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High School Track Choice and Non-Cognitive Skills: Evidence from Italy using PISA and INVALSI Data

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Abstract

This study examines the impact of high school track selection on the non-cognitive skills of Italian students. Using data from PISA 2022, merged with INVALSI data, both a selection-on-observables approach and a 2SLS model are employed to address the endogenous self-selection of students into academic and vocational tracks. The findings reveal that choosing an academic track decreases stress resistance. The analysis explores heterogeneity across subgroups. While acknowledging limitations due to the absence of pre-treatment outcome measures, the study emphasizes the need for targeted interventions to mitigate the negative effects of track choice on non-cognitive skill development.

Contents

1 Introduction

Both economists and psychologists recognize the multidimensionality of human development, highlighting the significant role that different types of skills play in predicting numerous outcomes throughout an individual's life course. This includes a wide array of variables, from economic aspects such as earnings in the labor market and involvement in criminal activities, to more subjective dimensions like personal well-being and health (Borghans et al., 2008; Almlund et al., 2011; Brunello and Schlotter, 2011). Although it is well-known that both cognitive and non-cognitive skills are highly correlated with educational attainment, there is little evidence on the causal effect of schooling on skills (Ollikainen et al., 2022). The economic literature has largely favored a structural modeling approach to estimate skill production functions (Cunha et al., 2006). These models provide insights into the mechanisms behind skill formation but rely on strong assumptions. Fewer studies have employed reduced-form approaches to estimate the causal impact of school choice on individuals' skills, likely due to the lack of an exogenous source to credibly isolate the treatment effect.

The impact of schooling on skill development is especially critical during secondary education. At this stage, students are making their first significant choices regarding their educational paths, often deciding between vocational education, which focuses on job-specific skills, and academic education, which emphasizes broader, more versatile skills. This decision is important, as it can have long-lasting effects on college choices and future labor market outcomes (Humphries et al., 2023). It also informs education policy, as governments worldwide strive to equip adolescents with the best tools to navigate the challenges of a rapidly evolving job market driven by technological advancements (Hanushek et al., 2017; Brunello and Rocco, 2017). The evidence on the influence of general education on both cognitive and non-cognitive skills is crucial in informing the debate about the relative merits of academic versus vocational education. Selection into general versus vocational tracks at the age of 14 leads to distinctly different educational environments over the next three to five years (see Section 3.1). General education is designed to prepare students for higher education, whereas vocational education is tailored to teach more practical, occupation-specific skills. Furthermore, the peer groups in these tracks differ significantly, with those in vocational education typically having lower peer quality as measured by academic performance and parental education levels (Agarwal et al., 2021).

This study aims to explore the impact of high school choice on the non-cognitive skills of Italian students, using data from PISA 2022. For the first time, PISA 2022 collected data on the social and emotional skills of students across surveyed countries, following the framework of the Survey on Social and Emotional Skills (Chernyshenko et al., 2018). Evidence suggests that non-cognitive capabilities remain malleable and subject to development well into adolescence (Dahl, 2004). This ongoing adaptability in non-cognitive skills is linked to the gradual maturation of the prefrontal cortex, a crucial area for executive functioning, which plays a significant role in shaping personality traits and regulating emotions. Given that PISA targets 15-year-old students, this age group provides an ideal sample for studying the short-term impact of high school choice on non-cognitive skills. Furthermore, the Italian sample of PISA is merged to different waves INVALSI data, in order to recover additional information on the students in different stages of schooling.

To address the endogenous self-selection of students into different tracks, two identification strategies are proposed. First, a selection-on-observables approach is adopted. In this approach, when appropriate determinants of school choice and non-cognitive skills are controlled for, the treatment is assumed to be as good as randomly assigned. To enhance the plausibility of this assumption, I estimate my model using a double-robust estimator, which relies on a common support assumption. Specifically, I use IPWRA, where correctly specifying either the model for the treatment or for the outcome is sufficient to obtain consistent estimates. Alternatively, given the limitations of the first strategy due to its strong assumptions, I also estimate 2SLS models, using the share of peer enrollment observed during the 8th grade, the period when the school choice is made, as an instrumental variable.

The most important and robust finding from my estimates is that choosing an academic track decreases students' stress resistance, leading to higher levels of neuroticism. This effect seems to be driven by students from central and southern Italy, while neither gender nor socio-economic background show a clear influence. Moreover, the effect appears to be stronger in lyceums that are perceived as "easier". According to the results of the second round of the "Survey on Social and Emotional Skills" OECD (2024), higher levels of stress resistance are, on average, associated with lower test scores, higher class anxiety, and lower overall well-being. Targeting interventions to reduce stress resistance in classrooms may be especially beneficial for groups whose high school choice has had a detrimental effect on emotional stability.

This work is organized as follows: Section 2 addresses terminological issues associated with personality traits, and summarizes prior research on the formation of non-cognitive skills and on the impact of high school choice on individual outcomes. Section 3 provides a comprehensive description of the PISA and INVALSI datasets, focusing on the construction and description of the dataset used in the analysis.Section 4 outlines the identification and estimation strategies adopted and presents and discusses the results. Finally, Section 5 presents concluding remarks.

2 Literature Review

2.1 The Economics of Personality Traits: some Definitions

My analysis aims to investigate the impact of high school choice on the social and emotional skills of students. Hence, it is essential to clarify the terminology used when referring to the outcome variables. First, it is necessary to differentiate cognitive and non-cognitive skills. Following the distinctions proposed by Borghans et al. (2008) and Brunello and Schlotter (2011), cognitive skills are associated with intelligence and the ability to solve abstract problems, typically measured through IQ tests and standardized assessments in areas such as reading, science, and mathematics. Notable international standardized assessments include the OECD Program for International Student Assessment (PISA), which has been regularly conducted among 15-year-old students from member and associated countries every three years since the early 1990s, focusing on mathematics, reading, and science. Other significant programs are the Trends in International Mathematics and Science Study (TIMSS) and the Progress in International Reading Literacy Study (PIRLS), both administered by the International Association for the Evaluation of Educational Achievement.

However, as emphasized by Borghans et al. (2008), the dichotomy between "cognitive" and "non-cognitive" can be problematic. The distinction can be confusing since few aspects of human behavior are entirely independent of cognitive processes. Many personality traits and behaviors are influenced by cognitive mechanisms. For example, social competences, often considered prime examples of "non-cognitive skills," are intricately linked with perception, memory, and reasoning. They can be viewed as a form of intelligence, representing a variant of cognitive skills, as discussed by Murphy and Hall (2011). In a recent paper on the impact of peers' non-cognitive traits on individual learning outcomes, Shure (2021) points out that a significant portion of the economics literature, particularly the work of Heckman and coauthors, employs the categorization of cognitive versus non-cognitive skills. In what follows, I will refer to this categorization, while remaining aware of the ongoing discussion in the literature regarding their validity.

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Economic literature has also employed the term "personality traits" to describe non-cognitive outcomes. In defining personality traits, I use the framework proposed by Almlund et al. (2011), which aligns with the widely accepted definition in personality psychology. Personality traits are defined as the relatively enduring patterns of thoughts, feelings, and behaviors that reflect an individual's tendency to respond in certain ways under certain circumstances (Roberts, 2009). Essentially, personality is the interconnected system that links traits and other determinants of behavior to observable actions. As underlined by Kautz et al. (2014), personality psychologists have spent the past century studying these traits, resulting in the development of a widely accepted taxonomy of non-cognitive skills known as the Big Five. This framework, commonly denoted by the acronym OCEAN, includes the dimensions of Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Table 1 summarizes the definitions of the five domains. Formulated through factor analysis, which integrates both observer and self-reports of behaviors, the Big Five theory proposes a hierarchical organization for personality traits. At the top of this hierarchy are five broad factors, with progressively more specific traits or facets delineated beneath them.

The term "social and emotional skills" is increasingly used in policy settings as it underscores the importance of the social and emotional aspects of these skills and highlights their malleability, indicating their potential for targeted interventions to promote improvement. For instance, Brunello and Schlotter (2011) and Heckman and Kautz (2012) document school-based social and emotional learning programs in the U.S. The program comprised lessons delivered by trained instructors, aiming to foster students' emotional intelligence, goal-setting, empathy, relationship skills, decision-making, and interpersonal efficacy. A comprehensive definition of socio-emotional skills is provided by De Fruyt et al. (2015). These skills are individual characteristics that (a) originate in the reciprocal interaction between biological predispositions and environmental factors; (b) are manifested in consistent patterns of thoughts, feelings, and behaviors; (c) continue to develop through formal and informal learning experiences; and (d) influence important socioeconomic outcomes throughout the individual's life. These skills have

Table 1: The Big Five Domains

Domain	**Definition of Domain**
Openness to Experience (Intellect)	The tendency to be open to new aesthetic, cultural, or intellectual experiences.
Conscientiousness	The tendency to be organized, responsible, and hardworking.
Extraversion	An orientation of one's interests and energies toward the outer world of people and things rather than the inner world of subjective experience; characterized by positive affect and sociability.
Agreeableness	The tendency to act in a cooperative, unselfish manner.
Neuroticism (Emotional Stability)	Neuroticism is a chronic level of emotional instability and proneness to psychological distress. Emotional stability is predictability and consistency in emotional reactions, with the absence of rapid mood changes.

Source: Adapted from American Psychological Association Dictionary (2007) in Almlund et al. (2011).

also been designated as a crucial component of "21st-century skills" (National Academy of Sciences, 2012). This label arises from their recognition as increasingly essential for individuals' overall development, employability, and healthy functioning within society. Social and emotional skills can be mapped onto the Big Five dimensions. In the conceptual framework of the OECD Study on Social and Emotional Skills, Chernyshenko et al. (2018) document an empirical investigation that sought to link contemporary 21st-century socio-emotional skills frameworks with the Big Five model. Conducted online, the study involved 452 volunteers who self-assessed their proficiency in 21st-century socio-emotional skills and completed items from the conventional Big Five inventory. Data analysis demonstrated a significant alignment between the 21st-century socio-emotional skills and the dimensions of the Big Five model.

2.2 The Production Function for Non-cognitive Skills

Numerous empirical studies in psychology and economics have highlighted the significant role of non-cognitive abilities in predicting various outcomes. Borghans et al. (2008) emphasize the importance of personality traits, illustrating the limitations of cognitive assessments in predicting specific results. A prime example is the seminal work by Heckman and Rubinstein (2001), which uses evidence from the General Education Development (GED) testing program, an exam-certified alternative to a high school diploma in the U.S. Their study reveals that GED recipients, despite having cognitive abilities similar to those of high school graduates who do not pursue post-secondary education (as indicated by Armed Forces Qualifying Test scores), paradoxically earn lower hourly wages and achieve lower levels of education compared to high school dropouts when cognitive aptitude is controlled for. This underperformance is attributed to an unmeasured factor, identified as non-cognitive skills. Since then, economists have dedicated considerable effort to quantifying the significance of non-cognitive skills in individual development.

Almlund et al. (2011) present a substantial body of evidence supporting the predictive power of personality assessments, particularly traits associated with Conscientiousness and, to a lesser extent, Neuroticism, across various domains. Conscientiousness, for instance, serves as a strong predictor of overall attainment and achievement, while Openness to Experience predicts more specific educational aspects such as attendance and course selection. The impact of Neuroticism on educational attainment is significant, although its relationship is not always straightforward. Moreover, the predictive capability of Conscientiousness can rival that of SAT scores regarding college degree attainment. Personality assessments also provide valuable insights into performance on achievement tests, although they are less informative for intelligence tests.

Personality traits evolve throughout an individual's life due to various influences, including social interactions, personal life circumstances, biological development factors, and varying levels of personal investment. There is an increasing empirical consensus suggesting that educational attainment, parental investment, and targeted interventions can causally influence an individual's personality traits. In their recent review, Attanasio et al. (2022) present the framework commonly used in economics to model parental investments and early childhood development, using it to assess empirical structural evidence in early childhood research. The conceptualization of the production function for child development, representing the accumulation of human capital over time, has evolved. While traditionally viewed as a simplified, low-dimensional variable in economic models, human capital is now recognized as a multidimensional construct. This shift allows for a more comprehensive understanding of individual heterogeneity, better reflecting the complexities of human development.

Cunha and Heckman (2007, 2009) are pioneers in presenting a comprehensive theoretical framework that provides a perspective on interpreting findings from a substantial body of empirical research on skill formation and child development. This framework acknowledges the dynamic nature of skill development throughout an individual's life. Central to their model is the concept of the "technology of skill formation," which captures the idea that individuals' traits can evolve in response to a range of investments and environmental factors they encounter. According to their model, abilities are shaped by a combination of both inherited factors and those created through investments and situational aspects. Skill development operates through a multiplier effect, where skill attainment at one stage of an individual's life cycle positively influences skill attainment at later stages. This mechanism is referred to as "self-productivity." Additionally, early investments in an individual's development enhance the productivity of subsequent investments, known as "complementarity." The model also incorporates the idea that human development is characterized by critical and sensitive periods for various traits. When modification can only occur during a limited time frame and is crucial for normal development, it is called a critical period, whereas periods when modification is more easily achieved are called sensitive periods.

These theoretical hypotheses have been tested through structural models. I will summarize the findings of a few notable papers on this subject, with a substantial reliance on Attanasio et al. (2022); this summary does not aim to provide a comprehensive review of the entire literature on this topic. Cunha and Heckman (2008) estimate a dynamic factor model that leverages cross-equation restrictions (covariance restrictions in linear systems) for robust identification. They employ a variant of dynamic state-space models to achieve this. The idea is to represent cognitive and non-cognitive skills, as well as parental investments, as low-dimensional latent variables. In other words, their empirical methodology considers the proxy nature of the measurements of parental investments and outcomes and the endogeneity of inputs. They estimate their model using a sample of 1,053 white males drawn from the children of the National Longitudinal Survey of Youth, 1979 dataset. Their analysis reveals significant self-productivity in the development of both cognitive and non-cognitive skills. Moreover, they find empirical evidence for the existence of sensitive periods for parental investments in both types of skills. Notably, the sensitive period for investments in cognitive skills occurs earlier in the life cycle compared to the sensitive period for investments in non-cognitive skills. These findings align with the evidence from Carneiro and Heckman (2003), which suggests that non-cognitive skills are more adaptable and responsive to interventions during later stages of development compared to cognitive skills. Working with the same dataset, Cunha et al. (2010) depart from the assumption of linearity in the production function. They use measures of parental investment and children's outcomes to estimate the parameters governing the substitutability between early and late investments in cognitive and non-cognitive skills. The study finds significantly less evidence of malleability and substitutability for cognitive skills during the later stages of a child's life. In contrast, the malleability of non-cognitive skills remains relatively stable across both early and late stages. These findings are consistent with the evidence on life cycle skill formation presented in Cunha et al. (2006). The findings suggest that effective interventions for disadvantaged adolescents should focus on enhancing non-cognitive skills. This underscores the potential for developing these skills even during adolescence. Hence, there is an interest in investigating how the choice of high school impacts the social and emotional skills of fifteen-year-old individuals.

Agostinelli et al. (2020) develop an empirical framework that integrates essential aspects from two distinct research programs: Child Development literature, as reviewed here, and the Education Production Function literature, which analyzes the value-added contributions of classrooms and educators using extensive administrative data (see for example Rivkin et al. (2005), Chetty et al. (2014a,b)). By incorporating elements from both home and school environments as latent factors with imperfect measurement, their model emphasizes the critical role of investments in shaping a child's development during kindergarten. Their findings highlight a negative complementarity between a child's initial skill level upon entering kindergarten and investments in both classroom and home environments, suggesting that children with lower initial skills benefit most from improvements in school and home quality. Attanasio et al. (2020c) investigates the developmental trajectory of socio-emotional skills across the lifespan and intergenerationally, aiming to determine whether parental socio-emotional skills during early childhood versus adolescence predict their children's socio-emotional skills more strongly. Drawing on data from the 1970 British Cohort Study, the study focuses on two dimensions of socio-emotional skills: internalizing and externalizing, which respectively relate to attentional focus and interpersonal engagement. The analysis reveals significant persistence in the evolution of socio-emotional skills, challenging the simplistic Markov dynamic models commonly used in literature. These findings underscore the enduring nature of socio-emotional skills throughout the life cycle, emphasizing the pivotal role of early childhood in skill formation and suggesting a need to expand models to include skills from earlier developmental stages.

Del Bono et al. (2022) develop a model that generates consistent estimates of the true distribution and evolution of child skills, even when parental assessments of child non-cognitive skills are contaminated. Contamination is defined as the influence of parents' own skills and traits on their evaluations of their children's non-cognitive skills. The study leverages data from the Millennium Cohort Study (MCS), an extensive longitudinal investigation of infants born between 2000 and 2002 in the United Kingdom. Assessments were conducted at ages 3, 5, 7, 11, 14, and 17, incorporating both cognitive and non-cognitive evaluations by parents, interviewers, or teachers. Notably, the child's non-cognitive skills were assessed by parents at each wave, as well as by interviewers or teachers, thereby providing measures from different evaluators at various stages of the child's development. The findings underscore the critical importance of involving multiple evaluators to alleviate contamination concerns. To enhance the accuracy and validity of future research on child development, it is crucial to diversify the sources of assessment for a child's non-cognitive skills. However, unlike the first wave of the SSES study that incorporated assessments from various informants, PISA 2022 collects only self-assessments of non-cognitive skills. Nonetheless, this limitation may be a secondary concern. As highlighted by Soto et al. (2011), issues regarding inflated self-perception and increased measurement error in self-reported non-cognitive skills are more pronounced among younger children rather than adolescents. Younger children may have a less developed understanding of assessment questions, leading to higher measurement error. Conversely, adolescents typically demonstrate lower susceptibility to response-style biases such as social desirability or acquiescence.

Other studies have explored the estimation of production functions for child development in developing countries. For instance, Helmers and Patnam (2011) investigate the determinants of both cognitive and non-cognitive skill development across different childhood stages, particularly focusing on self-productivity and cross-productivity effects. Using data from the India segment of the Young Lives project, specifically from the state of Andhra Pradesh, they estimate a linear structural relations model. This model allows them to assess latent levels of cognitive and non-cognitive skills, as well as parental investment, while linking these to observed child, parental, and household characteristics. To address potential endogeneity, they use household-specific shocks affecting household wealth and a child's birth order as instruments. Their findings for the older cohort indicate evidence of self-productivity in cognitive skills and cross-productivity between cognitive and non-cognitive skills during the transition from eight to twelve years of age.

Attanasio et al. (2020a) leverage data from a high-quality early education intervention in Colombia, targeting children from vulnerable families aged 1 to 7 years. They develop a model of child development encompassing three latent factors: health, cognitive abilities, and socio-emotional skills. Utilizing a translog production function, they model the output as a second-order polynomial in the (log of) prior achievement, investment, and other background variables. A striking observation from their analysis is the temporal evolution of the production function. They uncover notable shifts over time, reflected in both the varying impacts of distinct inputs and the observed persistence levels within each dimension of child development. Particularly for socio-emotional skills, the role of parental investment is highly significant. Their findings indicate that parental investment exerts a substantial influence across a wide range of developmental ages, with a pronounced effectiveness at age 5. Secondly, the study identifies cross-productivity, where current cognitive skills positively influence future socio-emotional skills, though the reverse relationship is not observed. Notably, parental investments play a pivotal role in developing both cognitive and socio-emotional skills.

Attanasio et al. (2020b) analyze data from an intervention in Colombia aimed at promoting effective parenting and stimulation for children over 18 months old. The intervention involved a structured stimulation curriculum delivered through weekly home visits by locally trained women, targeting children aged one to two from families receiving conditional cash transfers. Utilizing a dynamic latent factor model, the researchers assess the combined impact of parental investments and the intervention on early childhood cognitive and socio-emotional skill development. The findings highlight two crucial points. Firstly, there is strong evidence of self-productivity in skills, where a child's current cognitive or non-cognitive skill level significantly influences their future skills in the same domain, coupled with a mean reversion effect. Secondly, the study identifies cross-productivity, where current cognitive skills positively influence future socio-emotional skills, although this relationship does not hold in reverse. Finally, parental investments are found to play a pivotal role in the development of both cognitive and socio-emotional skills.

According to Attanasio et al. (2022), numerous estimates of the impact of parental investments on child development suggest that early investments are particularly influential. However, this evidence often overlooks the effects of schools or peers and does not consider the dynamic interactions between parental investments (and their effects on multiple developmental dimensions) and these subsequent inputs. High school choice can be seen as an extension of parental influence, acting as a crucial form of parental investment. This decision is not only shaped by socio-economic background but also by the active involvement of the family, such as the support provided in daily activities and educational guidance.

2.3 High School Choice and Individual Outcomes

Over the last 30 years, a substantial body of literature has investigated the impact of secondary school tracks on various individual outcomes. In what follows, I will review two overlapping areas of research concerning high school choice. This is not intended to be exhaustive but rather to delineate the main lines of research in these fields.

The first body of literature focuses on the impact of different curricula on individual outcomes. One of the pioneering works in this area is Altonji (1992), which uses the US National Longitudinal Survey of the High School Class of 1972 to examine how taking different subjects affects wages and years of college completion. The self-selection of students into various curricula is influenced by unobserved differences in pre-high school ability and preferences for post-secondary education, making OLS estimates incapable of producing causally credible results. Altonji addresses this issue by adopting an instrumental variable approach, using the variation in curricula across schools (specifically, the school's mean number of credits earned by students within each subject) as an instrument for each student's credits earned in that subject. However, this instrument is likely endogenous as it may correlate with variables such as primary school preparation, average family background, course quality, and student ability. Despite this, Altonji's work laid the groundwork for subsequent studies that have employed increasingly refined quasi-experimental methods to analyze the returns to high schooling.

A notable study is Cortes et al. (2015), which investigates an intensive math instruction policy implemented in the Chicago public school system. This policy assigned low-skilled ninth graders to an algebra course that doubled instructional time, changed peer composition, and emphasized problem-solving skills. To evaluate its impact, the authors employed a regression discontinuity design, comparing students just above and below the threshold for assignment to additional instructional time. Using longitudinal data tracking students from eighth grade through college, the study shows that the treatment doubled instructional time in math (replacing elective courses like music and art) without altering total coursework. It also increased the homogeneity of algebra classrooms and exposed students to lower-skilled peers in algebra class. The study further reveals positive and significant long-term effects of the double-dose algebra program on credits earned, test scores, high school graduation rates, and college enrollment rates. Similarly, Cole et al. (2016) studied the impact of mandated personal finance and mathematics courses. They addressed self-selection biases by leveraging plausibly exogenous variation in exposure to these courses induced by changes in state-level high school curriculum requirements. The study found that mandated high school personal finance courses in the United States did not significantly affect the financial outcomes of treated populations. However, requiring students to take an additional high school math course increased the propensity to accumulate assets, the amount of real estate equity, and reduced credit card delinquency and the likelihood of foreclosure.

Goodman (2019) provides convincing evidence regarding the impact of high school math coursework on earnings, particularly emphasizing its effects on black students. By analyzing a nationally representative time series of high school transcripts and exploiting variations in state-level graduation requirements triggered by the 1983 report "A Nation at Risk," the author employs a difference-in-difference framework with state and cohort fixed effects. The findings indicate that these policy reforms substantially increased the completion of yearlong math courses, especially among black students in public and minority-majority schools. This slight increase in math coursework is associated with a significant 3% to 4% rise in adult earnings for black graduates, highlighting a substantial economic benefit from additional math education. Moreover, these reforms played a crucial role in narrowing the black-white gap in math course completion rates and reducing disparities in earnings and cognitive skill levels across various occupations.

The second body of literature, developed primarily in the European context, focuses on how different educational qualifications influence educational and labor market outcomes. These studies often compare academic and vocational tracks, similar to the focus of my research. One of the main identification challenges researchers face is the endogenous self-selection of individuals into different curricula. To credibly quantify causal effects, many studies have leveraged exogenous policy changes. In many cases, these studies conclude that the labor market returns to vocational and academic education do not show significant differences.

For instance, Oosterbeek and Webbink (2007) evaluates the effect on earnings of an additional year of academic education added to the basic 3-year vocational programs in the Netherlands in 1975. Using a difference-in-differences strategy, they find that the extra year had no effect on wages 20 years later. Similarly, Malamud and Pop-Eleches (2010) utilizes a 1973 educational reform in Romania to examine the relative benefits of general education versus vocational training in a transition economy. They conclude that Romanian workers with vocational education are significantly more likely to be employed in manual and craft-related occupations compared to those with academic education. However, they find no significant differences between the two groups in terms of unemployment rates, periods of non-employment, and family income.

From a life-cycle perspective, another strand of this literature has focused on the trade-off between the short-term benefits and long-term drawbacks of vocational versus academic education. In the short term, vocational education facilitates the transition from school to work by providing practical skills, yet these skills tend to depreciate faster over time, reducing adaptability to technological changes compared to academic education. Hanushek et al. (2017) discusses this using cross-country and cross-cohort data from the International Adult Literacy Survey (IALS) to analyze employment and wage profiles. They find that younger individuals with academic education initially face worse employment conditions than their vocationally trained peers, but older individuals with academic education enjoy better prospects. Since IALS does not track individuals over time or distinguish between age and cohort effects, the authors assume constant selectivity into educational tracks given parental education and peer choices. Brunello and Rocco (2017) uses data from the National Child Development Survey to distinguish age and cohort effects, considering changes in vocational and academic curricula over time. They find no significant employment life-cycle differences across cohorts but note sharper cross-cohort differences in net real wages, where vocational education leads to higher early-life earnings but shifts to long-term disadvantages compared to academic education. In expected long-term earnings, vocational education is associated with lower earnings for less-educated older cohorts and higher earnings for more-educated younger cohorts.

More recently, part of this literature has focused on the varying returns of different educational pathways. Agarwal et al. (2021) examines how the returns to college differ by high school type, considering outcomes such as employment, hourly earnings, annual hours, type of occupation, time to the first job, and the probability of undergoing any training. Using data from the Italian Participation, Labour, Unemployment Survey (PLUS), which includes information on both the highest attained degree and intermediate degrees, the study provides insights into how the pathway to college influences the labor market outcomes of college graduates. To address the non-random selection into high school tracks and college, the study employs the inverse probability weighted regression adjustment (IPWRA) estimator, which assumes conditional independence. This methodology controls for selection based on ability and parental background into different high school curricula. The findings reveal that vocational high school graduates who have completed college experience lower returns to college compared to their academic high school counterparts in terms of employment probability, the likelihood of finding a job within a year of graduation, and hourly wages. The negative difference in returns is smaller for males than for females and for individuals from the north and center of the country compared to those from the south.

Humphries et al. (2023) use Swedish register data to explore how initial endowments and high school choices complement post-secondary education choices and how these complementarities affect labor market outcomes. They document sorting based on multidimensional abilities into high school tracks, as well as sorting of both abilities and high school tracks into college majors. Their study focuses on men born between 1974 and

1976 and employs a dynamic Roy model to account for selection driven by abilities, prior investments, and persistent unobservables. This model is identified using noisy measures of abilities combined with quasi-experimental variation at the high school tracking and college application stages. The analysis estimates dynamic complementarities between high school and college investments, showing that high school tracking decisions influence post-secondary choices and their returns. Their findings highlight that abilities at the start of high school and track choices are critical determinants of later labor market outcomes. Using a dynamic generalized Roy model, they estimate heterogeneous returns, finding that returns to the STEM track are generally larger than those to the vocational track, with modest gains when comparing STEM to academic tracks and academic to vocational tracks.

Ollikainen et al. (2022) investigate the impact of secondary education type on both cognitive and non-cognitive skills among young Finnish men, leveraging data from extensive psychological tests conducted during mandatory military service. They employ a regression discontinuity design based on Finland's centralized admission system, where admission thresholds are determined by compulsory school GPA. At age 16, Finnish students choose between general education, aimed at preparing for higher education, and vocational education, focused on practical, occupation-specific skills. This choice results in significant differences in school environments and peer groups, with students in general education typically surrounded by peers with higher academic backgrounds. Despite these disparities, the study reveals minimal causal effects of education on basic skills measured at ages 19-20. This suggests that observed differences in cognitive and non-cognitive skills between educational tracks may be more attributable to pre-existing student characteristics rather than the direct impact of schooling.

Brunello et al. (2023), using data from the PLUS survey, investigate how attending different types of high school curricula influences Big Five personality traits in individuals aged 25 to 64 who completed either a classical or scientific lyceum. The study employs a selection-on-observables identification strategy, utilizing entropy balancing and propensity score matching to account for non-random selection into either lyceum type. These methods aim to achieve a balanced comparison between students from classical and scientific lyceums based on various observed background characteristics. The findings indicate limited support for the hypothesis that classical studies, with their emphasis on ancient languages, foster higher conscientiousness and openness compared to curricula with a stronger focus on mathematics and science. Instead, the results suggest that classical studies are associated with higher levels of neuroticism and self-reported unhappiness among graduates. This study is similar to the present work in examining the impact of track choice on non-cognitive skills but differs as it focuses specifically on the choice within the academic track.

3 Background and Data

3.1 High School Education in Italy

In order to better contextualize our research question, a brief overview of the Italian high school education system is required.[1] The Italian education system is organized into three stages. Students attend primary school from the age of 6 until 11. After completing primary school, they enroll in middle school, remaining in the same institution from age 11 until 14. High school begins at age 14 and lasts for five years, but compulsory education terminates at age 16, resulting in some students not completing upper secondary school qualifications (Contini et al., 2017).

After completing the first cycle of education, which includes primary and lower secondary school, students must proceed to the second cycle of the education and training system. This second cycle offers two pathways: upper secondary school and three-year or four-year vocational education and training programs, known as *percorsi di istruzione e formazione professionale* (*IeFP*). *IeFP* are regionally managed and provided by accredited training agencies or in collaboration with upper secondary schools. In contrast, upper secondary education is state-run and divided into two tracks: a general track offered in *licei* and a vocational track offered in technical and vocational institutes. Both tracks last for five years.

The curriculum is generally organized at the national level, with all high schools required to offer compulsory subjects such as Italian, mathematics, sciences, history, one or two foreign languages, and physical education. However, there are significant differences in the time allocated to each subject and the specialized fields of study. *Licei* provide higher-level academic education, specializing in humanities, sciences, languages, or arts. Technical institutes offer a combination of general education and specialized technical training in fields such as business, accountancy, tourism, and technology. Vocational institutes focus on technical and practical subjects, preparing students to enter the workforce with skills in technology, informatics, engineering, construction, and accounting.

[1]This section is mainly based on `https://www.indire.it/lucabas/lkmw_img/eurydice/quaderno_eurydice_30_per_web.pdf`

Access to the different educational tracks is not determined by formal ability tracking. Consequently, the choice is determined by individual preferences and their interaction with parental decisions, as well as the beliefs held by both students and parents. It is also influenced by teachers, through grading (Burn et al., 2024) and track recommendations (Carlana et al., 2022b).

3.2 PISA and INVALSI Data

As emphasized by Brunello and Schlotter (2011), empirical investigations focused on the labor market implications of non-cognitive skills remain relatively scarce. One contributing factor to this scarcity is the limited availability of surveys that collect individual-level data encompassing both cognitive and non-cognitive skills. A similar challenge arises for economic research in education, stemming from issues related to comparability and the potential for introducing measurement errors. The Survey on Socio-Emotional Skills (SSES), now in its second wave, aims to provide data that, for the first time, facilitate cross-country comparisons of these skills.[2] PISA 2022 integrated the SSES framework, enhancing its assessment framework to encompass socio-emotional skills alongside traditional cognitive assessments (OECD, 2023a).

PISA not only evaluates students' ability to reproduce knowledge but also their capacity to apply learned concepts in new situations. It focuses on the mastery of processes, understanding of concepts, and functioning in various scenarios. The PISA 2022 survey primarily assessed mathematics, with reading and science as secondary domains. For the first time, it included creative thinking as an innovative domain and also assessed financial literacy. In addition to the assessments, students completed a background questionnaire that gathered information about their personal backgrounds, homes, schools, and learning experiences. From here, I retrieved information on personality traits. PISA targets 15-year-old students, encompassing 620,259 individuals from 80 countries in 2022, with sample sizes ranging from 3,000 to 31,000 per country, predominantly from OECD members. These students represent approximately 29 million students worldwide. They attend educational institutions in grades 7 and higher. At this age, in most OECD

[2]For a conceptualization of the survey, see Kankaraš and Suarez-Alvarez (2019)

countries, students are approaching the end of their compulsory schooling.

The PISA 2022 Technical Report (OECD, 2023b) details the sampling design employed in the study. A two-stage stratified sample design was used. In the first stage, schools were systematically sampled from a national list of PISA-eligible schools using probability proportional to size sampling, based on the estimated number of PISA-eligible 15-year-old students. Prior to selection, schools were assigned to mutually exclusive groups called explicit strata based on school characteristics to improve the precision of sample-based estimates. In the second stage, students within selected schools were sampled. For computer-based assessments, a target cluster size of 42 students was set, while for paper-based assessments, the target cluster size was 35 students, with possible variations in consultation with sampling contractors to account for factors like expected student nonresponse. A response rate of 85% was required for initially selected schools, and replacement schools were used if the initial response rate was between 65% and 85%. Schools with student participation rates below 33% were not considered for analysis to avoid bias and error variance.

Although the students included in the final PISA sample for a given country were chosen randomly, their selection probabilities vary. Survey weights must be incorporated into any analysis to ensure that each participating student appropriately represents the correct number of students in the full PISA population. Sampling weights control the proportional contribution of each participating unit to the overall population estimate. Adjustments are made due to the mis-sampling of some strata, inaccuracies in measuring school size, and adjustments for school and student nonresponse. Additionally, trimming survey weights is necessary to mitigate the impact of an unusually small subset of the school or student sample. Without trimming, a small group of students might end up with significantly larger weights compared to the average student from the same population segment. The final student weight reflects each student's contribution to survey outcomes and is calculated by multiplying a base weight by various adjustment factors to address potential biases. It consists of two base weights, the school base weight and the within-school base weight, along with four adjustment factors. These weights are incorporated into my estimates to compute unbiased coefficients.

I won't delve into the technical details of how test scores are computed; instead, I'll focus on how social and emotional skills are measured and scaled. The survey includes seven distinct skills, which can be mapped onto the domains from the Big Five model: Open-mindedness, Task Performance, Engagement with Others, Collaboration, and Emotional Regulation. These skills go beyond broad personality dimensions by incorporating lower-order characteristics, or facets, which offer more precise and specific assessments. Each skill is evaluated using a set of items, some directly sourced from the SSES and others unique to PISA. Table 2 provides a detailed description of the seven included skills. The scales[3] used a within-construct matrix sampling design that integrates the benefits of both multi-form and single-form booklet designs. In this approach, each student received a random subset of five items per construct. This method ensured that each item was presented to roughly the same number of students across all countries/economies and within the entire sample. It also enabled a comprehensive assessment of each construct while maintaining a comparable workload for individual students compared to previous cycles. Moreover, it significantly reduced the reading load for students by displaying only five items on each screen.

Table 2: Big Five Domains and Sub-Skills with Descriptions

Domain	**Skill**	**Description**
Open-mindedness (Openness to Experience)	Curiosity	Interest in ideas and love of learning, understanding and intellectual exploration; and inquisitive mindset
Task Performance (Conscientiousness)	Perseverance	Persevering in tasks and activities until they get done
Engagement with others (Extraversion)	Assertiveness	Able to confidently voice opinions, needs, and feelings, and exert social influence.

[3]In Appendix A, I report the questions used to construct the scales for the social and emotional skills.

Domain	Skill	Description
Collaboration (Agreeableness)	Empathy	Kindness and caring for others and their well-being that leads to valuing and investing in close relationships
	Cooperation	Living in harmony with others and valuing interconnectedness among all people
Emotional Regulation (Emotional Stability)	Stress resistance	Effectiveness in modulating anxiety and able to calmly solve problems (is relaxed, handles stress well)
	Emotional control	Effective strategies for regulating temper, anger, and irritation in the face of frustrations

Source: Adapted from OECD (2023a).

All items followed a Likert-type format with five response categories, encompassing both positively and negatively worded statements. The five categories were 'strongly disagree,' 'disagree,' 'neither agree nor disagree,' 'agree,' and 'strongly agree.' Some scales included items with negative valence, where a higher response category indicated a lower level of the measured construct, and vice versa. Prior to scaling, responses to these items were reverse-coded. To assess reliability, Cronbach's alpha coefficients were computed for the seven scales to evaluate internal consistency. A Cronbach's alpha of at least 0.60 was required for a scale's scores to be reported for a particular group. Scale scores were not reported for countries/economies where one or more language groups did not meet this reliability threshold. The scales were derived using the Generalized Partial Credit Model, an Item Response Theory model suitable for analyzing Likert-style items with ordered categories. It models the probability of an individual v selecting a certain response category k for an item i with $m + 1$ ordered categories.

$$P(x_i = k|\theta_v, \beta_i, \alpha_i, d_i) = \frac{exp \sum_{j=0}^{m} D\alpha_i(\theta_v - \beta_i + d_{ij})}{\sum_{j=1}^{m} exp \sum_{j=1}^{x} D\alpha_i(\theta_v - \beta_i + d_{ij})} \qquad x_i = 0, 1, ..., m.$$

θ_v is the estimated latent trait for respondent v, and β_i is an item parameter indicating the location on the latent continuum of the construct being measured. An item with a higher β_i requires a higher latent trait for a higher response category to be selected. d_{ij} is the step parameter j for item i, representing the deviation of the category intersection δ from the general location β_i. The category intersection δ is the point on the latent continuum θ where two neighboring category characteristic curves intersect, meaning it is the point at which a higher response category is more likely to be selected (e.g., when the individual is more likely to select 'disagree' rather than 'strongly agree'). α_i is the discrimination parameter for item i, which was scaled by a constant $D = 1.7$ starting in PISA 2015. It measures the item's ability to discriminate between individuals with different levels of the latent trait being assessed.

The scaling process generates weighted likelihood estimates for each individual. These estimates are then transformed into a reporting metric with a mean of 0 and a standard deviation of 1 across OECD countries using senate weights to standardize and enhance interpretability. The senate weight is a linear transformation of the student full sampling weight, ensuring that the sum of the senate weights for all cases within a country totals a constant value of 5,000. An average score of 0 is expected when calculated across all OECD countries. A negative scale score does not indicate that a student responded negatively to the items in the scale; instead, it signifies that the student's performance is below the OECD average.

INVALSI data are also used in my analysis. These administrative data, collected by the Italian National Institute for the Evaluation of the Education System (INVALSI), are low-stakes and administered annually in both public and private schools in Italy. The evaluation of students' attainments is carried out yearly at the conclusion of 2nd, 5th, 8th, 10th and 13th grade, with all students in these grades required to participate in the INVALSI assessment. The tests are administered on the same day, and correction is conducted externally, following a predetermined marking scheme. The testing comprises both multiple-choice and open-ended questions to assess students' key competencies in reading and math. The reading test evaluates mastery of grammar and reading comprehension, while the math test measures skills in problem-solving, logic, and interpretation of quantitative phenomena. All test scores are standardized to have a mean of 200 and a standard deviation of 40 for each subject and cohort.

I use data from INVALSI 2022 to identify the region of school attendance for students sampled in PISA 2022, during their 10th grade, along with data from INVALSI 2017, which provides information on the same students when they were in 5th grade. Unfortunately, INVALSI did not produce data in 2020 due to COVID-19, which would have provided information on students in their 8th grade, the last year of lower secondary school. This is a critical period when decisions about enrolling in a particular high school track are made, and the absence of this data implies significant limitations regarding some useful pre-treatment controls I can exploit in a selection-on-observables identification strategy. To address this limitation, I adopt an IV approach that incorporates information from students in 9th and 11th grades who were sampled in PISA 2022. I then merge these observations with data from INVALSI 2019 and 2021, corresponding to these students' 8th grade data.

3.3 Dataset Construction and Description

The Italian sample of PISA 2022 consists of 10,552 students from 344 schools. PISA sampling is based on age rather than grade, specifically targeting students born in 2006, aged from 15 years and 3 completed months to 16 years and 2 completed months at the beginning of the assessment period for PISA 2022. Some of the assessed students are in lower secondary school (up to the 8th grade in Italy), while others are in upper secondary school, as shown in Table 3. Based on the nature of the research question, I excluded 36 students who were from middle school. Table 4 shows the distribution of the students by high school track in the original sample. A total of 203 units were excluded because they could not be linked to INVALSI data due to the unavailability of a specific identifier (the so-called SIDI), and a duplicate observation was dropped. The sample was reduced to

10,312 units.

For my first identification strategy, relying on the unconfoundedness assumption, I considered only the students who were in the 10th grade in 2022, i.e., 8,654 observations. Out of these, I could only connect 7,756 individuals to the INVALSI 2022 dataset, as 898 students in PISA did not match in the INVALSI records. This discrepancy is unusual, given that INVALSI data are administrative and intended to encompass the entire student population. According to the INVALSI 2022 report (INVALSI, 2022), participation in the test exceeded 90% in every macro-area considered. Therefore, it is possible that some students who participated in the PISA test did not take the INVALSI. Out of the 898 students, 693 were enrolled in a vocational education and training program, where it is more common for students not to take the INVALSI examination. Additionally, 51 of the remaining students had repeated at least one year in the same school, potentially having taken the INVALSI in the previous year and not retaking it. Furthermore, 14 students had transferred to the school at the beginning or during the school year, making it unclear whether they were repeating the year or had simply moved to a new school. The 10th-grade sample was further enriched with 6 additional units for whom geographical information was retained from INVALSI 2019 at the 8th grade, as these students were possibly repeating the 10th grade for a second time. This results in a working sample of 7,762 units.

For my second identification strategy, I employ an instrumental variable approach. The instrument, discussed in Section 4.2, is based on the relative enrollment observed by students in the 8th grade at the time they were choosing their high school track. To construct this instrument, I use data from the Italian National Institute of Statistics (ISTAT), which provides enrollment data disaggregated by track type, gender, and province.To ensure sufficient variability in the instrument, I retain in my sample students from the 9th and 11th grades, in addition to those from the 10th grade. I also estimate the same IV model using only the 10th-grade students. Given that the instrument is province-specific, I matched these students with the INVALSI data that provide the relevant geographical information. For students in the 9th and 11th grades who did not

Table 3: Distribution of Students by
Month of Birth and Grade

Month of birth	Grade 7	8	9	10	11	Total
1	1	2	69	514	250	836
2	0	0	79	621	116	816
3	1	1	86	697	73	858
4	2	2	73	694	56	827
5	0	4	81	818	10	913
6	0	1	101	742	8	852
7	1	1	121	835	1	959
8	1	1	124	759	2	887
9	0	5	114	846	2	967
10	1	7	125	789	2	924
11	0	1	146	718	0	865
12	0	4	185	659	0	848
Total	7	29	1,304	8,692	520	10,552

Source: elaboration of PISA 2022 data.

repeat a year of high school, the respective INVALSI data from the 8th grade provide information on the province where they attended the last year of middle school, which is the period when they made their high school track decision.

Out of the 1,155 observations from the 9th grade that survived the initial data trimming, only 279 could be linked to INVALSI 2021 data, possibly because the others did not attend 8th grade the year before and may be repeating the 9th grade. For the 11th-grade students, who were attending the 8th grade in 2019, 498 out of 503 units were successfully matched to INVALSI. Additionally, using the same INVALSI 2019 data for the 8th grade, I matched 2 students from the 9th grade and 41 students from the 10th grade, who likely repeated one and two high school years, respectively. The final sample for the IV analysis consists of 8,514 observations.[4]

My treatment variable is a binary indicator representing whether the individual

[4]Thirty-four observations from the 11th grade were discarded due to the absence of province-specific enrollment data for the Aosta, Bolzano, and Trento provinces for the 2018-19 school year, which corresponds to the 8th grade for students attending the 11th grade in 2022.

Table 4: Distribution of Students by Study Program

Study program	Total	Frequency
Academic		
Lyceums	4,987	47.42%
	4,987	47.42%
Vocational		
Technical institutes	3,224	30.66%
Professional institutes	880	8.37%
Vocational education and training (*IeFP*)	1,425	13.55%
	5,529	52.58%
Total	10,516	100%

Source: elaboration of PISA 2022 data.

chose an academic track (1) or a vocational track (0). I aim to test whether choosing a track with a more general and academic focus has a different impact compared to attending a vocational-oriented high school. To enhance the comparability between the treatment and control groups in my selection-on-observables identification strategy, I define the control group as students attending a technical institute.[5] The first working sample reduces to 6,823 individuals, with 4,210 attending a lyceum and 2,613 attending a technical institute. In the IV strategy, I utilize the full sample, including students attending professional institutes and *IeFP*.

Outcome variables are computed in PISA, as explained in Section 3.2. Some students did not receive a scale score due to extreme straightlining or not having enough responses. Consequently, I estimate my models on the subsamples of students for whom I observe the related outcomes. Table 5 reports the summary statistics for the social and emotional skills of students in the sample. The first column refers to the sample comprising students from the 9th and 11th grades, used in the IV strategy, while the second column refers to the 10th-grade sample. The last column refers only to students enrolled in a technical high school. In the academic track, students exhibit, on average,

[5] In Appendix B.1, I show the main estimates considering a control group which also includes students attending professional institutes and *IeFP*.

higher levels of curiosity, perseverance, assertiveness, empathy, and cooperation compared to their counterparts in the vocational track. However, stress resistance and emotional control are reported to be better among vocational track students. Overall, students in the academic track demonstrate stronger openness to experience, conscientiousness, extraversion, and agreeableness, but also report higher levels of neuroticism compared to those in the vocational track.

Table 5: Summary Statistics - Outcomes

	Full Sample	10th Grade Sample	Academic Track	Vocational Track (Technical institutes)
Curiosity	0.108	0.100	0.154	0.047
	(0.965)	(0.967)	(0.975)	(0.932)
Perseverance	0.090	0.070	0.105	0.028
	(1.009)	(1.001)	(0.994)	(1.008)
Assertiveness	-0.044	-0.050	-0.008	-0.057
	(1.017)	(1.021)	(1.068)	(0.977)
Empathy	0.001	0.001	0.081	-0.093
	(0.990)	(0.990)	(0.977)	(0.986)
Cooperation	0.077	0.069	0.091	0.054
	(1.002)	(0.993)	(0.992)	(0.967)
Stress resistance	-0.221	-0.219	-0.280	-0.145
	(1.003)	(0.998)	(1.019)	(1.007)
Emotional control	-0.131	-0.132	-0.149	-0.083
	(0.995)	(0.998)	(1.018)	(0.957)

Note: Standard deviations are in parentheses.

My first identification strategy is selection on observables, so the selection of appropriate controls is crucial. First and foremost, any empirical analysis focusing on school choice should, in the baseline specification, account for gender differences. As highlighted by Contini et al. (2017), in Italy girls are overrepresented in school types that emphasize the humanities (such as classical, linguistic, social sciences, and art lyceums) and underrepresented in other school types (such as scientific lyceums, technical, and professional institutes), some of which offer educational programs with a stronger mathematical content. Another individual characteristic that should be controlled for is whether the student was born abroad. As documented by Carlana et al. (2022a), immigrants in Italy disproportionately enroll in technical high schools compared to natives of similar ability. An interaction between being a migrant and female is also included. Following a similar scheme to Agarwal et al. (2021), the rest of the covariates can be organized as follows:

– *Regional covariates*: dummies for the region where the individual attended school from primary to high school, and interactions between gender and a dummy indicating that the individual attended compulsory education in the north of the country. Additionally, interactions between migrant status and attendance at schools in the north, as well as a triple interaction between these two and gender, are included.

– *Parental background covariates*: a socio-economic background index and its square, dummies for at least one parent being born abroad, a dummy for a different language spoken at home, an index for family support, along with interactions of the background index with gender and with a dummy indicating that the individual attended school in the north.

– *Cognitive covariates*: the standardized score in the math INVALSI test when students were in the 5th grade, its square, and interactions of the score with gender, parental background, a dummy for growing up in the north, as well as a triple interaction between these last two factors and the math score.

– *School covariates*: a dummy for individuals who attended early education and a dummy indicating whether the high school is located in a rural area.

The first group of observables aims to capture the heterogeneity related to different regional characteristics that can affect students' growth paths and, consequently, their high school choice. For instance, certain regions of Italy have a significant manufacturing industry, which increases the demand for technicians and vocational graduates, thereby attracting students to vocational high school curricula. Conversely, regions with a large public sector primarily attract academic graduates (Agarwal et al., 2021). In this way, we capture local demand and supply effects. As already mentioned, I do not possess data on the region where the students now in the 10th grade attended junior high school.

However, by comparing INVALSI data from 2017 and 2022, I verified that the region of school location remained the same from 5th to 10th grade for the students in my sample. This suggests that households did not move to another region during this period, allowing us to accurately control for regional fixed effects. One might argue that controlling for regional characteristics that are constant across provinces is insufficient, as the self-selection process into a specific track is more likely influenced by decisions made at the provincial level, such as choosing a high school based on its reputation. However, given the limited size of the dataset, introducing fixed effects at the provincial level would absorb too much of the variation, leaving insufficient variation for the model to estimate the effects of the treatment on the outcomes.

One of the key factors that affect the choice of high school and college is parental background (Checchi and Flabbi, 2007; Agarwal et al., 2021). In my analysis, this is primarily captured by the indicator elaborated by PISA for economic, social, and cultural status. This socio-economic index is based on three indicators: highest parental occupation status, highest education of parents in years, and home possessions. Since no direct income measure is available in the PISA data, the existence of household items is used as a proxy for family income. Occupational data are coded into four-digit ISCO codes and linked to the socio-economic index of occupational status (ISEI). The higher ISEI score of either parent or the available parent's score determined the highest occupational status. Parental education was assessed using ISCED levels, and a variable was derived to represent the highest level of education of either parent. The index of the highest education of parents is calculated as the median cumulative years of education associated with the completion of the highest level of parental education. The household possessions index encompasses student-reported possessions at home, the number of books in the home, and site-specific wealth items. After the imputation of missing values, all three components, including the imputed values, were standardized to have a mean of 0 and a standard deviation of 1 across OECD countries, with each country weighted equally using senate weights. The arithmetic mean of the three standardized components was then calculated to create a preliminary score, which was further standardized to have a mean of 0 and a standard deviation of 1 across OECD countries.

To further control for any effects induced by migration, I include covariates that indicate whether the language spoken at home is different from Italian and whether at least one parent is an immigrant. In this way, we can capture the different effects of being a first- or second-generation immigrant. Parenting style may also play a role in high school choice and in the formation of non-cognitive abilities (Moroni et al., 2019). To account for this, I include an index that captures how often parents or other family members engage in behaviors indicative of family support. Cognitive ability also plays an important role in high school choice. Since I do not have access to the questionnaire completed by students for INVALSI 2022, I cannot use the junior high school final grade as a proxy for cognitive skills when the decision was made. The only available proxy comes from INVALSI 2017, specifically the standardized score in mathematics of the student in the 5th grade. I also account for the possibility that attending nursery education may have long-term effects on high school choice and the formation of non-cognitive skills. Furthermore, I take into account the location of the school in a rural area, as it may affect access to resources and extracurricular opportunities, which in turn could influence high school choice and skill development. Finally, I include interactions and squares of the main variables to account for nonlinearities.

Missing values for the control variables pose a potential challenge for an analysis relying on conditional independence. Given the limited size of the sample, the standard listwise deletion method is not feasible. To address the presence of missing data, I adopted a specific imputation strategy. For any control variable with missing observations, the absent values were replaced with a fixed constant, specifically the mean of the observed values. Simultaneously, a binary indicator variable was generated, which takes a value of 1 for observations where the control variable had missing data, and 0 otherwise. Estimates are then conducted using both the amended control variable and its corresponding indicator variable. This conservative approach aids in preserving the integrity of information in the dataset, while the dummy variable serves to adjust for potential imputation biases. Nevertheless, it is important to note that this process could introduce biases into the standard errors of the control coefficients. If missingness is not random—i.e., if values are missing systematically due to some underlying factor—this method may not fully correct for bias. Hence, interpretations of these estimates should be made cautiously.

Table 6 presents the descriptive statistics for observable characteristics among students in academic and vocational tracks attending the 10th grade. The vocational track does not include students from professional high schools and IPeF programs. Female students are more prevalent in the academic track compared to the vocational track. Migrant students and those with migrant parents are slightly more common in the vocational track. Additionally, a higher proportion of vocational track students speak a different language at home. Students in the academic track generally come from a higher socio-economic background and report higher family support scores. Moreover, academic track students performed better in the 5th-grade math INVALSI test. A greater percentage of academic track students attended early education programs and are slightly less likely to attend rural schools.

In order to determine the impact of high school choice on the social and emotional skills of students, it is important to first understand the factors that affect the probability of choosing an academic rather than a vocational track. I do this by estimating a linear probability model on the restricted sample of 10th-grade students, with the control group comprising only students from technical high schools. The estimates reported in Table 7 show that the probability of choosing academic education in high school is higher among females but lower for those attending school in the north. A student is more likely to attend a lyceum if they have a better socio-economic background and higher cognitive abilities. Not reported in the table,[6] the probability is lower in the industrialized north. Interestingly, being a migrant increases the probability of attending an academic high school, but this is not the case for female migrant students living in the north. Early education seems to play a role in the likelihood of attending an academic track, while living in a rural area does not. The table also shows that the R^2 increases progressively

[6]The dummy for schools attended in the north is collinear with regional dummies, therefore it is omitted.

Table 6: Descriptive Statistics - Main Control Variables

	Full Sample	10th Grade Sample	Academic Track	Vocational Track (Technical institutes)
Female	0.515	0.511	0.582	0.384
	(0.500)	(0.500)	(0.493)	(0.487)
Migrant	0.049	0.039	0.030	0.045
	(0.216)	(0.193)	(0.169)	(0.208)
Attended schools in north	0.365	0.385	0.366	0.407
	(0.481)	(0.487)	(0.482)	(0.491)
Socio-economic background	-0.055	-0.043	0.205	-0.278
	(0.910)	(0.895)	(0.840)	(0.837)
Migrant parent	0.199	0.189	0.164	0.203
	(0.400)	(0.392)	(0.370)	(0.402)
Different language at home	0.143	0.134	0.089	0.174
	(0.350)	(0.341)	(0.285)	(0.379)
Family support	0.031	0.029	0.080	-0.027
	(0.914)	(0.909)	(0.896)	(0.909)
5th grade math score	0.120	0.122	0.260	0.023
	(0.825)	(0.877)	(0.862)	(0.870)
Early education	0.421	0.423	0.449	0.380
	(0.494)	(0.494)	(0.497)	(0.485)
Rural school	0.151	0.151	0.134	0.155
	(0.358)	(0.358)	(0.341)	(0.362)

Note: Standard deviations are in parentheses.

from 0.036 in the baseline specification (col. 1) to 0.054 when regional variables are included (col. 2), to 0.078 when parental background variables are added but not the socio-economic index (col. 3), to 0.154 with the further addition of the socio-economic background index (col. 4), and finally to 0.174 after including the standardized math test score from the 5th grade (col. 5). The significant increase in the R^2 associated with the socio-economic background index suggests that this is the most important source of selection into high school type, consistent with Agarwal et al. (2021).

Table 7: Probability of Choosing Academic Track in High School
(10th Grade Sample)

	(1)	(2)	(3)	(4)	(5)
Female	0.182***	0.216***	0.216***	0.227***	0.242***
	(0.014)	(0.018)	(0.018)	(0.017)	(0.018)
Female ∗ attended schools in north		-0.074***	-0.089***	-0.069**	-0.048*
		(0.029)	(0.029)	(0.029)	(0.028)
Migrant			0.145*	0.139*	0.158**
			(0.077)	(0.074)	(0.073)
Migrant ∗ female			-0.275***	-0.226**	-0.235**
			(0.110)	(0.106)	(0.107)
Migrant ∗ attended schools in north			-0.251**	-0.202**	-0.202**
			(0.108)	(0.101)	(0.099)
Migrant ∗ Female ∗ attended schools in north			0.613***	0.526***	0.521***
			(0.151)	(0.145)	(0.144)
Migrant parent			-0.027	0.020	0.024
			(0.020)	(0.019)	(0.019)
Different language at home			-0.155***	-0.094***	-0.090***
			(0.024)	(0.024)	(0.023)
Family support			0.022***	0.014*	0.016**
			(0.008)	(0.008)	(0.008)
Socio-economic background				0.184***	0.175***
				(0.014)	(0.014)
Socio-economic background ^{2}				0.022***	0.023***
				(0.005)	(0.006)
Socio-economic background ∗ female				-0.045**	-0.043**
				(0.018)	(0.019)
Socio-economic background ∗ attended schools in north				0.005	-0.001
				(0.022)	(0.022)
Socio-economic background ∗ female ∗ attended schools in north				-0.033	-0.038
				(0.031)	(0.030)
5th grade math score					0.075***
					(0.013)
5th grade math score ^{2}					-0.019***
					(0.005)
5th grade math score ∗ female					-0.038**
					(0.015)
5th grade math score ∗ attended schools in north					0.057***
					(0.017)
5th grade math score ∗ socio-economic background					-0.008
					(0.010)
5th grade math score ∗ attended schools in north ∗ socio-economic background					-0.002
					(0.018)
Early education					0.034**
					(0.013)
Rural School					0.025
					(0.020)
Regional dummies	No	Yes	Yes	Yes	Yes
Dummies for missing values	No	No	Yes	Yes	Yes
Observations	6822	6822	6822	6822	6822
R^2	0.036	0.054	0.078	0.154	0.174

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Control group: students attending a technical institute.

4 Empirical analysis

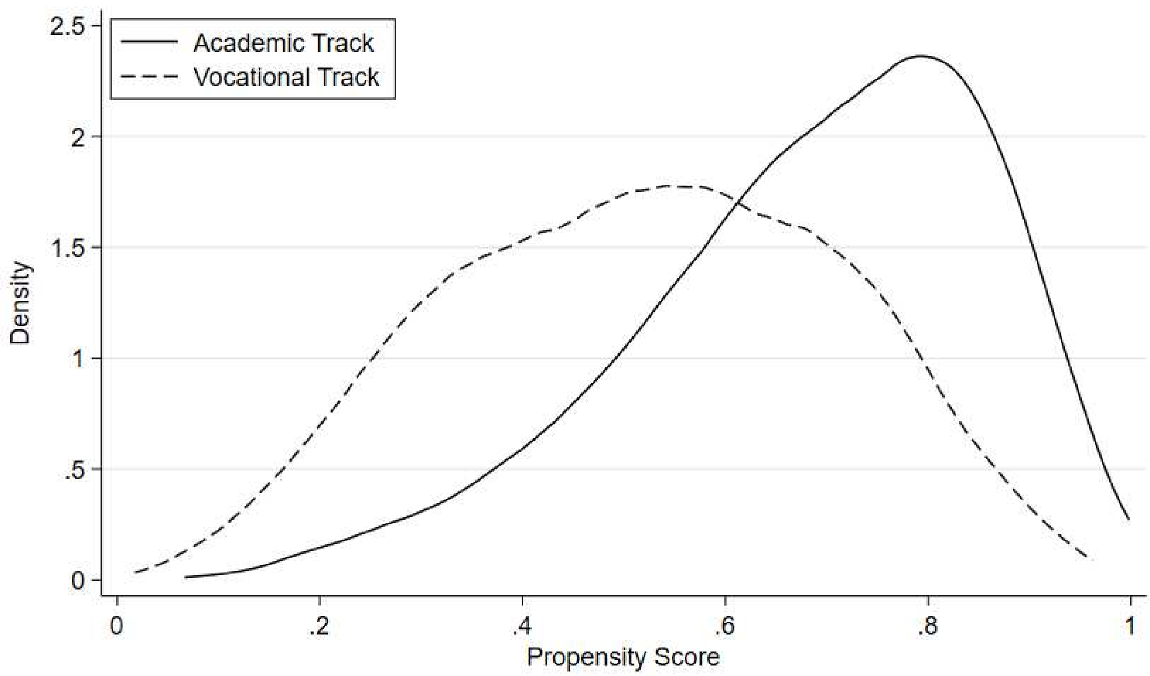
4.1 Selection-on-observables: Identification and Estimation

The aim of this work is to estimate the effect of high school track choice on the social and emotional skills of students. Self-selection into different curricula represents a significant threat to identification because educational choices are likely to be correlated with various factors that also influence skills (e.g. parental characteristics). Moreover, education may foster skills, but skills may also affect educational aspirations, leading to a reverse causation issue. The first approach I propose to tackle endogeneity relies on the conditional independence assumption (CIA). This means that after conditioning on observable variables, the assignment to treatment is as good as random. This assumption requires that the key determinants of educational choice are captured by the array of covariates and that any residual variation in education is either random or due to factors that do not influence the outcomes of interest. Although the CIA cannot be formally tested, I believe that the rich set of controls included increases its plausibility.

In order to estimate the effect of interest, I use the inverse probability weighted regression adjustment (IPWRA) estimator (Wooldridge, 2007, 2010; Wooldridge and Słoczyński, 2018). IPWRA addresses the fundamental problem of causal inference as a missing data problem, where we observe only one potential outcome out of the many possible outcomes. The intuition behind IPWRA is to impute the missing potential outcomes. IPWRA combines a model to predict treatment status (the propensity score) and another model to predict outcomes. Because IPWRA estimators have the double-robust property, only one of the two models must be correctly specified for the IPWRA estimator to be consistent. IPWRA estimation consists of three steps, which are jointly estimated using the general method of moments. In the context of binary treatment, the steps are as follows: first, the propensity scores for the treatment are estimated, and inverse probability weights are computed. Second, these weights are used to fit weighted regression models, obtaining the treatment-specific predicted outcomes for each subject. Third, the estimated average treatment effect (ATE) is calculated as the difference between the average predicted outcomes for the treated and untreated groups.

In addition to the CIA, the method requires that the overlap condition holds. This condition ensures that sample members with the same characteristics have a positive probability of receiving the treatment. To verify that this condition holds in my data, I inspect the marginal distribution of the propensity score, estimated with a logit model, in both treatment and control groups. The propensity score lies within the interval $[0.07, 0.99]$ in the treatment group and within $[0.02, 0.96]$ in the control group. There is considerable overlap in the middle range of the distribution of propensity scores between the two groups, spanning from 0.22 to 0.90 from the 1st to the 99th percentile. Adopting the minima and maxima criterion (see Caliendo and Kopeinig (2008)), I delete all observations whose propensity score is smaller than the minimum and larger than the maximum in the opposite group, retaining those in the interval $[0.07, 0.96]$. The IPWRA estimates are based on 6,778 units.

Figure 1: Propensity Score by Type of Track



Using the inverse probability weights obtained from the IPWRA procedure, I compare covariate balancing in the raw and weighted data for the treatment and control groups by reporting the standardized differences and the variance ratios for each covariate in Table 8. I compute the weights using the subsample of non-missing observations for perseverance, the most numerous outcome variable in the dataset (6,649 observations). In the weighted data, the differences and variance ratios are, in most cases, close to 0 and 1, respectively, suggesting that the level of balancing after weighting is satisfactory.

Table 8: Covariate Balancing

	Standardized Differences		Variance Ratio	
	Raw	Weighted	Raw	Weighted
Female	0.461	0.074	0.999	0.992
Female ∗ attended schools in north	0.202	0.051	1.180	1.039
Migrant	−0.028	−0.087	0.859	0.646
Migrant ∗ female	0.065	−0.106	1.714	0.489
Migrant ∗ attended schools in north	−0.037	−0.105	0.782	0.520
Migrant ∗ Female ∗ attended schools in north	0.057	−0.114	1.767	0.404
Migrant parent	−0.085	−0.034	0.872	0.949
Different language at home	−0.210	0.018	0.727	1.028
Family support	0.117	−0.008	0.939	0.902
Family support (dummy)	−0.081	0.038	0.780	1.126
Socio-economic background	0.521	0.011	1.045	1.008
Socio-economic background ^{2}	0.053	0.008	0.757	0.866
Socio-economic background ∗ female	0.338	0.054	1.587	1.095
Socio-economic background ∗ attended schools in north	0.389	0.019	0.995	0.952
Socio-economic background ∗ female ∗ attended schools in north	0.292	0.072	1.502	1.068
5th grade math score	0.245	0.003	1.134	1.104
5th grade math score ^{2}	0.100	0.049	1.349	1.187
5th grade math score ∗ female	0.169	0.002	1.644	1.139
5th grade math score ∗ attended schools in north	0.203	−0.021	1.101	1.078
5th grade math score ∗ socio-economic background	0.119	0.009	1.163	1.135
5th grade math score ∗ attended schools in north ∗ socio-economic background	0.131	0.019	1.304	1.050
Early education	0.153	0.003	1.096	1.002
Rural school	−0.129	−0.102	0.836	0.866

Note: Raw mean differences = covariate differences between treatment and control groups, raw data; weighted mean differences = covariate differences between treatment and control groups, weighted data; raw variance ratio = ratio of variances, raw data; weighted variance ratio = ratio of variances, weighted data. Standardized differences are computed as the ratio of mean differences to the square root of the sum of variances.

Table 9 presents estimates of the unconditional differences, average potential outcomes of the treatment and control groups, as well as the ATEs when controls are introduced.[7] The first column shows that choosing an academic track over a vocational one is positively and significantly associated with curiosity, perseverance, and empathy, while it has a negative relation with emotional stability facets. No significant association with assertiveness or cooperation emerges. Once appropriate covariates are used to estimate the treatment and outcome models, all effects drastically reduce and lose significance. Some even change sign, such as assertiveness and emotional control. Ultimately, I find no significant effect of completing an academic track compared to a vocational high school.

Table 9: Unconditional Differences, Average Potential Outcomes and ATEs (Estimation Method: IPWRA)

	Unconditional Differences	$E[Y_0]$	$E[Y_1]$	ATE
Curiosity	0.103***	0.121***	0.127***	0.006
	(0.031)	(0.034)	(0.020)	(0.038)
Perseverance	0.074**	0.072**	0.080***	0.009
	(0.032)	(0.035)	(0.020)	(0.039)
Assertiveness	0.045	0.026	-0.035*	-0.061
	(0.032)	(0.032)	(0.020)	(0.038)
Empathy	0.168***	-0.014	0.022	0.036
	(0.031)	(0.029)	(0.019)	(0.034)
Cooperation	0.032	0.082**	0.077***	-0.005
	(0.032)	(0.034)	(0.021)	(0.040)
Stress Resistance	-0.132***	-0.176***	-0.241***	-0.065
	(0.033)	(0.040)	(0.019)	(0.044)
Emotional Control	-0.061*	-0.133***	-0.118***	0.016
	(0.032)	(0.032)	(0.020)	(0.037)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Each model includes the controls detailed in Section 3.3, regional dummies, and dummies for missing values. Estimates are made on the 10th Grade Sample. Control group: students attending a technical institute.

[7] The estimates of the treatment and outcome models are shown in detail in Appendix B.2.

It is possible that the lack of significant overall effects is due to heterogeneous treatment effects, meaning the impact of the academic track choice might vary across different subgroups. To explore this, I divide the sample by gender, geographical area, and socio-economic background. The subgroups for socio-economic status are determined using the median value of the background index distribution. The results, reported in Table 10 reveal notable heterogeneity in the impact of the academic track choice. For females, the academic track is associated with a significant reduction in assertiveness and stress resistance compared to females attending a technical institute, while males experience a significant improvement in emotional control. Regionally, attending school in the North is linked to a significant positive effect on curiosity. Additionally, individuals from higher socio-economic backgrounds show a significant increase in empathy.

Table 10: Heterogeneous ATEs by Gender, Geographical Area, and Socio-Economic Background (Estimation Method: IPWRA)

	Female	Male	North	Centre & South	Higher SEB	Lower SEB
Curiosity	0.010	0.018	0.085*	-0.055	0.024	0.025
	(0.052)	(0.048)	(0.044)	(0.055)	(0.057)	(0.045)
Perseverance	-0.038	0.022	0.025	-0.003	0.052	-0.003
	(0.059)	(0.053)	(0.049)	(0.056)	(0.058)	(0.046)
Assertiveness	-0.168***	0.027	-0.032	-0.079	-0.071	0.010
	(0.061)	(0.042)	(0.054)	(0.052)	(0.054)	(0.046)
Empathy	0.074	-0.013	0.068	0.022	0.115**	-0.011
	(0.052)	(0.046)	(0.049)	(0.046)	(0.049)	(0.044)
Cooperation	-0.044	0.039	-0.029	0.005	0.053	-0.053
	(0.055)	(0.055)	(0.048)	(0.058)	(0.060)	(0.045)
Stress Resistance	-0.124**	-0.011	-0.007	-0.107	-0.063	-0.030
	(0.063)	(0.050)	(0.046)	(0.065)	(0.068)	(0.042)
Emotional Control	-0.067	0.105**	-0.019	0.042	0.060	-0.003
	(0.055)	(0.048)	(0.051)	(0.051)	(0.051)	(0.045)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Each model includes the controls detailed in Section 3.3, regional dummies and dummies for missing values, excluding those that are used for defining heterogeneous sub-samples. Estimates are made on the 10th Grade Sample. Control group: students attending technical institute.

4.2 A more Credible Approach: IV

Any approach that relies on a selection-on-observables identification strategy is often met with skepticism when used to make causal interpretations. When the units of observation are individuals and the assignment mechanism is based on individual choices, there may be concern that two individuals who appear identical in terms of pre-treatment observable characteristics could differ in unobserved ways, potentially invalidating a causal interpretation of the ATEs (Imbens and Rubin, 2015). Moreover, in this case, the baseline estimates indicate that the effect of high school choice on non-cognitive skills becomes statistically insignificant when appropriate covariates are controlled for. However, since these results rely on an approach with strong underlying assumptions, it would be premature to conclude that the effect is truly insignificant. To address the endogeneity of selection into treatment more credibly, I propose an alternative identification strategy using an instrumental variable (IV) approach.

The instrument is based on the share of students enrolled in a specific high school track in the province where an individual resided while attending the 8th grade, the period when high school choices are made. The underlying idea is that 14-year-old students are likely influenced by the local popularity of a school type, as indicated by relative enrollment levels (Brunello, 2020). This can be interpreted as a peer effect, where high school students influence the decisions of middle school students. Additionally, the instrument is gender-specific, recognizing that female students may be more likely to consider the proportion of females in a particular track rather than the overall presence of males when making their high school choices. I apply this instrument first to the sample that includes students in the 9th and 11th grades, for whom I have outcome data from PISA 2022, in order to exploit the additional temporal variation. In this case, the instrument also varies by grade. A potential concern with this approach is that the instrument may not be exogenous. The distinction between grade and cohort is important here: although we are considering students born in the same year, they are attending different grades. This suggests a form of selection into specific grades by the students. For instance, those sampled in the 11th grade may have started school a year earlier, potentially due to coming from wealthier families who chose to enroll them early. Conversely, those in the 9th grade may have repeated a grade, which could indicate different underlying characteristics. Moreover, this choice may, in turn, be influenced by the personality traits of the students. Therefore, I also estimate the IV effects on the subsample of students in the 10th grade.

Table 11 presents the IV estimates for both the full sample and the subsample of 10th-grade students. Each model is estimated using the units for which I observe the outcome variables. The specification for the full sample controls for both province and grade fixed effects to account for potential grade-specific shocks that may have differentially influenced students' decisions. Specifically, students in the 11th grade who made their choices in 2019 were not exposed to the COVID-19 pandemic, whereas 10th-grade students who made their choices in 2020 did so between the winter and spring of 2020, during the early stages of the outbreak. This may have affected their high school enrolment decisions. The standard errors are clustered at the level of variation of the instrument, specifically by province, grade, and gender for the estimation on the full sample, and by province and gender for the analysis on the 10th grade sample. To ensure the credibility of the instrumental variable, it must satisfy two key conditions: relevance (the first-stage condition) and exclusion restriction. While the latter cannot be directly tested (see Section 4.3), we can evaluate the instrument's relevance by determining whether it is strongly correlated with the endogenous regressor. To assess this, I compute the Kleibergen-Paap F-statistic, which accounts for cluster-robust standard errors. As a rule of thumb, if the Kleibergen-Paap F-statistic is greater than 10, the instrument is generally considered strong enough.As shown in Table 11, for both the full sample and the 10th-grade sample, the high Kleibergen-Paap F-statistics indicate that the instruments used are highly relevant.

The IV estimates[8] reveal a statistically significant positive effect of choosing an academic high school track on empathy in both the full and 10th-grade samples. The magnitudes are quite similar across samples, but in the 10th-grade sample, the effect

[8]Full estimates for the reduced form, first stage, and second stage are reported in Appendix B.3.

Table 11: IV Estimates (Estimation Method: 2SLS)

	Full Sample		10th Grade Sample	
Outcome	IV Estimate	Kleibergen-Paap F-stat	IV Estimate	Kleibergen-Paap F-stat
Curiosity	0.077	231.316***	0.043	165.178***
	(0.054)		(0.054)	
Perseverance	0.016	234.160***	-0.015	167.433***
	(0.061)		(0.065)	
Assertiveness	0.001	231.781***	-0.026	164.647***
	(0.052)		(0.057)	
Empathy	0.103**	232.574***	0.102*	166.060***
	(0.051)		(0.055)	
Cooperation	-0.053	231.238***	-0.013	165.356***
	(0.053)		(0.052)	
Stress Resistance	-0.138**	232.384***	-0.139**	165.306***
	(0.055)		(0.059)	
Emotional Control	0.008	235.028***	-0.025	166.255***
	(0.060)		(0.064)	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Each model includes the controls detailed in Section 3.3, provincial dummies, dummies for missing values, and grade dummies for the Full Sample estimates. Control group: students attending a technical institute, a professional institute or an IeFP.

is only significant at the 10% level. Similarly, the choice of an academic track shows a significant negative effect on stress resistance, with a p-value lower than 5% in both samples. For the other social and emotional skills, no significant effects of attending an academic high school track are observed.

Table 12 presents the baseline estimates broken down by subgroups, revealing heterogeneous local average treatment effects (LATE).The results show a positive and significant effect of general education on empathy for female students in the full sample, but this effect loses significance in the 10th-grade sample. For male students, the effect is consistently negative and insignificant. A positive effect on empathy is observed for both students from the North and those from the Centre and South, with a larger and statistically significant effect for students from the North. The effect is higher for individuals from a high socio-economic background, but the only weakly significant result is found in the 10th-grade sample.

While the pattern for empathy is unclear, a more consistent result emerges for stress

Table 12: Heterogeneous LATEs by Gender, Geographical Area, and Socio-Economic Background (Estimation Method: 2SLS)

	Full Sample					
	Female	Male	North	Centre & South	Higher SEB	Lower SEB
Empathy	0.082*	-0.046	0.163**	0.060	0.162	0.089
	(0.050)	(0.166)	(0.075)	(0.070)	(0.104)	(0.065)
Stress Resistance	-0.111**	-0.216	-0.106	-0.151**	-0.267**	-0.052
	(0.056)	(0.254)	(0.080)	(0.076)	(0.123)	(0.081)
	10th Grade Sample					
	Female	Male	North	Centre & South	Higher SEB	Lower SEB
Empathy	0.078	-0.066	0.141*	0.067	0.194*	0.076
	(0.051)	(0.187)	(0.074)	(0.078)	(0.113)	(0.072)
Stress Resistance	-0.117*	-0.194	-0.104	-0.159*	-0.231*	-0.078
	(0.059)	(0.290)	(0.083)	(0.085)	(0.133)	(0.089)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Each model includes the controls detailed in Section 3.3, provincial dummies, dummies for missing values, and grade dummies for the Full Sample estimates, excluding those that are used for defining heterogeneous sub-samples.Control group: students attending a technical institute, a professional institute or an IeFP.

resistance. The negative effect on stress resistance is less pronounced among females and is statistically significant, whereas it is stronger but not significant for males. Students from the Centre and South experience a greater reduction in stress resistance, which is significant in both samples. Similarly, students from higher socio-economic backgrounds also show a significant reduction in stress resistance. The negative effect on stress resistance is lower in magnitude and insignificant for students in the North and those from lower socio-economic backgrounds.

4.3 IV Validity

The estimates presented in Tables 11 and 12 rely on the assumption that the instrument is valid. The validity of the instrument could be compromised if it correlates with shocks that influence the decision to self-select into a given track, even after controlling for observable variables and province fixed effects. While I cannot rule out these possibilities a priori, in this section, I provide support for the exclusion restriction through some tests. For the reasons discussed in the previous paragraph, the exclusion restriction is more likely to fail when the instrument varies by grade. Therefore, I conduct my robustness checks only on the more credible estimates from the 10th-grade sample.

First, my identification strategy may fail if the instrument is correlated with unobservables. To investigate this possibility, I apply the method developed by Oster (2019) to both the first-stage and reduced-form estimates, focusing on the 10th-grade sample. Oster's method allows me to compute bounds for the true value of the parameters under two extreme cases. In the first case, no unobservables are present, and the empirical model is correctly specified, where the estimated R^2 from this model is denoted as $\hat{R}$. In the second case, unobservables are present, but observables and unobservables are assumed to be equally related to the treatment. I denote by R^2_{max} the hypothetical R^2 from a regression that controls for both observed and unobserved factors. When unobservables are included, I conservatively assume $R^2_{max} = \min(1.3\hat{R}, 1)$. If zero is excluded from the bounding set, it would imply that accounting for unobservables does not change the direction of my estimates. I run the test for the non-cognitive skills for which a significant effect is observed. The results are displayed in Table 13, which reports the first-stage and reduced-form estimates in column (1), the R^2 in column (2), and the Oster bounds, i.e., the bias-adjusted coefficients, under the assumption that $R^2_{max} = \min(1.3R^2, 1)$, in column (3).

Table 13: Oster's bounds

	Estimate	R^2	$R^2_{max} = 1.3R^2$
	(1)	(2)	(3)
First stage			
Academic	1.622***	0.721	1.936
Reduced form			
Empathy	0.165*	0.079	0.642
Stress Resistance	-0.225**	0.152	-0.834

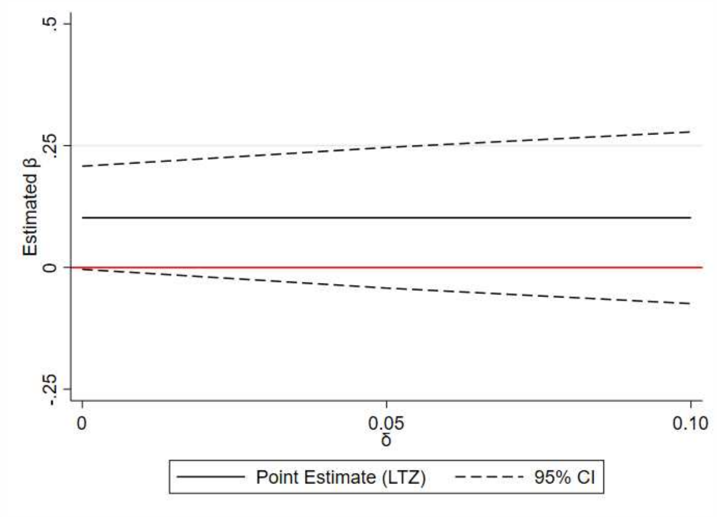
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Estimates a Each model includes the controls detailed in Section 3.3, provincial dummies and dummies for missing values.

In the first stage, zero is excluded from the bounding set, and accounting for unobservables increases the first-stage estimate, leading to a larger IV estimate in absolute terms. When examining the reduced-form estimates, the bounding set also never includes zero, supporting the direction of the effects presented in Table 11. A comparison of the estimates in columns (1) and (3) suggests that omitting unobservables likely leads to an underestimation, in absolute terms, of the reduced-form effects of the instrument on empathy and stress resistance.

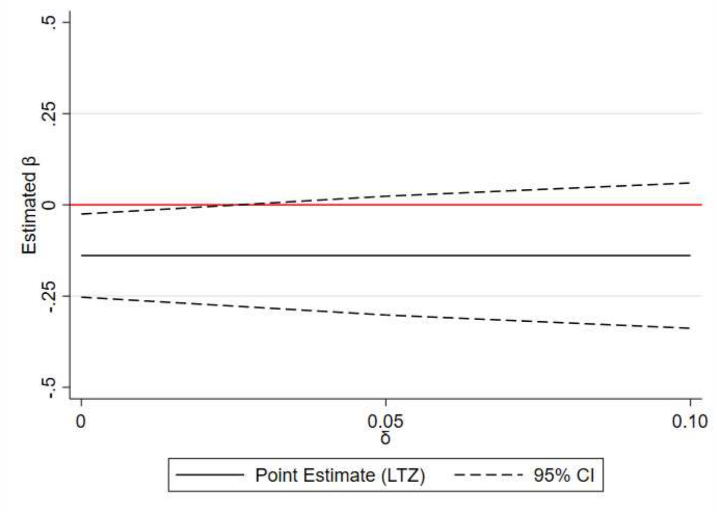
To further argue for the validity of the instrument, I construct bounds for the IV estimates following Conley et al. (2012) and Nevo and Rosen (2012). Instrument validity can be understood in two ways (Clarke and Matta, 2018). First, in terms of the exclusion restriction: the instrument must have no direct effect on the outcome variable beyond its impact through the endogenous treatment variable. Second, in terms of correlations with unobservables: if the instrument is uncorrelated with unobserved factors that influence the outcome, instrumental validity is satisfied. The approach proposed by Conley et al. (2012) relaxes the exact exclusion restriction by making assumptions about the range for the coefficient on the instrument in the structural equation, while the method from Nevo and Rosen (2012) replaces the zero-correlation assumption between the instrument and the unobserved error term with an assumption related to the "sign" of the correlation.

I begin by evaluating whether my estimates are robust to small deviations from excludability using the "local-to-zero" approach proposed by Conley et al. (2012). This method involves making distributional assumptions about the coefficient of the instrument in the structural equation to compute bounds for the IV estimate. Prior beliefs about the violation of the exclusion restriction can help determine the distribution of the coefficient of interest (see for example Bhalotra and Clarke (2020)). However, due to the lack of empirical studies directly addressing the relationship between peer enrollment and individual non-cognitive skills, I am unable to derive an empirically-driven prior. Therefore, I make a general assumption that the coefficient is normally distributed with a mean of zero and a standard deviation equal to $\rho\hat{\beta_{IV}}$, where $\hat{\beta_{IV}}$ is the IV estimate of the effect of choosing an academic track as reported in Table 11, and ρ varies between 0 and 0.10. This implies that, in 99% of cases, the direct effect of the peer enrollment share on social and emotional skills is between $-3\rho \times 100$ and $+3\rho \times 100$ percent of the baseline effect. In Figure 2, the estimated bounds for the effect of choosing an academic track on empathy and stress resistance, which are significant in the baseline estimates, are shown for the 10th-grade sample, where the exclusion restriction is more likely to hold.

Figure 2: 95% confidence interval for $\hat{\beta_{IV}}$ as ρ varies between 0 and 0.1 (Local-to-zero approach, Conley et al. (2012))



(a) Empathy



(b) Stress resistance

As for the bounds on the effect of empathy, the lower bound crosses zero relatively quickly, at ρ values below 0.01, indicating that the estimate is sensitive to small deviations from exact excludability. In contrast, the 95% confidence interval for the effect of an academic track on stress resistance appears more robust. The upper bound crosses zero between $\rho = 0.02$ and $\rho = 0.03$, implying that as long as the direct effect of relative peer enrollment on stress resistance is smaller than a value of ρ between 0.02 and 0.03, the second-stage results remain significant at the 5% level. To gauge the magnitude of this potential violation, I compare the implied direct effect to the total reduced-form effect, estimated at -0.228. For ρ values between 0.02 and 0.03, the implied direct effect is $\rho \times (-0.228)$, resulting in direct effects of -0.00456 at $\rho = 0.02$ and -0.00684 at $\rho = 0.03$. These represent approximately 2% and 3% of the total reduced-form effect, respectively. Thus, the potential violation of the exclusion restriction appears relatively minor, as the direct effect constitutes only a small fraction of the total effect of the instrument.

I further estimate an upper bound for the significant IV estimates using the procedure proposed by Nevo and Rosen (2012). The key assumption to relax the strict zero-correlation requirement is that the instrument Z has (weakly) the same direction of correlation with the omitted error term ϵ as the endogenous treatment variable T. An imperfect instrumental variable is an IV that has the same direction of correlation with the unobserved error term as the endogenous variable of interest, but is less endogenous, meaning $|\rho_{T\epsilon}| > |\rho_{Z\epsilon}|$. In other words, the instrument is flawed but less so than the endogenous variable. To quantify this, Nevo and Rosen (2012) introduce the ratio $\lambda^* = \frac{\rho_{T\epsilon}}{\rho_{Z\epsilon}}$, which reflects how much less endogenous Z is compared to T. While λ^* is unknown, it is bounded between 0 (if the instrument is valid) and 1 (if Z is as endogenous as T). They propose constructing a new instrument, $V(\lambda^*) = \sigma_T Z - \lambda^* \sigma_Z T$, which cancels out the endogenous components of T and Z. This approach generates bounds on the true parameter β by comparing the probability limits of the estimators: β_{OLS}, β_{IV}^{z} (using Z as an imperfect IV), and $\beta_{IV}^{v(1)}$ (using the transformed instrument $V(1)$). If $\sigma_{TZ} < 0$ (i.e., negative correlation between T and Z), the true parameter β can be bounded between β_{OLS} and $\beta_{IV}^{v(1)}$. If the correlation is positive, as is the case in my study, only one-sided bounds can be formed. This occurs because both the instrument Z and the endogenous variable T push the outcome in the same direction, preventing the formation of bounds on both sides. Table 14 presents the upper bounds on the effect of the academic track on empathy and stress resistance for the 10th-grade sample.

Table 14: Upper Bounds for Imperfect Instrument
(Nevo and Rosen (2012))

	β^z_{IV}	Upper Bound ($\beta^{v(1)}_{IV}$)	Confidence Interval Upper Bound
Empathy	0.102	-0.102	0.114]
Stress Resistance	-0.139	-0.135	-0.006]

For empathy, the confidence interval for the upper bound spans from -0.102 to 0.114, suggesting that the effect is not statistically significant, as the interval includes zero. In contrast, for stress resistance, the IV estimate and the confidence interval for the upper bound does not include zero, indicating a statistically significant negative effect. These results suggest that while the effect on empathy is inconclusive, the negative impact of the academic track on stress resistance is more robust, even when accounting for potential imperfections in the instrument.

4.4 Discussion

The most significant result from my LATE estimates is that stress resistance appears to be negatively impacted by the choice of an academic track. Specifically, general education leads to a 63% decrease in stress resistance relative to its mean level (-0.219). This effect can be interpreted as a short-term non-cognitive consequence of choosing a lyceum, as it appears to increase neuroticism after one and a half years of high school. As shown in Table 12, the effect of academic track choice on stress resistance varies across subgroups, being significant for females, students from the Center and South of Italy, and those from higher socio-economic backgrounds. While this subgroup analysis is informative about the treatment effects within each group, it does not allow for a formal test of whether the differences between subgroups are statistically significant. To formally test these differences, I run three separate regressions, each interacting the main endogenous regressor with gender, region, and socio-economic background. Table 15 presents the effect of academic track choice on stress resistance, along with the interaction terms.

For specification (1), the positive interaction term suggests that the negative effect

Table 15: Heterogeneous LATEs with Interaction Terms (Estimation Method: 2SLS)

	(1) Gender	(2) Region	(3) SEB
Academic	-0.279	-0.177*	-0.155**
	(0.375)	(0.093)	(0.071)
Academic × Female	0.118		
	(0.298)		
Academic × North		0.115	
		(0.109)	
Academic × High SEB			0.057
			(0.066)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Each model includes the controls detailed in Section 3.3, provincial dummies, dummies for missing values, and grade dummies for the Full Sample estimates. Control group: students attending a technical institute, a professional institute or an IeFP.

of academic track choice on stress resistance is less pronounced for females than for males, consistent with Table 12, but it is insignificant. The main effect, i.e. the effect for males, is negative but not statistically significant. Since both the main effect and interaction are not significant, we conclude that the impact of academic track choice on stress resistance is not significantly driven by gender differences. To interpret the results, we can contextualize them using findings from the second wave of the Survey on Social and Emotional Skills OECD (2024), which indicate that boys tend to report higher emotional regulation skills, particularly in stress resistance, with gender disparities already visible by age 10. This pattern is evident in Emilia-Romagna, the Italian region sampled in this study. Therefore, while the results do not show a significant gender difference in the effect of academic track choice on stress resistance, pre-existing gender disparities in emotional regulation skills may still play a role, making it unclear whether the observed effects are solely attributable to academic track choice.

In column (2), the sign of the interaction term between academic track and North suggests a less negative effect on stress resistance for students from the North compared to those in the Centre and South, but this interaction term is also not statistically significant. The main effect for students in the Centre and South is significant, indicating that academic track choice negatively impacts stress resistance for this group. This suggests that the negative impact of academic track choice on stress resistance is primarily driven by students from the Centre and South. In specification (3),the positive sign of the interaction term suggests a less severe, though statistically insignificant, negative effect on stress resistance for students from higher SEB backgrounds. The main effect for lower SEB students is negative and significant, meaning academic track choice has a negative impact on stress resistance for students from a lower socio-economic background. This stands in direct contradiction with subgroup heterogeneity analysis of Table 12, where a stronger effect for wealthier students emerged. This could indicate that the effect is more nuanced within each group and doesn't vary sharply enough between groups to be captured by the interaction term.

A key issue in this analysis is determining whether the estimated effects on stress resistance are due to selection effects—for instance, students' beliefs about the effort required for a specific track—or due to the track itself, meaning the curricula and academic environment. If the effect stems from selection, it would suggest that students self-select into tracks based on their expectations about the effort involved. Conversely, if the effect is due to the track itself, the outcome would be driven by features specific to the curriculum. It is important to note that the survey data were collected at the beginning of the second semester of the second year of high school for the 10th-grade sample. Although there are some curricular differences between lyceums, technical schools, and vocational institutes, the subjects that most distinguish these high school types are more intensively taught in the final three years of high school. To test whether the effect is driven by selection, I reran my analysis by dividing the treatment group into two categories: classical, scientific, and linguistic lyceums on one hand, and other lyceums, which are generally perceived as easier, on the other hand. Table 16 presents the results.

For classical, scientific, and linguistic lyceums, the effect on stress resistance is smaller than the baseline and not statistically significant, whereas for other lyceums,

Table 16: Stress Resistance - LATE for different treatment group

	Full Treatment Group	Classical, Scientific and Linguistic Lyceums	Other Lyceums
Stress Resistance	-0.139**	-0.106	-0.232***
	(0.059)	(0.071)	(0.076)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Each model includes the controls detailed in Section 3.3, provincial dummies and dummies for missing values.

the effect is larger and highly significant. This result may seem counterintuitive, as one might expect students in "easier" lyceums to experience less stress. One possible explanation is misaligned expectations—students may anticipate an easier experience but encounter higher demands than anticipated. Another possibility is that these lyceums attract students with lower pre-existing stress tolerance, who may struggle even in less demanding environments. In contrast, the smaller effect observed in more demanding tracks suggests that students in these lyceums may be better prepared or more resilient, reducing the negative impact on stress resistance. Based on these findings, I cannot exclude the possibility that the observed effect on stress resistance is driven by the track itself and not solely by selection effects.

Three limitations of this study should be highlighted. First, the LATE estimates apply only to the group of compliers—in this case, students whose high school choice is influenced by the high share of their gender in their province choosing general education. For students whose choices are not driven by this factor, the LATE estimates may not apply, limiting the broader policy relevance of the findings. Second, even if the instrument is valid and addresses endogeneity related to selection into treatment, the lack of a baseline measure of stress resistance limits the ability to fully determine whether the observed treatment effect is driven by the track itself or by pre-existing differences in students' stress tolerance. Without such a measure, it is difficult to separate the causal effect of the track from students' inherent stress levels, which might influence their track selection. If students with lower stress tolerance systematically choose easier tracks, the observed effect may be partly due to these unobserved baseline differences rather than the treatment itself. Finally, there is the possibility of a violation of the Stable Unit Treatment Value Assumption (SUTVA). Students' stress resistance might be influenced by peer effects, where the behavior or experiences of other students—whether in the same or different tracks—affect individual outcomes, violating the assumption of no interference between units. Additionally, there may be hidden variations in the treatment, as academic tracks may not be uniformly experienced by all students. Differences in teacher quality, resources, or extracurricular activities within the same track could undermine the assumption that the treatment is consistent across all treated units, potentially biasing the LATE estimates.

5 Conclusion

This study has investigated the impact of high school track selection on the non-cognitive skill development of Italian students. Using data from PISA 2022, merged with additional INVALSI data, I examined how choosing an academic track influences students' non-cognitive outcomes within the Italian secondary education system. To address the issue of endogenous self-selection into educational tracks, I employed two identification strategies. The first was a selection-on-observables approach, which assumes that, when key determinants of school choice and non-cognitive skills are controlled for, the treatment is as good as randomly assigned. This approach was strengthened using a double-robust estimator (IPWRA) to improve the validity of the estimates. Given the limitations of this strategy, I also applied a two-stage least squares (2SLS) model using peer enrollment share in 8th grade as an instrumental variable.

The findings show that choosing an academic track leads to a significant reduction in stress resistance, resulting in increased neuroticism. This effect is driven by students from central and southern Italy, while gender and socio-economic background do not play a clear role. Additionally, the effect was stronger in lyceums perceived as "easier," suggesting that the school environment and perceived difficulty also play a role in shaping noncognitive outcomes. However, there are limitations to this study. First, the LATE estimates apply only to compliers, limiting the generalizability of the findings to the wider population. Second, even if the IV strategy effectively addresses endogeneity, the absence of a baseline measure of stress resistance makes it difficult to distinguish between treatment effects and pre-existing characteristics. Finally, potential violations of SUTVA—such as peer effects or hidden variations in the treatment—may affect the consistency of the estimates.

These results offer important insights for both educational policy and practice. The findings suggest that non-cognitive outcomes, such as stress resistance, should be considered when evaluating the effects of different educational tracks. While academic tracks may foster cognitive skill development, they may inadvertently increase stress levels and emotional vulnerability, particularly among certain student groups. This highlights the need for targeted interventions aimed at improving stress resistance. This skill has been shown to be highly teachable when defined as coping strategies and the ability to resist negative internalizing behaviors such as anxiety (Steponavičius et al., 2023). While many efforts have focused on younger children as a preventative measure, it is equally important to address high school students, as non-cognitive abilities continue to develop throughout adolescence. Programs that emphasize social-emotional learning and resilience-building could help students manage academic pressures and improve their overall well-being. Additionally, further research should explore the long-term effects of educational track selection on non-cognitive skills and broader life outcomes, such as employment, mental health, and social integration.

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Appendix A. Questionnaire for Social and Emotional Skills

Skill	Questions
Curiosity	I am curious about many different things.
	I like to ask questions.
	I get frustrated when I have to learn the details of a topic.
	I like to know how things work.
	I love learning new things in school.
	I am more curious than most people I know.
	I like to develop hypotheses and check them based on what I observe.
	I find learning new things to be boring.
	I spend time to find more information about things that interest me.
	I like learning new things.
Perseverance	I keep working on a task until it is finished.
	I apply additional effort when work becomes challenging.
	I finish tasks that I started even when they become boring.
	I stop when work becomes too difficult.
	I am more persistent than most people I know.
	I give up after making mistakes.
	I quit doing homework if it is too long.
	I complete tasks even when they become more difficult than I thought.
	I finish what I start.
	I give up easily.
Assertiveness	I am comfortable with taking the lead role in a group.
	I know how to convince others to do what I want.
	I enjoy leading others.
	I keep my opinion to myself in group discussions.
	I speak up to others about things that matter to me.
	I take initiative when working with my classmates.
	I wait for others to take a lead.
	I find it hard to influence people.
	I want to be in charge.
	I like to be a leader in my class.
Empathy	I do not care what happens to other people.
	I can sense how others feel.
	It is important to me that my friends are okay.
	I can see situations from my friends' perspectives.

	I ignore the feelings of others.
	I am more compassionate than most people I know.
	It is difficult for me to sense what others think.
	I predict the needs of others.
	I get upset if bad things happen to other people.
	I understand what others want.
Cooperation	I like to help others.
	I get annoyed when I have to compromise with others.
	I work well with other people.
	I start arguments with others.
	I avoid working together with other students.
	I am ready to help anybody.
	I tend to be selfish.
	I work better when I am part of a team.
	I enjoy cooperating with my classmates.
	I argue a lot.
Stress Resistance	I get nervous easily.
	I am more relaxed than most people I know.
	I worry about many things.
	I panic easily.
	I am able to work under pressure.
	I remain calm under stress.
	I feel nervous about approaching exams.
	I can recover quickly after something bad has happened.
	I handle stress well.
	I am afraid of many things.
Emotional Control	I keep my emotions under control.
	I get mad easily.
	I change my mood a lot.
	I overreact to every little thing in life.
	I stay calm even in tense situations.
	I am easily upset.
	I know how to control my feelings.
	I have unpredictable emotions.
	I am moody.
	I get frustrated quickly.

Note: each of the 10 items included in this scale had five response options ("Strongly disagree", "Disagree", "Neither agree nor disagree", "Agree", "Strongly agree").

Appendix B. Additional Results

B.1 IPWRA Estimates - Control Group including Students from Technical Institutes and IFT

Table B.1: Average Potential Outcomes and ATEs
(Estimation Method: IPWRA)

	$E[Y_0]$	$E[Y_1]$	ATE
Curiosity	0.078**	0.114***	0.031
	(0.030)	(0.021)	(0.036)
Perseverance	0.065*	0.071***	0.006
	(0.033)	(0.021)	(0.038)
Assertiveness	-0.034	-0.051**	-0.017
	(0.027)	(0.021)	(0.034)
Empathy	-0.037	0.014	0.051
	(0.026)	(0.020)	(0.032)
Cooperation	0.049	0.072***	0.023
	(0.030)	(0.022)	(0.037)
Stress Resistance	-0.159***	-0.250***	-0.091**
	(0.033)	(0.020)	(0.038)
Emotional Control	-0.148***	-0.124***	0.024
	(0.028)	(0.021)	(0.035)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Each treatment model, estimated via logit, includes the controls detailed in Section 3.3.

B.2 IPWRA - Full Estimates

Table B.2.1: IPWRA Estimates (10th Grade Sample) - Curiosity

	Treatment Model	Outcome Model (Academic=1)	Outcome Model (Academic=0)
Female	1.286***	0.044	0.132
	(0.106)	(0.053)	(0.100)
Female ∗ attended	-0.386**	-0.205**	-0.256**
schools in north	(0.153)	(0.090)	(0.121)
Migrant	0.634	-0.012	-0.316
	(0.411)	(0.266)	(0.389)
Migrant ∗ female	-0.193	0.216	0.036
	(0.635)	(0.336)	(0.474)
Migrant ∗ attended	-1.073*	0.087	0.514
schools in north	(0.563)	(0.430)	(0.514)
Migrant ∗ female ∗	2.148**	-0.062	0.067
attended schools in north	(0.935)	(0.497)	(0.654)
Migrant parent	0.106	0.085	0.060
	(0.099)	(0.056)	(0.065)
Different language at home	-0.405***	0.083	-0.039
	(0.112)	(0.075)	(0.078)
Family support	0.078*	0.168***	0.187***
	(0.041)	(0.023)	(0.037)
Socio-economic background	0.881***	0.191***	0.075
	(0.079)	(0.049)	(0.055)
Socio-economic background ^{2}	0.201***	-0.004	0.034
	(0.045)	(0.030)	(0.035)
Socio-economic background ∗ female	0.082	-0.159**	0.139
	(0.120)	(0.064)	(0.116)
Socio-economic background ∗	-0.074	-0.101	0.016
attended schools in north	(0.129)	(0.084)	(0.079)
Socio-economic background ∗ female ∗	-0.390**	0.147	-0.181
attended schools in north	(0.180)	(0.101)	(0.144)
5th grade math score	0.365***	-0.041	0.142**
	(0.072)	(0.055)	(0.060)
5th grade math score ^{2}	-0.107***	0.005	-0.007
	(0.029)	(0.018)	(0.025)
5th grade math score ∗ female	-0.162*	0.054	-0.037
	(0.086)	(0.051)	(0.070)
5th grade math score ∗	0.270***	0.079	-0.068
attended schools in north	(0.089)	(0.053)	(0.067)
5th grade math score ∗	-0.005	0.021	0.080*
socio-economic background	(0.061)	(0.029)	(0.055)
Early education	0.177**	-0.008	0.042
	(0.072)	(0.040)	(0.065)
Rural School	0.212**	0.053	0.122
	(0.106)	(0.066)	(0.093)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	6621	6621	6621

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Control group: students attending a technical institute. The treatment model is estimated via logit, the outcome models via weighted OLS.

Table B.2.2: IPWRA Estimates (10th Grade Sample) - Perseverance

	Treatment Model	Outcome Model (Academic=1)	Outcome Model (Academic=0)
Female	1.309***	-0.019	0.058
	(0.105)	(0.057)	(0.107)
Female ∗ attended schools in north	-0.408***	-0.125	-0.054
	(0.152)	(0.088)	(0.131)
Migrant	0.517	-0.271*	0.465
	(0.403)	(0.158)	(0.331)
Migrant ∗ female	-0.082	0.253	-0.039
	(0.631)	(0.263)	(0.456)
Migrant ∗ attended schools in north	-0.941*	-0.113	-0.332
	(0.558)	(0.332)	(0.354)
Migrant ∗ female ∗ attended schools in north	2.028**	0.572	-0.219
	(0.932)	(0.440)	(0.504)
Migrant parent	0.098	0.074	0.016
	(0.098)	(0.058)	(0.068)
Different language at home	-0.119	0.058	-0.119
	(0.112)	(0.075)	(0.097)
Family support	0.249***	0.180***	0.249***
	(0.043)	(0.025)	(0.043)
Socio-economic background	0.054	0.137**	0.054
	(0.079)	(0.052)	(0.082)
Socio-economic background ^{2}	-0.003	-0.012	-0.003
	(0.045)	(0.024)	(0.040)
Socio-economic background ∗ female	-0.358**	-0.098	0.053
	(0.180)	(0.064)	(0.126)
Socio-economic background ∗ attended schools in north	-0.079	-0.002	0.021
	(0.128)	(0.080)	(0.100)
Socio-economic background ∗ female ∗ attended schools in north	-0.219	0.147	-0.181
	(0.181)	(0.106)	(0.144)
5th grade math score	0.022	0.022	0.021
	(0.072)	(0.039)	(0.060)
5th grade math score ^{2}	-0.045	-0.006	-0.045
	(0.030)	(0.013)	(0.029)
5th grade math score ∗ female	-0.157*	0.019	0.002
	(0.087)	(0.044)	(0.076)
5th grade math score ∗ attended schools in north	0.266***	0.024	0.037
	(0.089)	(0.050)	(0.079)
5th grade math score ∗ socio-economic background	-0.022	0.001	0.068
	(0.061)	(0.027)	(0.058)
Early education	0.176**	-0.011	-0.004
	(0.072)	(0.040)	(0.067)
Rural School	0.319***	0.038	0.319***
	(0.106)	(0.061)	(0.111)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	6,649	6,649	6,649

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Control group: students attending a technical institute. The treatment model is estimated via logit, the outcome models via weighted OLS.

Table B.2.3: IPWRA Estimates (10th Grade Sample) - Assertiveness

	Treatment Model	Outcome Model (Academic=1)	Outcome Model (Academic=0)
Female	1.290***	0.027	0.272**
	(0.106)	(0.050)	(0.108)
Female ∗ attended	-0.391**	-0.150	-0.134
schools in north	(0.152)	(0.092)	(0.136)
Migrant	0.569	-0.021	0.324
	(0.425)	(0.206)	(0.262)
Migrant ∗ female	-0.330	-0.433	-0.729*
	(0.643)	(0.306)	(0.391)
Migrant ∗ attended	-1.022	-0.006	-0.859**
schools in north	(0.574)	(0.355)	(0.361)
Migrant ∗ female ∗	2.274**	0.506	1.102*
attended schools in north	(0.939)	(0.458)	(0.647)
Migrant parent	0.109	0.020	-0.055
	(0.099)	(0.058)	(0.069)
Different language at home	-0.385***	0.151**	0.289**
	(0.113)	(0.062)	(0.133)
Family support	0.081**	0.069***	0.008
	(0.040)	(0.024)	(0.049)
Socio-economic background	0.873***	0.111***	0.030
	(0.079)	(0.041)	(0.050)
Socio-economic background ^{2}	0.198***	-0.033	0.040
	(0.045)	(0.025)	(0.033)
Socio-economic background ∗ female	-0.386**	-0.045	0.384***
	(0.181)	(0.056)	(0.118)
Socio-economic background ∗	-0.066	0.043	0.094
attended schools in north	(0.129)	(0.082)	(0.075)
Socio-economic background ∗ female ∗	-0.386**	0.056	-0.421***
attended schools in north	(0.181)	(0.106)	(0.153)
5th grade math score	0.365***	0.018	0.166***
	(0.073)	(0.037)	(0.053)
5th grade math score ^{2}	-0.105***	0.022	-0.038*
	(0.030)	(0.019)	(0.021)
5th grade math score ∗ female	-0.158*	0.088*	0.009
	(0.087)	(0.046)	(0.067)
5th grade math score ∗	0.261***	0.085	-0.056
attended schools in north	(0.090)	(0.055)	(0.072)
5th grade math score ∗	-0.022	0.001	0.068
socio-economic background	(0.061)	(0.027)	(0.058)
Early education	0.172**	0.015	0.075
	(0.072)	(0.041)	(0.063)
Rural School	0.240**	-0.098	-0.067
	(0.107)	(0.062)	(0.086)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	6572	6572	6572

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Control group: students attending a technical institute. The treatment model is estimated via logit, the outcome models via weighted OLS.

Table B.2.4: IPWRA Estimates (10th Grade Sample) - Empathy

	Treatment Model	Outcome Model (Academic=1)	Outcome Model (Academic=0)
Female	1.256***	0.431***	0.344***
	(0.105)	(0.049)	(0.087)
Female ∗ attended	-0.357**	0.011	-0.005
schools in north	(0.152)	(0.085)	(0.118)
Migrant	0.662	-0.299	-0.300*
	(0.408)	(0.262)	(0.182)
Migrant ∗ female	-0.052	0.162	0.335
	(0.649)	(0.309)	(0.274)
Migrant ∗ attended	-1.102*	-0.013	0.328
schools in north	(0.562)	(0.332)	(0.263)
Migrant ∗ female ∗	2.004**	-0.048	-0.827*
attended schools in north	(0.944)	(0.411)	(0.463)
Migrant parent	0.112	-0.018	0.161**
	(0.099)	(0.058)	(0.078)
Different language at home	-0.405***	-0.024	-0.015
	(0.113)	(0.069)	(0.079)
Family support	0.078	0.133***	0.149***
	(0.040)	(0.023)	(0.036)
Socio-economic background	0.885***	0.174***	0.099
	(0.079)	(0.043)	(0.059)
Socio-economic background ^{2}	0.201***	-0.030	0.006
	(0.045)	(0.027)	(0.031)
Socio-economic background ∗ female	-0.372**	-0.158**	-0.084
	(0.180)	(0.060)	(0.095)
Socio-economic background ∗	-0.071	-0.075	-0.080
attended schools in north	(0.129)	(0.073)	(0.088)
Socio-economic background ∗ female ∗	-0.372**	-0.370**	0.087
attended schools in north	(0.180)	(0.181)	(0.143)
5th grade math score	0.382***	0.008	0.014
	(0.072)	(0.037)	(0.049)
5th grade math score ^{2}	-0.097***	-0.009	-0.063***
	(0.030)	(0.014)	(0.018)
5th grade math score ∗ female	-0.177**	0.053	0.053
	(0.086)	(0.043)	(0.061)
5th grade math score ∗	0.257***	0.021	0.081*
attended schools in north	(0.089)	(0.048)	(0.064)
5th grade math score ∗	-0.022	0.046	-0.068
socio-economic background	(0.061)	(0.042)	(0.044)
Early education	0.176**	-0.177***	0.091*
	(0.072)	(0.058)	(0.039)
Rural School	0.244**	0.037	-0.182**
	(0.104)	(0.061)	(0.077)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	6615	6615	6615

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Control group: students attending a technical institute. The treatment model is estimated via logit, the outcome models via weighted OLS.

Table B.2.5: IPWRA Estimates (10th Grade Sample) - Cooperation

	Treatment Model	Outcome Model (Academic=1)	Outcome Model (Academic=0)
Female	1.302***	-0.019	0.112
	(0.106)	(0.063)	(0.105)
Female ∗ attended	-0.402***	0.049	-0.033
schools in north	(0.152)	(0.088)	(0.131)
Migrant	0.675	-0.110	-0.043
	(0.409)	(0.503)	(0.266)
Migrant ∗ female	-0.244	0.126	-0.549
	(0.633)	(0.526)	(0.398)
Migrant ∗ attended	-1.106**	-0.614	0.298
schools in north	(0.563)	(0.540)	(0.335)
Migrant ∗ female ∗	2.195**	0.749	-0.169
attended schools in north	(0.934)	(0.605)	(0.511)
Migrant parent	0.098	-0.092	0.137**
	(0.099)	(0.068)	(0.063)
Different language at home	-0.406***	0.136	-0.246***
	(0.112)	(0.107)	(0.074)
Family support	0.083**	0.161***	0.160***
	(0.040)	(0.023)	(0.039)
Socio-economic background	0.877***	0.009	-0.095
	(0.079)	(0.059)	(0.060)
Socio-economic background ^{2}	0.192***	-0.028	0.001
	(0.045)	(0.026)	(0.033)
Socio-economic background ∗ female	-0.376**	0.068	0.077
	(0.180)	(0.120)	(0.121)
Socio-economic background ∗	-0.074	0.095	-0.284
attended schools in north	(0.129)	(0.093)	(0.221)
Socio-economic background ∗ female ∗	-0.376**	-0.096	-0.103
attended schools in north	(0.180)	(0.101)	(0.158)
5th grade math score	0.362***	-0.017	0.034
	(0.072)	(0.060)	(0.074)
5th grade math score ^{2}	-0.104***	0.006	0.004
	(0.029)	(0.020)	(0.027)
5th grade math score ∗ female	-0.160*	-0.072	0.007
	(0.087)	(0.052)	(0.081)
5th grade math score ∗	0.273***	0.069	0.036
attended schools in north	(0.090)	(0.048)	(0.073)
5th grade math score ∗	-0.001	0.031	-0.015
socio-economic background	(0.061)	(0.061)	(0.062)
Early education	0.169**	0.114**	0.049
	(0.072)	(0.041)	(0.064)
Rural School	0.211**	0.006	0.147
	(0.106)	(0.068)	(0.122)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	6,630	6,630	6,630

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Control group: students attending a technical institute. The treatment model is estimated via logit, the outcome models via weighted OLS.

Table B.2.6: IPWRA Estimates (10th Grade Sample) - Stress Resistance

	Treatment Model	Outcome Model (Academic=1)	Outcome Model (Academic=0)
Female	1.295***	-0.738***	-0.525***
	(0.106)	(0.054)	(0.124)
Female ∗ attended	-0.398***	0.068	-0.136
schools in north	(0.153)	(0.077)	(0.146)
Migrant	0.607	-0.235	0.412
	(0.414)	(0.409)	(0.428)
Migrant ∗ female	-0.350	0.417	0.232
	(0.634)	(0.473)	(0.502)
Migrant ∗ attended	-1.057	0.367	-0.195
schools in north	(0.567)	(0.501)	(0.476)
Migrant ∗ female ∗	2.305**	-0.264	-0.200
attended schools in north	(0.935)	(0.574)	(0.579)
Migrant parent	0.102	0.020	0.173**
	(0.099)	(0.055)	(0.068)
Different language at home	-0.381***	-0.015	-0.079
	(0.113)	(0.063)	(0.077)
Family support	0.082**	-0.002	0.043
	(0.040)	(0.023)	(0.047)
Socio-economic background	0.859***	0.054	-0.016
	(0.079)	(0.045)	(0.089)
Socio-economic background ^{2}	0.204***	-0.000	0.038
	(0.046)	(0.029)	(0.043)
Socio-economic background ∗ female	-0.411**	0.104	0.442***
	(0.182)	(0.121)	(0.163)
Socio-economic background ∗	-0.075	-0.045	-0.224
attended schools in north	(0.130)	(0.129)	(0.516)
Socio-economic background ∗ female ∗	-0.411**	-0.018	-0.541***
attended schools in north	(0.182)	(0.093)	(0.198)
5th grade math score	0.375***	-0.006	-0.006
	(0.072)	(0.043)	(0.064)
5th grade math score ^{2}	-0.096***	0.008	-0.003
	(0.030)	(0.016)	(0.025)
5th grade math score ∗ female	-0.172*	0.011	0.028
	(0.087)	(0.045)	(0.069)
5th grade math score ∗	0.255***	0.033	0.059
attended schools in north	(0.090)	(0.043)	(0.064)
5th grade math score ∗	-0.006	0.012	0.064
socio-economic background	(0.061)	(0.031)	(0.090)
Early education	0.169**	0.017	-0.018
	(0.072)	(0.037)	(0.072)
Rural School	0.243**	-0.113	0.149*
	(0.106)	(0.069)	(0.080)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	6,572	6,572	6,572

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Control group: students attending a technical institute. The treatment model is estimated via logit, the outcome models via weighted OLS.

Table B.2.7: IPWRA Estimates (10th Grade Sample) - Emotional Control

	Treatment Model	Outcome Model (Academic=1)	Outcome Model (Academic=0)
Female	1.294***	-0.582***	-0.395***
	(0.106)	(0.053)	(0.093)
Female ∗ attended	-0.397***	0.072	-0.021
schools in north	(0.153)	(0.080)	(0.121)
Migrant	0.540	-0.395	-0.318
	(0.436)	(0.487)	(0.198)
Migrant ∗ female	-0.282	0.461	0.187
	(0.652)	(0.527)	(0.456)
Migrant ∗ attended	-0.978	0.041	0.405
schools in north	(0.582)	(0.614)	(0.254)
Migrant ∗ female ∗	2.225**	-0.068	-0.097
attended schools in north	(0.946)	(0.680)	(0.566)
Migrant parent	0.101	0.079	0.181**
	(0.099)	(0.052)	(0.078)
Different language at home	-0.403***	-0.048	-0.205**
	(0.113)	(0.063)	(0.084)
Family support	0.082**	0.064***	0.085**
	(0.040)	(0.025)	(0.039)
Socio-economic background	0.853***	0.065	-0.088
	(0.079)	(0.049)	(0.071)
Socio-economic background ^{2}	0.201***	-0.039	-0.015
	(0.046)	(0.030)	(0.038)
Socio-economic background ∗ female	-0.411**	0.107	0.232**
	(0.182)	(0.121)	(0.110)
Socio-economic background ∗	-0.075	-0.056	-0.128
attended schools in north	(0.130)	(0.129)	(0.441)
Socio-economic background ∗ female ∗	-0.411**	-0.002	-0.082
attended schools in north	(0.182)	(0.012)	(0.162)
5th grade math score	0.370***	0.014	-0.084*
	(0.072)	(0.040)	(0.051)
5th grade math score ^{2}	-0.107***	0.009	0.040*
	(0.030)	(0.015)	(0.023)
5th grade math score ∗ female	-0.161*	-0.021	0.057
	(0.087)	(0.045)	(0.067)
5th grade math score ∗	0.258***	0.015	0.096
attended schools in north	(0.090)	(0.054)	(0.067)
5th grade math score ∗	-0.002	-0.018	-0.007
socio-economic background	(0.061)	(0.029)	(0.059)
Early education	0.168**	0.022	-0.033
	(0.072)	(0.040)	(0.065)
Rural School	0.230**	0.002	0.120
	(0.106)	(0.061)	(0.070)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	6,555	6,555	6,555

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Control group: students attending a technical institute. The treatment model is estimated via logit, the outcome models via weighted OLS.

B.3 IV - Full Estimates

Table B.3.1: IV Estimates (Full Sample) - Curiosity

	Reduced Form	First Stage	Second Stage
Instrument	0.127	1.646***	
	(0.089)	(0.108)	
Academic			0.077
			(0.054)
Female	-0.007	-0.091***	-0.014
	(0.028)	(0.028)	(0.029)
Female ∗ attended	-0.128***	0.093**	-0.121**
schools in north	(0.049)	(0.041)	(0.049)
Migrant	-0.126	0.048	-0.123
	(0.139)	(0.044)	(0.139)
Migrant ∗ female	0.157	-0.052	0.153
	(0.186)	(0.049)	(0.186)
Migrant ∗ attended	0.086	-0.025	0.084
schools in north	(0.236)	(0.066)	(0.236)
Migrant ∗ female ∗	0.169	0.058	0.173
attended schools in north	(0.290)	(0.074)	(0.290)
Migrant parent	0.061*	0.010	0.061*
	(0.035)	(0.010)	(0.035)
Different language at home	0.005	-0.040**	0.002
	(0.043)	(0.013)	(0.043)
Family support	0.167***	0.010**	0.167***
	(0.016)	(0.004)	(0.016)
Socio-economic	0.114***	0.140***	0.125***
background	(0.025)	(0.016)	(0.022)
Socio-economic background ^{2}	0.030*	0.010*	0.030*
	(0.015)	(0.004)	(0.015)
Socio-economic background ∗ female	-0.062**	-0.118***	-0.071***
	(0.030)	(0.018)	(0.030)
Socio-economic background ∗	-0.005	-0.030	-0.008
attended schools in north	(0.040)	(0.023)	(0.040)
Socio-economic background ∗ female ∗	0.013	0.017	0.015
attended schools in north	(0.055)	(0.027)	(0.055)
5th grade math score	0.022	0.061***	0.027
	(0.036)	(0.014)	(0.036)
5th grade math score ^{2}	-0.007	-0.007**	-0.008
	(0.010)	(0.003)	(0.010)
5th grade math score ∗ female	0.008	-0.063***	0.003
	(0.037)	(0.013)	(0.037)
5th grade math score ∗	0.056	0.016	0.057
attended schools in north	(0.041)	(0.014)	(0.041)
5th grade math score ∗	0.022	-0.035**	0.002
socio-economic background	(0.023)	(0.014)	(0.023)
Early education	-0.000	0.014	0.001
	(0.027)	(0.010)	(0.027)
Rural School	0.036	0.071*	0.042
	(0.057)	(0.048)	(0.057)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	8254	8254	8254

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.2: IV Estimates (Full Sample) - Perseverance

	Reduced Form	First Stage	Second Stage
Instrument	0.026	1.647***	
	(0.101)	(0.108)	
Academic			0.016
			(0.061)
Female	-0.048	-0.087***	-0.047
	(0.032)	(0.028)	(0.030)
Female ∗ attended	-0.039	0.089**	-0.040
schools in north	(0.052)	(0.041)	(0.051)
Migrant	0.175	0.038	0.174
	(0.120)	(0.040)	(0.120)
Migrant ∗ female	-0.011	-0.046	-0.010
	(0.161)	(0.046)	(0.160)
Migrant ∗ attended	-0.070	-0.015	-0.070
schools in north	(0.208)	(0.063)	(0.208)
Migrant ∗ female ∗	0.253	0.051	0.253
attended schools in north	(0.278)	(0.072)	(0.278)
Migrant parent	0.022	0.009	0.022
	(0.040)	(0.010)	(0.040)
Different language at home	-0.008	-0.040***	-0.008
	(0.043)	(0.013)	(0.043)
Family support	0.199***	0.011**	0.198***
	(0.015)	(0.004)	(0.015)
Socio-economic	0.107***	0.139***	0.105***
background	(0.029)	(0.016)	(0.029)
Socio-economic background ^{2}	-0.012	0.009**	-0.012
	(0.014)	(0.004)	(0.014)
Socio-economic background ∗ female	-0.027	-0.118***	-0.025
	(0.037)	(0.017)	(0.037)
Socio-economic background ∗	-0.002	-0.029	-0.002
attended schools in north	(0.048)	(0.023)	(0.048)
Socio-economic background ∗ female ∗	-0.017	0.016	-0.017
attended schools in north	(0.058)	(0.026)	(0.058)
5th grade math score	0.006	0.062***	0.005
	(0.041)	(0.014)	(0.040)
5th grade math score ^{2}	-0.006	-0.007*	-0.006
	(0.012)	(0.004)	(0.012)
5th grade math score ∗ female	0.009	-0.063***	0.010
	(0.040)	(0.013)	(0.039)
5th grade math score ∗	0.040	0.015	0.040
attended schools in north	(0.039)	(0.014)	(0.039)
5th grade math score ∗	0.008	-0.031**	0.008
socio-economic background	(0.024)	(0.013)	(0.024)
Early education	-0.015	0.013	-0.015
	(0.023)	(0.010)	(0.023)
Rural School	0.148***	0.075*	0.147***
	(0.053)	(0.048)	(0.053)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	8292	8292	8292

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.3: IV Estimates (Full Sample) - Assertiveness

	Reduced Form	First Stage	Second Stage
Instrument	0.002	1.650***	
	(0.086)	(0.108)	
Academic			0.001
			(0.052)
Female	0.043	-0.092***	0.043
	(0.033)	(0.028)	(0.032)
Female ∗ attended	-0.043	0.094**	-0.043
schools in north	(0.052)	(0.040)	(0.052)
Migrant	0.080	0.041	0.080
	(0.113)	(0.041)	(0.113)
Migrant ∗ female	-0.341**	-0.049	-0.340**
	(0.166)	(0.047)	(0.166)
Migrant ∗ attended	-0.164	-0.039	-0.164
schools in north	(0.160)	(0.066)	(0.160)
Migrant ∗ female ∗	0.359	0.084	0.359
attended schools in north	(0.223)	(0.073)	(0.223)
Migrant parent	-0.001	0.009	-0.001
	(0.038)	(0.010)	(0.038)
Different language at home	0.111**	-0.038***	0.111**
	(0.044)	(0.013)	(0.044)
Family support	0.069***	0.011**	0.069***
	(0.017)	(0.004)	(0.017)
Socio-economic	0.111***	0.139***	0.111***
background	(0.030)	(0.016)	(0.031)
Socio-economic background ^{2}	-0.004	0.010**	-0.004
	(0.015)	(0.004)	(0.016)
Socio-economic background ∗ female	0.009	-0.118***	0.009
	(0.040)	(0.018)	(0.039)
Socio-economic background ∗	0.005	-0.028	0.005
attended schools in north	(0.039)	(0.023)	(0.039)
Socio-economic background ∗ female ∗	-0.030	0.015	-0.030
attended schools in north	(0.057)	(0.027)	(0.057)
5th grade math score	0.067***	0.061***	0.067***
	(0.021)	(0.014)	(0.022)
5th grade math score ^{2}	0.003	-0.007*	0.003
	(0.013)	(0.004)	(0.013)
5th grade math score ∗ female	0.053*	-0.063***	0.053*
	(0.028)	(0.013)	(0.028)
5th grade math score ∗	0.036	0.016	0.036
attended schools in north	(0.033)	(0.014)	(0.033)
5th grade math score ∗	-0.012	-0.035**	-0.012
socio-economic background	(0.020)	(0.014)	(0.020)
Early education	0.003	0.015	0.003
	(0.028)	(0.010)	(0.028)
Rural School	-0.073	0.081*	-0.073
	(0.055)	(0.046)	(0.055)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	8176	8174	8174

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.4: IV Estimates (Full Sample) - Empathy

	Reduced Form	First Stage	Second Stage
Instrument	0.169**	1.647***	
	(0.081)	(0.108)	
Academic			0.103**
			(0.051)
Female	0.330***	-0.093***	0.329***
	(0.034)	(0.028)	(0.033)
Female ∗ attended	0.024	0.094**	0.014
schools in north	(0.043)	(0.041)	(0.041)
Migrant	0.010	0.049	0.004
	(0.120)	(0.042)	(0.121)
Migrant ∗ female	-0.117	-0.054	-0.111
	(0.158)	(0.048)	(0.159)
Migrant ∗ attended	-0.134	-0.025	-0.131
schools in north	(0.189)	(0.065)	(0.190)
Migrant ∗ female ∗	0.216	0.068	0.209
attended schools in north	(0.264)	(0.073)	(0.265)
Migrant parent	0.028	0.009	0.027
	(0.038)	(0.010)	(0.038)
Different language at home	-0.028	-0.040***	-0.024
	(0.043)	(0.013)	(0.044)
Family support	0.127***	0.011**	0.125***
	(0.015)	(0.004)	(0.015)
Socio-economic	0.116***	0.140***	0.101***
background	(0.022)	(0.016)	(0.023)
Socio-economic background ^{2}	0.019	0.010**	0.018
	(0.016)	(0.004)	(0.016)
Socio-economic background ∗ female	-0.076**	-0.119***	-0.064**
	(0.033)	(0.017)	(0.031)
Socio-economic background ∗	-0.056	-0.030	-0.052
attended schools in north	(0.038)	(0.023)	(0.038)
Socio-economic background ∗ female ∗	0.050	0.016	0.048
attended schools in north	(0.055)	(0.027)	(0.055)
5th grade math score	0.010	0.065***	0.004
	(0.027)	(0.015)	(0.027)
5th grade math score ^{2}	-0.028***	-0.006**	-0.027***
	(0.009)	(0.003)	(0.009)
5th grade math score ∗ female	0.018	-0.066***	0.025
	(0.031)	(0.013)	(0.031)
5th grade math score ∗	0.043	0.013	0.042
attended schools in north	(0.035)	(0.014)	(0.035)
5th grade math score ∗	-0.009	-0.035***	-0.009
socio-economic background	(0.020)	(0.014)	(0.020)
Early education	0.037	0.014	0.036
	(0.024)	(0.010)	(0.024)
Rural School	-0.028	0.080*	-0.036
	(0.044)	(0.045)	(0.043)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	8244	8244	8244

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.5: IV Estimates (Full Sample) - Cooperation

	Reduced Form	First Stage	Second Stage
Instrument	-0.088	1.645***	
	(0.087)	(0.108)	
Academic			-0.053
			(0.052)
Female	-0.015	-0.091***	-0.015
	(0.036)	(0.028)	(0.036)
Female ∗ attended	0.032	0.094**	0.032
schools in north	(0.048)	(0.040)	(0.048)
Migrant	0.020	0.057	0.020
	(0.150)	(0.040)	(0.150)
Migrant ∗ female	-0.259	-0.055	-0.259
	(0.182)	(0.046)	(0.182)
Migrant ∗ attended	-0.161	-0.028	-0.161
schools in north	(0.221)	(0.064)	(0.221)
Migrant ∗ female ∗	0.512	0.060	0.512
attended schools in north	(0.281)	(0.072)	(0.281)
Migrant parent	-0.018	0.009	-0.018
	(0.041)	(0.010)	(0.041)
Different language at home	-0.069	-0.042***	-0.069
	(0.046)	(0.013)	(0.046)
Family support	0.171***	0.011**	0.171***
	(0.015)	(0.004)	(0.015)
Socio-economic	0.019	0.139***	0.019
background	(0.030)	(0.016)	(0.030)
Socio-economic background ^{2}	0.000	0.009**	0.000
	(0.014)	(0.004)	(0.014)
Socio-economic background ∗ female	0.027	-0.117***	0.027
	(0.039)	(0.018)	(0.039)
Socio-economic background ∗	0.004	-0.030	0.004
attended schools in north	(0.043)	(0.023)	(0.043)
Socio-economic background ∗ female ∗	-0.065	0.016	-0.065
attended schools in north	(0.059)	(0.027)	(0.059)
5th grade math score	-0.008	0.061***	-0.008
	(0.033)	(0.014)	(0.033)
5th grade math score ^{2}	0.007	-0.007**	0.007
	(0.012)	(0.003)	(0.012)
5th grade math score ∗ female	-0.055	-0.063***	-0.055
	(0.034)	(0.013)	(0.034)
5th grade math score ∗	0.034	0.016	0.034
attended schools in north	(0.038)	(0.014)	(0.038)
5th grade math score ∗	0.025	-0.035**	0.025
socio-economic background	(0.024)	(0.014)	(0.024)
Early education	0.071**	0.013	0.071**
	(0.028)	(0.010)	(0.028)
Rural School	0.043	0.077*	0.043
	(0.062)	(0.047)	(0.062)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	8272	8272	8272

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.6: IV Estimates (Full Sample) - Stress Resistance

	Reduced Form	First Stage	Second Stage
Instrument	-0.227**	1.648***	
	(0.090)	(0.108)	
Academic			-0.138**
			(0.055)
Female	-0.674***	-0.093***	-0.687***
	(0.034)	(0.028)	(0.032)
Female ∗ attended	0.029	0.095**	0.042
schools in north	(0.047)	(0.040)	(0.045)
Migrant	0.084	0.057	0.092
	(0.139)	(0.040)	(0.139)
Migrant ∗ female	0.144	-0.057	0.136
	(0.176)	(0.046)	(0.175)
Migrant ∗ attended	0.066	-0.041	0.060
schools in north	(0.161)	(0.064)	(0.161)
Migrant ∗ female ∗	-0.082	0.073	-0.072
attended schools in north	(0.215)	(0.073)	(0.214)
Migrant parent	0.089**	0.008	0.090**
	(0.037)	(0.010)	(0.037)
Different language at home	-0.042	-0.039***	-0.047
	(0.041)	(0.013)	(0.042)
Family support	0.010	0.011**	0.011
	(0.016)	(0.005)	(0.016)
Socio-economic	0.023	0.138***	0.042
background	(0.025)	(0.016)	(0.027)
Socio-economic background ^{2}	0.011	0.010**	0.013
	(0.016)	(0.004)	(0.016)
Socio-economic background ∗ female	0.046	-0.116***	0.030
	(0.035)	(0.018)	(0.034)
Socio-economic background ∗	0.055	-0.027	0.052
attended schools in north	(0.041)	(0.023)	(0.041)
Socio-economic background ∗ female ∗	-0.100*	0.013	-0.098*
attended schools in north	(0.052)	(0.027)	(0.052)
5th grade math score	0.037	0.064***	0.046
	(0.029)	(0.016)	(0.030)
5th grade math score ^{2}	0.004	-0.005	0.003
	(0.010)	(0.003)	(0.010)
5th grade math score ∗ female	-0.002	-0.066***	-0.011
	(0.035)	(0.014)	(0.035)
5th grade math score ∗	0.054	0.015	0.056
attended schools in north	(0.037)	(0.015)	(0.037)
5th grade math score ∗	0.017	-0.001	0.017
socio-economic background	(0.025)	(0.007)	(0.025)
Early education	0.003	0.014	0.005
	(0.030)	(0.010)	(0.030)
Rural School	0.015	0.086*	0.027
	(0.060)	(0.046)	(0.062)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	8178	8176	8176

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.7: IV Estimates (Full Sample) - Emotional Control

	Reduced Form	First Stage	Second Stage
Instrument	0.013	1.649***	
	(0.099)	(0.108)	
Academic			0.008
			(0.060)
Female	-0.563***	-0.091***	-0.562***
	(0.031)	(0.028)	(0.031)
Female ∗ attended	0.050	0.092**	0.049
schools in north	(0.040)	(0.041)	(0.040)
Migrant	-0.226	0.047	-0.226
	(0.154)	(0.041)	(0.154)
Migrant ∗ female	0.354	-0.053	0.353
	(0.195)	(0.047)	(0.195)
Migrant ∗ attended	0.071	-0.035	0.071
schools in north	(0.191)	(0.064)	(0.191)
Migrant ∗ female ∗	-0.230	0.070	-0.230
attended schools in north	(0.263)	(0.072)	(0.263)
Migrant parent	0.108***	0.008	0.108***
	(0.037)	(0.010)	(0.037)
Different language at home	-0.107**	-0.039***	-0.107**
	(0.045)	(0.013)	(0.045)
Family support	0.070***	0.010**	0.070***
	(0.015)	(0.004)	(0.015)
Socio-economic	0.023	0.139***	0.022
background	(0.031)	(0.017)	(0.032)
Socio-economic background ^{2}	-0.004	0.010**	-0.004
	(0.016)	(0.004)	(0.016)
Socio-economic background ∗ female	0.020	-0.117***	0.021
	(0.041)	(0.018)	(0.041)
Socio-economic background ∗	-0.005	-0.030	-0.005
attended schools in north	(0.051)	(0.024)	(0.051)
Socio-economic background ∗ female ∗	0.019	0.017	0.019
attended schools in north	(0.059)	(0.027)	(0.059)
5th grade math score	-0.025	0.062***	-0.025
	(0.026)	(0.015)	(0.026)
5th grade math score ^{2}	0.016	-0.007*	0.016
	(0.009)	(0.004)	(0.009)
5th grade math score ∗ female	-0.013	-0.063***	-0.013
	(0.035)	(0.014)	(0.035)
5th grade math score ∗	0.067	0.014	0.067
attended schools in north	(0.037)	(0.014)	(0.037)
5th grade math score ∗	-0.017	0.000	-0.017
socio-economic background	(0.023)	(0.006)	(0.023)
Early education	0.019	0.014	0.019
	(0.028)	(0.009)	(0.028)
Rural School	0.098	0.079*	0.098
	(0.062)	(0.046)	(0.062)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	8162	8160	8160

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.8: IV Estimates (10th Grade Sample) - Curiosity

	Reduced Form	First Stage	Second Stage
Instrument	0.069	1.618***	
	(0.088)	(0.126)	
Academic			0.043
			(0.054)
Female	-0.002	-0.084***	-0.002
	(0.029)	(0.032)	(0.029)
Female ∗ attended	-0.147***	0.088**	-0.147***
schools in north	(0.048)	(0.043)	(0.048)
Migrant	-0.174	0.046	-0.174
	(0.202)	(0.058)	(0.202)
Migrant ∗ female	0.265	-0.063	0.265
	(0.235)	(0.065)	(0.235)
Migrant ∗ attended	-0.015	-0.051	-0.015
schools in north	(0.318)	(0.073)	(0.318)
Migrant ∗ female ∗	0.235	0.092	0.235
attended schools in north	(0.355)	(0.084)	(0.355)
Migrant parent	0.063*	0.010	0.063*
	(0.038)	(0.011)	(0.038)
Different language at home	0.014	-0.041***	0.014
	(0.047)	(0.014)	(0.047)
Family support	0.170***	0.013***	0.170***
	(0.017)	(0.005)	(0.017)
Socio-economic	0.118***	0.135***	0.118***
background	(0.026)	(0.019)	(0.026)
Socio-economic background ^{2}	0.020	0.008	0.020
	(0.017)	(0.005)	(0.017)
Socio-economic background ∗ female	-0.078**	-0.112***	-0.078**
	(0.033)	(0.020)	(0.033)
Socio-economic background ∗	-0.034	-0.021	-0.034
attended schools in north	(0.041)	(0.026)	(0.041)
Socio-economic background ∗ female ∗	0.054	0.006	0.054
attended schools in north	(0.056)	(0.030)	(0.056)
5th grade math score	0.027	0.062***	0.027
	(0.037)	(0.014)	(0.037)
5th grade math score ^{2}	-0.008	-0.007**	-0.008
	(0.010)	(0.003)	(0.010)
5th grade math score ∗ female	0.009	-0.062***	0.009
	(0.038)	(0.013)	(0.038)
5th grade math score ∗	0.059	0.013	0.059
attended schools in north	(0.042)	(0.014)	(0.042)
5th grade math score ∗	0.020	-0.035*	0.020
socio-economic background	(0.023)	(0.014)	(0.023)
Early education	0.010	0.009	0.010
	(0.029)	(0.010)	(0.029)
Rural School	0.007	0.092*	0.007
	(0.061)	(0.054)	(0.061)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	7531	7531	7531

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.9: IV Estimates (10th Grade Sample) - Perseverance

	Reduced Form	First Stage	Second Stage
Instrument	-0.024	1.619***	
	(0.105)	(0.125)	
Academic			-0.015
			(0.065)
Female	-0.045	-0.079***	-0.045
	(0.031)	(0.032)	(0.031)
Female ∗ attended	-0.049	0.083*	-0.049
schools in north	(0.051)	(0.043)	(0.051)
Migrant	0.093	0.029	0.093
	(0.152)	(0.052)	(0.152)
Migrant ∗ female	0.005	-0.045	0.005
	(0.208)	(0.060)	(0.208)
Migrant ∗ attended	-0.263	-0.033	-0.264
schools in north	(0.253)	(0.068)	(0.253)
Migrant ∗ female ∗	0.521	0.072	0.521
attended schools in north	(0.349)	(0.081)	(0.349)
Migrant parent	0.019	0.009	0.019
	(0.042)	(0.011)	(0.042)
Different language at home	0.013	-0.041***	0.013
	(0.046)	(0.014)	(0.046)
Family support	0.198***	0.014***	0.198***
	(0.016)	(0.005)	(0.016)
Socio-economic	0.118***	0.135***	0.118***
background	(0.031)	(0.018)	(0.031)
Socio-economic background ^{2}	-0.018	0.007	-0.018
	(0.016)	(0.005)	(0.016)
Socio-economic background ∗ female	-0.056	-0.112***	-0.056
	(0.040)	(0.020)	(0.040)
Socio-economic background ∗	-0.022	-0.021	-0.022
attended schools in north	(0.049)	(0.026)	(0.049)
Socio-economic background ∗ female ∗	0.023	0.007	0.023
attended schools in north	(0.060)	(0.029)	(0.060)
5th grade math score	0.008	0.063***	0.008
	(0.041)	(0.014)	(0.041)
5th grade math score ^{2}	-0.007	-0.007*	-0.007
	(0.012)	(0.004)	(0.012)
5th grade math score ∗ female	0.010	-0.061***	0.010
	(0.041)	(0.013)	(0.041)
5th grade math score ∗	0.037	0.012	0.037
attended schools in north	(0.039)	(0.014)	(0.039)
5th grade math score ∗	0.007	-0.031**	0.007
socio-economic background	(0.024)	(0.014)	(0.024)
Early education	0.004	0.008	0.004
	(0.022)	(0.010)	(0.022)
Rural School	0.137**	0.096*	0.137**
	(0.058)	(0.054)	(0.058)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	7566	7566	7566

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.10: IV Estimates (10th Grade Sample) - Assertiveness

	Reduced Form	First Stage	Second Stage
Instrument	-0.042	1.620***	
	(0.091)	(0.126)	
Academic			-0.026
			(0.057)
Female	0.061	-0.086***	0.061*
	(0.036)	(0.032)	(0.036)
Female ∗ attended	-0.058	0.090**	-0.056
schools in north	(0.054)	(0.043)	(0.054)
Migrant	0.088	0.033	0.088
	(0.156)	(0.052)	(0.157)
Migrant ∗ female	-0.393*	-0.051	-0.392*
	(0.216)	(0.060)	(0.216)
Migrant ∗ attended	-0.314	-0.054	-0.312
schools in north	(0.199)	(0.072)	(0.199)
Migrant ∗ female ∗	0.634**	0.094	0.634**
attended schools in north	(0.277)	(0.082)	(0.277)
Migrant parent	-0.007	0.010	-0.007
	(0.041)	(0.011)	(0.041)
Different language at home	0.149***	-0.040***	0.149***
	(0.047)	(0.014)	(0.047)
Family support	0.062***	0.013***	0.062***
	(0.018)	(0.005)	(0.018)
Socio-economic	0.102***	0.134***	0.105***
background	(0.034)	(0.018)	(0.035)
Socio-economic background ^{2}	-0.010	0.007	-0.010
	(0.018)	(0.005)	(0.018)
Socio-economic background ∗ female	0.006	-0.110***	0.003
	(0.044)	(0.020)	(0.044)
Socio-economic background ∗	0.011	-0.020	0.011
attended schools in north	(0.043)	(0.026)	(0.043)
Socio-economic background ∗ female ∗	-0.043	0.006	-0.043
attended schools in north	(0.060)	(0.030)	(0.060)
5th grade math score	0.069***	0.062***	0.068***
	(0.021)	(0.014)	(0.021)
5th grade math score ^{2}	0.002	-0.007*	0.002
	(0.013)	(0.004)	(0.013)
5th grade math score ∗ female	0.056**	-0.061***	0.056**
	(0.028)	(0.013)	(0.028)
5th grade math score ∗	0.038	0.014	0.038
attended schools in north	(0.033)	(0.014)	(0.033)
5th grade math score ∗	-0.012	-0.028**	-0.018
socio-economic background	(0.020)	(0.013)	(0.020)
Early education	0.015	0.011	0.015
	(0.030)	(0.010)	(0.030)
Rural School	-0.105	0.103**	-0.103*
	(0.061)	(0.052)	(0.061)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	7463	7463	7463

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.11: IV Estimates (10th Grade Sample) - Empathy

	Reduced Form	First Stage	Second Stage
Instrument	0.165*	1.619***	
	(0.084)	(0.126)	
Academic			0.102
			(0.055)
Female	0.319***	-0.086***	0.327***
	(0.032)	(0.032)	(0.031)
Female ∗ attended	0.038	0.090**	0.029
schools in north	(0.039)	(0.043)	(0.039)
Migrant	-0.086	0.049	-0.091
	(0.136)	(0.054)	(0.137)
Migrant ∗ female	-0.031	-0.068	-0.024
	(0.174)	(0.062)	(0.176)
Migrant ∗ attended	-0.159	-0.052	-0.154
schools in north	(0.262)	(0.070)	(0.262)
Migrant ∗ female ∗	0.151	0.096	0.142
attended schools in north	(0.327)	(0.082)	(0.328)
Migrant parent	0.021	0.009	0.020
	(0.041)	(0.011)	(0.041)
Different language at home	-0.015	-0.041***	-0.011
	(0.048)	(0.014)	(0.049)
Family support	0.122***	0.013***	0.121***
	(0.017)	(0.005)	(0.017)
Socio-economic	0.116***	0.135***	0.103***
background	(0.023)	(0.018)	(0.024)
Socio-economic background ^{2}	0.020	0.007	0.019
	(0.018)	(0.005)	(0.018)
Socio-economic background ∗ female	-0.096***	-0.113***	-0.085***
	(0.033)	(0.020)	(0.032)
Socio-economic background ∗	-0.062	-0.020	-0.060
attended schools in north	(0.039)	(0.026)	(0.039)
Socio-economic background ∗ female ∗	0.070	0.007	0.069
attended schools in north	(0.056)	(0.030)	(0.056)
5th grade math score	0.008	0.066***	0.001
	(0.027)	(0.015)	(0.027)
5th grade math score ^{2}	-0.028***	-0.006**	-0.027***
	(0.009)	(0.003)	(0.009)
5th grade math score ∗ female	0.025	-0.065***	0.031
	(0.031)	(0.013)	(0.031)
5th grade math score ∗	0.044	0.010	0.043
attended schools in north	(0.035)	(0.014)	(0.035)
5th grade math score ∗	0.046	-0.034***	0.031
socio-economic background	(0.035)	(0.013)	(0.050)
Early education	0.059**	0.010	0.058**
	(0.025)	(0.010)	(0.025)
Rural School	-0.043	0.101**	-0.053
	(0.047)	(0.051)	(0.047)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	7520	7520	7520

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.12: IV Estimates (10th Grade Sample) - Cooperation

	Reduced Form	First Stage	Second Stage
Instrument	-0.021	1.617***	-0.013
	(0.084)	(0.126)	(0.052)
Academic			-0.013
			(0.052)
Female	-0.006	-0.083***	-0.007
	(0.038)	(0.032)	(0.037)
Female ∗ attended	0.017	0.087**	0.018
schools in north	(0.049)	(0.043)	(0.049)
Migrant	-0.114	0.047	-0.114
	(0.166)	(0.051)	(0.166)
Migrant ∗ female	-0.064	-0.056	-0.065
	(0.215)	(0.060)	(0.215)
Migrant ∗ attended	-0.127	-0.050	-0.128
schools in north	(0.287)	(0.068)	(0.287)
Migrant ∗ female ∗	0.343	0.083	0.344
attended schools in north	(0.356)	(0.080)	(0.356)
Migrant parent	-0.043	0.009	-0.043
	(0.044)	(0.011)	(0.044)
Different language at home	-0.040	-0.041***	-0.040
	(0.050)	(0.014)	(0.050)
Family support	0.161***	0.014***	0.161***
	(0.015)	(0.005)	(0.015)
Socio-economic	0.015	0.134***	0.016
background	(0.032)	(0.019)	(0.033)
Socio-economic background ^{2}	-0.006	0.007	-0.006
	(0.016)	(0.005)	(0.016)
Socio-economic background ∗ female	-0.005	-0.112***	-0.006
	(0.042)	(0.020)	(0.041)
Socio-economic background ∗	0.019	-0.021	0.018
attended schools in north	(0.046)	(0.026)	(0.046)
Socio-economic background ∗ female ∗	-0.056	0.006	-0.056
attended schools in north	(0.063)	(0.030)	(0.063)
5th grade math score	-0.012	0.062***	-0.011
	(0.032)	(0.014)	(0.032)
5th grade math score ^{2}	0.008	-0.007**	0.008
	(0.012)	(0.003)	(0.012)
5th grade math score ∗ female	-0.048	-0.062***	-0.048
	(0.033)	(0.013)	(0.034)
5th grade math score ∗	0.026	0.014	0.026
attended schools in north	(0.038)	(0.014)	(0.038)
5th grade math score ∗	0.020	-0.034***	0.020
socio-economic background	(0.024)	(0.013)	(0.024)
Early education	0.084***	0.008	0.084***
	(0.030)	(0.010)	(0.030)
Rural School	0.081	0.094*	0.082
	(0.069)	(0.053)	(0.068)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	7547	7547	7547

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.13: IV Estimates (10th Grade Sample) - Stress Resistance

	Reduced Form	First Stage	Second Stage
Instrument	-0.225**	1.619***	-0.139**
	(0.093)	(0.126)	(0.059)
Academic			-0.139**
			(0.059)
Female	-0.662***	-0.085***	-0.674***
	(0.034)	(0.032)	(0.033)
Female ∗ attended	0.034	0.089**	0.047
schools in north	(0.047)	(0.043)	(0.045)
Migrant	0.168	0.045	0.175
	(0.195)	(0.053)	(0.195)
Migrant ∗ female	0.085	-0.062	0.077
	(0.236)	(0.060)	(0.236)
Migrant ∗ attended	-0.100	-0.050	-0.107
schools in north	(0.223)	(0.069)	(0.223)
Migrant ∗ female ∗	0.056	0.089	0.068
attended schools in north	(0.280)	(0.081)	(0.280)
Migrant parent	0.084**	0.009	0.085**
	(0.038)	(0.011)	(0.038)
Different language at home	-0.039	-0.039***	-0.044
	(0.044)	(0.014)	(0.045)
Family support	0.014	0.014***	0.016
	(0.018)	(0.005)	(0.018)
Socio-economic	0.021	0.133***	0.040
background	(0.029)	(0.019)	(0.031)
Socio-economic background ^{2}	0.011	0.008	0.012
	(0.019)	(0.005)	(0.019)
Socio-economic background ∗ female	0.057	-0.109***	0.041
	(0.039)	(0.020)	(0.038)
Socio-economic background ∗	0.065	-0.019	0.063
attended schools in north	(0.043)	(0.026)	(0.044)
Socio-economic background ∗ female ∗	-0.112**	0.004	-0.112**
attended schools in north	(0.056)	(0.030)	(0.056)
5th grade math score	0.060	0.064***	0.046
	(0.037)	(0.015)	(0.031)
5th grade math score ^{2}	0.003	-0.005	0.002
	(0.010)	(0.003)	(0.010)
5th grade math score ∗ female	-0.005	-0.065***	-0.014
	(0.036)	(0.014)	(0.036)
5th grade math score ∗	0.059	0.012	0.061
attended schools in north	(0.037)	(0.014)	(0.037)
5th grade math score ∗	0.018	-0.032**	0.020
socio-economic background	(0.050)	(0.014)	(0.051)
Early education	0.009	0.009	0.009
	(0.031)	(0.010)	(0.032)
Rural School	-0.024	0.106**	-0.009
	(0.064)	(0.052)	(0.066)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	7464	7464	7464

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Table B.3.14: IV Estimates (10th Grade Sample) - Emotional Control

	Reduced Form	First Stage	Second Stage
Instrument	-0.041	1.618***	-0.025
	(0.103)	(0.125)	(0.064)
Academic			-0.025
			(0.064)
Female	-0.546***	-0.084***	-0.544***
	(0.033)	(0.032)	(0.035)
Female ∗ attended schools in north	0.036	0.087**	0.038
	(0.040)	(0.043)	(0.040)
Migrant	-0.150	0.031	-0.149
	(0.196)	(0.055)	(0.196)
Migrant ∗ female	0.188	-0.050	0.187
	(0.244)	(0.062)	(0.244)
Migrant ∗ attended schools in north	-0.044	-0.036	-0.045
	(0.259)	(0.071)	(0.259)
Migrant ∗ female ∗ attended schools in north	0.023	0.079	0.025
	(0.337)	(0.081)	(0.337)
Migrant parent	0.102***	0.008	0.102***
	(0.039)	(0.011)	(0.039)
Different language at home	-0.106**	-0.041***	-0.107**
	(0.047)	(0.014)	(0.047)
Family support	0.071***	0.012***	0.071***
	(0.017)	(0.005)	(0.017)
Socio-economic background	0.032	0.133***	0.029
	(0.036)	(0.019)	(0.034)
Socio-economic background ^{2}	-0.012	0.008	-0.012
	(0.018)	(0.005)	(0.018)
Socio-economic background ∗ female	0.007	-0.110***	0.007
	(0.047)	(0.021)	(0.047)
Socio-economic background ∗ attended schools in north	-0.003	-0.022	-0.004
	(0.055)	(0.026)	(0.055)
Socio-economic background ∗ female ∗ attended schools in north	0.036	0.007	0.036
	(0.065)	(0.030)	(0.065)
5th grade math score	0.066*	0.063***	-0.021
	(0.037)	(0.015)	(0.027)
5th grade math score ^{2}	0.016	-0.007**	0.015
	(0.010)	(0.004)	(0.010)
5th grade math score ∗ female	-0.014	-0.062***	-0.016
	(0.036)	(0.014)	(0.036)
5th grade math score ∗ attended schools in north	0.065	0.012	0.065
	(0.037)	(0.014)	(0.037)
5th grade math score ∗ socio-economic background	-0.017	-0.030***	-0.017
	(0.037)	(0.013)	(0.037)
Early education	0.019	0.010	0.019
	(0.030)	(0.010)	(0.030)
Rural School	0.085	0.103**	0.088
	(0.068)	(0.052)	(0.069)
Regional dummies	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Observations	7446	7446	7446

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors are in parentheses. Control group: students attending a professional institute or an IeFP.

Appendix C. STATA Code

```
//DATA CLEANING AND MERGING
global root "Z:\Desktop\Galileian school thesis"
global datain "$root\Data"

//PISA 2022
import spss "$datain\PISA 2022\Microdati PISA 2022 Cognitivi.sav"

//inspection
rename TFGrade grade
rename  TFMonthB monthbirth
tab grade monthbirth
rename TFStudyProg track
// eliminate middle school students
drop if  track == 4
tab track

//merging key
rename FCNTSCHID SchoolID
rename SIDI_INVALSI SIDI_Invalsi
//drop SIDI_INVALSI "non disponibile"
drop if SIDI_Invalsi == "NON DISPONIBILE"
//eliminate 1 duplicate observation
duplicates report SIDI_Invalsi
duplicates drop SIDI_Invalsi, force
destring SIDI_Invalsi, replace

//consider IFP as professional institutes
 replace track =3 if track ==5

//treatment variable: acdemic track
gen academic = (track==1)

//outcomes: big five
rename ASSERAGR assertiveness
lab var assertiveness "Assertiveness"
rename COOPAGR cooperation
lab var cooperation "Cooperation"
rename EMPATAGR empathy
lab var empathy "Empathy"
```

```
rename CURIOAGR curiosity
lab var curiosity "Curiosity"
rename EMOCOAGR emotionalcontrol
lab var emotionalcontrol "Emotional control"
rename STRESAGR stressresistance
lab var stressresistance "Stress resistance"
rename PERSEVAGR perseverance
lab var perseverance "Perseverance"

//student- and family-level controls, dummy variables for missing data
rename ST004D01T gender
gen female = (gender==1)
 rename ST019AQ01T student_origin
gen student_migrant = (student_origin!=1)
rename ST019BQ01T mother_origin
gen mother_migrant = (mother_origin!=1)
rename ST019CQ01T father_origin
gen father_migrant = (father_origin!=1)
gen parent_migrant = (mother_migrant==1|father_migrant==1)
rename ST022Q01TA languageathome
gen difflanguageathome = (languageathome!=1)
gen ESCS_d=missing(ESCS)
sum ESCS if ESCS_d ==0, meanonly
replace ESCS=r(mean) if ESCS_d==1
rename FAMSUP family_support
gen family_support_d=missing(family_support)
sum family_support if family_support_d ==0, meanonly
replace family_support=r(mean) if family_support_d==1
rename PA018Q02NA early_educ
gen early_education = (early_educ==1)
 keep SIDI_Invalsi SchoolID grade assertiveness cooperation empathy curiosity emotionalcontrol stressresistance perseverance academic track gender female student_migrant parent_migrant difflanguageathome ESCS ESCS_d family_support family_support_d early_education w_fstuwt
save "$datain\Created dataset\PISA22.dta", replace

//school-level controls
clear
import spss "$datain\PISA 2022\Microdati PISA 2022 Questionario
```

```
Scuola.sav"
rename FCNTSCHID SchoolID
rename SC001Q01TA urbanrural
gen rural_school =(urbanrural==1|urbanrural==2)
keep SchoolID  rural_school
merge m:m SchoolID  using "$datain\Created dataset\PISA22.dta"
drop if _merge==1
drop _merge
save "$datain\Created dataset\Pisa22_merged", replace

//INVALSI 2022 G10
 clear
 import spss "$datain\INVALSI\Invalsi G10 2021-22\Microdati Popolazione G10 2021-22 Matematica.sav"
 save "$datain\Created dataset\ INVALSI G10 2021-22 Matematica.dta",replace

clear
import spss "$datain\INVALSI\Invalsi G10 2021-22\Microdati Popolazione G10 2021-22 Italiano.sav"
 merge 1:1 SIDI_Invalsi using "$datain\Created dataset\ INVALSI G10 2021-22 Matematica.dta"
drop _merge
decode Cod_Reg, gen(Reg)
gen regione =upper(Reg)
drop Reg
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV. AUT. BOLZANO (L. TED.)"
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV. AUT. BOLZANO (L. IT.)"
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV. AUT. BOLZANO (L. LAD.)"
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV. AUT. TRENTO"
replace regione = "EMILIA ROMAGNA" if regione == "EMILIA-ROMAGNA"
keep SIDI_Invalsi regione provincia
merge 1:1 SIDI_Invalsi using "$datain\Created dataset\PISA22_merged.dta"
//drop those for which I don't have data on outcome
drop if _merge == 1
drop _merge
```

```
save "$datain\Created dataset\ PisaInvalsi22_merged", replace

//INVALSI 2017 G05
clear
import spss "$datain\INVALSI\Invalsi G05 2016-17\Microdati
    Popolazione G05 2016-17 Italiano 0_1.sav"
drop if SIDI_Invalsi=="NON DISPONIBILE"
save "$datain\Created dataset\ INVALSI G05 2016-17
    Italiano",replace

clear
import spss "$datain\INVALSI\Invalsi G05 2016-17\Microdati
    Popolazione G05 2016-17 Matematica 0_1.sav"
drop if SIDI_Invalsi=="NON DISPONIBILE"
merge 1:1 SIDI_Invalsi using "$datain\Created dataset\ INVALSI
    G05 2016-17 Italiano.dta"
drop _merge
destring SIDI_Invalsi, replace
save "$datain\Created dataset\ INVALSI G05 2016-17 merged.dta",
    replace

clear
import spss "$datain\INVALSI\Invalsi G05 2016-17\Microdati
    Popolazione G05 2016-17 Questionario.sav"
merge 1:1 CODICE_STUDENTE using "$datain\Created dataset\
    INVALSI G05 2016-17 merged.dta"
egen mean_math = mean(WLE_mat)
egen sd_math = sd(WLE_mat)
gen score_math_G05 = (WLE_mat-mean_math)/sd_math
decode Cod_reg, gen(Reg)
gen regione =upper(Reg)
drop Reg
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV.
    AUT. BOLZANO (L. IT.)"
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV.
    AUT. TRENTO"
replace regione = "EMILIA ROMAGNA" if regione == "EMILIA-ROMAGNA"
keep SIDI_Invalsi regione score_math_G05
duplicates report SIDI_Invalsi
duplicates drop SIDI_Invalsi, force
save "$datain\Created dataset\ INVALSI G05 2016-17 final.dta",
```

```
    replace

clear
use  "$datain\Created dataset\ PisaInvalsi22_merged"
merge 1:1 SIDI_Invalsi regione using "$datain\Created dataset\
    INVALSI G05 2016-17 final.dta"
drop if _merge == 2
drop _merge
gen score_math_G05_d=missing(score_math_G05)
sum score_math_G05 if score_math_G05_d ==0, meanonly
replace score_math_G05=r(mean) if score_math_G05_d==.
encode regione, gen(region)
//dummy for region in North
gen north = (regione=="TRENTINO-ALTO ADIGE" |
    regione=="PIEMONTE" | regione=="VALLE D'AOSTA" |
    regione=="FRIULI-VENEZIA GIULIA" | regione=="LOMBARDIA" |
    regione=="VENETO" | regione=="EMILIA-ROMAGNA" |
    regione=="LIGURIA")
save "$datain\Created Dataset\Final22.dta", replace

//INSTRUMENT CONSTRUCTION
clear
global root "Z:\Desktop\Galileian school thesis"
global datain "$root\Data\Iscrizioni\Dati Portale Unico della
    Scuola"
global created "$root\Data\Created dataset"

//2019-2020
import delimited "$datain\Studenti statale 2019-20.csv"
save "$datain\Studenti statale 2019-20.dta",replace
clear
import delimited "$datain\Studenti paritaria 2019-20.csv"
append using "$datain\Studenti statale 2019-20.dta"
//duplicate the dataset to generate a variable for gender
tempfile original_data
save "`original_data'"
use "`original_data'", clear
//generate a new variable for gender
gen gender = "Male"
append using "`original_data'"
replace gender = "Female" if _n > _N/2
```

```
gen studenti =alunnifemmine if gender == "Female"
replace studenti = alunnimaschi if gender == "Male"
sort codicescuola annocorso gender
save "$datain\Iscrizioni_studenti 2019-20.dta",replace
//schools
clear
import delimited "$datain\Anagrafica statali 2019-20.csv"
save "$datain\Anagrafica statali 2019-20.dta",replace
clear
import delimited "$datain\Anagrafica paritarie 2019-20.csv"
save "$datain\Anagrafica paritarie 2019-20.dta",replace
clear
import delimited "$datain\Anagrafica statali aut 2019-20.csv"
save "$datain\Anagrafica statali aut 2019-20.dta",replace
clear
import delimited "$datain\Anagrafica paritarie aut 2019-20.csv"
append using "$datain\Anagrafica statali aut 2019-20.dta", force
append using "$datain\Anagrafica statali 2019-20.dta", force
append using "$datain\Anagrafica paritarie 2019-20.dta", force
merge 1:m codicescuola using "$datain\Iscrizioni_studenti 2019-20.dta"
drop if _merge==1
drop _merge
gen grade = 10
save "$created\Iscrizioni_studenti_noaut 2019-20.dta", replace

//2018-19
clear
import delimited "$datain\Studenti statale 2018-19.csv"
save "$datain\Studenti statale 2018-19.dta",replace
clear
import delimited "$datain\Studenti paritaria 2018-19.csv"
append using "$datain\Studenti statale 2018-19.dta"
tempfile original_data
save "‘original_data’"
use "‘original_data’", clear
*generate a new variable for gender
gen gender = "Male"
append using "‘original_data’"
replace gender = "Female" if _n > _N/2
gen studenti =alunnifemmine if gender == "Female"
```

```
replace studenti = alunnimaschi if gender == "Male"
sort codicescuola annocorso gender
save "$datain\Iscrizioni_studenti 2018-19.dta",replace
*schools
clear
import delimited "$datain\Anagrafica statali 2018-19.csv"
save "$datain\Anagrafica statali 2018-19.dta",replace
clear
import delimited "$datain\Anagrafica paritarie 2018-19.csv"
save "$datain\Anagrafica paritarie 2018-19.dta",replace
clear
import delimited "$datain\Anagrafica stataliaut 2018-19.csv"
save "$datain\Anagrafica stataliaut 2018-19.dta",replace
clear
import delimited "$datain\Anagrafica paritarieaut 2018-19.csv"
append using "$datain\Anagrafica stataliaut 2018-19.dta", force
append using "$datain\Anagrafica statali 2018-19.dta", force
append using "$datain\Anagrafica paritarie 2018-19.dta", force
merge 1:m codicescuola using "$datain\Iscrizioni_studenti
    2018-19.dta"
drop if _merge==1
drop _merge
gen grade = 11
save "$created\Iscrizioni_studenti_noaut 2018-19.dta", replace

//2020-21
clear
import delimited "$datain\Studenti statale 2020-21.csv"
save "$datain\Studenti statale 2020-21.dta",replace
clear
import delimited "$datain\Studenti paritaria 2020-21.csv"
append using "$datain\Studenti statale 2020-21.dta"
tempfile original_data
save "`original_data'"
use "`original_data'", clear
*generate a new variable for gender
gen gender = "Male"
append using "`original_data'"
replace gender = "Female" if _n > _N/2
gen studenti =alunnifemmine if gender == "Female"
replace studenti = alunnimaschi if gender == "Male"
```

```
sort codicescuola annocorso gender
save "$datain\Iscrizioni_studenti 2020-21.dta",replace
*schools
clear
import delimited "$datain\Anagrafica statali 2020-21.csv"
save "$datain\Anagrafica statali 2020-21.dta",replace
clear
import delimited "$datain\Anagrafica paritarie 2020-21.csv"
save "$datain\Anagrafica paritarie 2020-21.dta",replace
clear
import delimited "$datain\Anagrafica stataliaut 2020-21.csv"
save "$datain\Anagrafica stataliaut 2020-21.dta",replace
clear
import delimited "$datain\Anagrafica paritarieaut 2020-21.csv"
append using "$datain\Anagrafica stataliaut 2020-21.dta", force
append using "$datain\Anagrafica statali 2020-21.dta", force
append using "$datain\Anagrafica paritarie 2020-21.dta", force
merge 1:m codicescuola using "$datain\Iscrizioni_studenti
    2020-21.dta"
drop if _merge==1
drop _merge
gen grade = 9
save "$created\Iscrizioni_studenti_noaut 2020-21.dta", replace

//merge the three datasets
append using "$created\Iscrizioni_studenti_noaut 2019-20.dta",
    force
append using "$created\Iscrizioni_studenti_noaut 2018-19.dta",
    force
keep annoscolastico regione provincia tipopercorso gender
    alunnimaschi alunnifemmine grade
replace tipopercorso="1" if tipopercorso=="LICEO"
replace tipopercorso="2" if tipopercorso=="TECNICO"
replace tipopercorso="3" if tipopercorso=="PROFESSIONALE"
replace tipopercorso="3" if tipopercorso=="PROFESSIONALE IeFP"
destring tipopercorso, replace
rename tipopercorso track
save "$created\Iscrizioni_studenti_noaut.dta", replace
//sum over the schools to get number of students
collapse (sum) alunnimaschi alunnifemmine, by(regione provincia
    track gender annoscolastico grade)
```

```
gen enrolment = .
replace enrolment = alunnimaschi if gender == "Male"
replace enrolment = alunnifemmine if gender == "Female"
drop alunnimaschi alunnifemmine
//add data on autonomous provinces
preserve
import excel using "$root\Data\Iscrizioni\Dati ISTAT\Iscrizioni_regaut.xlsx", firstrow clear
save "$created\Instrument_geo_autonomprov.dta",replace
restore
append using "$created\Instrument_geo_autonomprov.dta"
sort grade regione provincia track gender
//create instrument: province-by-gender relative enrollments in a given track (as % of total enrolments)
bysort gender grade regione provincia: egen enrolment_total = total(enrolment)
gen instrument = enrolment/enrolment_total
drop if grade == .
replace regione="FRIULI-VENEZIA GIULIA" if regione=="FRIULI-VENEZIA G."
replace provincia="FORL -CESENA" if provincia=="FORLI'-CESENA"
save "$created\Instrument_genderprovince.dta",replace

//MERGING INSTRUMENT TO MAIN DATASET
clear
global root "Z:\Desktop\Galileian school thesis"
global datain "$root\Data"

//INVALSI 2021 G08
import spss "$datain\INVALSI\Invalsi G08 2020-21\Matrice_Popolazione_ITA08_Area Dati_anonima.sav"
drop if SIDI_Invalsi=="NON DISPONIBILE"
save "$datain\Created dataset\ INVALSI G08 2020-21 Italiano",replace
clear
import spss "$datain\INVALSI\Invalsi G08 2020-21\Matrice_Popolazione_MAT08_Area Dati_anonima.sav"
drop if SIDI_Invalsi=="NON DISPONIBILE"
merge 1:1 SIDI_Invalsi using "$datain\Created dataset\INVALSI G08 2020-21 Italiano.dta"
drop _merge
```

```
decode Cod_Reg , gen (Reg)
gen regione = upper(Reg)
drop Reg
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV. AUT. BOLZANO (L. TED.)"
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV. AUT. BOLZANO (L. IT.)"
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV. AUT. BOLZANO (L. LAD.)"
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV. AUT. TRENTO"
replace regione = "EMILIA ROMAGNA" if regione == "EMILIA-ROMAGNA"
rename nome_provincia_ISTAT provincia
keep SIDI_Invalsi regione provincia
destring SIDI_Invalsi, replace
merge 1:1 SIDI_Invalsi using "$datain\Created dataset\Final22.dta"
tab _merge grade
drop if _merge == 1
drop _merge
save "$datain\Created dataset\Final2122",replace

//INVALSI 2019 G08
clear
import spss "$datain\INVALSI\Invalsi G08 2018-19\Matrice_8_ita_popolazione_0_1_WLE_anonima.sav"
rename  SIDI_invalsi SIDI_Invalsi
drop if SIDI_Invalsi=="NON DISPONIBILE"
save "$datain\Created dataset\INVALSI G08 2018-19 Italiano", replace
clear
import spss "$datain\INVALSI\Invalsi G08 2018-19\Matrice_8_mat_popolazione_0_1_WLE_anonima.sav"
rename  SIDI_invalsi SIDI_Invalsi
drop if SIDI_Invalsi=="NON DISPONIBILE"
merge 1:1 SIDI_Invalsi using "$datain\Created dataset\INVALSI G08 2018-19 Italiano.dta"
drop _merge
decode Cod_reg , gen (Reg)
gen regione = upper(Reg)
drop Reg
```

```
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV.
    AUT. BOLZANO (L. TED.)"
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV.
    AUT. BOLZANO (L. IT.)"
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV.
    AUT. BOLZANO (L. LAD.)"
replace regione = "TRENTINO-ALTO ADIGE" if regione == "PROV.
    AUT. TRENTO"
replace regione = "EMILIA ROMAGNA" if regione == "EMILIA-ROMAGNA"
rename nome_provincia_ISTAT provincia
keep SIDI_Invalsi regione provincia
destring SIDI_Invalsi, replace
merge 1:1 SIDI_Invalsi using "$datain\Created
    dataset\Final2122.dta"
tab _merge grade
drop if _merge==1
drop _merge
label define tracklabel 1 "Liceo" 2 "Istituto tecnico" 3
    "Istituto professionale"
label values track tracklabel
label define gradelabel 9 "9" 10 "10" 11 "11"
label values grade gradelabel
save "$datain\Created dataset\Final192122",replace

//merge to instrument dataset
clear
use "$datain\Created dataset\Final192122"
gen gender_str = ""
replace gender_str = "Female" if gender == 1
replace gender_str = "Male" if gender == 2
drop gender
rename gender_str gender
replace provincia="REGGIO CALABRIA" if provincia=="REGGIO DI
    CALABRIA"
replace provincia="REGGIO EMILIA" if provincia=="REGGIO
    NELL'EMILIA"
merge m:1 grade regione provincia track gender using
    "$datain\Created dataset\Instrument_genderprovince.dta"
keep if _merge==3
drop region north
encode regione, gen(region)
```

```
gen north = (regione=="TRENTINO-ALTO ADIGE" | regione=="PIEMONTE" | regione=="VALLE D'AOSTA" | regione=="FRIULI-VENEZIA GIULIA" | regione=="LOMBARDIA" | regione=="VENETO" | regione=="EMILIA-ROMAGNA" | regione=="LIGURIA")

//generate interactions
gen female_north = female*north
gen student_migrant_female = student_migrant*female
gen student_migrant_north = student_migrant*north
gen student_migrant_female_north = student_migrant*female*north
gen ESCS_squared = ESCS^2
gen ESCS_female =ESCS*female
gen ESCS_north =ESCS*north
gen ESCS_female_north =ESCS*female*north
gen score_math_G05_squared = score_math_G05^2
gen score_math_G05_female = score_math_G05*female
gen score_math_G05_north = score_math_G05*north
gen score_math_G05_ESCS =score_math_G05*ESCS
gen score_math_G05_north_ESCS = score_math_G05*north*ESCS
global controls_all "female female_north student_migrant student_migrant_female student_migrant_north student_migrant_female_north parent_migrant difflanguageathome family_support family_support_d ESCS ESCS_squared ESCS_d ESCS_female ESCS_north ESCS_female_north score_math_G05 score_math_G05_squared score_math_G05_d score_math_G05_female score_math_G05_north score_math_G05_ESCS score_math_G05_north_ESCS early_education rural_school"
save "$datain\Created dataset\Finalwithinstrument",replace

//ANALYSIS
clear
global root "Z:\Desktop\Galileian school thesis\Data"
use  "$root\Created Dataset\Finalwithinstrument.dta"
global outcomes "curiosity perseverance assertiveness empathy cooperation stressresistance emotionalcontrol"
global controls_base "female north student_migrant parent_migrant difflanguageathome family_support family_support_d ESCS ESCS_d score_math_G05 score_math_G05_d early_education rural_school"
```

```
//descriptive statistics: outcome and control variables
tabstat curiosity perseverance assertiveness empathy cooperation
    stressresistance emotionalcontrol [aw=w_fstuwt],  c(stat)
    stat(mean sd)
preserve
keep if grade==10
tabstat curiosity perseverance assertiveness empathy cooperation
    stressresistance emotionalcontrol [aw=w_fstuwt], c(stat)
    stat(mean sd)
restore
preserve
keep if grade==10
drop if track ==3
tabstat curiosity perseverance assertiveness empathy cooperation
    stressresistance emotionalcontrol [aw=w_fstuwt], by(academic)
    c(stat) stat(mean sd)
restore
tabstat $controls_base [aw=w_fstuwt], c(stat) stat(mean sd)
preserve
keep if grade==10
tabstat $controls_base [aw=w_fstuwt],  c(stat) stat(mean sd)
restore
preserve
keep if grade==10
drop if track ==3
tabstat $controls_base [aw=w_fstuwt],  by(academic) c(stat)
    stat(mean sd)
restore

//sample for selection on observables: 2nd year high school
    students
keep if grade ==10
//control group for selection on observables: technical
    institute students only
drop if track ==3
tab track

//linear probabilty model
reg academic female [pw=w_fstuwt]
areg academic female female_north [pw=w_fstuwt], absorb(region)
```

```
areg academic female female_north student_migrant student_migrant_female student_migrant_north student_migrant_female_north parent_migrant difflanguageathome family_support family_support_d [pw=w_fstuwt], absorb(region)
areg academic female female_north student_migrant student_migrant_female student_migrant_north student_migrant_female_north parent_migrant difflanguageathome family_support family_support_d c.
ESCS ESCS_squared ESCS_d ESCS_female ESCS_north ESCS_female_north [pw=w_fstuwt], absorb(region)
areg academic female female_north student_migrant student_migrant_female student_migrant_north student_migrant_female_north parent_migrant difflanguageathome family_support family_support_d ESCS ESCS_squared  ESCS_d ESCS_female ESCS_north ESCS_female_north score_math_G05 score_math_G05_squared score_math_G05_d score_math_G05_female score_math_G05_north score_math_G05_ESCS score_math_G05_north_ESCS early_education rural_school [pw=w_fstuwt], absorb(region)

//check common support
logit academic female female_north student_migrant student_migrant_female student_migrant_north student_migrant_female_north parent_migrant difflanguageathome family_support family_support_d ESCS ESCS_squared ESCS_d ESCS_female ESCS_north ESCS_female_north score_math_G05 score_math_G05_squared score_math_G05_d score_math_G05_female score_math_G05_north score_math_G05_ESCS score_math_G05_north_ESCS early_education rural_school i.region [pw=w_fstuwt]
predict pscore, pr
su pscore if academic==1, detail
su pscore if academic==0, detail
twoway (kdensity pscore if academic==1, bwidth(0.04) lcolor(black) lpattern(solid) lwidth(medium) legend(label(1 "Academic Track")))///
 (kdensity pscore if academic==0, bwidth(0.04) lcolor(grey) lpattern(dash) lwidth(medium) legend(label(2 "Vocational Track"))), ///
 xtitle("Propensity Score") ///
```

```
    ytitle("Density") ///
    legend(order(1 2) position(10) ring(0) cols(1) region(lcolor(black)) bcolor(gs16) bfcolor(white) box) ///
    ylab(, nogrid) xlab(, nogrid) ///
    graphregion(color(white)) ///
    bgcolor(white) ///
    yline( 0.5  1 1.5 2, lstyle(dash) lcolor(gs14))
gen in_support = (pscore >= 0.07 & pscore <= 0.96)
tab in_support

//check covariate balance
teffects ipwra (perseverance $controls_all i.region) (academic $controls_all  i.region)  [pw=w_fstuwt] if in_support==1
tebalance summarize

//SELECTION ON OBSERVABLES
//unconditional differences
teffects ipwra (curiosity) (academic) [pw=w_fstuwt] if in_support==1
teffects ipwra (perseverance) (academic) [pw=w_fstuwt] if in_support==1
teffects ipwra (assertiveness) (academic) [pw=w_fstuwt] if in_support==1
teffects ipwra (empathy) (academic) [pw=w_fstuwt] if in_support==1
teffects ipwra (cooperation) (academic) [pw=w_fstuwt] if in_support==1
teffects ipwra (emotionalcontrol) (academic) [pw=w_fstuwt] if in_support==1
teffects ipwra (stressresistance)
//CIA with IPWRA
(academic) [pw=w_fstuwt] if in_support==1
teffects ipwra (curiosity $controls_all i.region) (academic $controls_all  i.region)  [pw=w_fstuwt] if in_support==1, pomeans
teffects ipwra (perseverance $controls_all i.region) (academic $controls_all  i.region)  [pw=w_fstuwt] if in_support==1, pomeans
teffects ipwra (assertiveness $controls_all i.region) (academic $controls_all  i.region) [pw=w_fstuwt] if in_support==1, pomeans
```

```
teffects ipwra (empathy $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1, pomeans
teffects ipwra (cooperation $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1, pomeans
teffects ipwra (stressresistance $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1, pomeans
teffects ipwra (emotionalcontrol $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1,pomeans
teffects ipwra (curiosity $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (perseverance $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (assertiveness $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (empathy $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra  (cooperation $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (stressresistance $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (emotionalcontrol $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1
//full estimates
teffects ipwra (curiosity $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1, aequation
teffects ipwra (perseverance $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1, aequation
teffects ipwra (assertiveness $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1, aequation
teffects ipwra (empathy $controls_all i.region) (academic $controls_all i.region) [pw=w_fstuwt] if in_support==1, aequation
```

```
teffects ipwra (cooperation $controls_all i.region) (academic
    $controls_all  i.region)  [pw=w_fstuwt] if in_support==1,
    aequation
teffects ipwra (stressresistance $controls_all i.region)
    (academic  $controls_all  i.region)  [pw=w_fstuwt] if
    in_support==1, aequation
teffects ipwra (emotionalcontrol $controls_all i.region)
    (academic  $controls_all  i.region)  [pw=w_fstuwt] if
    in_support==1,aequation

//heterogeneity: gender, area, socio-economic background
global controls_nogender "student_migrant student_migrant_north
    parent_migrant difflanguageathome family_support
    family_support_d ESCS ESCS_squared ESCS_d  ESCS_north
    score_math_G05 score_math_G05_squared  score_math_G05_d
    score_math_G05_north score_math_G05_ESCS
    score_math_G05_north_ESCS early_education rural_school"
global controls_noarea "female student_migrant
    student_migrant_female parent_migrant difflanguageathome
    family_support family_support_d ESCS ESCS_squared ESCS_d
    ESCS_female   score_math_G05 score_math_G05_squared
    score_math_G05_d score_math_G05_female  score_math_G05_ESCS
    early_education rural_school"
global controls_nobackground "female female_north
    student_migrant student_migrant_female student_migrant_north
    student_migrant_female_north parent_migrant
    difflanguageathome family_support family_support_d
    c.score_math_G05 score_math_G05_squared score_math_G05_d
    score_math_G05_female score_math_G05_north early_education
    rural_school"
preserve
keep if female==1
teffects ipwra (curiosity $controls_nogender i.region )
    (academic  $controls_nogender  i.region)  [pw=w_fstuwt]  if
    in_support==1
teffects ipwra (perseverance $controls_nogender i.region)
    (academic  $controls_nogender  i.region)  [pw=w_fstuwt]  if
    in_support==1
teffects ipwra (assertiveness $controls_nogender i.region)
    (academic  $controls_nogender  i.region) [pw=w_fstuwt]  if
    in_support==1
```

```
teffects ipwra (empathy $controls_nogender i.region) (academic
    $controls_nogender  i.region)  [pw=w_fstuwt]  if in_support==1
teffects ipwra (cooperation $controls_nogender i.region)
    (academic  $controls_nogender  i.region)  [pw=w_fstuwt]  if
    in_support==1
teffects ipwra (stressresistance $controls_nogender i.region)
    (academic  $controls_nogender  i.region)  [pw=w_fstuwt]  if
    in_support==1
teffects ipwra (emotionalcontrol $controls_nogender i.region)
    (academic  $controls_nogender  i.region)  [pw=w_fstuwt]  if
    in_support==1
restore
preserve
keep if female==0
teffects ipwra (curiosity $controls_nogender i.region )
    (academic  $controls_nogender  i.region)  [pw=w_fstuwt] if
    in_support==1
teffects ipwra (perseverance $controls_nogender i.region)
    (academic  $controls_nogender  i.region)  [pw=w_fstuwt] if
    in_support==1
teffects ipwra (assertiveness $controls_nogender i.region)
    (academic  $controls_nogender  i.region) [pw=w_fstuwt] if
    in_support==1
teffects ipwra (empathy $controls_nogender i.region) (academic
    $controls_nogender  i.region)  [pw=w_fstuwt] if in_support==1
teffects ipwra  (cooperation $controls_nogender i.region)
    (academic  $controls_nogender  i.region)  [pw=w_fstuwt] if
    in_support==1
teffects ipwra (stressresistance $controls_nogender i.region)
    (academic  $controls_nogender  i.region)  [pw=w_fstuwt] if
    in_support==1
teffects ipwra (emotionalcontrol $controls_nogender i.region)
    (academic  $controls_nogender  i.region)  [pw=w_fstuwt] if
    in_support==1
restore
preserve
keep if north==1
keep if HighSEB==1teffects ipwra (curiosity $controls_noarea
    i.region ) (academic  $controls_noarea i.region)
    [pw=w_fstuwt]  if in_support==1
teffects ipwra (perseverance $controls_noarea i.region)
```

```
(academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (assertiveness $controls_noarea i.region) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (empathy $controls_noarea i.region) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (cooperation $controls_noarea i.region) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (stressresistance $controls_noarea i.region) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (emotionalcontrol $controls_noarea i.region) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
restore
preserve
keep if north==0
teffects ipwra (curiosity $controls_noarea i.region ) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (perseverance $controls_noarea i.region) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (assertiveness $controls_noarea i.region) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (empathy $controls_noarea i.region) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (cooperation $controls_noarea i.region) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (stressresistance $controls_noarea i.region) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
teffects ipwra (emotionalcontrol $controls_noarea i.region) (academic $controls_noarea i.region) [pw=w_fstuwt] if in_support==1
restore
sum ESCS, detail
gen HighSEB = ESCS > r(p50)
```

```
preserve
keep if HighSEB==1
teffects ipwra (curiosity $controls_nobackground i.region )
    (academic  $controls_nobackground i.region)  [pw=w_fstuwt]
    if in_support==1
teffects ipwra (perseverance $controls_nobackground i.region)
    (academic  $controls_nobackground i.region)  [pw=w_fstuwt]
    if in_support==1
teffects ipwra (assertiveness $controls_nobackground i.region)
    (academic  $controls_nobackground i.region) [pw=w_fstuwt]  if
    in_support==1
teffects ipwra (empathy $controls_nobackground i.region)
    (academic  $controls_nobackground i.region)  [pw=w_fstuwt]
    if in_support==1
teffects ipwra  (cooperation $controls_nobackground i.region)
    (academic  $controls_nobackground i.region)  [pw=w_fstuwt]
    if in_support==1
teffects ipwra (stressresistance $controls_nobackground
    i.region) (academic  $controls_nobackground i.region)
    [pw=w_fstuwt]  if in_support==1
teffects ipwra (emotionalcontrol $controls_nobackground
    i.region) (academic  $controls_nobackground i.region)
    [pw=w_fstuwt]  if in_support==1
restore
preserve
keep if HighSEB==0
teffects ipwra (curiosity $controls_nobackground i.region)
    (academic  $controls_nobackground i.region)  [pw=w_fstuwt]
    if in_support==1
teffects ipwra (perseverance $controls_nobackground i.region)
    (academic  $controls_nobackground i.region)  [pw=w_fstuwt]
    if in_support==1
teffects ipwra (assertiveness $controls_nobackground i.region)
    (academic  $controls_nobackground i.region) [pw=w_fstuwt]  if
    in_support==1
teffects ipwra (empathy $controls_nobackground i.region)
    (academic  $controls_nobackground i.region)  [pw=w_fstuwt]
    if in_support==1
teffects ipwra  (cooperation $controls_nobackground i.region)
    (academic  $controls_nobackground i.region)  [pw=w_fstuwt]
    if in_support==1
```

```
teffects ipwra (stressresistance $controls_nobackground
    i.region) (academic  $controls_nobackground i.region)
    [pw=w_fstuwt]  if in_support==1
teffects ipwra (emotionalcontrol $controls_nobackground
    i.region) (academic  $controls_nobackground i.region)
    [pw=w_fstuwt]  if in_support==1
restore
save "$datain\Created dataset\Finalwithinstrument",replace

//IV ANALYSIS
clear
ssc install ranktest
net install ftools, from
    ("https://raw.githubusercontent.com/sergiocorreia/ftools/master/src/")
net install reghdfe, from
    ("https://raw.githubusercontent.com/sergiocorreia/reghdfe/master/src/")
ssc install ivreg2
net install ivreghdfe, from
    (https://raw.githubusercontent.com/sergiocorreia/ivreghdfe/master/src/)
ssc install psacalc
ssc install plausexog
ssc install imperfectiv

use "$datain\Created dataset\Finalwithinstrument"
egen clu=group(provincia female grade)

//full sample
ivreghdfe curiosity $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu) sfirst
ivreghdfe perseverance $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu) sfirst
ivreghdfe assertiveness $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu) sfirst
areg assertiveness instrument i.grade $controls_all
    [aw=w_fstuwt], absorb(provincia) cluster(clu)
ivreghdfe empathy $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu) sfirst
ivreghdfe cooperation $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu) sfirst
ivreghdfe stressresistance $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade) cluster(clu) first
```

```
areg stressresistance instrument i.grade $controls_all
    [aw=w_fstuwt], absorb(provincia) cluster(clu)
ivreghdfe emotionalcontrol $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu) first
areg emotionalcontrol instrument i.grade $controls_all
    [aw=w_fstuwt], absorb(provincia) cluster(clu)

//10th grade sample
preserve
keep if grade==10
ivreghdfe curiosity $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu) sfirst
ivreghdfe perseverance $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu) sfirst
ivreghdfe assertiveness $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu) first
areg assertiveness instrument $controls_all [aw=w_fstuwt],
    absorb(provincia) cluster(clu)
ivreghdfe empathy $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu) sfirst
ivreghdfe cooperation $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu) sfirst
ivreghdfe stressresistance $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu) first
areg stressresistance instrument $controls_all [aw=w_fstuwt],
    absorb(provincia) cluster(clu)
ivreghdfe emotionalcontrol $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu) first
areg emotionalcontrol instrument $controls_all [aw=w_fstuwt],
    absorb(provincia) cluster(clu)
restore

//heterogeneity: gender, area, socio-economic background
preserve
keep if female==1
ivreghdfe empathy $controls_nogender (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu)
ivreghdfe stressresistance $controls_nogender
    (academic=instrument) [aw=w_fstuwt], absorb(provincia grade)
    cluster(clu)
keep if grade==10
```

```
ivreghdfe empathy $controls_nogender (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu)
ivreghdfe stressresistance $controls_nogender
    (academic=instrument) [aw=w_fstuwt], absorb(provincia)
    cluster(clu)
restore

preserve
keep if female==0ivreghdfe empathy $controls_nogender
    (academic=instrument) [aw=w_fstuwt], absorb(provincia grade)
    cluster(clu)
ivreghdfe stressresistance $controls_nogender
    (academic=instrument) [aw=w_fstuwt], absorb(provincia grade)
    cluster(clu)
keep if grade==10
ivreghdfe empathy $controls_nogender (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu)
ivreghdfe stressresistance $controls_nogender
    (academic=instrument) [aw=w_fstuwt], absorb(provincia)
    cluster(clu)
restore
preserve
keep if north==1
ivreghdfe empathy $controls_noarea (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu)
ivreghdfe stressresistance $controls_noarea
    (academic=instrument) [aw=w_fstuwt], absorb(provincia grade)
    cluster(clu)
keep if grade==10
ivreghdfe empathy $controls_noarea (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu)
ivreghdfe stressresistance $controls_noarea
    (academic=instrument) [aw=w_fstuwt], absorb(provincia)
    cluster(clu)
restore
preserve
keep if north==0
ivreghdfe empathy $controls_noarea (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu)
ivreghdfe stressresistance $controls_noarea
    (academic=instrument) [aw=w_fstuwt], absorb(provincia grade)
```

```
    cluster(clu)
keep if grade==10
ivreghdfe empathy $controls_noarea (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu)
ivreghdfe stressresistance $controls_noarea
    (academic=instrument) [aw=w_fstuwt], absorb(provincia)
    cluster(clu)
restore
preserve
keep if HighSEB==1
ivreghdfe empathy $controls_nobackground (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu)
ivreghdfe stressresistance $controls_nobackground
    (academic=instrument) [aw=w_fstuwt], absorb(provincia grade)
    cluster(clu)
keep if grade==10
ivreghdfe empathy $controls_nobackground (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu)
ivreghdfe stressresistance $controls_nobackground
    (academic=instrument) [aw=w_fstuwt], absorb(provincia)
    cluster(clu)
restore
preserve
keep if HighSEB==0
ivreghdfe empathy $controls_nobackground (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu)
ivreghdfe stressresistance $controls_nobackground
    (academic=instrument) [aw=w_fstuwt], absorb(provincia grade)
    cluster(clu)
keep if grade==10
ivreghdfe empathy $controls_nobackground (academic=instrument)
    [aw=w_fstuwt], absorb(provincia)  cluster(clu)
ivreghdfe stressresistance $controls_nobackground
    (academic=instrument) [aw=w_fstuwt], absorb(provincia)
    cluster(clu)
restore

//IV VALIDITY
keep if grade==10

//Oster test (2019), set R^2max=1.3R^2
```

```
//first stage
areg academic instrument $controls_all [aw=w_fstuwt],
    absorb(provincia) cluster(clu)
R^2=0.721
psacalc beta instrument, rmax(0.937)
//reduced form
areg empathy instrument $controls_all [aw=w_fstuwt],
    absorb(provincia) cluster(clu)
//R^2=0.079
psacalc beta instrument, rmax(0.103)
areg stressresistance instrument $controls_all [aw=w_fstuwt],
    absorb(provincia) cluster(clu)
//R^2=0.152
psacalc beta instrument, rmax(0.198)

//Conely et al. (2012) local-to-zero approach, set mean to 0
tab provincia, generate(province_dummy)
plausexog ltz empathy $controls_all
    province_dummy1-province_dummy79 (academic=instrument)
    [aw=w_fstuwt], ///
     mu(0) omega(0.0103) vce(cluster clu)  ///
  graph(academic) graphomega(0 0.005 0.0103) graphmu(0 0 0)
      graphdelta(0 0.05 0.10) scheme(sj) ytitle(Estimated
      {&beta}) xtitle({&delta}) xlabel   (0 "0" 0.05 "0.05"  0.1
      "0.10") legend(order(1 "Point Estimate (LTZ)" 2 "95% CI"))
      ylabel(-0.25(0.25)0.5) bcolor(gs16) bfcolor(white)
      graphregion(color(white)) plotregion(color(white)) yline(0,
      lcolor(red) lwidth(medium))
plausexog ltz stressresistance $controls_all
    province_dummy1-province_dummy79 (academic=instrument)
    [aw=w_fstuwt], ///
mu(0) omega( 0.0138) vce(cluster clu)  ///
graph(academic) graphomega(0 0.007 0.0138) graphmu(0 0 0)
    graphdelta(0 0.05 0.10) scheme(sj) ytitle(Estimated {&beta})
    xtitle({&delta}) xlabel   (0 "0" 0.05 "0.05"  0.1 "0.10")
    legend(order(1 "Point Estimate (LTZ)" 2 "95% CI"))
    ylabel(-0.5(0.25)0.5) bcolor(gs16) bfcolor(white)
    graphregion(color(white)) plotregion(color(white)) yline(0,
    lcolor(red) lwidth(medium))

//Nevo and Rosen (2012)
```

```
imperfectiv empathy female female_north student_migrant
    student_migrant_female student_migrant_north
    student_migrant_female_north parent_migrant
    difflanguageathome family_support family_support_d ESCS
    ESCS_squared ESCS_d ESCS_female ESCS_north ESCS_female_north
    score_math_G05 score_math_G05_squared score_math_G05_d
    score_math_G05_female score_math_G05_north
    score_math_G05_ESCS score_math_G05_north_ESCS early_education
    rural_school province_dummy1-province_dummy79
    (academic=instrument) [aw=w_fstuwt], ///
 vce(cluster clu)
imperfectiv stressresistance  female female_north
    student_migrant student_migrant_female student_migrant_north
    student_migrant_female_north parent_migrant
    difflanguageathome family_support family_support_d ESCS
    ESCS_squared ESCS_d ESCS_female ESCS_north ESCS_female_north
    score_math_G05 score_math_G05_squared score_math_G05_d
    score_math_G05_female score_math_G05_north
    score_math_G05_ESCS score_math_G05_north_ESCS early_education
    rural_school province_dummy1-province_dummy79
    (academic=instrument) [aw=w_fstuwt], ///
 vce(cluster clu)

//DISCUSSION
//test heterogeneity through interaction terms
gen academic_female=academic*female
gen academic_north=academic*north
gen academic_HighSEB=academic*HighSEB
ivreghdfe stressresistance academic_female  $controls_all
    (academic=instrument) [aw=w_fstuwt], absorb(provincia)
    cluster(clu)
ivreghdfe stressresistance academic_north $controls_all
    (academic=instrument) [aw=w_fstuwt], absorb(provincia)
    cluster(clu)
ivreghdfe stressresistance academic_HighSEB $controls_all
    (academic=instrument) [aw=w_fstuwt], absorb(provincia)
    cluster(clu)

//split the treatment group by type of lyceum
preserve
drop if subtrack==1
```

```
ivreghdfe stressresistance $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu)
restore
preserve
drop if subtrack==2
ivreghdfe stressresistance $controls_all (academic=instrument)
    [aw=w_fstuwt], absorb(provincia grade)  cluster(clu)
restore
```