targeted and stage-specific policy interventions to promote equity across all levels of education.

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Introduction

Education is a key determinant of people's life opportunities. Individuals with higher levels of education are more likely to be employed and generally earn higher incomes (OECD, 2024). Beyond this, education impacts various other aspects of life, such as health, financial stability, and overall happiness (Farquharson, McNally, & Tahir, 2024). That is why, the inequality of opportunity in education is often referred to as one of the most important concepts to understand social disparities (Heath, 2001). As found by Palomino, Marrero, & Rodríguez (2019) the attained level of education channels up to 30% of total inequality of opportunity. As shown by Bukodi and Goldthorpe (2016), when education is considered as an “investment good”, it often assumes a role as a source of upward social mobility. With regards to education inequalities measures, Italy has been found among the most unequal countries in Europe (Braga, Checchi, & Meschi, 2011). Further evidence of this is found in the small number of students from low educated families choosing a more academic school track, rather than a vocational one (Pensiero, Giancola, & Barone, 2019). Thus, it is vital to investigate the origins and the causes of disparities in this field, in order to develop targeted solutions to such issue and its repercussions on the society as a whole.

The purpose of this research is to shed light on this issue, investigating the correlation between family income and students' performance on standardised tests within the Italian education system. The central question is whether, and to what extent, a student's financial background influences its academic outcomes. To ensure a thorough evaluation, a range of additional variables has been included to control for other relevant factors. The study uses a regression model applied across five school grades and all the Italian provinces, enabling the identification of patterns linked to students' age and geographic location, such as stronger income–achievement correlations in southern regions and among students from lower-income households. Initial findings suggest that the influence of income tends to grow in later school grades, with especially notable effects in disadvantaged areas. These findings have potential effects on the design of educational policies and allocation of public funds. In particular, the study concludes with a comparative analysis of policy measures adopted in other OECD countries and offers recommendations on their possible adaptation to the Italian context.

To address these objectives and frame the analysis, the structure of the study is as follows: Section I reviews the existing literature on inequality of opportunity in education and outlines the relevance of the research question, while also providing an overview of the Italian education system. Section II describes the data and methodology used. Section III presents the results of the analysis. Section IV discusses the findings and delves into their policy implications. Section V concludes.

Section I

Context and Significance

The issue of inequality of opportunity in education has long been a major focus for social science researchers. In the *International Encyclopaedia of the Social & Behavioural Sciences*, Heath (2001) describes it as "*a special case of the notion of fairness*," emphasising that individuals with the same relevant traits or abilities should be treated equally. In the context of education, this means that people with similar academic potential should have equal access to high-quality educational opportunities. However, in today's world, this ideal is rarely achieved.

In their thorough review of the literature on educational inequality, Blanden, Doepke, & Stuhler (2022) confirmed significant disparities in student achievement based on socio-economic background. Analysing the 2015 PISA (Programme for International Student Assessment) scores, they found that even in top-performing countries like Finland and Canada, students from disadvantaged backgrounds scored below the OECD average. These socio-economic disparities go beyond test scores and also affect educational attainments. Children from high-income families are more likely to enrol in post-secondary education, and once enrolled, they are more likely to complete their studies and earn a degree. In a study covering 30 international large-scale assessments conducted over 50 years (spanning 100 countries and approximately 5.8 million students) Chmielewski (2019) found that achievement gaps between students from different socio-economic backgrounds widened in most of the countries examined between 1964 and 2015. The largest increases were observed in countries with rapidly expanding school enrolment, suggesting that broader access to education often exposes inequalities that were previously hidden outside the formal education system. This shows that inequality of opportunity in education remains a serious and growing problem, even in developed countries. As Heath argues, such inequality threatens fairness among citizens and risks violating the core principles of modern democracies. As the American philosopher John Dewey (1916) put it "*an undesirable society, [...], is one which internally and externally sets up barriers to free intercourse and communication of experience. A society which makes provision for participation in its good of all its members on equal terms [instead] [...] is in so far democratic*".

Italy is no exception to these educational inequalities. Recent OECD reports place Italy below the OECD average in several key areas that affect equality in education, including the proportion of tertiary education graduates and average expenditure per student. Italy also ranks significantly below average in multiple dimensions, such as equity in cognitive achievement, student well-being, and educational attainment (OECD, 2018). In addition, Italy is among the countries with the lowest levels of educational mobility (OECD, 2018). A more detailed comparison between Italy and the OECD averages will follow in the paragraph *Italy vs. OECD.*

Many scholars have examined the causes of these educational inequalities, aiming to find viable policy solutions to these issues. In their analysis of the 2006 PIRLS (Progress in International Reading Literacy Study) results, Raimondi, De Luca, & Barone (2013) found that parents' educational level has a significant effect on their children's learning outcomes. Looking at data from the end of World War II to the 1980s, Brunello & Checchi (2003) showed that in Italy, parental education has a stronger impact on educational attainment than the student–teacher ratio. Ballarino, Meraviglia, & Panichella (2021) argued that studies considering only the father's education level significantly underestimate its effect on student achievement, suggesting that the real influence of parental education is likely even greater than previously reported. Finally, Cattani & Celik (2024) found that parental education also significantly affects early language development. Specifically, they showed that both mothers' and fathers' education levels influence word production in children aged 33 to 41 months.

While the influence of parental education on student achievement is clearly significant, research shows that it is not the only important factor. In a study of over 800 children in the United States, Davis-Kean (2005) found that both parental education and family income indirectly affected academic performance, often through parents' beliefs and behaviours. The direct impact of income on student achievement has also been widely studied. Using instrumental variables, Dahl & Lochner (2012) demonstrated a causal relationship in the U.S. context: a $1,000 increase in family income led to a short-term improvement in combined math and reading scores by 6 percent of a standard deviation, with even greater effects for children from disadvantaged backgrounds. These findings are supported by a more recent study by Bradley (2022) which examined achievement gaps in U.S. public schools. The study found that students from lower-income families perform significantly worse on academic tests by about one standard deviation, equivalent to falling behind by approximately three academic years.

In the Italian context, however, there is less literature specifically examining the impact of household income. Using a recent methodology developed by the World Bank, Cannari & D'Alessio (2018) found that while the influence of parental education on children's future income is declining, the role of other household characteristics is becoming increasingly important. Pensiero, Giancola, & Barone (2019) reported that students from lower socio-economic backgrounds tend to receive lower grades and are at greater risk of dropping out. In a more recent study on tertiary education outcomes Graziosi, Sneyers, Agasisti, & De Witte (2021) found that university grants for disadvantaged students have a positive, significant, and statistically robust effect on both academic performance and the likelihood of completing undergraduate degrees. Specifically, the probability of dropping out decreased by between 3% and 22% for those who received the grant.

However, with regards to standardised test performances, there is still limited research on their link with family income, particularly regarding how this relationship changes as students progress through different stages of schooling. While international literature clearly shows a correlation between income and academic achievement, few studies explore how this connection changes over time. For example, Reardon (2011) found that income has become an increasingly strong predictor of children's academic success, as educational attainment and cognitive skills have become more closely linked to adult earnings, reinforcing barriers that may limit intergenerational mobility. Similarly, Dynarski & Michelmore (2017) observed that achievement gaps between students from different socio-economic backgrounds have widened over the past 25 years, noting that test scores are early indicators of college attendance and future income. Investigating this trend in Italy could provide useful information for education policy, as a deeper understanding of the relationship between income and test scores is essential for designing effective interventions. Identifying how this correlation varies across different stages of education could also help policymakers develop more targeted strategies to address educational inequality.

This study aims to address exactly this issue. Using data from INVALSI standardised tests collected over a five-year period and across five school grades, it will examine the correlation between family income and student test scores. The analysis will identify how this relationship changes across different stages of schooling, followed by an in-depth discussion of the results. Finally, the study will include a section analysing relevant policy measures adopted in other OECD countries, along with a discussion of their potential applicability and effectiveness in the Italian context.

1.1 The Italian school system

Compulsory education in Italy lasts 10 years, from ages 6 to 16, covering the eight years of the first education cycle and the first two years of the second cycle (Law 296/2006). The latter can be completed either in state upper secondary schools or through regional vocational education and training programs. Additionally, all young people are subject to the right and duty to education and training for at least 12 years or until they obtain a three-year professional qualification by the age of 18, as stipulated by Law 53/2003.

Compulsory education can be fulfilled in state schools or accredited private schools (Law 62/2000), which together form the public education system. However, it can also be completed in non-accredited private schools (Law 27/2006) or through homeschooling. In these latter cases, compliance with compulsory education requirements is subject to certain conditions, such as passing eligibility exams (Ministero dell'Istruzione e del Merito, 2025).

The Italian education system is structured as follows:

1.1.1 Integrated early childhood system (ages 0–6)

This non-compulsory system spans six years and is divided into two main components:

- Early childhood education services, managed by local authorities either directly or through agreements, as well as by other public or private entities, catering to children aged 3 to 36 months.
- Preschool (*Scuola dell'Infanzia*), which welcomes children aged 3 to 6 years. It can be run by the state, local authorities (directly or via agreements), other public institutions, or private entities.

1.1.2 First education cycle:

This compulsory cycle lasts eight years and is further divided into:

- Primary school *(Scuola Primaria*): A five-year program for children aged 6 to 11.
- Lower secondary school (*Scuola Secondaria di Primo Grado*): A three-year program for students aged 11 to 14.

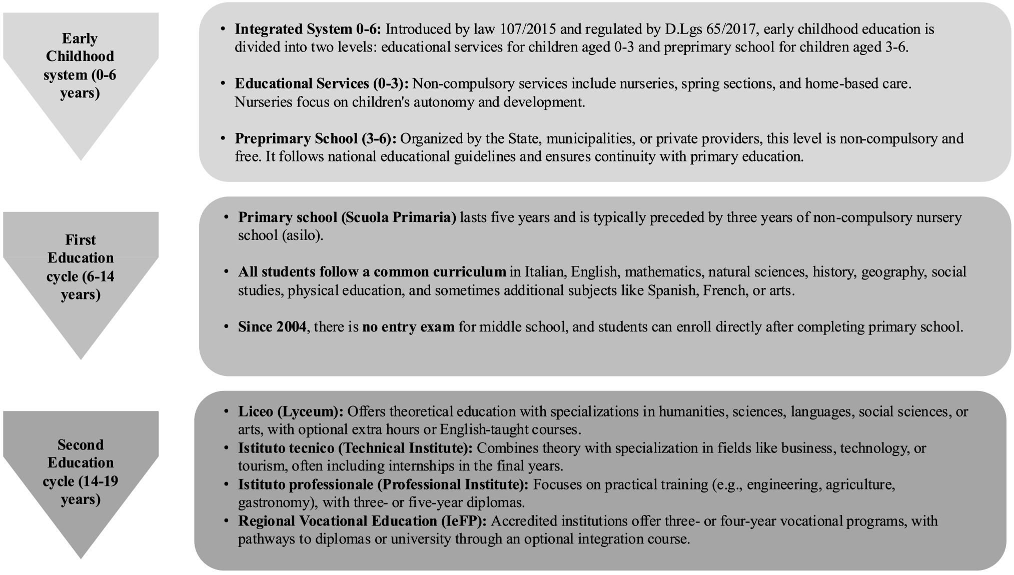

Figure 1: The Figure shows the structure of the Italian School System, with a brief description of each cycle main features.

1.1.3 Second education cycle:

This stage offers two distinct pathways for students who have successfully completed the first cycle:

- Upper secondary school (*Scuola Secondaria di Secondo Grado*): A five-year program designed for students aged 14 to 19. Schools offer three options: academic (*Licei*), technical (*Istituti Tecnici*), or vocational schools (*Istituti Professionali*).
- Regional vocational education and training programs (*IeFP*): These are three- or four-year courses aimed at students who have completed the first education cycle and wish to pursue professional qualifications. These programs fall under regional jurisdiction.

Students can first choose a pathway at the end of the first education cycle. The majority of students selects one of the educational tracks provided by upper secondary schools (World Bank, 2025). All these pathways require five years to complete and grant access to higher education in any field, regardless of a student's prior academic performance. Ability grouping within these tracks is rare. However, students in the general track have significantly higher post-secondary enrolment rates, with about nine out of ten pursuing university education compared to only three out of ten graduates from vocational schools (Azzolini & Barone, 2013). In Grade 8, teachers provide a formal non-binding track recommendation. Once a track is selected, students have very limited options to choose individual school subjects. In contrast with other countries, school results have been found to mediate less than half of the association between social origins and track choice (Contini & Scagni, 2013). Azzolini and Barone (2013) found further evidence that track choice is strongly dependent on social class. Their research shows that first-generation immigrant children are the most disadvantaged group, facing higher dropout risks and greater segregation into the vocational track, which significantly reduces their chances of accessing university education and leads to poorer labour market outcomes. Furthermore, children of more educated parents are more likely to choose high school (*Liceo*), but their advantage does not end there: even in technical and vocational schools, university enrolment rates for the children of graduates are significantly higher than those of their peers from less-educated families (Panichella & Ballarino, 2014). This is influenced by several factors: returns to education, in terms of wages, are comparatively low, and job-status attainment is closely tied to social status. While direct schooling costs remain low, opportunity costs are significant for students from lower social backgrounds. Conversely, children from more advantaged families are encouraged to pursue university qualifications to maintain their social status. These factors highlight the significant role of social-origin differences over academic performance in shaping educational choices (Contini & Scagni, 2013). Thus, it is clear that when it comes to choosing a secondary education pathway, the influence of family income and background is high.

On a positive note, the implementation of the "Bologna process" yielded a positive impact for students from less educated backgrounds, particularly those with strong academic abilities (Cappellari & Lucifora, 2008). The reform transitioned the Italian higher education system from a single four- or five-year degree structure to a two-tier model, consisting of a three-year undergraduate degree (first cycle) followed by a two-year master's degree (second cycle) (Ballarino & Perotti, 2012). This change effectively shortened the time required to obtain a university degree and increased the likelihood of enrolment by 10% for secondary school graduates under the new system, independent of any long-term trends in enrolment. Furthermore, the reform reduced university drop-out rates for students who would not have enrolled under the previous system, highlighting its role in supporting broader access to higher education (Cappellari & Lucifora, 2008).

1.2 Italy vs. OECD

According to OECD (2024), Italian school system falls behind OECD averages in several indicators. First, as seen before, compulsory education in Italy lasts from the age of 6 to 16 for a total of 10 years. This is below the OECD and the EU average of 11 years (Statista, 2018). Research shows that an increase in compulsory schooling of just one year has beneficial impacts both on earnings and across generations: one extra year of parental education reduces the dropout probability of the child by 7% (Harmon, 2017). Furthermore, Italy has the oldest teaching workforce in the EU, with 58% of primary and secondary teachers over the age of 50 in 2017, compared to the EU average of 37%. Additionally, 17% of teachers were over 60, almost double the EU average of 9%. This aging workforce presents a significant challenge as many teachers approach retirement (European Commission, 2019). As found by Bryson et al., (2022) in a study specifically on Italian teacher population, an increased proportion of older teachers is associated with a decline in student performances. Specifically, a six-year rise in average teacher age, comparable to changes over the past two decades, correlates with a reduction of one standard deviation in average graduation scores. This relationship persists even after controlling for teacher tenure, which has a modest positive effect on student outcomes. This trend of aging is partially explained by the limited career prospects and low salaries compared to other professions. Furthermore, teachers follow a single career path with pay increases based only on seniority, reaching the maximum salary after 35 years (OECD average: 25 years). Without performance-related incentives, improving working conditions relies on school transfers, leading disadvantaged schools to rely on inexperienced, temporary staff. Teacher shortages are especially evident in science, mathematics, foreign languages, and learning support, mainly in northern regions. In 2018-19, temporary teachers made up 18.5% of the workforce, reflecting high turnover and job instability due to a lack of automatic post renewals (European Commission, 2019). A vast literature demonstrates that instability and high turnover within a school's teaching staff negatively impact student achievement and reduce overall teacher effectiveness and quality. Moreover, frequent staff changes impose significant economic costs related to recruitment and training, diverting resources that could be more efficiently allocated to other educational needs (García & Weiss, 2019).

With regards to trends in pursuing further education, in 2021 only 20% of Italians aged 25-64 had completed tertiary education, compared to the OECD average of 41%. Italy remains one of 12 OECD countries where upper secondary or post-secondary non-tertiary education is still more prevalent than tertiary education among 25-34 year-olds (Fondazione Agnelli, 2022). This represents a significant issue. It is indeed well established that university graduates tend to live healthier lives than those with lower levels of education. Research shows a strong causal link between university degree attainment and better health outcomes in young adulthood. While financial, occupational, social, cognitive, and psychological factors account for part of this relationship, the healthier behaviours of graduates are also influenced by factors beyond socioeconomic and psychosocial resources, such as human capital development and educational sorting (Lawrence, 2017).

On the subject of learning time, in Italy the number of days of instruction in a school year in lower secondary public school is especially low (OECD, 2024). This poses a significant problem as it negatively impacts student learning. Recent studies show that school closures due to the COVID-19 pandemic have led to a 2.4% decline in test scores for each additional day of closure, with national estimates indicating a loss of between 1.8% and 4% in Mathematics and Italian language. These findings are consistent with research from the Netherlands, where similar reductions in learning, ranging from 4% to 5%, have been observed (Battisti & Maggio, 2023). Thus, the low number of days of instruction poses a further burden on Italian students' performances.

With respect to data on student-teacher ratio, Italy shows positive figures. The country has one of the lowest student-to-teacher ratios in primary schools among OECD and partner countries, with a ratio of 10.8 students per teacher. The student-teacher ratio at the upper secondary level is also notably low, at 10 students per teacher (OECD, 2024). A low student-teacher ratio has been found to yield a significantly positive impact on students' performances, both on standardized and curriculum-based tests. Most notably, project STAR, begun in 1985 in Tennessee found that smaller class sizes led to significant improvements in early learning and cognitive development, particularly for minority children, whose achievement gains were initially about twice as large as those of majority children. Notably, students who had initially experienced smaller classes continued to perform better than their peers, even after transitioning to regular-sized classes in later grades (Mosteller, 1995).

With regards to public expenditure on education in absolute terms, Italy shows an uneven distribution of finances. The country's annual expenditure per pupil is notably high at the primary and pre-primary levels compared to other OECD and partner countries, with expenditures of USD 13,799 and USD 10,912, respectively. However, the average annual expenditure across all educational levels in Italy is equal to USD 12,760, slightly lower than the OECD average of USD 14,209. Specifically, Italy spends USD 11,739 per secondary education student, while the OECD average for secondary education is USD 13,300. Expenditure per student for core educational services in tertiary education is comparatively low, with Italy spending USD 13,717 per student, below the OECD average of USD 20,500 (OECD, 2024). Figure 2 summarises the information schematically.

It is well established that increased investment in education positively influences a range of outcomes across various domains. A study by Jackson and colleagues (2015) found that a 10 percent increase in per-pupil spending each year for all twelve years of public school leads to 0.27 more completed years of education, 7.25 percent higher wages, and a 3.67 percentage-point reduction in the annual incidence of adult poverty.

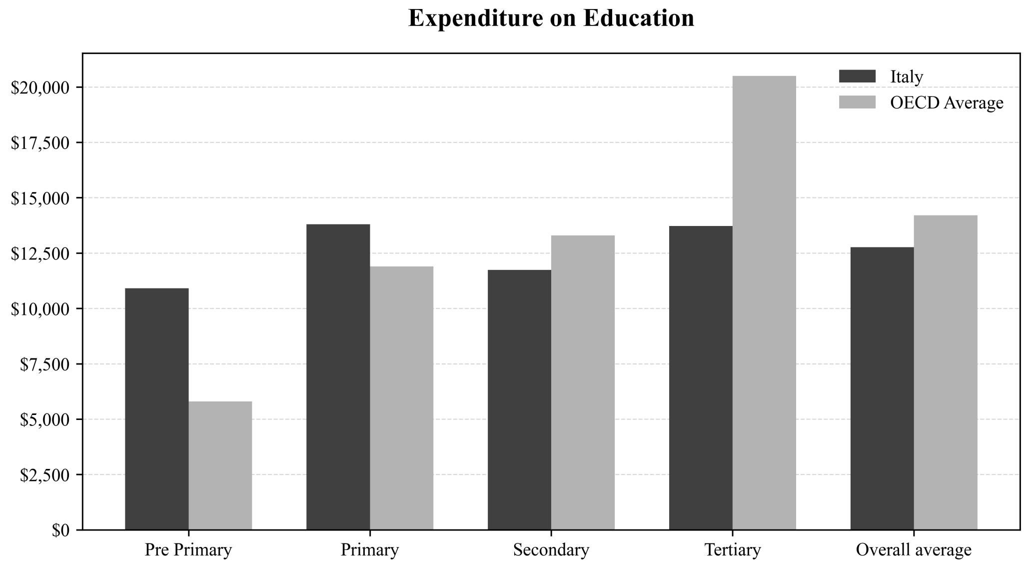

Figure 2: The graph shows the public expenditure on education per children in Italy compared to the OECD average. Data refer to 2024.

Section II

Data and Methodology

This section presents the data source and the methodology used in the study. First, the results of the INVALSI test, used as the main data source, are described. INVALSI assessments are administered nationally and designed to provide objective, comparable data across schools, making them especially functional for analysing educational inequalities. Unlike school-assigned grades, which are influenced by local grading practices and teacher discretion, standardised test scores offer a more consistent measure of student performance. This is particularly important in the Italian context, where significant regional disparities in grading standards exist. As shown by Argentin & Triventi (2015), students in Southern Italy often receive higher school marks than peers in the North, despite performing worse on standardised assessments, highlighting how grades alone may offer a distorted view of students' abilities. For this reason, INVALSI data provide a more reliable source for examining the relationship between income and academic achievement across the country. A brief overview of the INVALSI test's history and its main characteristics is presented below.

2.1 Data

2.1.1 The INVALSI Test

The National Institute for the Evaluation of the Education and Training System (INVALSI) traces its roots back to the Centro Europeo dell'Educazione (CEDE), established by DPR 419/1974 to conduct pedagogical research and foster international collaboration among universities and research centres (INVALSI, 2014). CEDE became operational in the early 1980s under the guidance of eminent educators such as Aldo Visalberghi and Giovanni Gozzer, pioneering studies on teaching methods and school effectiveness. In the 1990s, together with broader debates on school autonomy, Italy began to recognize the need for a systematic, national approach to evaluating its schools. Following feasibility studies by CENSIS and recommendations from OECD experts, Legislative Decree 258/1999 transformed CEDE into INVALSI (Gazzetta Ufficiale, 1999), explicitly charged with developing and administering the first nationwide tests of student achievement (INVALSI, 2014). From the mid-1990s onward, INVALSI's mandate expanded to include not only the measurement of learning outcomes but also research into school "value added" and the organizational, managerial, and pedagogical quality of individual institutions. After two years of pilot testing, the first INVALSI tests in Italian and Mathematics were rolled out in the 2005–2006 school year (INVALSI, 2014). Over time, both the timing of the assessments and their format have been refined, most recently by Legislative Decree 62/2017, which added English tests for fifth-grade primary and third-grade lower-secondary students beginning in spring 2018 (Gazzetta Ufficiale, 2017).

The main goal of the INVALSI tests is to measure the actual competencies that students in Italy develop in reading, writing, and mathematics during their school years (INVALSI, 2025). Unlike classroom tests, which are usually created and corrected by individual teachers, INVALSI assessments are designed by teams of researchers and educators and tested in advance to make sure they are clear and fair. Each question is meant to evaluate a specific skill in a reliable and objective way (INVALSI, 2014).

Since the first national trials in 2005–06, INVALSI has followed the example of international initiatives like the OECD's PISA program. Like PISA, which assesses how well 15-year-olds can use their knowledge in practical situations, INVALSI provides national data on whether students meet certain learning standards at key points in their education. This helps determine, for example, whether a fifth-grader's reading skills are on track with the national curriculum, or whether students in lower secondary school are developing the problem-solving abilities expected for their age group (OECD, 2025).

2.1.2 Test Description

Each test comprises a mix of item formats, including multiple-choice questions, short open-response prompts, and cloze-type tasks (where students select or insert words into gaps) (INVALSI, 2013).

Competencies are assessed on three domains:

- *Italian* assesses text comprehension (authentic passages drawn from literature, journalism or daily life) and language reflection (grammar and usage).
- *Mathematics* evaluates problem-solving in both disciplinary and real-world contexts, including logical reasoning, graph interpretation, and basic modelling.

- *English* (for Grades 5, 8 and 13) tests reading and listening comprehension using real-world texts and audio excerpts.

Standard administration allows 90 minutes per test. Students with specific learning disorders (DSA) receive an additional 15 minutes and may use approved compensatory tools (e.g., calculators, screen-readers) as specified in their individualized education plans (INVALSI Open, 2025). Until 2018, primary tests (Grades 2 and 5) were paper-based; since then, most assessments (Grades 8, 10 and 13, plus English in Grade 5) have been delivered via computer-based testing (CBT) (INVALSI Open, 2025), with items randomized to ensure equivalent difficulty across different test forms.

Table 1: The Table summarises the delivery mode and the subjects of the test for each school Grade.

Grade Level	**School Grade**	**Delivery Mode**	**Subjects Tested**
2	II Primary	Paper-Based (PPT)	Italian; Mathematics
5	V Primary	Paper-Based (PPT)	Italian; Mathematics; English
8	III Lower Secondary	Computer-Based (CBT)	Italian; Mathematics; English
10	II Upper Secondary	Computer-Based (CBT)	Italian; Mathematics
13	Final Year Upper Secondary	Computer-Based (CBT)	Italian; Mathematics; English

Scores from the INVALSI tests are reported on a Rasch scale, a psychometric model widely used in educational assessment to ensure fairness and comparability. Developed by Danish statistician Georg Rasch, this model places both student ability and item difficulty on the same scale, allowing the probability of a correct answer to be calculated as a function of the difference between the two. This ensures that scores are not affected by differences in test difficulty across years or versions, and that comparisons across cohorts are valid and reliable (Bond, 2015).

INVALSI adopts a Rasch scale structure where the national average is conventionally set at 200 points, with a standard deviation of 40 (Bendinelli & Martini, 2021). This fixed metric enables longitudinal comparisons and the use of common reference points over time, similar to international surveys like PISA, TIMSS, and PIRLS (INVALSI, 2017). Each school receives its aggregate scores, compared with regional and national levels, and since 2018 (2019 for grade 13), competence levels are also reported. These levels indicate whether students have reached basic, intermediate, or advanced proficiency of the tested skills. This classification helps families and educators interpret scores more effectively and identify where support or improvement is needed (INVALSI Open, 2025).

2.2 Methodology

For the purposes of this analysis, data from the INVALSI tests in Italian language and mathematics between 2017 and 2022 have been used. As outlined above, students take these assessments in Grades 2, 5, 8, 10, and 13, allowing for the examination of test results across five distinct age groups. This structure makes it possible to estimate the effects of the selected variables at different stages of schooling. Such results are available on territorial basis, following the pattern of the Italian administrative division. Such regulation divides the country into 107 *province,* following a surface rather than a population criterion (Istat.it, 2024).

To check the preliminary consistency of the starting idea, a descriptive analysis on the correlation between income and test scores has been carried out. The provinces have been divided into tertiles based on income, with Tertile 1 being the richest and Tertile 3 being the poorest. Scatter plots and correlations matrices were used to check the correlation between income and test scores, both unconditionally and conditionally upon tertiles and school grades.

Following this preliminary test, the actual regression model has been developed. Test results have been divided by subject: Italian language and Mathematics. Each subject has 3 different regressions: a Lin-Lin one, to estimate the mere unit impact of each regressor on the score; a log-linear one, to estimate the percentage impact on scores of a linear change in estimators; a log-log one, to compare percentage changes in both the dependent and the independent variables.

For the estimation of the variables' effects, a multivariate regression model has been used, with the standardized test's result as the dependent variable. As for the independent variables, estimators for the following factors have been calculated.

i. Income

The average income of the province in the given year. Data have been collected from the Italian Ministry of Finances' tax declarations. Data are in thousands of Euros.

ii. Year Fixed Effect

Dummy variable representing each year in the analysis (2018-2022). Useful to control for time-specific factors.

iii. Grade

Set of dummy variables representing each school grade in the analysis (2,5,8,10,13). Certain INVALSI waves are lacking a Grade, due either to COVID pandemic (missing Grade 10 in 2020), or a change in regulation (missing Grade 13 in 2018, the test became compulsory for Grade 13 in 2019) (Gazzetta Ufficiale, 2017).

iv. Income*Grade

Interaction variable between income and the dummies for the various grades. Useful to identify the combined effect of taking the test in a specific Grade given a certain level of income.

v. Province Fixed Effect

107 dummies representing the effect of living in each province. Useful to control for province specific factors.

Section III

Results

3.1 Descriptive Statistics

The preliminary analysis, based on an unconditional scatter plot that includes all tertiles, revealed a weak correlation between income and test scores. Figure 3 illustrates the scatter plot, with the province's average income represented on the X-axis and the province's average score on the Y-axis, using data from 2018. The plot exhibits a high degree of dispersion, suggesting a relatively limited correlation between the two variables. This finding is supported by the correlation matrix, which, across 2461 observations, reports a correlation coefficient slightly above 0.3.

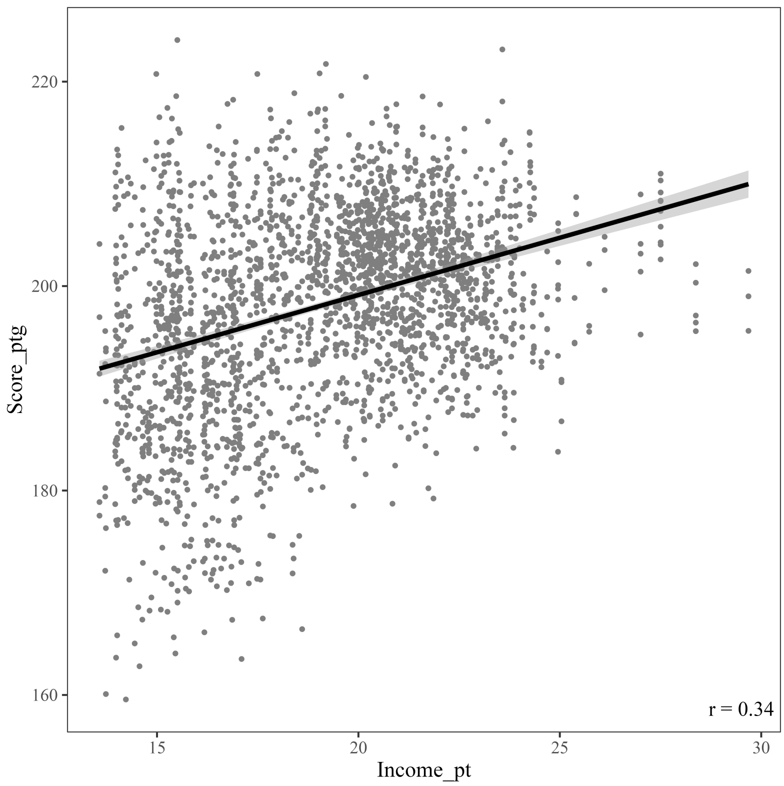

Figure 3: The figure shows a scatter plot of test scores. The X axis represents the Income, while the Y axis the Italian language Score in 2018.

Table 2: Correlation matrix (n = 2461).

Variable	Income_pt	Score_ptg
Income_pt	1.000	0.342
Score_ptg	0.342	1.000

An additional analysis was conducted on the same dataset, this time divided by school grade. The results indicate that the correlation between income and test scores increases as students progress through school. Specifically, test scores for students within all tertiles show a stronger correlation with income at higher grades. For instance, Figure 4 compares scores and income for Grade 2 and Grade 8 students. The graphs clearly show that the correlation between the two variables increases significantly with additional years of schooling. Specifically, while there is a slight negative correlation in Grade 2 (r = -0.106), by Grade 8 the relationship becomes strongly positive (r = 0.715). These findings align with a study by Hassink and Kiiver (2007) on the German education system, which similarly concluded that the influence of income becomes more significant as children grow older.

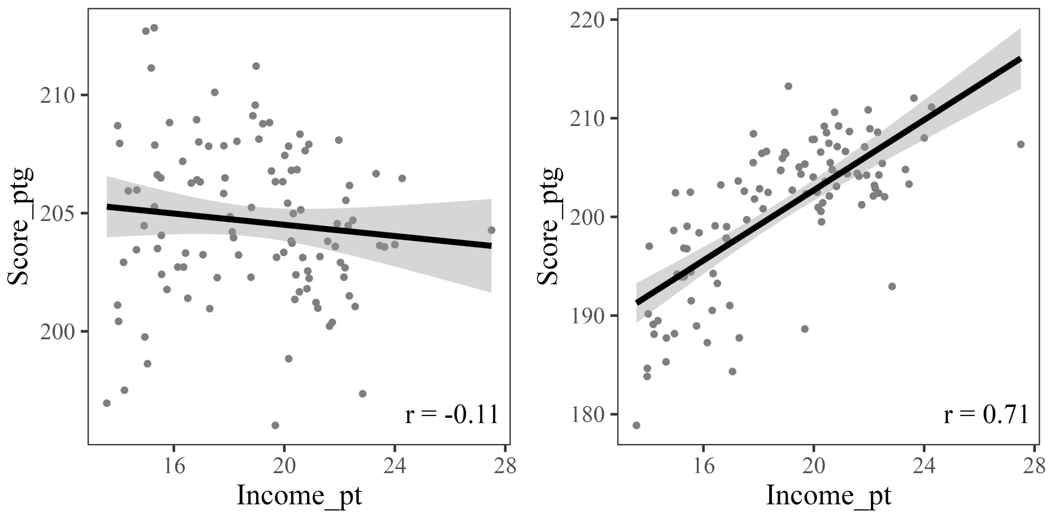

Figure 4: The first diagram shows a scatter plot of income and Italian language test scores of Grade 2 students, the second of Grade 8. Data from 2018.

A comparison of the three tertiles within each grade reveals additional confirmation of such findings. For Grade 2, the trends are irregular: the richest tertile shows a near-zero correlation, the second-richest tertile exhibits a noticeably negative correlation, and the poorest tertile displays a significant increase, with the correlation coefficient raising significantly between the first and last tertiles (Figure 5). In Grade 8, however, the patterns align more closely with the overall trend. While the richest tertile continues to show a correlation coefficient close to zero, the two poorer tertiles exhibit a steady and regular increase in correlation (Figure 6).

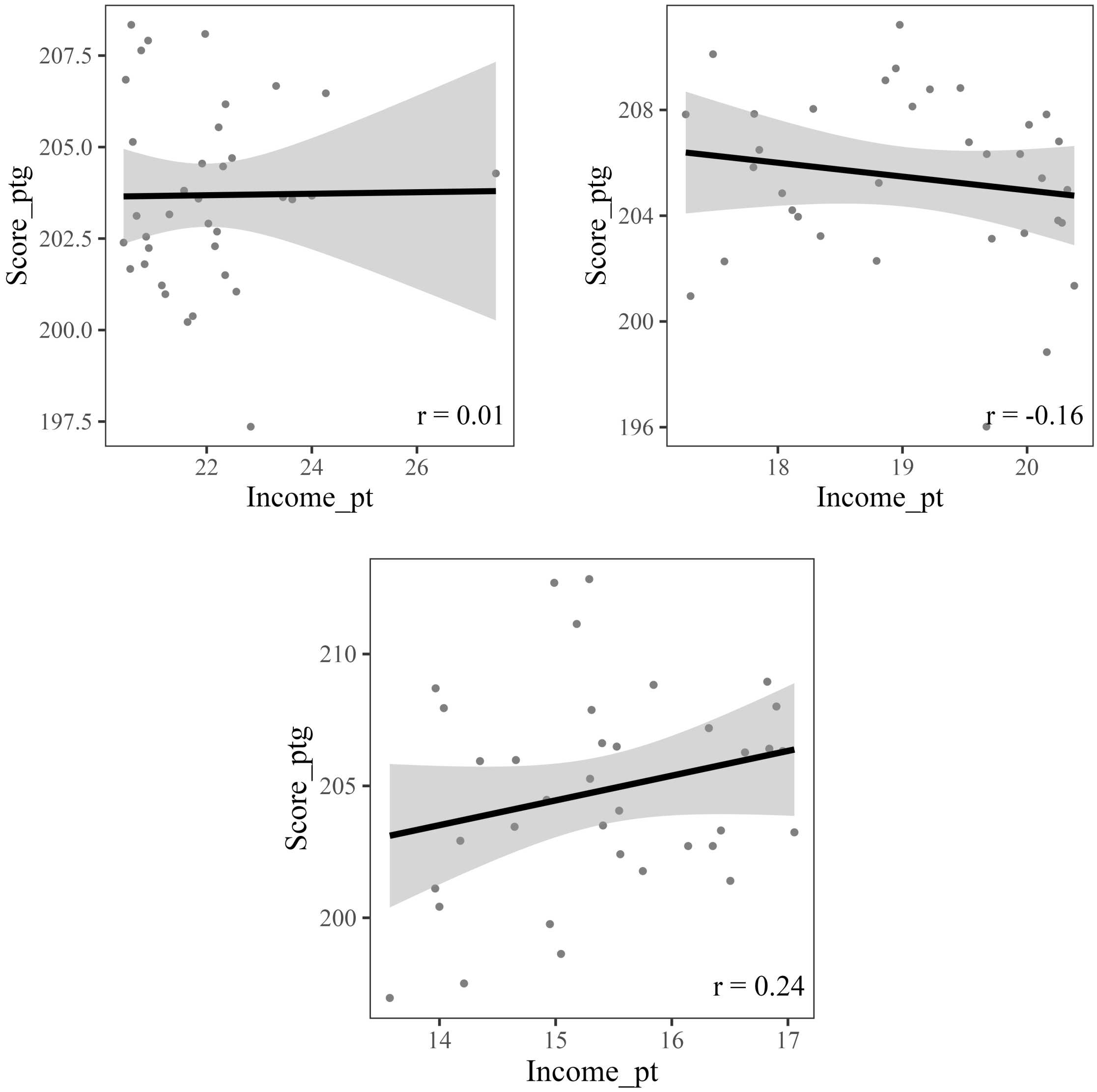

Figure 5: The diagrams show the scatter plots of income and test scores in Grade 2 for the three tertiles. Top: first and second tertiles. Bottom: third tertile. Data from 2018, Italian language test.

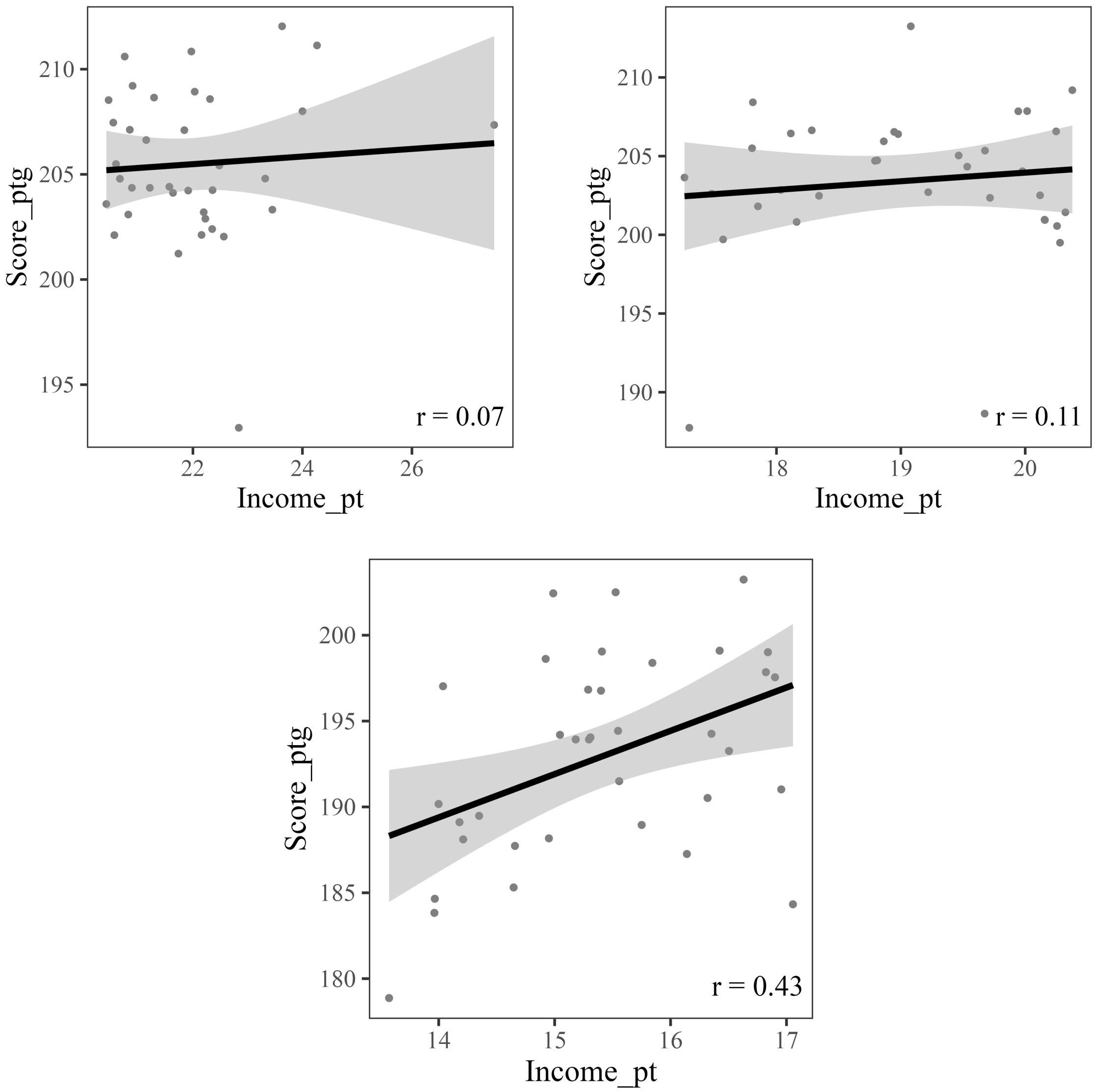

Figure 6: The diagrams show the scatter plots of income and test scores in Grade 8 for the three tertiles. Top: first and second tertiles. Bottom: third tertile. Data from 2018.

These two observations suggest that income has a more significant impact on the performance of older students. The correlation is higher in Grade 8 than in Grade 2, and the trends across the tertiles are more consistent in the higher grade.

3.2 Regression Analysis

The unconditional scatterplot in Figure 3 which examines the correlation between income and test scores, does not reveal a clear relationship between the two variables. In contrast, Figure 5 and Figure 6 suggest a slight increase in correlation between income and test scores in higher grades compared to lower ones, providing a mild indication that income may have a greater impact on older students.

To assess this hypothesis more rigorously, a multivariate regression model has been developed to estimate more precisely the effects of income and other factors on test scores.

3.2.1 Italian language

For Italian language, INVALSI calculates WLE results, which using psychometric methods, provides a composite score that accounts for differences in item difficulty. Socio-economic factors are not considered in the construction of this score. The WLE scores obtained in our sample range between 159 and 224. Income is expressed in thousands of euros.

Lin-Lin Model

The equation used for the estimation of the Lin-Lin model is as follows:

$$Score_{ptg} = \alpha_t + \beta_1 Income_{pt} + \eta_g + \sum_{g=2}^{g} \lambda_g \ Income_{pt} * 1(Grade_g) + \gamma_p + \varepsilon \qquad (1)$$

where t is the index of time, g the index of Grade, and p is the index of provinces.

Results show that the impact of income on test scores is significant. Specifically, an increase in income of €10.000 is associated with a 45-point increase in test scores in Grade 13. To better illustrate the magnitude of this effect, expressing it relative to the median test score of 199 points shows that this corresponds to an approximate 22% increase.

Another set of coefficients yielding significant results is the interaction variable *Income*Grade*. To quantify the effect of an income change across different Grades, we calculate the partial derivative of the Lin-Lin model with respect to income. This derivative is expressed as follows:

$$\frac{\delta \ Score_{ptg}}{\delta \ Income_{pt}} = \beta_1 + \lambda_g Grade_g \qquad (1.2)$$

The eq. (1.2) shows that the effect of a unit change in income is represented by β_1 for the excluded grade, that is Grade 13. For each grade g, the effect is instead calculated as $\beta_1 + \lambda_g$.

Basic algebraic calculations indicate that a €10.000 increase in income corresponds to different increases in test scores across Grades. Specifically, students in Grade 2 gain 16,7 points (8,38% with respect to the median), while those in Grade

5 gain 23,9 points (+12,1%). In Grade 8, the increase is 32,7 points (+16,4%). The effect further increases in grade 10, where students gain 35,8 points (+17,9%).

Table 3: The table shows the Lin-Lin Model results Italian Language.

VARIABLES	**(1)**
Income_pt	4.589***
	(0.320)
Y_2021	5.469***
	(0.388)
Y_2020	12.160***
	(0.508)
Y_2019	13.940***
	(0.468)
Y_2018	10.540***
	(0.480)
Grade_2	71.470***
	(1.760)
Grade_5	54.790***
	(1.768)
Grade_8	33.500***
	(1.749)
Grade_10	26.000***
	(1.847)
IncomeGrade_2	-2.922***
	(0.0910)
IncomeGrade_5	-2.200***

VARIABLES	(1)
	(0.0918)
IncomeGrade_8	-1.319***
	(0.0893)
IncomeGrade_10	-1.008***
	(0.0938)
Constant	71.470***
	(9.258)
Observations	2,461
R-squared	0.829

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Lin-Lin Model

The equation used for the estimation of the Log-Linear model is as follows:

$$\ln\left(Score_{ptg}\right) = \alpha_t + \beta_1 Income_{pt} + \eta_g + \sum_{g=2}^{g} \lambda_g \; Income_{pt} \cdot 1(Grade_g) + \gamma_p + \varepsilon \quad (2)$$

The results of this model align with previous findings, confirming the persistent effect of household income on academic performance. A €10.000 increase in income is associated with a 22,9% increase in test scores in Grade 13, consistent with the earlier model. The interaction terms between income and grade level (*Income*Grade)* yield comparable figures to those previously observed. In particular, a €10.000 increase in household income is linked to a 7,4% increase in test scores for Grade 2 students, 11% for Grade 5, 15,6% for Grade 8, and 17,2% for Grade 10.

Table 4: The table shows the Log-Linear Model results for Italian Language.

VARIABLES	**(1)**
VARIABLES	ln_Score_ptg
Income_pt	0.0229***
	(0.00163)
Y_2021	0.0268***
	(0.00198)
Y_2020	0.0595***
	(0.00259)
Y_2019	0.0695***
	(0.00239)
Y_2018	0.0522***
	(0.00245)
Grade_2	0.377***
	(0.00898)
Grade_5	0.294***
	(0.00902)
Grade_8	0.184***
	(0.00892)
Grade_10	0.144***
	(0.00942)
IncomeGrade_2	-0.0155***
	(0.000464)
IncomeGrade_5	-0.0119***

VARIABLES	(1)
	(0.000468)
IncomeGrade_8	-0.00733***
	(0.000456)
IncomeGrade_10	-0.00567***
	(0.000479)
Constant	4.662***
	(0.0472)
Observations	2,461
R-squared	0.832
Observations	2,461
R-squared	0.829

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Log-Log Model

The equation used for the estimation of the log-log model follows:

$$\ln\left(Score_{ptg}\right) = \alpha_t + \beta_1 \ln(Income_{pt}) + \eta_g + \sum_{g=2}^{g} \lambda_g \; Income_{pt} \cdot 1\left(Grade_g\right) + \gamma_p + \varepsilon \quad (3)$$

This model increases ease of results' interpretation, allowing to see a 1% change in X as b% change in Y.

As regards income, a 1% increase in its value will produce a 0,4% increase in tests' scores for Grade 13's students. Thus, this model suggests a lower impact for income alone. As regards the set of variables *Income*Grade*, effects follow a linear path. For a 1% increase in income, students in Grade 2 earn 0,46% points, students in Grade 5 get 0,47%, students in Grade 8 earn 0,48% more points, 10^{th} graders 0,48%, while Grade 13's students get 0,49% more points.

Table 5: The table shows the Log-Log Model results Italian Language.

VARIABLES	**(1)**
VARIABLES	ln_Score_ptg
ln_Income_pt	0.486***
	(0.0321)
Y_2021	0.0284***
	(0.00197)
Y_2020	0.0622***
	(0.00260)
Y_2019	0.0722***
	(0.00241)
Y_2018	0.0550***
	(0.00247)
Grade_2	0.389***
	(0.00904)
Grade_5	0.306***
	(0.00906)
Grade_8	0.188***
	(0.00889)
Grade_10	0.145***
	(0.00935)
IncomeGrade_2	-0.0161***

VARIABLES	(1)
	(0.000465)
IncomeGrade_5	-0.0125***
	(0.000468)
IncomeGrade_8	-0.00751***
	(0.000454)
IncomeGrade_10	-0.00570***
	(0.000475)
Constant	3.681***
	(0.108)
Observations	2,461
R-squared	0.834

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.2.2 Mathematics

For mathematics, INVALSI does not publish test scores adjusted using WLE correction. As a result, obtained scores range between 162 and 230 points. Income is expressed in thousands of euros.

Lin-Lin Model

As with the Italian language model, eq. (1) is used. A €10.000 increase in income is associated with a 57-point increase in mathematics scores, equivalent to a 29,2% increase relative to the median.

Regarding the interaction terms *Income*Grade*, the effect of income varies substantially across grades. For Grade 2 students, the impact of a €10.000 income increase yields an additional 21 points, or +11,2% relative to the median for Grade 13's. The effect increases steadily with age. In Grade 5, the gain is 29,6 points

(+15,1%); in Grade 8, 49,4 points (+25,2%); and in Grade 10, 51,2 points (+26,4%).

Table 6: The table shows the Lin-Lin Model results for Mathematics.

VARIABLES	**(1)**
	(1)
VARIABLES	Score_ptg
Income_pt	5.728***
	(0.322)
Y_2021	6.382***
	(0.390)
Y_2020	10.93***
	(0.512)
Y_2019	15.85***
	(0.471)
Y_2018	15.30***
	(0.483)
Grade_2	76.30***
	(1.772)
Grade_5	58.98***
	(1.780)
Grade_8	15.75***
	(1.761)
Grade_10	12.12***
	(1.860)
IncomeGrade_2	-3.538***

VARIABLES	**(1)**
	(0.0916)
IncomeGrade_5	-2.764***
	(0.0924)
IncomeGrade_8	-0.782***
	(0.0899)
IncomeGrade_10	-0.553***
	(0.0944)
Constant	45.01***
	(9.321)
Observations	2,461
R-squared	0.848

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Log-Lin Model

As with the Italian language model, eq. (2) is applied. Overall, the results are consistent with previous trends. A €10.000 increase in income is associated with a 28,9% increase in test scores in Grade 13. The interaction terms *Income*Grade* estimates are consistent with previous findings. In Grade 2, a €10.000 increase in income corresponds to an 10,6% increase in scores. Similarly, Grade 5 students show a 14,5%. The trend accentuates in Grade 8, where the increase is equal to 24,8%. In Grade 10, the pattern continues, with a €10.000 increase in income associated to a 25,8% increase in test scores.

Table 7: The table shows the Log-Linear results for Mathematics.

VARIABLES	**(1)**
	(1)
VARIABLES	ln_Score_ptg
Income_pt	0.0289***
	(0.00164)
Y_2021	0.0321***
	(0.00199)
Y_2020	0.0547***
	(0.00261)
Y_2019	0.0796***
	(0.00240)
Y_2018	0.0766***
	(0.00246)
Grade_2	0.394***
	(0.00902)
Grade_5	0.308***
	(0.00906)
Grade_8	0.0833***
	(0.00897)
Grade_10	0.0672***
	(0.00947)
IncomeGrade_2	-0.0183***
	(0.000467)

VARIABLES	**(1)**
IncomeGrade_5	-0.0144***
	(0.000471)
IncomeGrade_8	-0.00409***
	(0.000458)
IncomeGrade_10	-0.00307***
	(0.000481)
Constant	4.518***
	(0.0475)
Observations	2,461
R-squared	0.850

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Log-Log Model

As with the Italian language model, eq. (3) is applied. With regards to income, a 1% increase in earnings is associated with a 0,58% increase in test scores in Grade 13. The interaction terms *Income*Grade* produce results consistent with previous findings. In Grade 2, a 1% increase in income leads to a 0,56% increase in scores. A similar effect is observed in Grade 5, with a 0,57% increase. This trend persists in Grade 8 and in Grade 10, where a 1% income increase corresponds to an 0,58% improvement in scores.

Table 8: The table shows the Log-Log Model results for Mathematics.

VARIABLES	**(1)**
	(1)

VARIABLES	**(1)**
VARIABLES	ln_Score_ptg
ln_Income_pt	0.581***
	(0.0324)
Y_2021	0.0325***
	(0.00198)
Y_2020	0.0558***
	(0.00262)
Y_2019	0.0809***
	(0.00243)
Y_2018	0.0781***
	(0.00250)
Grade_2	0.407***
	(0.00913)
Grade_5	0.321***
	(0.00915)
Grade_8	0.0860***
	(0.00897)
Grade_10	0.0661***
	(0.00944)
IncomeGrade_2	-0.0189***
	(0.000470)
IncomeGrade_5	-0.0151***
	(0.000472)
IncomeGrade_8	-0.00423***

VARIABLES	(1)
	(0.000458)
IncomeGrade_10	-0.00301***
	(0.000479)
Constant	3.392***
	(0.109)
Observations	2,461
R-squared	0.850

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.3 Robustness Checks

Before proceeding to analyse the implications of such results and draw conclusions on their economic implications, it is necessary to make sure that none of the estimates and their standard errors is biased.

To understand whether standard errors are biased or not by heteroskedasticity, a Breusch-Pagan test has been run. This test evaluates whether the variance of the residuals from an OLS regression depends systematically on the explanatory variables (Breusch & Pagan, 1979). It does so by testing the null hypothesis:

H: Homoskedasticity

H: Heteroskedasticity

In this analysis, the Breusch-Pagan test returned a p-value of 0.0179, leading to the rejection of the null hypothesis at 0.05 significance level. Consequently, the suspect on the presence of heteroskedasticity was confirmed.

To assess to which extent this rendered the standard errors inconsistent, a robustness check was conducted by re-estimating the model using heteroskedasticity-robust standard errors. This approach adjusts the standard errors to ensure they remain reliable even when the assumption of constant variance in the error terms does not hold. As is well established in econometric theory, using robust standard errors allows for valid inference without affecting the estimated coefficients themselves (White, 1980) (Stock & Watson, 2015).

As displayed in the tables in *Appendix 1*, the robust standard errors differ only marginally from those produced under the initial OLS specification. In this case, the similarity between robust and conventional standard errors indicates that heteroskedasticity seem to have a negligible effect on inference. Therefore, while robust inference is theoretically required under heteroskedasticity, the results indicate that has little impact on the conclusions drawn from this analysis.

Another potential threat to the robustness of the results may come from the presence of outliers. To assess whether any observations have a strong influence on the estimates, an analysis based on Cook's distance and standardized residuals was conducted (Mendenhall & Sincich, 2012). Observations with standardized residuals greater than 3 were considered outliers. As shown Figure 7 and Figure 8, a small number of provinces (four in the case of Italian Language and four for Mathematics) were identified as particularly influential.

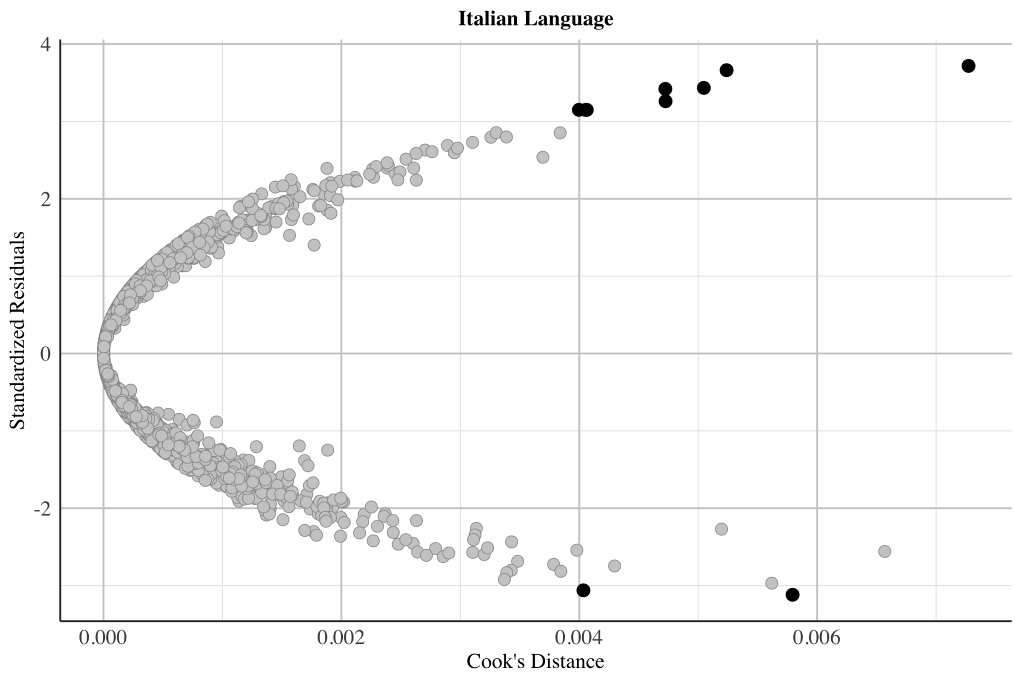

Figure 7: The graph plots Cook's distance and the standardized residuals for *Italian Language*. The values correspond to the income value of the outlier observation.

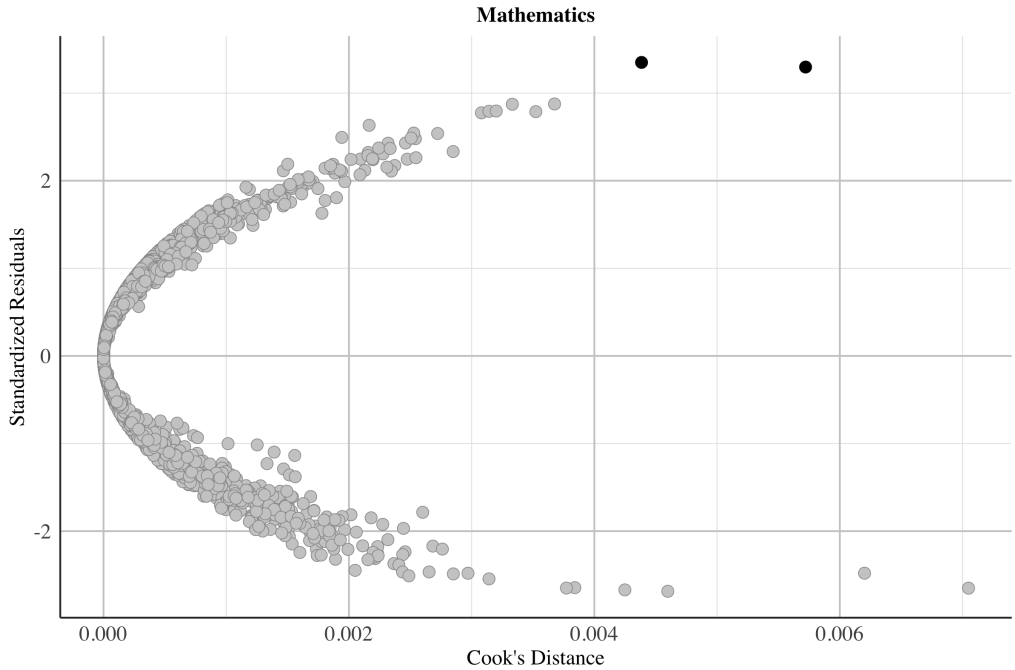

Figure 8: The graph plots Cook's distance and the standardized residuals for *Mathematics*. The values correspond to the income value of the outlier observation.

These cases were temporarily excluded, and the regression models were re-estimated. The results showed no important changes in the estimated coefficients or their statistical significance, suggesting that the overall findings remain robust. A full description of the analysis and the updated models is available in *Appendix 2*

3.4 Limitations

While the robustness checks and outlier analysis ultimately indicated that none of the identified data issues had a significant effect on the significance of the estimates, it is important to acknowledge the presence of additional factors that may influence the results, either by introducing bias into the errors estimates or by omitting variables relevant to the economic and policy interpretation of the findings.

First, a concern typical of panel data analysis is the presence of autocorrelation in the error terms (Stock & Watson, 2015). To assess this issue, the Wooldridge test for autocorrelation in panel data (Wooldridge, 2002) has been conducted, with the results presented in table 9.

Table 9: The table summarises the results of the Wooldridge test conducted on the Italian Language data.

Test	F_statistic	p_value	Alternative
Wooldridge Test for Autocorrelation in Panel Data	148.973	0.0001	Serial correlation

The Wooldridge test confirms the presence of autocorrelation, supporting the alternative hypothesis. This result is expected given the structure of the dataset, which comprises repeated observations for each province over five consecutive years. Most independent variables, particularly provincial income, exhibit little to no variation over time, as income values remain practically constant for each province across all years and grades. The province fixed effect dummies, which are identically repeated throughout the dataset, represent time invariant characteristics such as teacher quality, infrastructure or average educational attainment, factors that plausibly remain stable over the observed period. However, such a persistence of unmeasured factors within provinces, generate error terms that are correlated over time. As Stock and Watson (2015) emphasize, such serial dependence violates the assumption of independently distributed error terms, so the usual OLS standard errors may be biased and overstate the precision of the estimates. This autocorrelation therefore represents a limitation of the analysis: although it does not affect the point estimates themselves, any inference about coefficient significance based on those standard errors should be treated with caution.

A second major limitation of this analysis arises from the omission of a variable capturing the impact of parental education on student's test outcomes. A substantial body of literature has consistently highlighted the significance of parental education as a key predictor of children's academic attainment. Eccles (2005) reviews several influential studies on the topic, identifying a range of mechanisms through which parental education influences educational outcomes. These include associations between parental education and the socioeconomic context, such as the quality of neighbourhoods families can afford to live in, which in turn affects children's access to resources and their psychological development. Longitudinal evidence from Dubow et al., (2009) confirms that the influence of parental education can persist for decades, with effects on children's outcomes observed up to 40 years after the original measurement. Chevalier et al., (2013) in an attempt to identify a causal relationship, find that the effect of parental education on student outcomes remains significant even after controlling for household income. Dickson et al., (2016) exploit a 1972 policy reform in England that increased the compulsory school-leaving age. Their analysis shows that children whose parents were affected by the reform perform approximately 0.1 standard deviations better on standardized assessments than children whose parents were not.

Given this robust evidence, the omission of parental education from the present analysis represents a notable limitation for the economic and policy suggestions, as it excludes a factor widely recognized as significantly impacting students' academic achievements.

Section IV
Discussion

4.1 Results Discussion

Overall, the results indicate a significant and consistent effect of income on test scores across both subjects and all model specifications, with the impact increasing progressively across school grades. Notably, the effect of income appears stronger in mathematics, as clearly illustrated in Figure 9 and Figure 10. This pattern is consistent with a substantial body of existing literature. For example, Workman (2021) using a 27-year dataset from the United States, found that students from states with higher income inequality demonstrated lower average achievement in mathematics, whereas reading performance remained unaffected. Similarly, a 2023 report on the impact of the pandemic on educational outcomes in England found that, by Spring 2022, reading scores had largely recovered across most year groups, while mathematics scores remained significantly below pre-pandemic levels (Education Policy Institute, 2023). This divergence in recovery trends, taken together with the findings of Svraka & Ádám (2024) on the impact of SES on learning abilities, supports the view that socio-economic status plays a critical role in shaping student mathematical outcomes. Indeed, the family socio-economic status appears to be a strong predictor of success expectancy in mathematics (Haataja, Niemivirta, Holm, Ilomanni, & Laine , 2024).

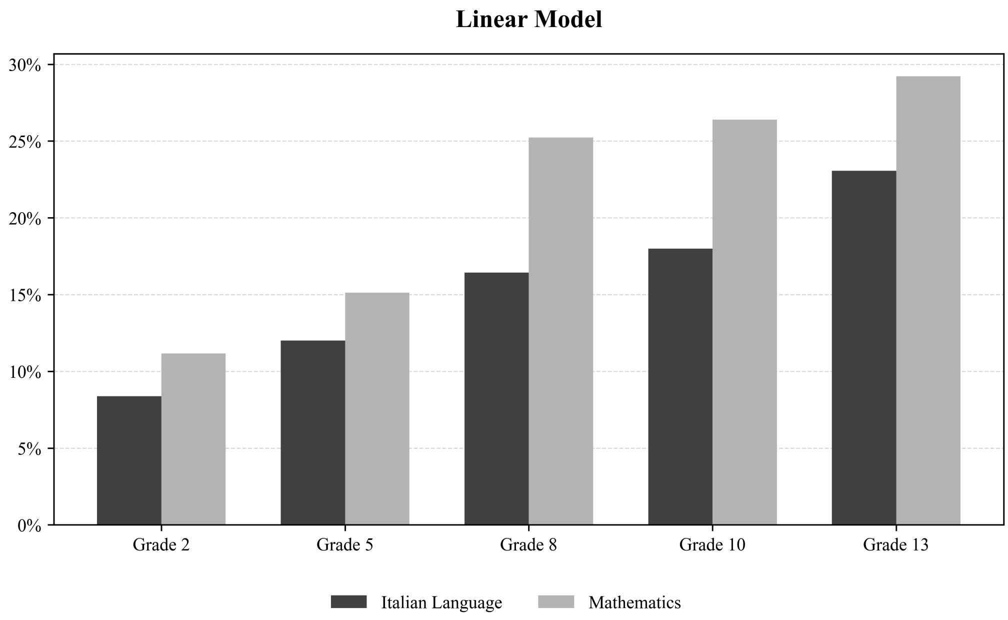

Figure 9: The graph shows the trend of the impact of income on test scores overall and by school grade, across the three regression models for *Italian Language*.

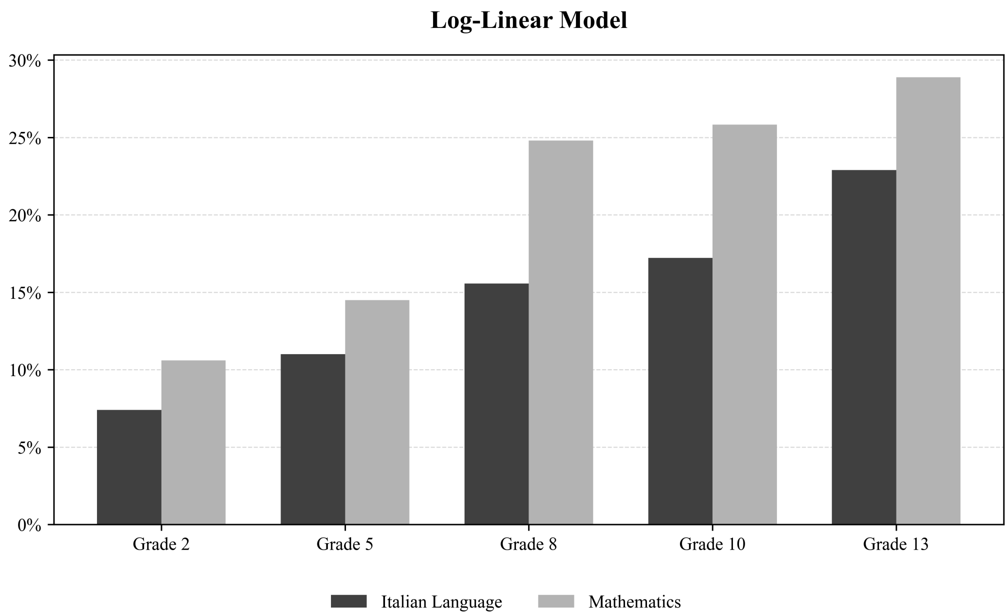

Figure 10: The graph shows the trend of the impact of income on test scores overall and by school grade, across the three regression models for *Mathematics*.

These findings are particularly alarming considering mathematics' growing importance across modern economies and societies. Socioeconomic disparities in this foundational discipline are likely to foster the advantages enjoyed by students from higher-income families, making it more difficult for their lower-income peers to close the achievement gap and access comparable academic and career opportunities in today's economy. As a matter of fact, plenty for scholars advocate for the growing importance of STEM subjects. Kelley & Knowles (2016) stress the need for a more structured and rigorous mathematics and science curriculum to meet modern demands. Tosto et al. (2016) argue that mathematics is not only essential for individual progress but also for economic growth, as even modest improvements in performance can lead to measurable increases in national GDP per capita. Moreover, mathematical skills are closely tied to socio-economic outcomes, playing an important role beyond formal education. Longitudinal studies in the UK show that individuals with low numeracy are more than twice as likely to end up in low-status jobs and face a higher risk of poor mental and physical health (Bynner & Parsons, 2005).

Therefore, the stronger influence of income on mathematics achievement should be a serious concern for policymakers, especially considering the increasing importance of scientific and quantitative skills in today's economy.

Another interesting trend is to be found in the significant difference in impact that income has between the first education cycle (that is, until Grade 5) and from Grade 8 onwards. Specifically, household income appears to yield an average score increase of 12,8% during primary school, while from Grade 8 this impact surpasses 25%. This finding suggests that in primary school income-related differences are less pronounced than in higher grades. This trend of growing impact of income with grade finds confirmation also in other countries. A study by Sandsør et al. (2023) on Norwegian students found that achievement gaps based on parental income widened significantly between 5th and 10th grade. In particular, the gap increased by approximately 10 percentage points from Grade 5 to Grade 8, with a similar increase observed by Grade 10, in line with OECD projections. Moreover, the Norwegian findings reveal a consistent difference across subjects: gaps linked to family income are more pronounced in mathematics than in reading. This holds true both in Grade 5 and in Grade 10's GPA, with the gap amounting to roughly 8% of a standard deviation in each case. These results thus reflect a similar trend to that observed in the Italian data.

Such results shed a positive light on the Italian primary school system. According to the OECD, two-thirds of the achievement gaps observed at age 15 (through the PISA test) and more than half of the gaps found among 25–29-year-olds (PIAAC programme) was already present by age 10. This suggests that socio-economic disparities in educational outcomes begin to emerge relatively early, already by the end of primary education (OECD, 2018). Thus, less pronounced differences at early stages of education may represent a step forward towards a more equal system.

The evidence on the widening disparities for older students is unsurprising given the disparity in per-child spending between the first and second educational cycles. As illustrated in Figure 2, Italian government expenditure on pre-primary school pupils is 47% higher than the OECD average, and spending on primary school pupils is 13% higher. In contrast, secondary school students receive, on average, 13% less funding than their counterparts in other OECD countries. These findings are particularly concerning given the crucial role of educational equity in reducing social disparities at that key stage in education (OECD, 2018). The 2018 PISA report highlights that students' academic performance at age 15 (typically in Grade 10) is strongly associated with outcomes in early adulthood. Specifically, students who score in the top quartile on the PISA assessment are up to 53% more likely to complete university compared to those in the bottom quartile. Moreover, performance at this stage is also linked to future labour market outcomes: students in the top quartile of reading achievement are significantly more likely to be employed in roles requiring tertiary education by the age of 25, compared to their peers in the bottom quartile (OECD, 2018). The substantial rise in income's influence during Grade 10 is thus alarming. In the short term, this affects fairness in education and raises the risk of dropout among students from poorer backgrounds (Lee & Burkam, 2003). In the long term, these differences result in increased risk of economic hardship, consequently limiting social mobility, as the effects of early educational inequality often continue into adulthood (Campbell, 2015). The growing impact of income in Grade 13 underlines an even more alarming trend. Longitudinal studies in the United States have shown that participation in Advanced Placement (AP) and other college-preparatory programs in high school senior year is a strong predictor of both college enrolment and degree completion (Adelman, 2006) and is also associated with higher earnings in early adulthood (Jackson, 2012). Because family income greatly influences both enrolment in and performance on AP courses (Owen, 2025) (Kim-Christian & McDermott, 2022), the growing income-related gap in Grade 13 is likely to lead to larger differences in university success and foster social inequalities over time.

The evidence regarding the widening disparities among older students becomes even more concerning when dropout rates are included in the analysis. Previous research on the relationship between test scores and dropout rates has shown that Italian regions with the lowest test scores also tend to exhibit higher dropout rates, suggesting a correlation between academic performance and early school leaving

(Vegliante, Pellecchia, Miranda, & Marzano, 2024). This finding is further supported by the present analysis Figure 11 and Figure 12 illustrate the distribution of Grade 10 scores and dropout rates across Italian regions in 2022. The maps clearly demonstrate that regions with higher test scores in Grade 10 generally experience lower dropout rates, and vice versa. Additional support for this correlation comes from a micro-level study conducted by Vandellen et al. (2012) in North Carolina, which found that the pattern holds at the school level, with higher-achieving schools showing lower dropout rates.

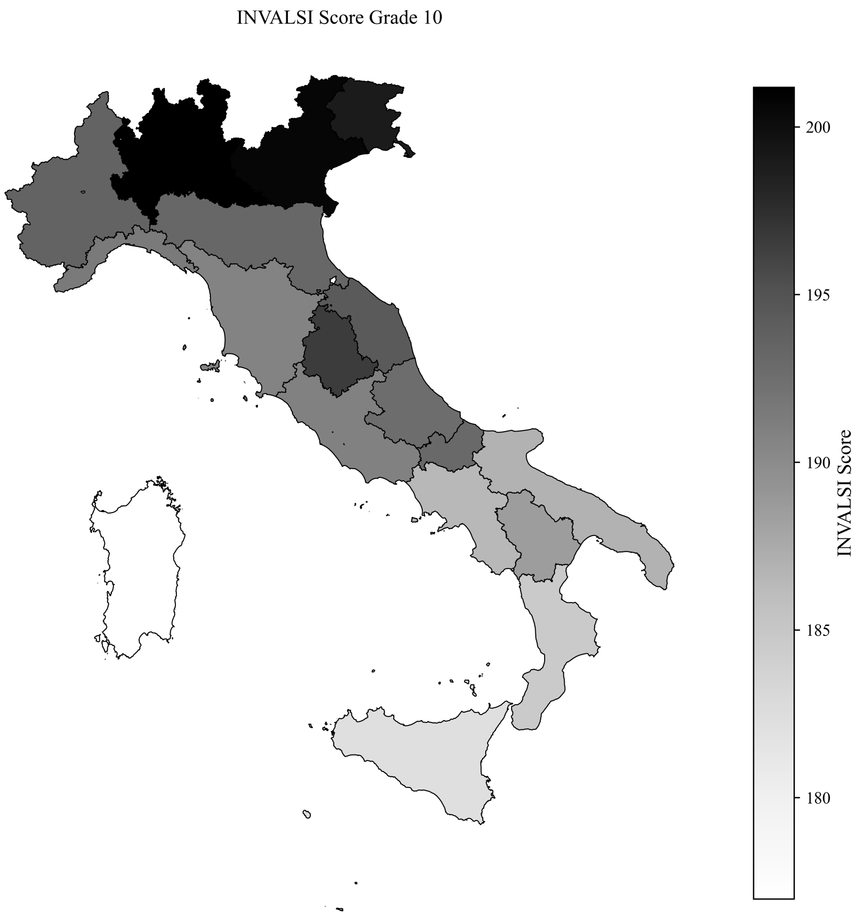

Figure 11: The map shows the INVALSI scores obtained by Grade 10 students in 2022. Data are presented on a regional basis.

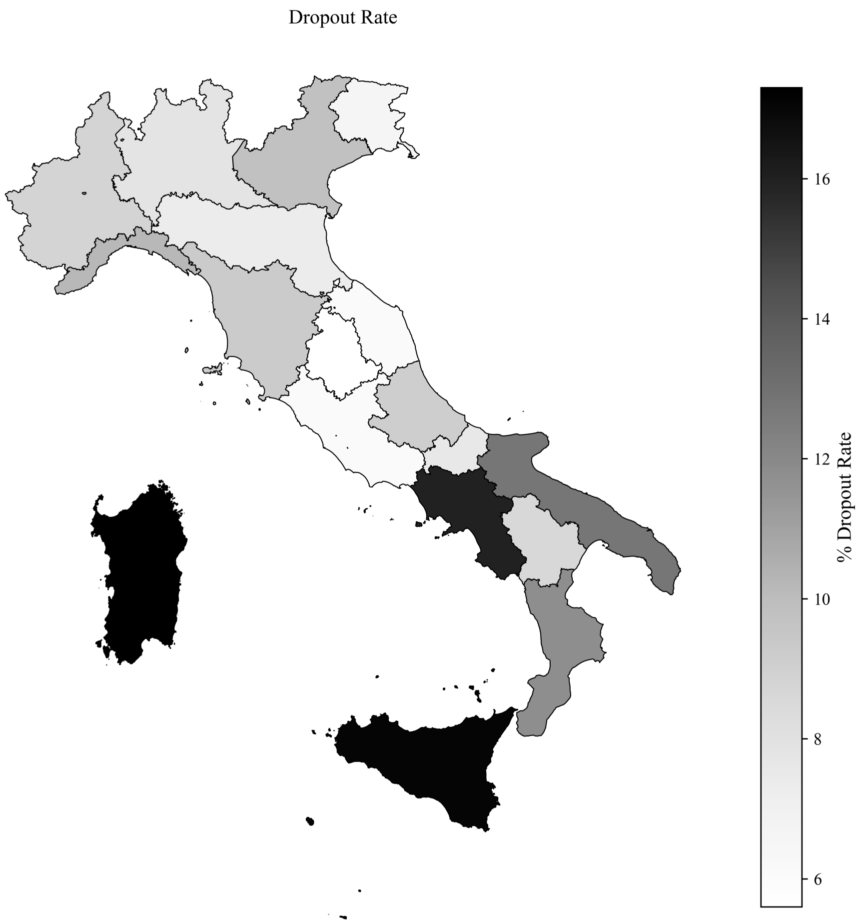

Figure 12: The map shows the drop-out rates in 2022. Data are presented on a regional basis.

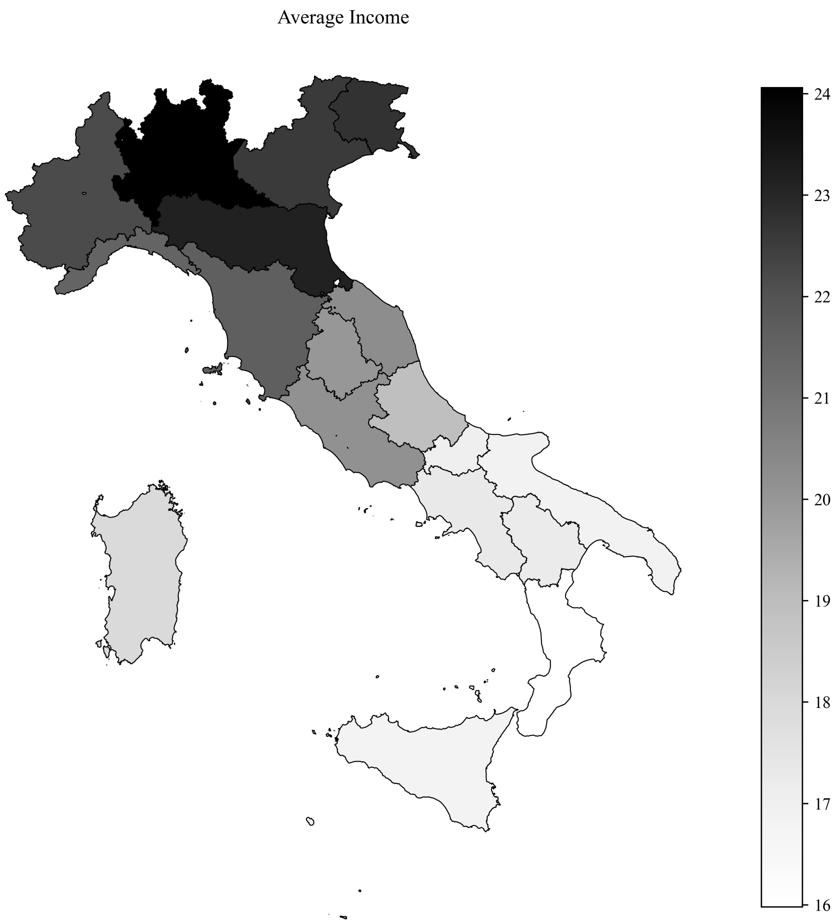

Figure 13: The map shows the average income in 2022. Data are presented on a regional basis.

If INVALSI scores in Grade 10 were distributed independently of income, this evidence would not only be expected but also relatively less problematic. Unfortunately, this is not the case. Figure 13 shows the distribution of income across the Italian regions. It is clear that income is unevenly distributed, with northern regions, which also exhibit higher Grade 10 test scores and lower dropout rates, corresponding to higher income levels. This confirms the correlation not only between income and test scores but also between income and dropout rates. This observation is supported by extensive literature, which indicates that early school leaving is primarily a reflection of parents' socio-economic status (The National Center for Education Statistics, 2018) (Mocetti, 2010).

The trend remains unchanged in Grade 13, despite low-performing students have dropped out. Prior research has indeed shown that the presence of such students can substantially lower the overall cognitive performance of a cohort. A study by

Lavy et al. (2012) found that a 10 percentile decrease in the proportion of 'low-performing' peers in school is associated with an improvement of approximately 10-11% of the standard deviation in the within-pupil attainment level distribution for both boys and girls in secondary school. Consequently, it would be expected that dropouts occurring before Grade 13 would lead to improved performance within the cohorts. Unfortunately, evidence does not support this statement in the Italian context. Figure 14 provides further evidence of this claim. With the exception of Sardinia, regions with higher dropout rates also exhibit the largest disparities in scores between Grade 10 and Grade 13.

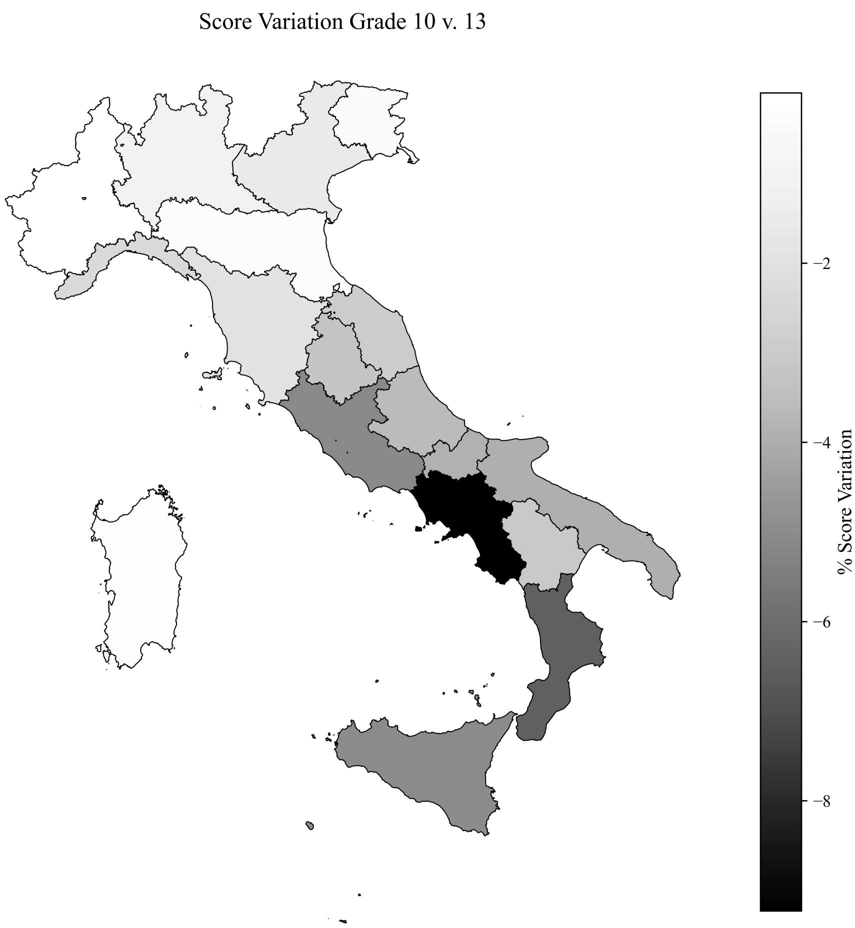

Figure 14: The map shows the difference in scores obtained by students who attended Grade 10 in 2019 and, consequently, Grade 13 in 2022. Data are presented on a regional basis.

While the map shows that all the regions seem to show a decrease in scores in Grade 13, it is evident how regions with the lowest incomes are also the ones with the largest points losses between the two grades. Indeed, once the measure has been adjusted for dropouts, the difference in results attainments between richer and poorer do not show signs of alleviating. It is therefore evident that any potential improvement resulting from the dropout of low-performing students is largely outweighed by the more substantial, long-term effects of income-based inequality. This confirms that income disparities not only increase the likelihood of dropout among low-performing students but also continue to negatively affect higher-achieving students from disadvantaged backgrounds. To illustrate this point, consider a student from a low-income household who performs well enough throughout their school career to remain in education beyond Grade 10, valuing three additional years of schooling over entering employment at an earlier age. Despite this commitment, the student is still likely to perform significantly worse than peers from wealthier families, with the adverse impact of income becoming even more pronounced by the final year of high school compared to Grade 10.

Such trend finds confirmation in an extensive study conducted in the US by Wyner et al. (2007). The report shows that high achieving students from lower income backgrounds are significantly less likely to remain high achievers during their academic career, despite being almost as likely to drop out as wealthier peers (Renzulli & Park, 2000). Specifically, among students who begin high school in the top quartile for math achievement, 28% of those from the lowest-income backgrounds drop out of that top tier by graduation, compared to just 14% of their wealthiest peers. Conversely, while 12% of students from the highest income quartile manage to move up into the top quartile by the end of high school, only 3% of students from the lowest income quartile do the same.

These figures highlight a persistent inequality: students from wealthier backgrounds are far more likely to complete high school with strong academic results, regardless of whether they started as high achievers. In contrast, students from disadvantaged backgrounds, even those who begin as top performers, face a much greater risk of falling behind, suggesting that socioeconomic status continues to have a powerful and penalizing impact on educational outcomes.

These findings reveal a deeply concerning reality: in Italy, educational success remains closely linked to socioeconomic background, threatening the principle of equal opportunity. Even high-achieving students, if coming from low-income families, face significant structural barriers to maintaining their performance, highlighting an urgent need for policies that address not only access to education, but also the conditions that enable students to succeed regardless of their economic circumstances.

4.2 Policy Implications

The analysis as a whole confirmed the growing impact of income disparities on students achievement by grade for Italian students. Such inequality can be partially explained by the funding disparities presented above. Substantial government funding for primary school students helps to slightly alleviate the impact of household income disparities. However, for secondary school students, limited public spending per pupil makes income-related differences more apparent in academic performances. Studying US low-performing districts, Lafortune et al. (2018) found that increased spending improved the absolute and relative achievement of students in low-income districts. Furthermore, low academic performance is considered a key factor contributing to high drop-out rates (Vandellen, Dodge, Bonneau, & Glennie, 2012) (Vegliante, et al., 2024), and Italy is one of the worst-performing countries in Europe in terms of early school leaving, 3 percentage points above the EU average (European Commission, 2024). Therefore, the effects of limited public spending for older students may not be limited only to lower performances, but also to increased chances of early school abandonment. However, an extensive review by Rumberger & Lim (2008) showed that students' decisions to drop out before graduation are influenced by multiple factors, with no single cause fully explaining this decision. While students report various reasons for leaving school, research similarly highlights several influecing elements. The decision to drop out is shaped by both in-school and out-of-school experiences. Although academic performance and behaviour within the school environment are critical, activities beyond the classroom, particularly those involving deviant or criminal behaviour, also play a significant role. Additionally, dropping out tends to be a gradual process rather than a sudden event, often beginning in early elementary school. Longitudinal studies tracking students from early education to high school completion have identified early academic performance and social behaviour as reliable predictors of dropout risk. Finally, contextual factors such as family, school, and community resources, both material and social, significantly impact the likelihood of graduating. Supportive relationships across these environments are especially critical in determining students' educational outcomes.

As such, while it is likely that performances become more unequal in higher grades due to decreased public spending per pupil, it is not possible to establish a clear relationship between the level of public spending on education and early school leaving. Some factors, such as demotivation, play a much more significant role than socio-economic status in influencing such a decision (Sacco & Le Rose , 2022). Therefore, public spending alone should not be viewed as the sole factor which can contribute to reduce the differences in educational attainment across income groups.

A further impactful factor, which is often overlooked in current literature, is the structural difference in allocation of learning time between the first and second education cycles. In elementary school, all assignments are completed in class: teachers provide students with all the necessary materials, and children spend longer hours at school. The amount of homework, specifically individual study and research outside of school, is minimal. However, from Grade 6 onward, this pattern begins to change. Teachers focus on teaching the key aspects of each subject, but most of the work is now carried out at home. Students must rely on their own resources to study, to deepen their understanding, and to engage with the material. As a result, students from higher-income and more educated families have access to more resources than their lower-income peers from less-educated backgrounds. Consequently, from this point on, the impact of income and parents' education becomes crucial to a student's development. Thus, a non-negligible impact on results should be ascribed to the differences in learning time between the first and second instruction cycles. Bovini et al. (2016) provided evidence that the amount of time students spend learning at school affects their test results. In their analysis of the Italian primary school system, they found that a longer time spent at school would raise the first decile of mathematics test scores. Furthermore, they showed that effects are stronger in fifth than in second grade, suggesting a growing importance of such term with age. This suggests that the problem is of a more structural nature: curricula are so extensive that the learning time allocated in schools covers only a small portion of the required content. Longer school days have been found to narrow the gap between low and high social-economic status students in several ways. Fischer et al. (2014) found that all-day schools in Germany could not only help with homework, but also in providing access to a broad range of extracurricular activities, eventually reducing social inequalities.

Therefore, simply increasing overall public spending on the education system may not be an effective strategy for addressing educational inequality: either expenditure is increased up to the point where high school students' time in school is doubled, or there will always be significant differences between pupils.

Given the differences in disparities over different school grades in Italy, an approach potentially more effective could be to provide targeted subsidies or grants, particularly for students from Grade 8 onward coming from disadvantaged backgrounds. A positive example of such an initiative is the EMA (Education Maintenance Allowance) program introduced in England in 1999. As a study found, in the first year, full-time education participation rates increase by around 4.5 percentage points while the proportion receiving two years of education increases by around 6.7 percentage points (Dearden et al., 2005). Additional evidence of the positive impact of similar initiatives has been observed in Australia, where the AUSTUDY programme has significantly increased participation rates among students from low-income backgrounds in Years 11 and 12 (Daerden & Heat, 1996). Solutions developed in growing economies, such as Mexico or Columbia, have been designed to target both the direct costs of attending school and the opportunity costs of studying (Rawlings & Rubio, 2005). The Colombian programme in particular, allocates twice the amount of funding to secondary school students compared to primary school students (Attanasio, et al., 2006), recognising the higher dropout risk related to increased working opportunities. While comparing Italy with countries still often classified as developing economies, such as Mexico or Colombia, may seem debatable, the data suggest notable similarities in terms of student enrolment and dropout rates. In Italy, 90% of students attend public upper secondary schools, and the drop-out rate among them was 11.5% in 2022 (OECD, 2022) (OpenPolis, 2024). In Mexico, for 85% of students enrolled in public upper secondary education institutions the drop-out rate was 8.7% (OECD, 2022) (Gobierno de Mexico, 2024). These figures indicate similarities in education system with such economies, specifically in certain Italian regions with particularly high dropout rates, such as Sicily (17.3%) and Sardinia (17.1%) (OpenPolis, 2024), where education may carry an opportunity cost that is too high for many students to bear. In such contexts, targeted subsidies could represent a crucial measure to reduce school abandonment and, by extension, address broader social inequalities.

Nevertheless, while these initiatives are highly effective in increasing access to more comprehensive educational opportunities for students, their impact on test scores has generally been found to be minimal at best (Baird, Ferreira, Özler, & Woolcock, 2014). Thus, while participation rates might be increased, part of the alleged structural issue remains, highlighting the need for further studies on the matter.

Section V
Conclusions and Further Studies

5.1 Conclusions

In summary, this research contributes to the body of literature proving the importance of household income on students' test results, specifically analysing the Italian case. An accent is posited on the growing importance of such factor with school grade, calling for urgent further research to thoroughly identify the reasons behind this trend. Finally, policy suggestions have been elaborated based on other countries' experiments.

The analysis of the impact of income on educational outcomes revealed several important findings regarding its role across different educational stages and subjects. Overall, income has a significant correlation with student performance, with limited intra-model variations and increased impact with school grade. While the correlation is overall strong, its magnitude varies depending on the subject analysed. For example, the increase in test scores linked to income is more evident in Mathematics than in Italian language.

When examining the relationship between income and academic performance in conjunction with students' grade, a consistent pattern emerges. Income has a relatively smaller degree of correlation with scores during primary school. This finding aligns with research indicating that socio-economic disparities tend to show an increased impact on educational outcomes by the end of primary education. Indeed, as students' progress into lower secondary school, the link between income and scores becomes increasingly significant, particularly in later grades, where a €10.000 increase in income leads to notable rise in scores. This pattern suggests that the disparity in income-related academic performance begins to widen as students advance through their education, reflecting an accumulation of advantages or disadvantages linked to household income.

This trend is further exacerbated by disparities in public funding between primary and secondary education. In some educational systems, there is significantly higher public spending on primary school pupils compared to secondary school students, which helps reduce the impact of socio-economic disparities at the elementary level. However, once students reach secondary school, these funding gaps become more visible, contributing to widening achievement gaps as income becomes a more influential factor in academic performance.

The correlation of scores with income appears to further increase in the final stages of secondary education, particularly in Grade 13, despite the adjustment of the cohorts for dropouts. This aligns with research that analyses the academic performance of students from lower SES, indicating that high achieving students from more disadvantaged backgrounds are much less likely to remain high achievers along all their academic career.

One of the most significant findings is that increasing public spending on education alone is unlikely to fully address the issue of educational inequality. Although higher spending has been shown to improve outcomes for low-income students, it does not resolve the structural factors contributing to educational disparities. An important issue is the shift in the nature of learning responsibilities between primary and secondary school, with the latter requiring more independent study. This shift disproportionately affects students from lower-income families, who may lack the resources necessary for thorough independent learning.

Given these findings, a more targeted approach is recommended to reduce educational inequalities, particularly for students in secondary school. Programs designed to provide financial support to low-income students, such as those implemented in other countries, have shown promise in increasing educational participation and reducing dropout rates. Targeted subsidies or grants for students from disadvantaged backgrounds, especially in the later grades, could help address part of these disparities and improve educational outcomes. While such initiatives have proven effective in increasing access to education, their impact on test scores is more limited, suggesting that further interventions may be needed to address the underlying structural challenges in the education system.

To conclude, this research highlights the growing correlation between income and scores as students progress through school, especially in mathematics and in later grades. While increased public spending and targeted subsidies may offer partial solutions, addressing deeper structural issues, such as unequal access to learning resources, remains essential. Further research is thus needed to analyse more deeply the system and its weaknesses, in order to find solutions to ensure all students can fully develop, providing a fair and comprehensive education at all levels, and fostering equal opportunities for everyone.

5.2 Further Studies

The results of this analysis raise further questions on the matter. The new perspective on the importance of the interaction between income and grade may be deeply relevant for further studies on the impact of other socio-economic factors on the performances. In Italy, the main difference between elementary and high school is the amount of individual study required. While in elementary school most learning takes place during school hours, in high school more than 50% of learning occurs through individual study. As a result, the influence of income and parents' education becomes crucial for older students' development. Therefore, it would be interesting to examine how varying amounts of individual study impact students from different income backgrounds. To answer this question, a viable solution might be to adopt a comparative perspective. Therefore, it is advisable to select a sample of countries that differ in their levels of educational equality and allocation of learning time. If the hypothesis regarding the impact of learning time is confirmed, a detailed analysis should be conducted on the characteristics of each country's educational system. Specifically, the following questions should be answered: How is learning time allocated? How is this allocation funded? What are the outcomes in terms of student performance on standardized tests and reductions in dropout rates? A thorough analysis of these issues, providing clear answers to these questions, would serve as a useful tool for policymakers. Any contribution to improving educational equity is a step toward shaping a better future for children, the most vital hope for the future of our world.

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Appendix 1

Table 10: The Table presents the results of the Lin-Lin model using Robust Standard Errors for Italian Language.

VARIABLES	**(1)**
	(1)
VARIABLES	Score_ptg
Income_pt	4.589***
	(0.329)
Y_2021	5.469***
	(0.366)
Y_2020	12.16***
	(0.544)
Y_2019	13.94***
	(0.458)
Y_2018	10.54***
	(0.467)
Grade_2	71.47***
	(2.333)
Grade_5	54.79***
	(2.131)
Grade_8	33.50***
	(2.096)
Grade_10	26.00***
	(2.192)

VARIABLES	(1)
IncomeGrade_2	-2.922***
	(0.121)
IncomeGrade_5	-2.200***
	(0.111)
IncomeGrade_8	-1.319***
	(0.107)
IncomeGrade_10	-1.008***
	(0.113)
Constant	71.47***
	(9.499)
Observations	2,461
R-squared	0.829

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11: The Table presents the results of the Log-Linear model using Robust Standard Errors for Italian Language.

VARIABLES	(1)
	(1)
VARIABLES	ln_Score_ptg
Income_pt	0.0229***

VARIABLES	(1)
	(0.00167)
Y_2021	0.0268***
	(0.00187)
Y_2020	0.0595***
	(0.00274)
Y_2019	0.0695***
	(0.00233)
Y_2018	0.0522***
	(0.00236)
Grade_2	0.377***
	(0.0123)
Grade_5	0.294***
	(0.0114)
Grade_8	0.184***
	(0.0112)
Grade_10	0.144***
	(0.0117)
IncomeGrade_2	-0.0155***
	(0.000635)
IncomeGrade_5	-0.0119***
	(0.000591)
IncomeGrade_8	-0.00733***
	(0.000570)
IncomeGrade_10	-0.00567***
	(0.000597)

VARIABLES	(1)
Constant	4.662***
	(0.0482)
Observations	2,461
R-squared	0.832

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12: The Table presents the results of the Log-Log model using Robust Standard Errors for Italian Language.

VARIABLES	(1)
	(1)
VARIABLES	ln_Score_ptg
ln_Income_pt	0.486***
	(0.0330)
Y_2021	0.0284***
	(0.00183)
Y_2020	0.0622***
	(0.00268)
Y_2019	0.0722***
	(0.00233)
Y_2018	0.0550***

VARIABLES	(1)
	(0.00236)
Grade_2	0.389***
	(0.0125)
Grade_5	0.306***
	(0.0116)
Grade_8	0.188***
	(0.0112)
Grade_10	0.145***
	(0.0116)
IncomeGrade_2	-0.0161***
	(0.000639)
IncomeGrade_5	-0.0125***
	(0.000593)
IncomeGrade_8	-0.00751***
	(0.000568)
IncomeGrade_10	-0.00570***
	(0.000588)
Constant	3.681***
	(0.111)
Observations	2,461
R-squared	0.834

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13: The Table presents the results of the Lin-Lin model using Robust Standard Errors for Mathematics.

VARIABLES	**(1)**
	(1)
VARIABLES	Score_ptg
Income_pt	5.728***
	(0.337)
Y_2021	6.382***
	(0.383)
Y_2020	10.93***
	(0.559)
Y_2019	15.85***
	(0.477)
Y_2018	15.30***
	(0.510)
Grade_2	76.30***
	(2.453)
Grade_5	58.98***
	(2.170)
Grade_8	15.75***
	(2.015)
Grade_10	12.12***
	(2.261)
IncomeGrade_2	-3.538***
	(0.128)

VARIABLES	(1)
IncomeGrade_5	-2.764***
	(0.113)
IncomeGrade_8	-0.782***
	(0.103)
IncomeGrade_10	-0.553***
	(0.116)
Constant	45.01***
	(9.731)
Observations	2,461
R-squared	0.848

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 14: The Table presents the results of the Log-Linear model using Robust Standard Errors for Mathematics.

VARIABLES	(1)
	(1)
VARIABLES	ln_Score_ptg
Income_pt	0.0289***
	(0.00172)
Y_2021	0.0321***

VARIABLES	(1)
	(0.00196)
Y_2020	0.0547***
	(0.00284)
Y_2019	0.0796***
	(0.00243)
Y_2018	0.0766***
	(0.00260)
Grade_2	0.394***
	(0.0127)
Grade_5	0.308***
	(0.0114)
Grade_8	0.0833***
	(0.0107)
Grade_10	0.0672***
	(0.0118)
IncomeGrade_2	-0.0183***
	(0.000660)
IncomeGrade_5	-0.0144***
	(0.000591)
IncomeGrade_8	-0.00409***
	(0.000544)
IncomeGrade_10	-0.00307***
	(0.000603)
Constant	4.518***
	(0.0495)

VARIABLES	(1)
Observations	2,461
R-squared	0.850

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 15: The Table presents the results of the Log-Log model using Robust Standard Errors for Mathematics.

VARIABLES	(1)
	(1)
VARIABLES	ln_Score_ptg
ln_Income_pt	0.581***
	(0.0338)
Y_2021	0.0325***
	(0.00195)
Y_2020	0.0558***
	(0.00282)
Y_2019	0.0809***
	(0.00245)
Y_2018	0.0781***
	(0.00261)
Grade_2	0.407***
	(0.0129)

VARIABLES	**(1)**
Grade_5	0.321***
	(0.0115)
Grade_8	0.0860***
	(0.0105)
Grade_10	0.0661***
	(0.0115)
IncomeGrade_2	-0.0189***
	(0.000666)
IncomeGrade_5	-0.0151***
	(0.000593)
IncomeGrade_8	-0.00423***
	(0.000534)
IncomeGrade_10	-0.00301***
	(0.000587)
Constant	3.392***
	(0.114)
Observations	2,461
R-squared	0.850

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 2

As part of the outlier diagnostic process, standardized residuals and leverage values were initially examined to identify observations that deviated substantially from the expected distribution or exerted disproportionate influence on the model. Observations with standardized residuals exceeding ±3 were flagged as potential outliers, in line with established diagnostic guidelines (Williams, 2016). These diagnostics, presented in Figure 15 and Figure 16, highlight specific data points, identified by their row numbers, that call for further scrutiny due to their potential impact on the regression estimates.

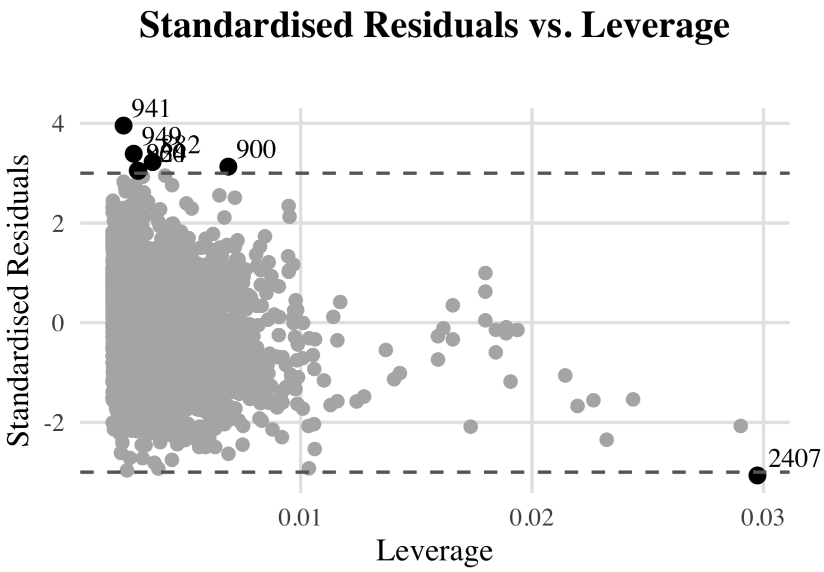

Figure 15: The figure plots the leverage versus the standardised residuals of the regression analysis components for Italian Language.

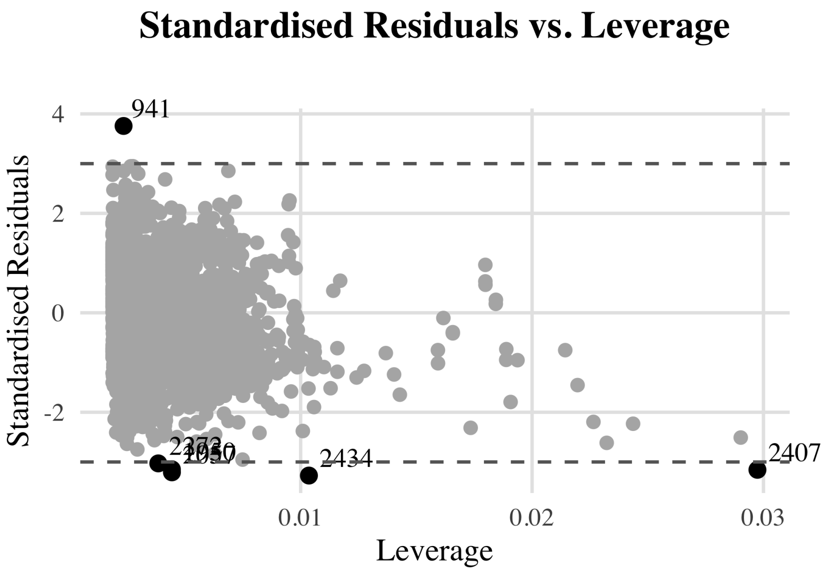

Figure 16: The figure plots the leverage versus the standardised residuals of the regression analysis components for Mathematics.

To expand this analysis, Cook's distance was subsequently calculated. Observations with Cook's distance values exceeding $4/n$ were considered indicative of influential observations, in line with established diagnostic guidelines (Williams, 2016). Figure 7 and Figure 8 display the results, confirming that the same observations identified via leverage and standardized residuals also exhibit high influence according to this metric. Based on this analysis, the following provinces were identified as influential:

– *Italian Language*: Reggio Emilia (RE), Brescia (BS), Lecce (LE), and Bari (BA);

– *Mathematics*: Chieti (CH), Caltanissetta (CL), Cremona (CR), and Rieti (RI).

To assess the robustness of the model estimates, regression analyses excluding these provinces were conducted for both subjects. The updated models are presented in table 16 and table 17.

Table 16: The table presents the results of the Lin-Lin model without the outliers for Italian Language.

VARIABLES	**(1)**
	(1)
VARIABLES	Score_ptg
Income_pt	4.561***
	(0.328)
Y_2021	5.458***
	(0.396)
Y_2020	12.17***
	(0.519)
Y_2019	13.91***
	(0.478)
Y_2018	10.50***
	(0.489)
Grade_2	71.05***
	(1.800)
Grade_5	54.39***
	(1.808)
Grade_8	33.09***
	(1.789)
Grade_10	25.78***
	(1.889)
IncomeGrade_2	-2.898***
	(0.0931)

VARIABLES	(1)
IncomeGrade_5	-2.178***
	(0.0939)
IncomeGrade_8	-1.297***
	(0.0914)
IncomeGrade_10	-0.996***
	(0.0960)
Constant	72.11***
	(9.476)
Observations	2,369
R-squared	0.830

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 17: The table presents the results of the Lin-Lin model without the outliers for Mathematics.

VARIABLES	(1)
	(1)
VARIABLES	Score_ptg
Income_pt	5.688***
	(0.326)
Y_2021	6.345***
	(0.397)

VARIABLES	(1)
Y_2020	10.87***
	(0.520)
Y_2019	15.77***
	(0.478)
Y_2018	15.17***
	(0.490)
Grade_2	75.86***
	(1.802)
Grade_5	58.64***
	(1.809)
Grade_8	15.73***
	(1.791)
Grade_10	12.46***
	(1.891)
IncomeGrade_2	-3.515***
	(0.0930)
IncomeGrade_5	-2.745***
	(0.0938)
IncomeGrade_8	-0.779***
	(0.0913)
IncomeGrade_10	-0.572***
	(0.0958)
Constant	46.14***
	(9.431)

VARIABLES	**(1)**
Observations	2,369
R-squared	0.847

Note. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notably, the exclusion of these observations did not lead to substantial changes in either the estimated coefficients or the statistical significance of the explanatory variables. This indicates that, although outliers are present, their influence on the regression results is limited.