The gender gap in mathematics achievements: evidence from Italian data.

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Abstract

This paper describes the gender gap in math test scores using data from an Italian national level learning assessment involving all children in school in selected grades from second to tenth. Gender differences in the STEM (Science Technology Engineering and Mathematics) subjects are widespread in most OECD countries and mathematics is the only subject where typically girls tend to underperform with respect to boys.

The magnitude of the gender gap is measured using OLS and school fixed effects models. Our results show that girls systematically underperform boys, even after controlling for socio-economic status, parental education, maternal professional status, geographical areas, number of siblings, pre-school attendance, type of high school and math self-beliefs. In order to check whether the gap is increasing with the age of the child, lacking longitudinal data, we use a pseudo panel technique and find that the gap is increasing from age 7 to age 15 with a slight decrease at age 11.

Finally, we study the distribution of the gap across test scores, using quantile regressions, and find that the gap is nil at the lowest percentiles, but large among top performing children. This result is confirmed using a metric-free technique.

JEL: J16; I24; C31.

Keywords: Math gender gap, education, discrimination, pseudo panel, quantile regression

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1. **Introduction**

Gender differences in the so-called STEM (Science Technology Engineering and Mathematics) disciplines are widespread in most countries in the world. According to PISA test scores (OECD 2015), the average gender gap among OECD countries in mathematics is equal to 11 score points in favor of boys, where the average test score among OECD countries is 500 score points. This gender gap increases to 20 score points among the 10% top achievers[4]. The largest average differences in favor of boys are observed in Luxembourg (33 points), Austria (32 points), Chile (29 points) and Italy (24 points). The presence of a gender gap in math is of particular importance, because it has consequences for the gender gap in the study of STEM subjects at university, for gender segregation in the labour market, and for gender pay gaps (European Commission 2006, 2012, 2015; National Academy of Science, 2007).

It is important noticing that the gender gap in math test scores is the only educational outcome still favouring boys, as in most countries girls tend to outperform boys in reading test scores, overall grades at school, in the propensity to choose academic educational programs in upper secondary school, and in tertiary education attendance and graduation rates. This makes the girls' disadvantage in math even more subtle and important to explain.

Several different explanations have been proposed for the existence of the gender gap in mathematics, including biological (Baron-Cohen and Wheelwright 2004, Baron Cohen et al 2001) and socio-economic or cultural factor (de San Roman and de La Rica Goiricelaya, 2012; Guiso et al., 2008; OECD 2015).

Societal factors that have been found to affect math performance are socioeconomic status, the parent's education, their profession, and their involvement in their children's homework (de San

[4] The score for each country is the average of all student scores in that country. The average score among OECD countries is 500 points and the average standard deviation is 100 points. About two-thirds of students across OECD countries score between 400 and 600 points.

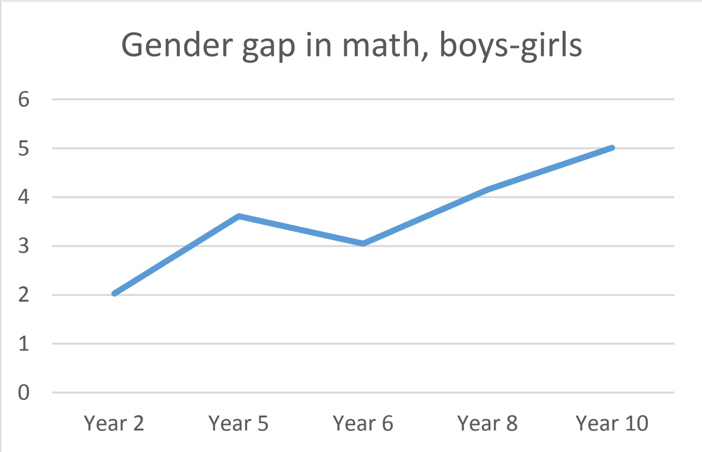
Roman and de La Rica 2012; Jacobs 1991; Jacobs and Bleeker 2004; Jacobs and Eccles 1992; Bhanot and Jovanovic 2009; Del Boca, et al 2014, Brilli et al. 2016). In addition, parents' and teachers' beliefs about boys and girls abilities (Robinson et al 2014), the way math is taught (Boaler 2002; Zohar and Sela 2003; OECD 2015), and whether the textbooks include images of female scientists affect the math performance by gender (Boaler et al. 2011; Good, Woodzicka, and Wingfield 2010; Brownlow and Durham, S. (1997). Longitudinal studies based on the US dataset "Early Childhood Longitudinal Study, Kindergarten Class of 1998– 1999" find that the math gender gap increases with the age of the child (Robinson and Lubiensky, 2011; Fryer and Levitt, 2010; Penner and Paret, 2008).

Individual factors correlated with the gender gap in math are math self-efficacy (self-confidence in solving math related problems), math self-concept (students' beliefs in their own abilities), and anxiety and stress in doing math related activities (OECD 2015, Heckman and Kautz 2012, 2014; Twenge and Campbell 2001).

This paper aims at describing the Italian gender gap in math utilizing available data. Unfortunately, longitudinal data are not available in Italy. Among international data sets, PISA data are only for 15 years old students, and TIMMS data are cross sectional data sets at year 4 and 8. Therefore, we utilize the National Test INVALSI[5] for year 2013 where all Italian children in schools are tested in year 2, 5, 6, 8 and 10. We select the subsamples of children whose test was supervised by an external INVALSI inspector and final samples consists of nearly 30,000 – 40,000 students for each school year. Figure 1 shows that the gender gap in math seems to increase from 2 percentage points in year 2 to 5 percentage points in year 10 with a slight decrease in year 6.

[5] INVALSI stands for "Istituto nazionale per la valutazione del sistema educativo di istruzione e di formazione" (National Institute for the evaluation of education and training).

Figure 1. Italian Gender gap in math: boys' average test scores minus girls' average test scores. INVALSI 2013.



Note: INVALSI 2013, subsamples of children whose tests were directly supervised by INVALSI inspectors

In order to analyse the math gender gap in Italyin greater detail, this paper utilizes different methodologies. We begin by using a simple Ordinary Least Squares model for test scores and, following previous literature, we control for gender, parents' education, mother' professional status, socio-economic status of the family, geographical areas, number of siblings, an index for self-concept, and pre-school attendance. For year 10, we also control for types of high school attended and expectations about attending university. Then, we estimate a school fixed effects model, in order to control for unobserved school characteristics that may have a separate effect on the results. In order to increase the robustness of our results for the development of the gender gap over childhood, given that we do not have longitudinal dataset, we use imputed regression techniques for pseudo-panel data, estimating how girls perform relative to boys at time t, given past performances (De Simone 2013, Contini and Grand 2015).

The results confirm the descriptive evidence presented in figure 1: the indicator variable for girls is negative and significant after having controlled for all the variables listed above both for the

OLS and the school fixed effect model. The results for the pseudo panel show that the math gender gap increases substantially with the age of the children with a slight decrease in year 6.

Another relevant aspect underlined in the literature (OECD 2015; Robinson and Lubiensky 2011; Fryer and Levitt 2010) is that the math gender gap is higher for top performing students. Therefore, the paper applies quantile regression techniques to study the distribution of the gender gap across test scores. We find that the math gender gap changes for different quantiles in the distribution of the test scores and while it is negligible for low performing children, it is larger at the top of the distribution. Finally, in order to increase comparability of tests at different ages, we utilize a metric-free method to analyse the main results (Robinson and Liubenski 2011).

This paper contributes to the existing literature in a number of ways. Firstly, it provides detailed evidence on the gender gap in math test scores in Italy, one of the countries with the largest differential favoring boys over girls at age 15 (OECD 2015). In particular, we analyze the gender gap at different school years, from second to tenth grade, to identify when the gap first emerges, and to study its evolution throughout compulsory school. Secondly, using pseudo-panel techniques, we investigate the mechanisms underlying the gender gap evolution, disentangling “new” effects developing between two given school years from carryover effects of previously established inequalities. Given the lack of longitudinal data both in Italy and in most European countries, this paper is the first attempt to analyse the evolution of the gender gap during childhood in a European country. Lastly, by focusing on differentials along the entire test score distribution, this study sheds some light about where the girls’ disadvantage is more severe, and it provides useful empirical evidence for policy recommendations.

2. Estimation methods

2.1 Cross sectional linear modelling

We begin our empirical analysis by considering how girls' and boys' test scores of girls and boys differ on average at each survey with linear regression.

Test scores are not measured on the same scale in different school years, and therefore the gender gap on original scores is not comparable across grades. For this reason, we use standardized scores and the gender gap results show by how many standard deviations girls and boys differ, net of control variables.

As a benchmark, we run the basic OLS model: $z_i = \mu + \gamma x_i + \delta c_i + \varepsilon_i$, where z are standardized test scores, x is the binary variable representing gender and c is a set of control variables. However, this model does not account for unobserved school effects. If the true model is $z_{is} = \mu + \gamma x_{is} + \delta c_{is} + \tau_s + \varepsilon_{is}$, the existence of the school component τ_s might hamper the estimates of interest, because the error terms of children in the same school will not be mutually independent, and more importantly, because unobserved school effects and the explanatory variables might be correlated, yielding to biased estimates. This is likely to occur, as school choices often depend on children and families' characteristics. Fixed effects models, exploiting only within-school variability, deliver valid estimates of the gender gap (and of the effects of the other explanatory variables) given individual controls and school characteristics.

2.2 Dynamic linear modelling

Cross-sectional analyses do not allow exploring the mechanisms underlying the *development* of inequalities as children grow. In particular, they do not allow distinguishing between direct effects of gender operating at each stage of schooling and carryover effects of preexisting achievement gaps between girls and boys. In addition, if we use standardized achievement measures – as advocated above – we cannot even distinguish between the observed changes due to specific mechanisms involving gender from mechanisms involving other characteristics unrelated to gender.[6]

In the absence of longitudinal data, we use pseudo-panel techniques proposed by De Simone (2013) and Contini and Grand (2015). The method allows to estimate simple dynamic models with repeated cross-sectional data, where achievement at a given time point (t=2) is related to previous achievement (at t=1) and the individual characteristics of interest. The basic idea is that the lagged dependent variable can be replaced by a predicted value from an auxiliary regression using individuals observed in previous cross-sections. Under quite restrictive conditions (for example, if there are no time-varying exogenous variables or the time-varying exogenous variables are not auto-correlated), this strategy delivers consistent estimates (Verbeek and Vella, 2005). These conditions are met in our study, because the explanatory variable of main interest is gender, and the other control variables are (nearly) time-invariant sociodemographic individual characteristics.[7]

Drawing from Contini and Grand (2015), we first consider two cross sectional assessments using a single scale to measure achievement (i.e. "vertically equated" scores). Subsequent scores follow the relation: $y_{i2} = y_{i1} + \delta_i$, where δ_i is achievement growth, that may vary across individuals and depend linearly on individual characteristics x_i and previous achievement: $\delta_i = \Delta + \beta x_i + \theta y_{i1} + \varepsilon_{i2}$. Under these assumptions, the dynamic model relating achievement at the two occasions is $y_{i2} = \Delta + (1+\theta) y_{i1} + \beta x_i + \varepsilon_{i2}$.

The parameter of interest is β, capturing gender inequalities developed between the two surveys (more precisely, β represents the difference between test scores of a boy and a girl with identical performance at t=1). Instead, θ are carry-over effects of inequalities already existing at t=1. Now, if achievement scores are not equated, the relation between subsequent scores is: $y_{i2} =$

[6] Consider for example differentials in test scores across socioeconomic backgrounds; if these differentials widen as children age, the test score standard deviation will increase. Other things being equal, this will reduce the relative gender-gap. In other terms, the measured gender gap reduces, although no mechanism operating differently on girls and boys has been at work to make the girls catch up their disadvantage relative to boys (Contini and Grand, 2015).

[7] Notice that the inclusion of school characteristics in the model would invalidate the estimation. The reason is that since the error term incorporates innate ability, school features are typically correlated to the error term, because higher ability children usually choose schools with more favorable characteristics (Contini and Grand, 2015). Similar conclusion would apply if we were to include other endogenous variables capturing behavior and attitudes.

$\tilde{y}_{i1} + \delta_i$, where $\tilde{y}_{i1}$ represents achievement at t=1 in the measurement scale employed at t=2. Assuming that $\tilde{y}_{i1} = \varphi + \omega y_{i1}$ (where φ and ω are not known and not identifiable), the dynamic model becomes:

$$y_{i2} = \varphi(1+\theta) + \Delta + \omega(1+\theta)y_{i1} + \beta x_i + \varepsilon_{i2} \quad (1)$$

If test scores are measured on different scales, θ is always unidentified. Instead, β can be consistently estimated even with repeated cross-sectional data.

In the first step, we estimate the cross sectional model for test scores at t=1: $y_{i1} = \mu_1 + \rho x_i + \delta w_i + \varepsilon_{1i}$, where w is an appropriate instrumental variable affecting achievement at t=1 but not affecting achievement at t=2 given achievement at t=1. Following Contini and Grand (2015), we use the month of birth, since there is widespread evidence (confirmed by our data), that younger children generally underperform their older peers, in particular at early school stages. Further, it is reasonable to assume that, conditioning on previous achievement, the month of birth should not affect later performance.[8]

In the second step, we substitute y_1 with its OLS estimate $\hat{y}_1$ and plug it in model (1). This introduces measurement error $\hat{y}_1 - y_1$ in previous scores; however, due to properties of OLS estimates, this measurement error (which enters the error term) will be uncorrelated to x and $\hat{y}_1$. Hence, standard estimation of model $y_{i2} = \mu_2 + \gamma\hat{y}_{1i} + \beta x_i + u_{2i}$ will deliver consistent estimates of β. Clearly, the drawback is that standard errors will be largely inflated.[9]

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[8] The use of the season of birth as an instrumental variable has recently been questioned by Buckles and Hungerman (2013). These scholars refer to the use of season of birth to account for the endogeneity of children's age on later outcomes, under the assumption that the season of birth influences the age of the child but does not influence other outcomes given age. Buckles and Hungerman (2013) argue that contrary to the common belief, the season of birth is not totally idiosyncratic. On the contrary, they show that in USA winter births are disproportionally represented by teenagers and unmarried mothers. Notice however that in this paper we are making a different use of the month of birth: we are using the month of birth (and not the season) to measure the age of the child, as our assumption is that the age of the child affects earlier achievement, but does not affect later achievement given earlier achievement. If *this* assumption is credible, we can estimate the effects of sociodemographic variables net of previous achievement consistently.

[9] As a consequence, for reliable estimation we need large samples and a good instrument. According to the simulation study in Contini and Grand (2015), a sample size of approximately 30000 individuals (the size of our sample) is large enough to ensure reliable estimates, making reasonable assumptions on the strength of our instrument

Test scores distribution (quantile regression)

As a further step, we shift the focus from the expected value of test scores given gender and other control variables, to the entire test score distribution. To this aim, we estimate quantile regression models (Koenker and Basset, 1978). In essence, with these models we inspect the gender gap at different percentiles of the distribution, and assess whether female's disadvantage in math exists throughout the distribution, or instead if it is stronger among low performing or top performing children. In the simplest case with only gender as explanatory variable, the quantile regression coefficient gives the difference between the score corresponding to a specific percentile of the girls' distribution and the score corresponding to the same percentile of the boys' distribution. To ensure consistency with our previous analyses, we analyse standardized scores.

2.3 Test scores distribution (metric free methods)

All the methods employed up to this point rely on psychometric assumptions defining each assessment test scores scale; hence, test scores are treated as an interval scaled variable. This implies that we assume there is the same difference in cognitive ability between two children scoring 0.70 and 0.80 and between two children scoring 0.40 and 0.50. An alternative approach that does not rely on such assumption is given by metric-free measures, relying on the relative position that girls and boys occupy in the overall ranking. Following Robinson and Lubienski (2011), we analyze the gender gap throughout the distribution by estimating at specific percentiles θ the following:

$$\lambda_\theta = \begin{cases} \frac{\varphi_M(\theta)}{\varphi_M(\theta)+\varphi_F(\theta)} & if\ \theta < 50 \\ \frac{1-\varphi_F(\theta)}{2-(\varphi_M(\theta)+\varphi_F(\theta))} & if\ \theta \geq 50 \end{cases} \tag{2}$$

month of birth to estimate the dynamic model relating 5th and 6th grade. Since the age of the child affects earlier outcomes more than later outcomes, our estimates should be reliable at least up to 6th grade. Instead, and we are aware of this, the instrument might be too weak for the models involving 8th and 10th grades.

where $\varphi_M(.)$ and $\varphi_F(.)$ are the cumulative distribution functions of males and females at the θth percentile of the overall distribution. Values of λ_θ below 0.5 indicate a girls' disadvantage (and vice versa). For example, $\varphi_F(20)$ is the percentage of females below or at the 20th percentile of the overall distribution. If $\varphi_F(20) > \varphi_M(20)$, more girls perform below the 20th percentile than boys and thus λ_θ<0.50. Instead, $1 - \varphi_F(80)$ is the percentage of females above or at the 80th percentile of the overall distribution. So, if $1 - \varphi_F(80) < 1 - \varphi_M(80)$, a lower share of girls perform above the 80th percentile as compared to the share of boys, and, again, λ_θ<0.50.

3. The Italian Education system and the Data

The Italian education system is organised in three stages. Students attend primary school from the age of 6 until the age of 10 years old. At the end of primary school they enrol in middle school, and they stay within the same school from the age of 11 until the age of 13 years old. Lastly, they attend high school from the age of 14 until the age of 16 (end of compulsory education), although the vast majority of high school now lasts for 5 years, so students complete them at age 19. At the end of middle school, students choose among different kinds of high schools, with significant differences in the curriculum. There are three main types of high school in Italy: the Lyceum, the Technical High School and the Vocational High School. The curriculum is generally organised at national level and all high schools have to provide some compulsory subjects (Italian, Mathematics, Sciences, History, one or two foreign languages and Physical Education). However, there are significant differences in terms of the hours allocated to each subject, and the specialised field of studies. Lyceums generally provide a higher level theoretical education, with a specialisation in the humanities, the sciences, the languages or the arts. Technical institutes usually provide students with both a theoretical education and a qualified technical specialization in a particular field (e.g.: business, accountancy, tourism, technology). Vocational institutes have specified structures for technical activities, with the objective of preparing students to enter the workforce. In our analysis of data from the second year of high school, the type of school attended will be taken into consideration.

This study uses data from the National Test INVALSI for 2013. Since 2009, all Italian children have been tested by the Italian Institute for the Evaluation of the Education System (INVALSI) during school years 2, 5, 6, 8 and 10. More than half a million students in each grade sit this test each year. These tests aim at assessing the reading and mathematical skills of Italian pupils. INVALSI data also includes information on parental characteristics and socio-economic status, collected from the children's school record. INVALSI assesses the overall population of students enrolled in Italian schools but a subsample of schools and students performs the tests under the supervision of an external inspector. In our analysis, we only use the subsample of children whose test was supervised by an external INVALSI inspector. We also restrict the sample to children with Italian citizenship, mostly because recent migrants may be enrolled in classes which are not necessarily aligned with their age, depending on their level of fluency in Italian. Further, immigrants experience grade repetition more frequently than native students. Our final sample includes around 23,000 observations from year 2; 22,000 from year 5; 24,000 from year 6 (first year middle school); 25,111 from year 8 (third year of middle school) and 34,000 from year 10 (second year high school).

Table 1 shows average test scores in mathematics for the estimation samples, by school year and gender. Boys seem to perform better than girls in all mathematics tests and the gap is increasing across the school years. These differences persist when we analyse the sample by region of residence. The dependent variable in our models is the standardised test scores in the mathematics assessments.

TABLE 1 APPROXIMATELY HERE

Full descriptive statistics for all set of covariates used in the estimations are provided in tables A1 and A2. They include a socio-economic synthetic indicator for year 5, 6, and 10 only (ESCS index), calculated by taking into consideration parents' educational background, as well as employment and occupation, and family income.

We progressively include the set of independent variables in our model. Specification 1 only includes child's gender as an independent variable; specification 2 includes several families' characteristics such as: region of residence, parental education, and an indicator of socio-economic status, called ESCS (not available in year 8 data); specification 3 includes the above variables plus pre-school attendance and maternal occupation.

In specification 3, we also include the variable "mathematics self-concept" as a control for school year 5 and 6, in order to test the stability of our main results where these characteristics are accounted for. Students in year 5 and 6 are asked some questions regarding their beliefs on their own abilities in math. Table A2 in Appendix A reports the list of questions and the descriptive statistics. We run factor analysis (reported in Table A3 in appendix A) to create an index that, in line with current literature, we define "mathematics self-concept" (see OECD 2015). Summarizing the results, girls display on average much lower levels of math self-concept. PISA data for 2012 show that on average across OECD countries 63% of boys, but only 52% pf girls, reported that they disagree that they are just not good at mathematics. Also 30% of girls, but 45% of boys, reported that they understand even the most difficult work in math (see OECD 2015, tab 3.4a, p. 75). In our data, 78 % Italian boys in year 5 report that "they are good at math" against 70 % of girls. Similar patterns are found in year 6 and 10 where girls self-concept in math is always lower than boys (see table A2 in Appendix A). Gender differences in math self-concept remain large even among students who perform at the same level in math. This result is confirmed by the literature, according to which girls who perform as well as boy report a much lower level of math self-concept (Jacobs et al 2002). Similarly, in Specification 3, we also control for an index on the importance of math for future studies, life, and career for year 10 students (see table A2 in Appendix A), created using factor analysis.

The variable pre-school attendance is a binary variable equal 1 if the child has attended kindergarten at least for 1 year before entering primary school. The percentages of children attending kindergarten vary from 73% (for children in year 8) to 97% (for children in year 10).

4. Results

We begin presenting the results for the OLS and school fixed effects model. Results are presented using the standardized test scores, for ease of comparison. Table 2 shows the results for the female indicator variable of three different specifications.

TABLE 2 APPROXIMATELY HERE

As explained above, we test the stability of our findings by progressively increasing the set of independent variables. Specification 1 only includes child's gender as an independent variable. Specification 2 includes several families' characteristics such as: region of residence, parental education, and an indicator of socio-economic status, called ESCS (not available in year 8 data). Specification 3 includes the above variables plus pre-school attendance and maternal occupation. In specification 3, we also conduct a sensitivity test for the main results from year 5, 6 and 10, by including information regarding the children's attitudes toward studying mathematics (see section 3 for its definition), and in year 10 we control for the type of high school attended and for expectations regarding tertiary education. One obvious concern related to these variables is that they might be endogenous with respect to test scores (students getting good results are more likely to put more effort in a subject and enjoying it more). However, we believe that they are a very good proxy for non-cognitive skills such as effort and conscientiousness, which have been found to have a strong effect on educational achievements (see for example Mendolia and Walker, 2014).

Results clearly show that gender has a significant effect on test scores in mathematics at all ages. In year 2, girls' test scores in Maths are about 0.10 standard deviations lower than the mean in Model 2. The gap expands in year 5, 6, 8 and 10, with girls underperforming boys in Mathematics test scores by about 0.18 standard deviations from the mean in year 5 and over 0.40 standard deviations in year 10. Results from Specification 3 are slightly more conservative than findings from Specification 2, but are consistent and confirm a significant gender gap in mathematics achievements.

Further, we re-estimate all the specifications of the various models using school fixed effects, in order to take into consideration the common characteristics of children attending the same school. This method takes into account that students attending the same school might have some additional unobserved characteristics that are likely to affect their performance in test scores and that are related to gender gaps (e.g. teachers that systematically value boys and girls differently, schools located in areas where gender stereotypes are particularly strong and systematically undermine girls' performance, etc.). The main findings are unchanged and the gender gap varies from almost 0.10 standard deviations below the mean in year 2 to 0.28 standard deviations in year 10 when we use fixed effects in Model 2.

TABLE 3 APPROXIMATELY HERE

Table 3 presents the effects of the other independent variables affecting test scores in mathematics for the OLS in specification 3[10]. As expected, parents' socio-economic status is a strong determinant of students' achievements, and students with highly educated, employed mothers and living in the North West of Italy, are more likely to achieve good results in their maths

[10] Tables of results regarding all the other covariates in specifications 1 and 2 are available from the authors upon request.

tests. Pre-school attendance seems to increase achievements in maths in year 6, 8, and 10, while growing up in a family with many siblings has a detrimental effect. Not surprisingly, students attending Lyceums perform better than their peers in technical or vocational high schools in the maths tests. These results are similar to findings for other countries (de San Roman and de La Rica 2012; Jacobs 1991; Jacobs and Bleeker 2004; Jacobs and Eccles 1992; Bhanot and Jovanovic 2009) and for Italy (Brunello and Checchi 2005; De Simone 2013).

The self-concept index for year 5 and 6 and the importance of math index for year 10 (described in section 3) are positive and significant.

TABLE 4 APPROXIMATELY HERE

Table 4 presents results for the gender dummies from the pseudo-panel methodology[11]. In this framework, the coefficients measure the extent to which achievement growth between t=1 and t=2 differs across gender, when comparing two children performing at the same level in t=1 (Contini and Grand, 2015)[12]. Columns 1, 2, 4, 6 and 8 in Table 4 present results from cross-section models while the other columns report results for dynamic models. Results confirm the findings from OLS and school fixed effects: the gap in mathematics achievement between girls and boys clearly increases over time, and the only slight improvement is found in year 6, at the beginning of middle school. This result is consistent with Robinson and Lubiesky (2011) who show that the gap reduces in middle school years. In the Italian education system, this could partially be explained by the fact that students change school and teachers when they enter middle school and teachers' expectations about study habits and performance increase steadily with respect to primary school. Girls might somehow be able to cope better with these changes but this does not reverse the overall trend in gender gaps in maths test scores.

Pseudo panel models deliver results on how gender inequalities develop between two school years, on top of previously established inequalities. For this reason, the estimates are smaller

[11] Full estimates available from the authors upon request.
[12] See section 2.2.

than those from cross-sections. This seems to occur steadily throughout compulsory schooling, from primary to the beginning of high school.

Our results are consistent with the literature for the US (Robinson and Lubiensky, 2011; Fryer and Levitt, 2010; Penner and Paret, 2008) but it is the first time that this result is shown for Italy .

Further, we exploit quantile regression in order to investigate heterogeneous effects of gender across test scores.

TABLE 5 APPROXIMATELY HERE

Table 5 presents the gender dummies from quantile regression[13]. These findings clearly show that the gap between girls' and boys' performance in mathematics increases through the grade distribution in all years. In year 2, the gap between girls and boys at the 25th percentile of the grade distribution is about 0.05 standard deviations but it is more than 0.14 standard deviations for the top quartile. These gaps widens in later grades. In year 6, girls in the bottom quartile of the grade distribution underperform with respect to boys by just over 0.2 standard deviations, but the gap between students in the top 10% of the distribution is almost 0.5 standard deviations. Our results confirm previous results for the US (Robinson and Lubiensky 2011; Fryer and Levitt 2010) but it is the first time that such results are found for Italian children in year 2, 5, 6, and 8. OECD (2015) found similar results for Italian children in PISA data exclusively for year 10.

One of the purposes of this study is to analyse the gender gap throughout the distribution and in order to check the robustness of our estimates in the quantile regression, we utilise a measure that reflects the metric-free gap at different points in the achievement distribution (see Section 2.4 for details). Interestingly, metric-free findings confirm the quantile regression results.

FIGURE 2 APPROXIMATELY HERE

[13] Full estimates available from the authors upon request.

Figures 2 presents metric-free measures of the math gap throughout the grade distribution in year 2, 5, 6, 8 and 10. As explained in Section 2.4, for the percentiles below the median, λ is the proportion of males at or below a specific percentile, relative to the sum of the separate proportions of males and females at or below that percentile. For percentiles at or above the median, λ represents the proportion of females above a specific percentile, relative to the sum of the separate proportions of males and females above that percentile. For example, λ equal to 0.5 at each percentile of the grade distribution means that boys' and girls' grades are aligned across the distribution. λ ranges from 0 to 1 and values closer to 0 benefiting boys while values closer to 1 favour girls.

For instance, in year 2 (see Fig.2), λ_{95} is equal to 0.4, which means that the top 5% of the grade distribution is composed by 40% of girls and 60% of boys. On the other hand, the proportion of boys and girls is even (λ equal to 0.5) at the 10th percentile of the grade distribution. Interestingly, the value of λ_{95} and λ_{90} do not move towards equality in the higher grades showing that girls are systematically under-represented in the top of the distribution. The biggest gap is observed in year 10, where in the top 10% of the grade distribution, the proportion of female is equal to 33%.

Looking at the bottom of the grade distribution in year 2, λ_{20} is equal to 48%, and this means that in the bottom 20% of the grade distribution, 48% are males and 52% are females. Figure 2 shows that the gap significantly favours males at all percentiles and the values of λ never reach 0.5, which means that we do not see an equal representation of boys and girls at any point of the distribution.

Lastly, we analysed the gender gap in different sub-areas of mathematics, as INVALSI questions are organised in four areas: numbers, geometry, working mathematically and data. Results are reported in Appendix B. Interestingly, the gap between girls and boys is greater in the areas of numbers, data, and working mathematically, but it is very small in the area of geometry. Further analyses are needed in order to understand possible reasons behind these findings.

5. Conclusion

The paper utilises several techniques (OLS, School fixed effects, Pseudo-panel, quantile regressions, and metric free measures) to explore the gender gap in math in Italy. In 2013, Invalsi data show that boys outperform girls in math from age 7 until age 15. Results show that gender dummy for girls is negative even after controlling for many covariates related to the family socioeconomic status, geographical areas, parental education, maternal employment, preschool attendance, number of siblings'.

Pseudo panel estimations confirm that the gap is increasing with age of the child while quantile regressions show that the gender gap in math is higher for top performer kids. Metric free results confirm the quantile regression results.

Obviously, the lack of longitudinal data for Italy is a major problem for analysing changes in gender gaps across years. Unfortunately, while the improvement of the educational system seems to have been a priority of all Italian governments in the last ten years, there has been no discussion about the importance of having reliable longitudinal data to study inequalities (not only gender inequalities) in the Italian educational system.

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Table 1 – Average test scores in Maths

% of correct answers	Year 2	Year 5	Year 6	Year 8	Year 10
All	54.9	55.6	45.3	51.8	42.7
	(20.7)	(18.8)	(16.7)	(18.9)	(17.8)
Boys	55.9	57.4	46.8	53.8	45.2
	(21.1)	(19.0)	(17.3)	(19.0)	(18.6)
Girls	53.9	53.8	43.8	49.7	40.2
	(20.2)	(18.4)	(16.0)	(18.5)	(16.6)
P values for the T test	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Note: Standard deviation in brackets.
P values for tests of significant differences between Maths score for boys and girls are reported in square brackets.

Table 2 – Gender gap in achievements in Mathematics

	Year 2		Year 5		Year 6		Year 8		Year 10	
	OLS	**School FE**	**OLS**	**School FE**	**OLS**	**School FE**	**OLS**	**School FE**	**OLS**	**School FE**
Spec. 1										
Female	- 0.102	-0.097	-0.185	-0.191	-0.169	-0.178	-0.181	-0.222	-0.298	-0.286
	(0.013)***	(0.012)***	(0.013)***	(0.012)***	(0.013)***	(0.011)***	(0.012)***	(0.011)***	(0.010)***	(0.008)***
Spec. 2										
Female	-0.105	-0.099	-0.180	-0.183	-0.166	-0.168	-0.184	-0.220	-0.435	-0.285
	(0.014)***	(0.013)***	(0.014)***	(0.013)***	(0.013)***	(0.013)***	(0.012)***	(0.011)***	(0.009)***	(0.009)***
Spec. 3										
Female	-0.098	-0.093	-0.118	-0.123	-0.093	-0.091	-0.185	-0.188	-0.393	-0.290
	(0.014)***	(0.014)***	(0.014)***	(0.014)***	(0.013)***	(0.013)***	(0.014)***	(0.013)***	(0.009)***	(0.009)***

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%.
Spec.1 does not include any other covariates. Spec.2 also includes region of residence, parental education, and socio-economic status. Covariates from spec 3 are listed in Table 3.

Table 3 – Effect of other independent variables on achievements in Mathematics (OLS and School FE– Specification 3)

	OLS					School Fixed effects				
	Year 2	**Year 5**	**Year 6**	**Year 8**	**Year 10**	**Year 2**	**Year 5**	**Year 6**	**Year 8**	**Year 10**
Escs index	n.a	0.085	0.104	n.a	0.026	n.a	0.075	0.068	n.a	0.011
		(0.011)***	(0.011)***		(0.007)***		(0.011)***	(0.011)***		(0.007)*
Region of residence										
(North west is omitted)										
North-East	0.057	-0.021	-0.091	0.054	0.014	n.a	n.a	n.a	n.a	n.a
	(0.022)***	(0.022)	(0.020)***	(0.021)***	(0.015)					
Centre	-0.047	-0.156	-0.301	-0.119	-0.349	n.a	n.a	n.a	n.a	n.a
	(0.023)**	(0.024)***	(0.021)***	(0.023)***	(0.015)***					
South	-0.210	-0.291	-0.538	-0.227	-0.672	n.a	n.a	n.a	n.a	n.a
	(0.021)***	(0.021)***	(0.019)***	(0.021)***	(0.014)***					
Islands	-0.247	-0.432	-0.761	-0.055	-0.788	n.a	n.a	n.a	n.a	n.a
	(0.024)***	(0.024)***	(0.021)***	(0.022)**	(0.015)***					
Maternal education										
(University is omitted)										
High school	-0.118	-0.096	-0.042	-0.159	0.008	-0.115	-0.088	-0.049	-0.122	0.012
	(0.023)***	(0.025)***	(0.023)*	(0.023)***	(0.015)	(0.022)***	(0.023)***	(0.022)**	(0.022)***	(0.013)
Middle school	-0.316	-0.214	-0.198	-0.378	-0.006	-0.299	-0.204	-0.204	-0.357	0.003
	(0.027)***	(0.030)***	(0.028)***	(0.025)***	(0.018)	(0.026)***	(0.029)***	(0.027)***	(0.024)***	(0.016)
Paternal education										
(University is omitted)										
High school	-0.106	-0.030	-0.029	0.018	0.024	-0.109	-0.048	-0.050	0.016	0.035
	(0.023)***	(0.026)	(0.024)	(0.022)	(0.015)	(0.023)***	(0.025)**	(0.023)**	(0.021)	(0.013)***
Middle school	-0.316	-0.214	-0.198	-0.378	-0.006	-0.310	-0.163	-0.160	-0.196	0.024
	(0.027)***	(0.030)***	(0.028)***	(0.025)***	(0.018)	(0.024)***	(0.028)***	(0.026)***	(0.022)***	(0.015)
Mother employment										
(Professional is omitted)										
Not working	-0.143	-0.016	-0.042	-0.131	-0.016	-0.102	-0.011	-0.050	-0.103	-0.014
	(0.030)***	(0.031)	(0.029)	(0.029)***	(0.018)	(0.029)***	(0.030)	(0.028)*	(0.027)***	(0.016)
Self-employed	-0.033	0.016	-0.083	-0.064	-0.033	-0.025	-0.005	-0.090	-0.070	-0.021
	(0.035)	(0.036)	(0.032)**	(0.034)*	(0.020)*	(0.034)	(0.034)	(0.031)***	(0.032)**	(0.018)
Employee	0.055	0.125	0.077	0.046	0.098	0.060	0.096	0.031	0.010	0.071
	(0.028)**	(0.029)***	(0.027)***	(0.028)	(0.017)***	(0.027)**	(0.028)***	(0.026)	(0.026)	(0.016)***
Worker	-0.078	-0.010	-0.012	-0.161	0.004	-0.087	-0.069	-0.056	-0.158	-0.000
	(0.035)**	(0.036)	(0.032)	(0.033)***	(0.019)	(0.033)***	(0.034)**	(0.032)*	(0.031)***	(0.017)
Other	-0.265	0.400	0.063	-0.090	-0.114	-0.380	0.233	0.057	-0.381	0.021
	(0.254)	(0.279)	(0.186)	(0.132)	(0.091)	(0.243)	(0.265)	(0.180)	(0.132)***	(0.083)
Preschool	-0.038	-0.088	0.133	0.183	0.233	0.196	0.065	0.167	0.175	0.160
attendance	(0.027)	(0.027)***	(0.024)***	(0.023)***	(0.036)***	(0.058)***	(0.057)	(0.051)***	(0.055)***	(0.032)***
N. siblings	n.a.			n.a.		n.a			n.a	
(0 is omitted)										
1		-0.004	0.009		0.060		0.014	0.012		0.049
		(0.021)	(0.019)		(0.013)***		(0.020)	(0.019)		(0.012)***
2		-0.044	-0.035		0.058		-0.026	-0.015		0.060

		(0.024)*	(0.022)		(0.016)***		(0.023)	(0.022)		(0.014)***
3		-0.022	-0.037		0.085		-0.044	-0.015		0.098
		(0.038)	(0.035)		(0.025)***		(0.037)	(0.034)		(0.022)***
>4		-0.150	-0.126		0.008		-0.147	-0.090		0.051
		(0.052)***	(0.047)***		(0.034)		(0.050)***	(0.046)**		(0.030)*
Type of High school	n.a.	n.a.	n.a.	n.a		n.a	n.a	n.a	n.a	
(Lyceum is omitted)										
Technical high school					-0.372					-0.163
					(0.012)***					(0.042)***
Vocational high school					-0.749					-0.559
					(0.015)***					(0.054)***
Expects to go to university	n.a.	n.a.	n.a.	n.a	0.275	n.a	n.a	n.a	n.a	0.203
					(0.011)***					(0.010)***
Math self-concept	n.a.	0.330	0.360	n.a.	n.a.		0.344	0.388		
		(0.007)***	(0.007)***				(0.007)***	(0.007)***		
Importance of math for the future	n.a.	n.a.	n.a.	n.a.	0.219					0.144
					(0.005)***					(0.005)***

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%.

Table 6 – Gender gap in achievements in Mathematics - Pseudo panel model (Specification 2)

	Year 2 Cross section	**Year 5 Cross section**	**Year 5 Dynamic**	**Year 6 Cross Section**	**Year 6 Dynamic**	**Year 8 Cross Section**	**Year 8 Dynamic**	**Year 10 Cross Section**	**Year 10 Dynamic**	**Year 10 Dynamic (base Year 6)**
Female	-0.105	-0.183	-0.113	-0.170	-0.043	-0.219	-0.171	-0.343	-0.244	-0.321
	(0.014)***	(0.014)***	(0.0167)***	(0.014)***	(0.023)*	(0.013)***	(0.026)***	(0.012)***	(0.092)***	(0.023)***
Month of birth	-0.032	-0.021		-0.0150		-0.004		-0.001		
	(0.022)***	(0.002)***		(0.002)***		(0.002)***		(0.016)		

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Additional variables included are listed at p. 13.

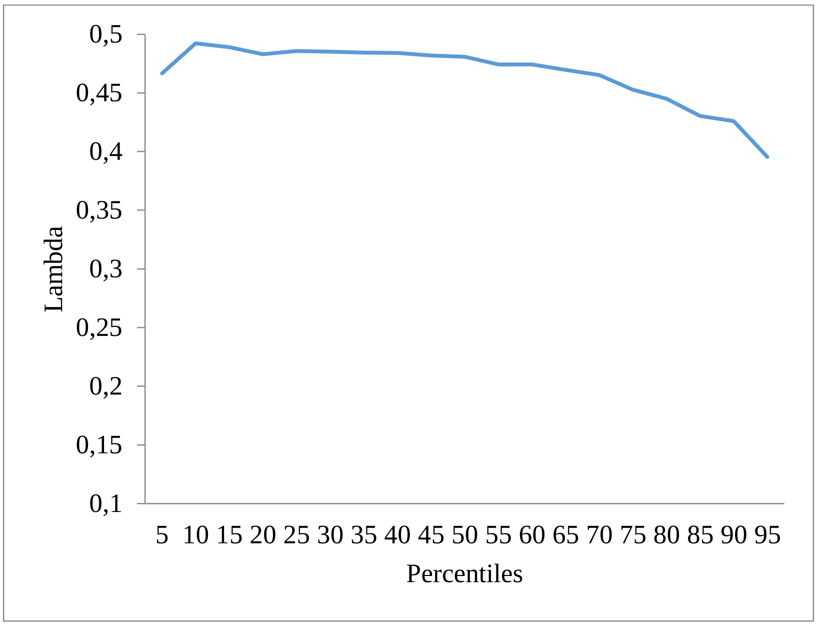
Table 7 - Gender gap in achievements in Mathematics – Quantile Regression (Specification 2)

	Year 2	Year 5	Year 6	Year 8	Year 10
Q10	0.000 (0.008)	-0.136 (0.019)***	-0.070 (0.016)***	-0.116 (0.026)***	-0.232 (0.012)***
Q25	-0.048 (0.023)***	-0.176 (0.020)***	-0.124 (0.0165)***	-0.233 (0.028)***	-0.284 (0.011)***
Q50	-0.145 (0.038)***	-0.211 (0.020)***	-0.189 (0.018)***	-0.233 (0.034)***	-0.389 (0.012)***
Q75	-0.145 (0.021)***	-0.233 (0.020)***	-0.250 (0.020)***	-0.233 (0.032)***	-0.449 (0.014)***
Q90	-0.145 (0.026)***	-0.190 (0.019)***	-0.268 (0.024)***	-0.233 (0.031)***	-0.483 (0.018)***

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Additional variables included are identical to those included in Specification 2 for the OLS and school FE models and are listed at p. 13.

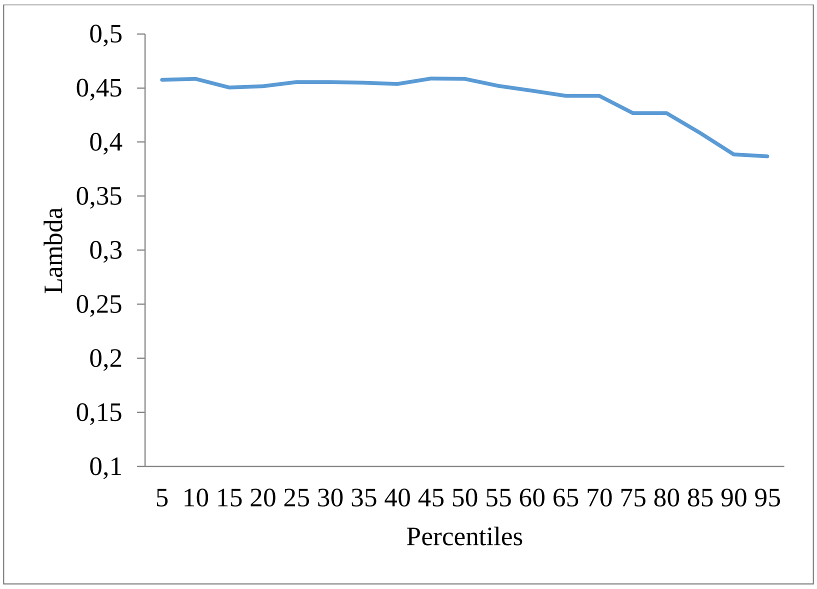
Figure 2 – Metric-free gender gap in achievements in Maths through the grade distribution

Lambda Year 2



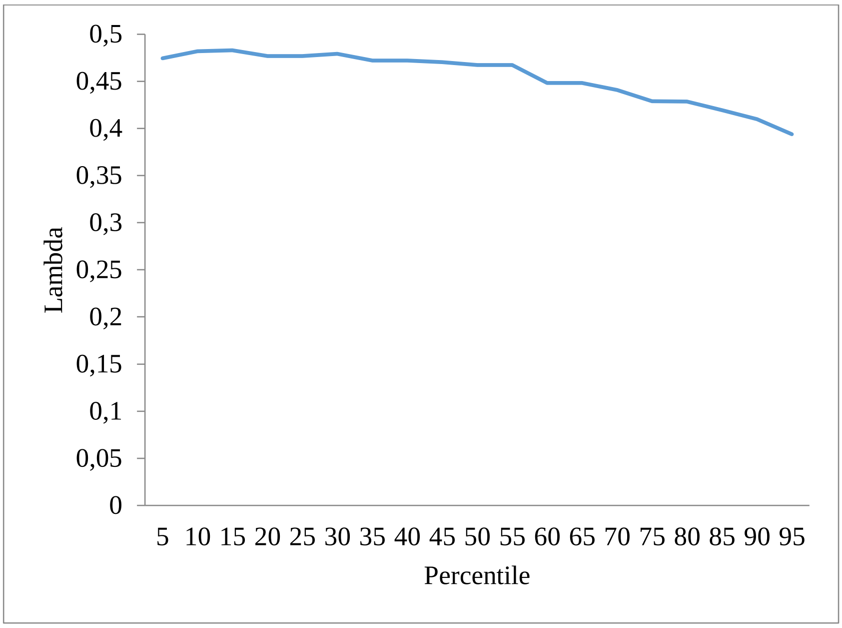
Note: λ equal to 0.5 means that boys' and girls' grades are aligned. λ values closer to 0 benefit boys while values closer to 1 favour girls.

Lambda Year 5



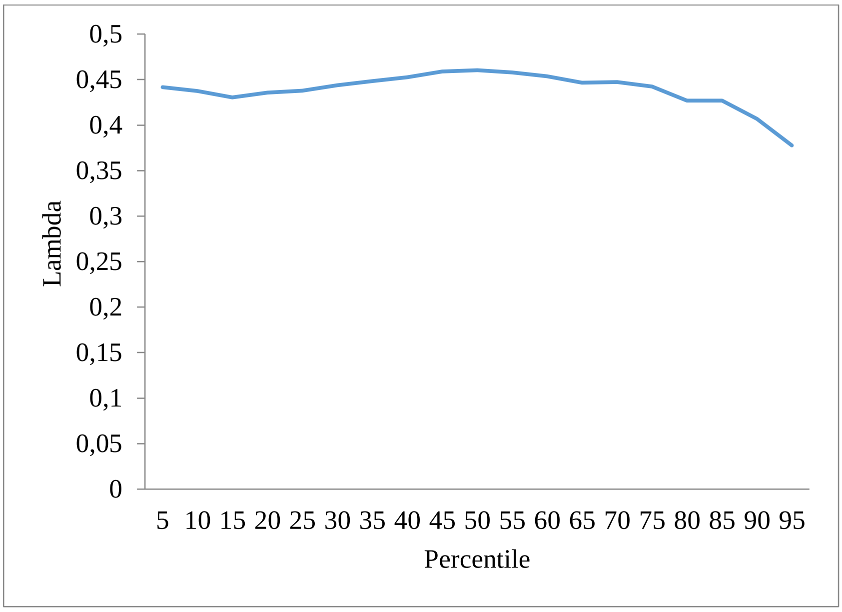
Note: λ equal to 0.5 means that boys' and girls' grades are aligned. λ values closer to 0 benefit boys while values closer to 1 favour girls.

Lambda Year 6



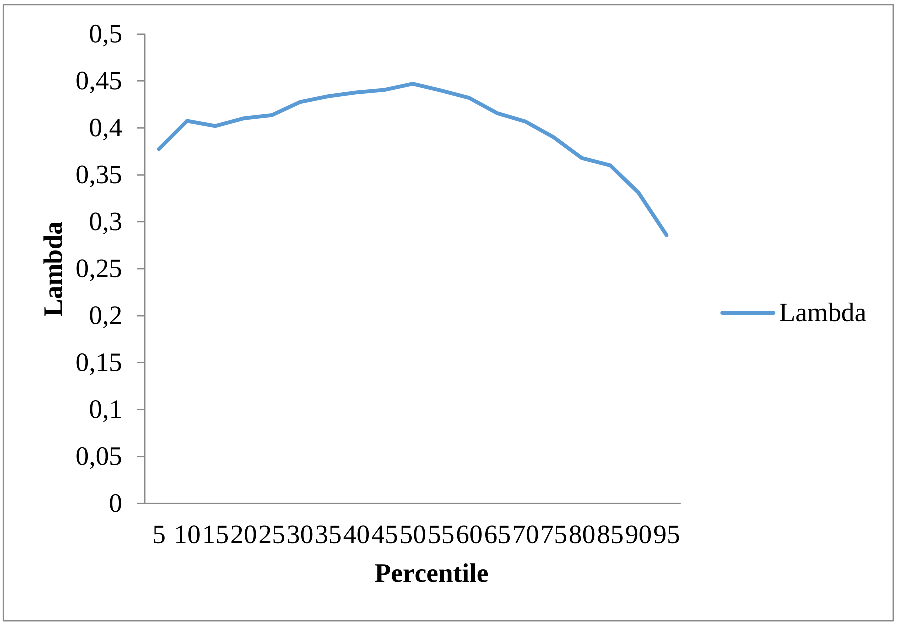
Note: λ equal to 0.5 means that boys' and girls' grades are aligned. λ values closer to 0 benefit boys while values closer to 1 favour girls.

Lambda Year 8



Note: λ equal to 0.5 means that boys' and girls' grades are aligned. λ values closer to 0 benefit boys while values closer to 1 favour girls.

Lambda Year 10



Note: λ equal to 0.5 means that boys' and girls' grades are aligned. λ values closer to 0 benefit boys while values closer to 1 favour girls.

Appendix A

Table A1: Descriptive statistics of independent variables (estimation samples from Invalsi 2013)

Gender	**Year 2**	**Year 5**	**Year 6**	**Year 8**	**Year 10**
Male	48.39	49.97	50.29	50.40	50.80
Female	51.61	50.03	49.71	49.60	48.79
Missing					0.41
ESCS index					
Mean	n.a.	0.0664	0.1033	n.a.	-0.0013
Standard deviation		1.0194	0.9842		0.9795
Region of residence					
North-West	16.67	16.26	19.29	18.47	18.78
North-East	19.90	19.83	21.04	20.41	20.75
Centre	18.05	17.32	18.06	19.01	17.62
South	25.60	26.19	23.61	23.02	24.52
Islands	19.78	20.39	18.00	19.08	18.33
Maternal education					
Degree	16.49	14.21	13.23	12.70	18.95
High school	34.01	33.73	32.21	29.64	35.20
Middle school	29.49	32.76	36.86	35.27	37.56
Missing	20.01	19.29	17.70	22.39	8.29
Paternal education					
Degree	12.27	11.49	11.17	10.90	17.56
High school	29.76	28.66	27.05	25.67	31.81
Middle school	36.54	39.49	42.80	39.94	39.79
Missing	21.43	20.36	18.98	23.49	10.84
Maternal employment					
Not working	31.28	32.07	33.67	31.01	37.17
Professional	8.05	7.72	7.84	6.96	10.24
Self-employed	7.72	8.02	7.90	8.11	11.22
Employee	22.67	22.42	21.78	21.51	19.50
Worker	10.14	10.75	11.54	10.44	17.36
Other	0.09	0.12	0.15	0.21	0.31
Missing	20.04	18.91	17.13	21.51	4.20
Number of siblings	n.a.			n.a.	
0		15.19	15.40		14.74
1		54.50	56.24		55.32
2		19.65	20.68		22.06
3		4.61	4.70		4.93
>=4		2.24	2.56		2.40
Missing		3.81	0.42		0.56
Preschool attendance					
Yes	74.28	74.95	75.97	73.28	97.18
No	13.64	13.25	10.59	13.64	1.95
Missing	12.08	11.80	13.44	13.08	0.86
Type of high school attended	n.a.	n.a.	n.a	n.a.	
Lyceum					44.57
Technical HS					21.97
Vocational HS					33.46
Expects to go to university	n.a.	n.a.	n.a	n.a.	
Yes					51.21
No					46.98
Missing					1.81

Table A2 – Attitudes towards maths

	(% all sample)	%Girls	%Boys
What do you think of mathematics?	**Year 5**		
I am good at maths	74.49	70.33	78.64
Maths is hard	23.26	27.31	19.20
I learn maths easily	63.30	59.14	67.47
I have fun doing maths	61.18	56.75	65.61
I'd like to do more maths a school	37.16	31.68	42.65
What do you think of mathematics?	**Year 6**		
I am good at maths	(%)		
Strongly disagree			
Disagree	4.10	4.90	3.36
Agree	18.73	21.50	16.01
Strongly agree	54.93	56.00	53.87
Missing	22.03	17.50	26.52
	0.21	0.17	0.25
Mathematics is hard			
Strongly disagree	38.11	36.51	39.69
Disagree	38.30	38.40	38.21
Agree	17.71	18.86	16.58
Strongly agree	5.54	5.96	5.12
Missing	0.34	0.26	0.41
I learn maths easily			
Strongly disagree	7.56	8.74	6.40
Disagree	19.89	21.97	17.84
Agree	44.70	45.61	43.81
Strongly agree	27.50	23.39	31.56
Missing	0.35	0.30	0.39
I have fun doing maths			
Strongly disagree	20.62	22.13	19.13
Disagree	22.87	24.46	21.30
Agree	31.95	31.76	32.13
Strongly agree	24.29	21.43	27.11
Missing	0.27	0.22	0.33
I'd like to do more maths at school			
Strongly disagree			
Disagree	37.12	39.63	34.63
Agree	28.82	29.55	28.10
Strongly agree	20.68	19.72	21.63
Missing	13.18	10.92	15.42
	0.20	0.18	0.22
I believe that being good at Maths will help me in life	**Year 10 (%)**		
Strongly disagree	6.14	5.64	6.62
Disagree	27.4	29.43	25.59
Agree	51.49	51.98	50.98
Strongly agree	14.33	12.35	16.21
Missing	0.60	0.60	0.60
I need to understand Maths in order to learn other subjects at school			
Strongly disagree			
Disagree	10.68	12.28	9.16
Agree	35.48	39.71	31.46
Strongly agree	42.01	39.07	44.80
Missing	11.20	8.35	13.91
	0.63	0.60	0.67
I need to be good at Maths in order to choose what to do after school			
Strongly disagree			
Disagree	18.65	21.69	15.76
Agree	34.77	38.19	31.56
Strongly agree	33.41	29.70	36.96
Missing	12.49	9.80	14.97
	0.69	0.62	0.75

I need to be good at Maths in order to get a good job			
Strongly disagree	18.78	21.85	15.85
Disagree	31.87	34.50	29.42
Agree	32.93	30.61	35.17
Strongly agree	15.71	12.37	18.80
Missing	0.72	0.68	0.76

Table A3 – Factor Analysis. Attitudes towards maths

Factor	**Eigenvalues**	**Variables**
Year 5		
Math self-concept	0.7635	I am good at maths
	0.8133	Maths is hard
	0.7943	I learn maths easily
	0.2617	I have fun doing maths
	0.0754	I'd like to do more maths a school
Year 6		
Math self-concept	0.7737	I am good at maths
	0.6509	Maths is hard
	0.7997	I learn maths easily
	0.7864	I have fun doing maths
	0.7146	I'd like to do more maths a school
Year 10		
Importance of math for the future	0.7054	I believe that being good at Maths will help me in life
	0.7429	I need to understand Maths in order to learn other subjects at school
	0.7887	I need to be good at Maths in order to choose what to do after school
	0.7907	I need to be good at Maths in order to get a good job

Table A4 – Effect of other independent variables on achievements in Mathematics (Pseudo Panel – Specification 2)

	Cross Section					**Dynamic**				
	Year 2	**Year 5**	**Year 6**	**Year 8**	**Year 10**	**Year 5**	**Year 6**	**Year 8**	**Year 10**	**Year 10 (base Y. 6)**
Escs index	n.a.	0.111	0.157	n.a.	n.a.	0.111	0.080	n.a.	n.a.	n.a.
		(0.011)***	(0.011)***			(0.011)***	(0.016)***			
Y hat						0.666	0.692	0.283	0.452	0.127
						(0.072)***	(0.103)***	(0.133)**	(0.417)	(0.112)
Region of residence (North west is omitted)										
North-East	0.046	-0.008	-0.097	0.084	0.019	-0.039	-0.091	0.111	-0.019	0.030
	(0.021)**	(0.022)	(0.022)***	(0.020)***	(0.019)	(0.022)*	(0.022)***	(0.024)***	(0.039)	(0.022)
Centre	-0.037	-0.158	-0.276	-0.133	-0.378	-0.133	-0.166	-0.055	-0.318	-0.343
	(0.022)	(0.023)***	(0.023)***	(0.020)***	(0.018)***	(0.024)***	(0.028)***	(0.042)	(0.059)***	(0.037)***
South	-0.196	-0.257	-0.428	-0.284	-0.717	-0.126	-0.250	-0.163	-0.588	-0.661
	(0.021)***	(0.021)***	(0.020)***	(0.019)***	(0.017)***	(0.026)***	(0.034)***	(0.061)***	(0.121)***	(0.054)***
Islands	-0.235	-0.376	-0.655	-0.150	-0.841	-0.219	-0.395	0.036	-0.773	-0.756
	(0.023)***	(0.024)***	(0.022)***	(0.021)***	(0.019)***	(0.031)***	(0.046)***	(0.091)	(0.066)***	(0.080)
Maternal education (University is omitted)										
High school	-0.179	-0.162	-0.053	-0.046	-0.078	-0.043	0.060	-0.031	-0.057	-0.071
	(0.021)***	(0.025)***	(0.024)**	(0.021)**	(0.018)***	(0.027)	(0.029)**	(0.022)	(0.026)**	(0.019)***
Middle school	-0.435	-0.358	-0.244	-0.291	-0.267	-0.069	0.004	-0.222	-0.136	-0.236
	(0.024)***	(0.030)***	(0.029)***	(0.022)***	(0.020)***	(0.042)	(0.046)	(0.039)***	(0.123)	(0.034)***
Paternal education (University is omitted)										
High school	-0.103	-0.004	-0.039	0.140	-0.058	0.065	-0.036	0.151	-0.122	-0.053
	(0.023)***	(0.027)	(0.026)	(0.021)***	(0.018)***	(0.027)**	(0.026)	(0.022)***	(0.062)**	(0.019)***
Middle school	-0.308	-0.143	-0.164	-0.111	-0.259	0.062	-0.065	-0.064	-0.209	-0.237
	(0.025)***	(0.030)***	(0.029)***	(0.022)***	(0.019)***	(0.037)*	(0.032)**	(0.031)**	(0.050)***	(0.027)***

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%.

Table A5 – Sensitivity test including an interaction between gender and Maths self-concept

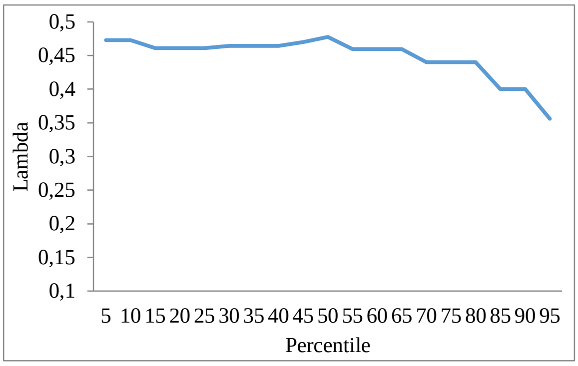
	OLS			**SCHOOL FIXED EFFECTS**		
	Year 5	**Year 6**	**Year 10**	**Year 5**	**Year 6**	**Year 10**
Female	-0.114	-0.091	-0.394	-0.119	-0.089	-0.289
	(0.014)***	(0.013)***	(0.009)***	(0.014)	(0.013)***	(0.009)***
Maths self-concept	0.367	0.385		0.377	0.411	
	(0.011)***	(0.009)***		(0.011)***	(0.009)	
Importance of math for the future	n.a.	n.a.	0.200	n.a.	n.a.	0.150
			(0.007)***			(0.006)***
Female*maths self-concept	-0.064	-0.050	n.a.	-0.059	-0.047	n.a.
	(0.015)***	(0.013)***		(0.014)***	(0.013)***	
Female*Importance of maths for the future	n.a.	n.a.	0.036	n.a.	n.a.	-0.015
			(0.009)***			(0.008)***

Appendix B: Subscales in mathematics achievement[14].

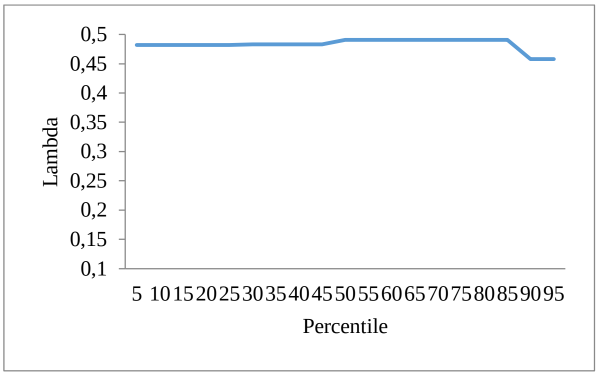
Figure B1 - Metric-free gender gap in achievements in Maths through the grade distribution by domains

Year 2

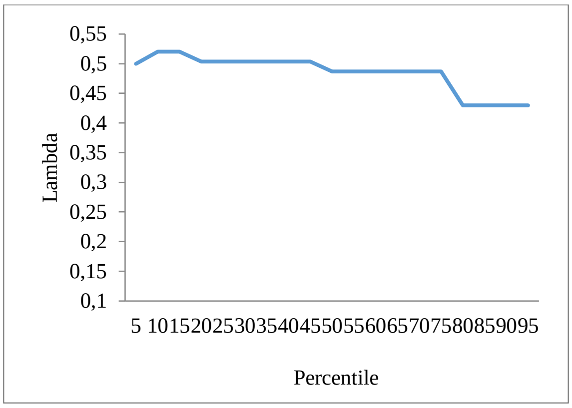
Numbers and Algebra



Geometry



Data and Statistics

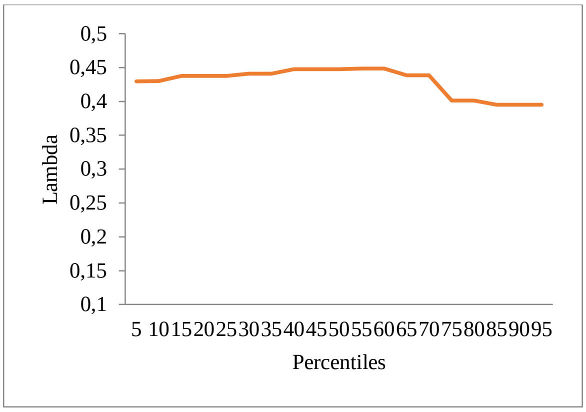


Note: λ equal to 0.5 means that boys' and girls' grades are aligned. λ values closer to 0 benefit boys while values closer to 1 favour girls.

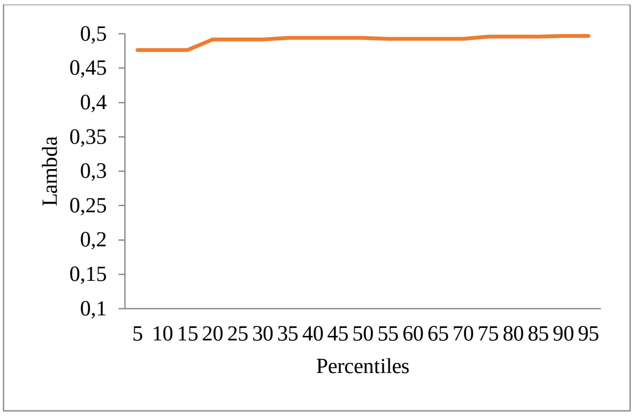
[14] For a complete description of the tests and for some examples of tests in the different domains and grades see: https://invalsi-areaprove.cineca.it/docs/autori/QdR_Mat_I_ciclo.pdf

Year 5

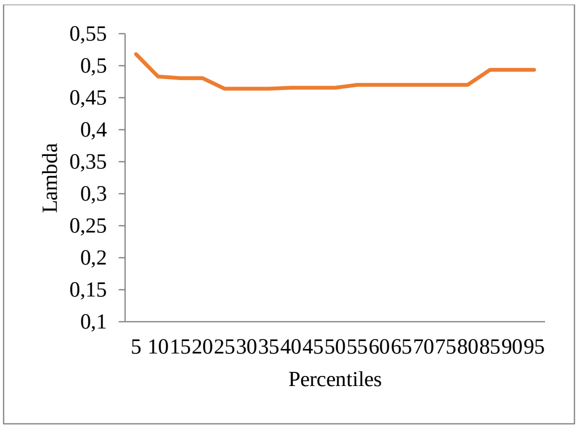
Numbers and Algebra



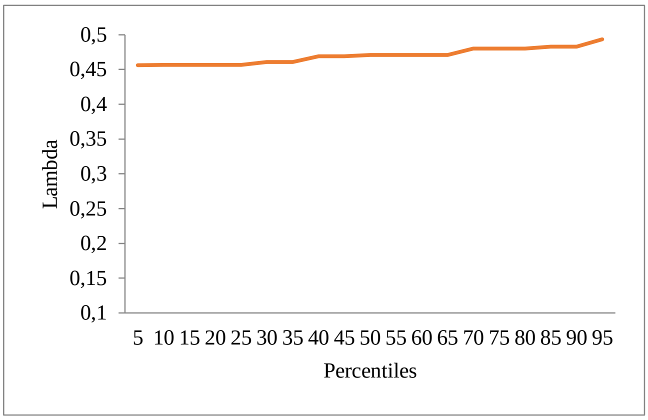
Geometry



Data and Statistics



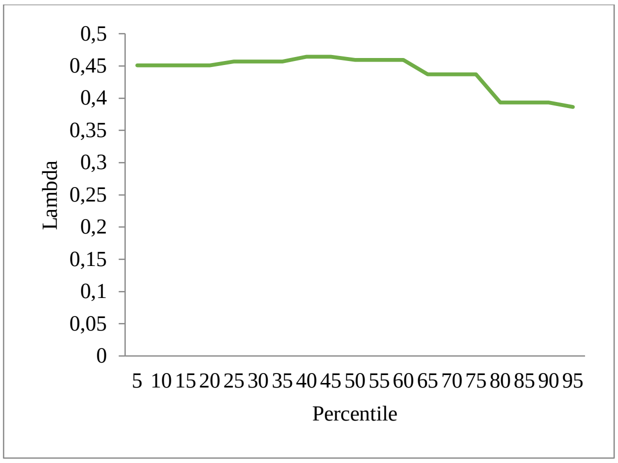
Working Mathematically



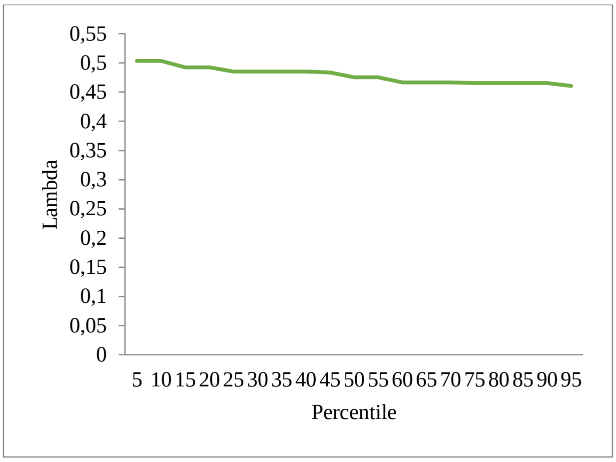
Note: λ equal to 0.5 means that boys' and girls' grades are aligned. λ values closer to 0 benefit boys while values closer to 1 favour girls.

Year 6

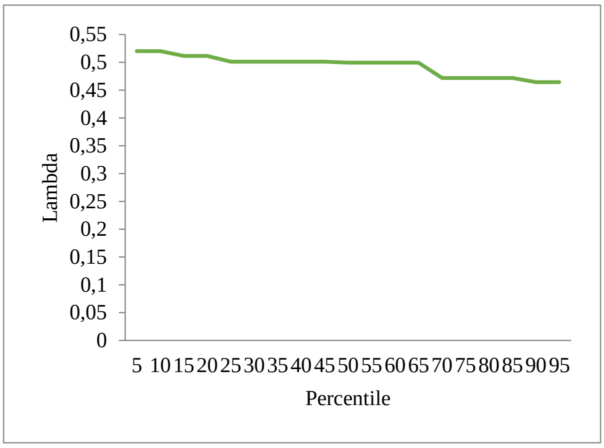
Numbers and Algebra



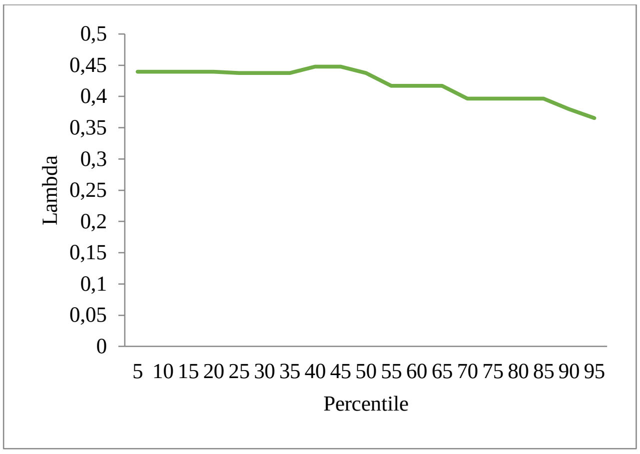
Geometry



Data and Statistics



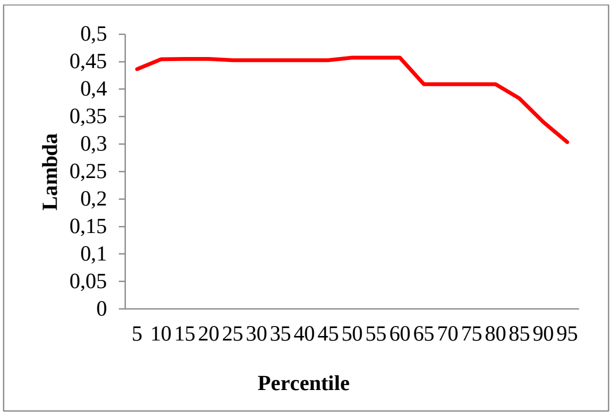
Working Mathematically



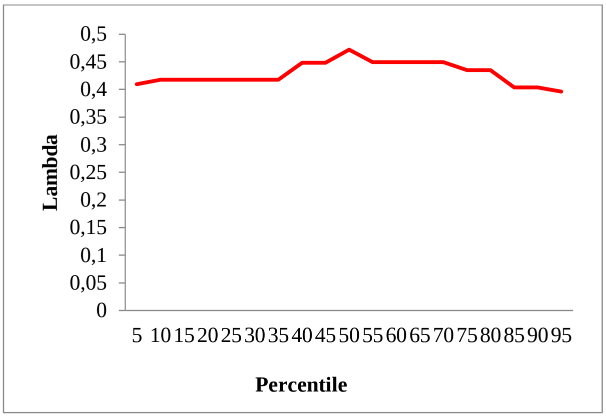
Note: λ equal to 0.5 means that boys' and girls' grades are aligned. λ values closer to 0 benefit boys while values closer to 1 favour girls.

Year 10

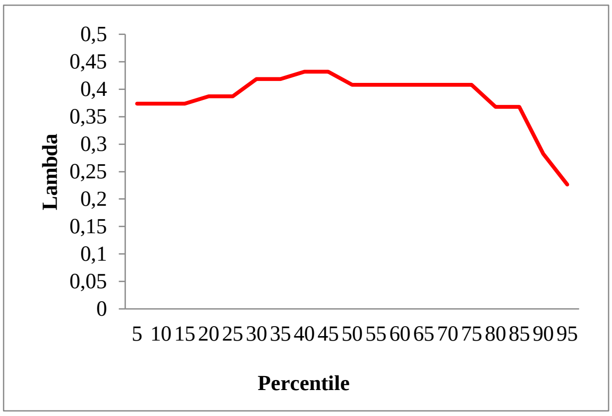
Numbers and Algebra



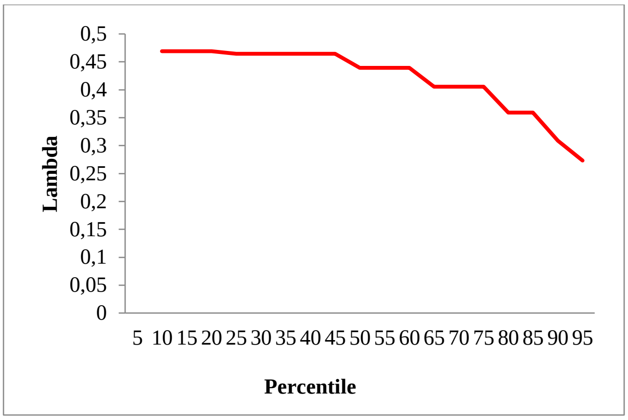
Geometry



Data and Statistics



Working Mathematically



Note: λ equal to 0.5 means that boys' and girls' grades are aligned. λ values closer to 0 benefit boys while values closer to 1 favour girls.

Mathematics domains: description of the domains in INVALSI

Numbers

Natural numbers: ordinal, cardinal, …), operations (calculus) e properties, ranking, representation with base ten, representation on an axis.

Integers: meaning and operations (calculus) e properties, rankings, representation with base ten, representation on an axis.

Rational numbers: fractions, decimal numbers, meanings, operations, representation with base ten, representation on an axis.

Even and odd numbers, prime numbers, multiples and divisors: properties and representations.

Ratios and percentages: meaning, operation, properties and representation.

Roots, powers: meaning, operation, properties.

Expressions with parenthesis: meanings and rules.

Space and figures: geometry

Maps, orienting.

Figures on a plane and in the space: definition, relation with the elements, building, properties.

Calculation of lengths, area, volumes.

Pithagora's theorem

2D and 3D space

Working Mathematically

Relationships between numbers and figures.

Number series, data interpretation, proportions

Interpretations of graphs and tables

Formulas and equations

Measuring system

Data

Collection and interpretation of data

Tables, graphs, histograms, bar charts

Frequencies and percentages

Mean, mode, median,

Probability theory