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THE GENDER GAP IN MATHEMATICS ACHIEVEMENTS: EVIDENCE FROM ITALIAN DATA

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

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Abstract

This paper describes the Italian gender gap in math utilizing the National Test “Invalsi” for the year 2013, in which all Italian children in school year 2, 5, 6, 8 and 10 are tested. The magnitude of the gender gap is measured using OLS and a school fixed effect model. We find that the female dummy is negative for all years, even after controlling for a socio-economic indicator, parental education, maternal professional status, geographical areas, number of siblings, kindergarten attendance, math self-beliefs (only year 5 and 6), belief about the importance of math and the type of high school (only year 10). In order to check if 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 higher for 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 (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 achievers⁴. 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).

Both biological factors (Baron-Cohen and Wheelwright 2004, Baron Cohen et al 2001) and societal factors (de San Roman and de La Rica Goiricelaya, 2012; Guiso et al., 2008; OECD 2015) have been proposed as explanations for the existence of the gender gap in mathematics.

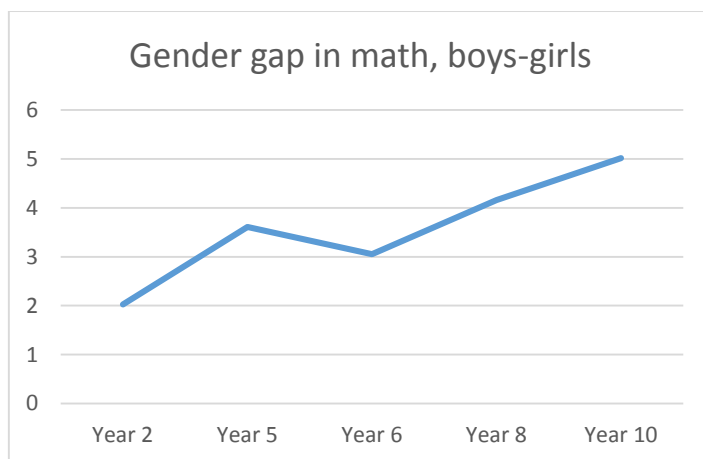
Societal factors that have been found to affect math performance are socioeconomic status, the parent's education, their profession, and their involvement in their children's homework (de San Roman and de La Rica 2012; Jacobs 1991; Jacobs and Bleeker 2004; Jacobs and Eccles 1992; Bhanot and Jovanovic 2009). 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).

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 standard deviation is 100 points. About two-thirds of students across OECD countries score between 400 and 600 points.

This paper aims at describing the Italian gender gap in math utilizing available data. There are not national longitudinal data 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.

Figure 1. Italian Gender gap in math: boys’ average test scores (% of correct answers) minus girls’ average test scores (% of correct answers). INVALSI 2013.



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

In order to analyse in more details the math gender gap in the Invalsi data set, the 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 kindergarten attendance. For year 10, we also control for types of high school attended and expectations about attending university. Then, we run a school fixed effects model, in order to control for time-invariant 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

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).

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 what figure 1 shows: The dummy 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 Lubienksy 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, to increase comparability of tests at different ages, we utilize a metric-free method (Robinson and Liubenski 2011).

2. Estimation methods

2.1 Cross sectional linear modelling

First, we analyse how (standardized) test scores⁶ of girls and boys differ on average at each survey with linear regression. 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. Differently from OLS, fixed effects models, exploiting only within-school variability, deliver valid estimates of the gender gap (and of the

⁶ Since test scores are not measured on the same scale at different school years, the gender gap on original scores is not comparable across school years. For this reason, we use standardized scores: in this way, the gender gap tells us by how many standard deviations girls and boys differ.

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.⁷

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 case study, because the explanatory variable of main interest is gender, and the other control variables are sociodemographic individual characteristics.⁸

Drawing from Contini and Grand (2015), consider first two cross sectional assessments using a single scale to measure achievement (i.e. “vertically equated” scores). Subsequent scores

⁷ 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.

⁸ 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.

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 main 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: $y_{i2} = \tilde{y}_{i1} + \delta_i$, 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 are more poorly performing than their older peers, in particular at early school stages, while it is reasonable to posit that given previous achievement, the month of birth should not affect later performance. 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 . The drawback is that standard errors will be largely inflated. As a

consequence, for reliable estimation we need large samples and a good instrument.

2.3 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 lower performing or better 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.

2.4 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:

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

where $\varphi_M(\cdot)$ and $\varphi_F(\cdot)$ are the cumulative distribution functions of males and females at the θ th 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 $\lambda_\theta < 0.50$. 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, $\lambda_\theta < 0.50$.

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 the second and fifth years of primary school, the first and third year of middle school and second year of high school. More than half a million students in each grade sit this test each year. These tests aim at analyse the reading and mathematical skills of Italian pupils and 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 and 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 percentage of correct answers in the mathematics assessments.

Table 1 – Average test scores in Maths

% of correct answers	Year 2	Year 5	Year 6	Year 8	Year 10
All	54.9 (20.7)	55.6 (18.8)	45.3 (16.7)	51.8 (18.9)	42.7 (17.8)
Boys	55.9 (21.1)	57.4 (19.0)	46.8 (17.3)	53.8 (19.0)	45.2 (18.6)
Girls	53.9 (20.2)	53.8 (18.4)	43.8 (16.0)	49.7 (18.5)	40.2 (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 presents other descriptive statistics of the estimation sample. Interestingly, mothers have on average higher education levels than fathers, in the estimation samples. We also analysed average test scores by maternal education and child’s gender and results are reported in Table 3. Not surprisingly, kids with highly educated mothers generally perform better in the tests, and this is true for both boys and girls. The gender gap in mathematics does not vary according to mothers’ education in our estimation sample. Boys tend to perform better than girls, regardless of maternal qualifications, and the gap expands over time in all groups.

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

We also include the variable “mathematics self-concept” for year 5 and 6. Students in year 5 and 6 are asked some questions regarding their own beliefs in their own abilities in math. Table A2 in Appendix A reports the list of questions and the descriptive statistics. We have run a factor analysis (reported in Table A3 in appendix A) to create an index that, in line with current literature, we call “mathematics self-concept” (see OECD 2015). Girls have usually much lower levels of math self-concept. PISA data for 2012 show that on average across OECD countries 63% of boys, but only 52% of 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). Gender differences in math self-concept remain large even among students who perform at the same level in math. Girls who perform as well as boy report a much lower level of math self-concept (Jacobs et al 2002).

Another variable included among independent variables for year 10 is an index about the importance of math for future studies, life and career (see table A2 in Appendix A for detail). We combine these questions using factor analysis and create an index of “importance of math for the future” and include it as a control variable.

The variable pre-school attendance is a dummy 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).

Table 2 – Maternal and paternal education, Region of residence (estimation samples from Invalsi 2013)

	Year 2	Year 5	Year 6	Year 8	Year 10
Maternal education (%)					
Degree	16.5	14.2	13.2	12.7	18.9
High school	34.0	33.7	32.2	29.7	35.2
Middle school	29.5	32.7	36.9	35.3	37.6
Missing	20.0	19.3	17.7	22.4	8.3
Paternal education (%)					
Degree	12.3	11.5	11.2	10.9	17.6
High school	29.7	28.7	27.0	25.7	31.8
Middle school	36.5	39.5	42.8	39.9	39.8
Missing	21.4	20.4	19.0	23.5	10.8
Region of residence (%)					
North-West	16.7	16.3	19.3	18.5	18.8
North-East	19.9	19.8	21.0	20.4	20.7
Centre	18.0	17.3	18.1	19.0	17.6
South	25.6	26.2	23.6	23.0	24.5
Islands	19.8	20.4	18.0	19.1	18.3

Table 3 – Average test scores in Maths by maternal education (estimation samples from Invalsi 2013)

% of correct answers	Year 2	Year 5	Year 6	Year 8	Year 10
Mother has completed a degree					
Boys	63.6 (19.63)	65.9 (17.6)	54.4 (16.99)	62.0 (18.5)	50.8 (20.1)
Girls	61.0 (18.88)	62.0 (17.7)	51.0 (16.58)	57.7 (18.5)	45.7 (17.5)
Mother has completed high school					
Boys	57.8 (20.4)	59.9 (18.1)	49.7 (16.9)	56.8 (18.5)	47.3 (18.4)
Girls	56.1 (19.3)	55.8 (18.0)	46.1 (15.5)	52.0 (18.0)	42.6 (17.4)
Mother has completed middle school					
Boys	50.5 (20.7)	51.5 (18.5)	42.0 (16.0)	48.8 (17.9)	40.6 (17.0)
Girls	48.2 (20.0)	49.0 (17.6)	39.8 (14.9)	45.3 (17.7)	36.1 (14.9)

4. Results

We begin presenting the results for the OLS and school fixed effect model. Results are presented using the standardized test scores, for ease of comparison. Table 4 shows the results only for the gender dummy of three different specifications⁹.

TABLE 4 APPROXIMATELY HERE

Specification 1 only includes child's gender as an independent variable. Specification 2 include 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 include the above variables plus kindergarten attendance and maternal occupation. When we analyse data from year 5, 6 and 10, we are also able to include information regarding the children's attitudes toward studying mathematics (see section above for its definition), and in year 10 we control for the type of high school attended and for expectations regarding tertiary education. We are aware that these variables 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), but, on the other hand, 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 age. 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

⁹ Tables for the results regarding all the other covariates are available from the authors upon request.

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 5 APPROXIMATELY HERE

Table 5 presents the effects of the other independent variables affecting test scores in mathematics for the OLS in specification 3. 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 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 might have 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 results 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 (described in section 3) for year 5 and 6 turns out to be positive and significant. Also the importance of math index (described in section 3) is positive and significant.

TABLE 6 APPROXIMATELY HERE

Table 6 presents results for the gender dummies from the pseudo-panel methodology¹⁰. In this framework, the coefficients measure the extent which achievement growth between $t=1$ and $t=2$ differs across categories, when comparing two children performing at the same level in $t=1$ (Contini and Grand, 2015)¹¹. Columns 1, 2, 4, 6 and 8 in Table 6 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 somewhat smaller than those from cross-sections. Our results are consistent with the literature in the field (Robinson and Lubiesky, 2011; Fryer and Levitt, 2010; Penner and Paret, 2008) and suggest that the math performance of girls and boys keeps differentiating as children grow. This seems to occur steadily throughout compulsory schooling, from elementary to the beginning of high school.

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

TABLE 7 APPROXIMATELY HERE

¹⁰ Full estimates available from the authors upon request.

¹¹ See section 2.2.

Table 7 presents the gender dummies from quantile regression¹². These findings confirm previous results (OECD 2015; Robinson and Lubiensky 2011; Fryer and Levitt 2010) and 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.

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

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.

¹² Full estimates available from the authors upon request.

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 1 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.

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, math self-beliefs.

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.

Future work includes the estimation of separate models for girls and boys to understand the importance of the covariates on each sub sample.

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Table 4 – 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 (0.013)***	-0.097 (0.012)***	-0.185 (0.013)***	-0.191 (0.012)***	-0.169 (0.013)***	-0.178 (0.011)***	-0.181 (0.012)***	-0.222 (0.011)***	-0.298 (0.010)***	-0.286 (0.008)***
Spec. 2 Female	-0.105 (0.014)***	-0.099 (0.013)***	-0.180 (0.014)***	-0.183 (0.013)***	-0.166 (0.013)***	-0.168 (0.013)***	-0.184 (0.012)***	-0.220 (0.011)***	-0.435 (0.009)***	-0.285 (0.009)***
Spec. 3 Female	-0.098 (0.014)***	-0.092 (0.014)***	-0.118 (0.014)***	-0.135 (0.014)***	-0.093 (0.013)***	-0.091 (0.013)***	-0.185 (0.014)***	-0.187 (0.013)***	-0.393 (0.009)***	-0.289 (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 includes also region of residence, parental education, and socio-economic status. For spec 3 see tab 5.

Table 5 – Effect of other independent variables on achievements in Mathematics (OLS – Specification 3)

	Year 2	Year 5	Year 6	Year 8	Year 10
Escs index	n.a	0.085 (0.011)***	0.104 (0.011)***	n.a	0.026 (0.007)***
Region of residence (North west is omitted)					
North-East	0.057 (0.022)***	-0.021 (0.022)	-0.091 (0.020)***	0.054 (0.021)***	0.014 (0.015)
Centre	-0.047 (0.023)**	-0.156 (0.024)***	-0.301 (0.021)***	-0.119 (0.023)***	-0.349 (0.015)***
South	-0.210 (0.021)***	-0.291 (0.021)***	-0.538 (0.019)***	-0.227 (0.021)***	-0.672 (0.014)***
Islands	-0.247 (0.024)***	-0.432 (0.024)***	-0.761 (0.021)***	-0.055 (0.022)**	-0.788 (0.015)***
Maternal education (University is omitted)					
High school	-0.118 (0.023)***	-0.096 (0.025)***	-0.042 (0.023)*	-0.159 (0.023)***	0.008 (0.015)
Middle school	-0.316 (0.027)***	-0.214 (0.030)***	-0.198 (0.028)***	-0.378 (0.025)***	-0.006 (0.018)
Paternal education (University is omitted)					
High school	-0.106 (0.023)***	-0.030 (0.026)	-0.029 (0.024)	0.018 (0.022)	0.024 (0.015)
Middle school	-0.316 (0.027)***	-0.214 (0.030)***	-0.198 (0.028)***	-0.378 (0.025)***	-0.006 (0.018)
Mother employment (Professional is omitted)					
Not working	-0.143 (0.030)***	-0.016 (0.031)	-0.042 (0.029)	-0.131 (0.029)***	-0.016 (0.018)
Self-employed	-0.033 (0.035)	0.016 (0.036)	-0.083 (0.032)**	-0.064 (0.034)*	-0.033 (0.020)*
Employee	0.055 (0.028)**	0.125 (0.029)***	0.077 (0.027)***	0.046 (0.028)	0.098 (0.017)***
Worker	-0.078 (0.035)**	-0.010 (0.036)	-0.012 (0.032)	-0.161 (0.033)***	0.004 (0.019)
Other	-0.265 (0.254)	0.400 (0.279)	0.063 (0.186)	-0.090 (0.132)	-0.114 (0.091)
Preschool attendance	-0.038 (0.027)	-0.088 (0.027)***	0.133 (0.024)***	0.183 (0.023)***	0.233 (0.036)***
N. siblings (0 is omitted)	n.a.			n.a.	
1		-0.004 (0.021)	0.009 (0.019)		0.060 (0.013)***
2		-0.044 (0.024)*	-0.035 (0.022)		0.058 (0.016)***

3		-0.022 (0.038)	-0.037 (0.035)		0.085 (0.025)***
>4		-0.150 (0.052)***	-0.126 (0.047)***		0.008 (0.034)
Type of High school (Lyceum is omitted)	n.a.	n.a.	n.a.		
Technical high school					-0.372 (0.012)***
Vocational high school					-0.749 (0.015)***
Expects to go to university	n.a.	n.a.	n.a.		0.275 (0.011)***
Math self-concept	n.a.	0.330 (0.007)***	0.360 (0.007)***	n.a.	n.a.
Importance of math for the future	n.a.	n.a.	n.a.	n.a.	0.219 (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

	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
Female	-0.105 (0.014)***	-0.183 (0.014)***	-0.113 (0.0167)***	-0.169 (0.014)***	-0.043 (0.023)*	-0.218 (0.013)***	-0.171 (0.026)***	-0.467 (0.011)***	-0.409 (0.086)***
Month of birth	-0.032 (0.022)***	-0.021 (0.002)***		-0.0150 (0.002)***		-0.004 (0.002)***		-0.001 (0.016)	

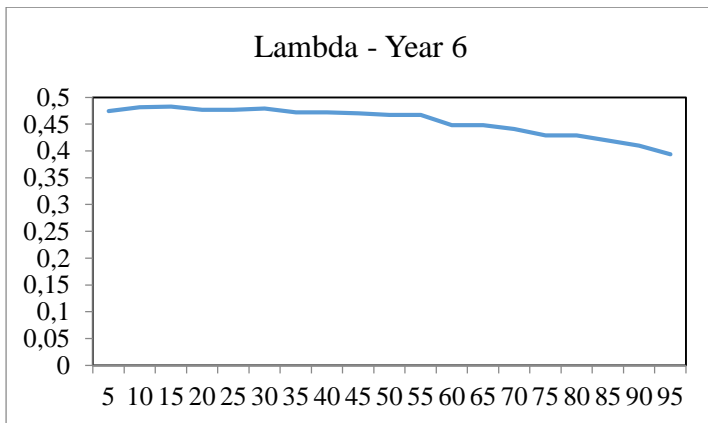
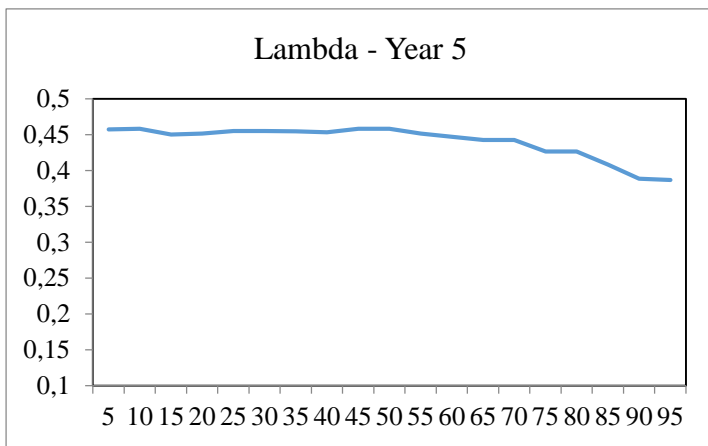
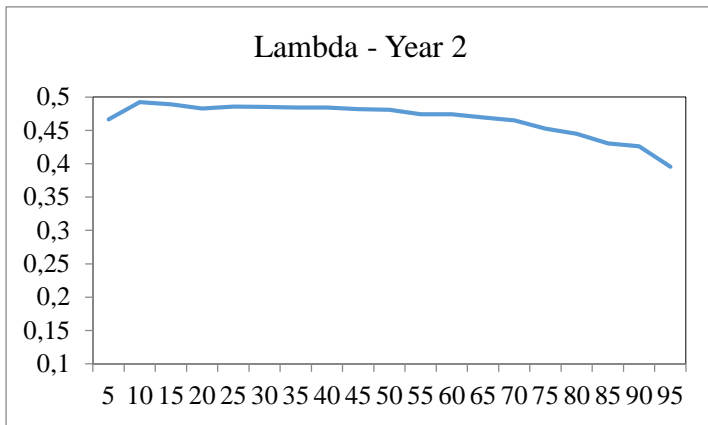
Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Additional variables included are listed at p. 11.

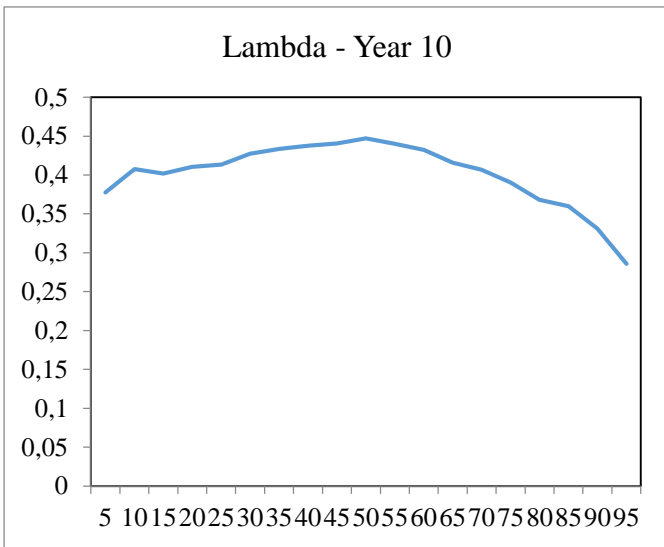
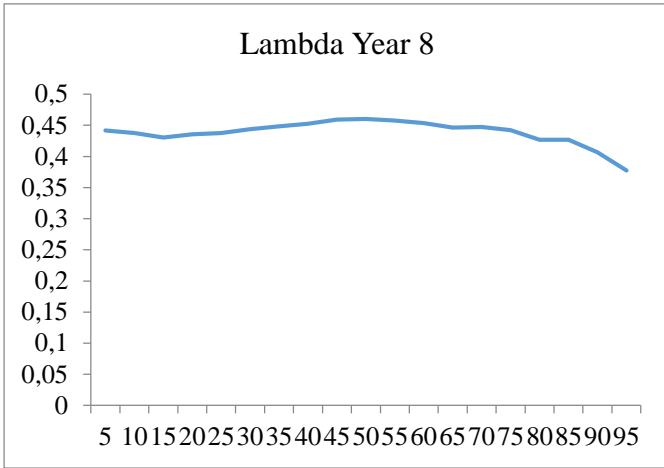
Table 7 - Gender gap in achievements in Mathematics – Model 2 – Quantile Regression

	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 listed at p. 11.

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





Appendix A-

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

	Year 2	Year 5	Year 6	Year 8	Year 10
Gender					
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					
0	n.a.	15.19	15.40	n.a.	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					
Lyceum	n.a.	n.a.	n.a.	n.a.	44.57
Technical HS					21.97
Vocational HS					33.46
Expects to go to university					
Yes	n.a.	n.a.	n.a.	n.a.	51.21
No					46.98
Missing					1.81

Table A2 – Attitudes towards maths

What do you think of mathematics?	Year 5
I am good at maths	(% yes)
Maths is hard	74.49
I learn maths easily	23.26
I have fun doing maths	63.30
I'd like to do more maths a school	61.18
	37.16
What do you think of mathematics?	Year 6
I am good at maths	(%)
Strongly disagree	
Disagree	4.10
Agree	18.73
Strongly agree	54.93
Missing	22.03
	0.21
Mathematics is hard	
Strongly disagree	38.11
Disagree	38.30
Agree	17.71
Strongly agree	5.54
Missing	0.34
I learn maths easily	
Strongly disagree	7.56
Disagree	19.89
Agree	44.70
Strongly agree	27.50
Missing	0.35
I have fun doing maths	
Strongly disagree	20.62
Disagree	22.87
Agree	31.95
Strongly agree	24.29
Missing	0.27
I'd like to do more maths at school	
Strongly disagree	
Disagree	37.12
Agree	28.82
Strongly agree	20.68
Missing	13.18
	0.20
I believe that being good at Maths will help me in life	Year 10
Strongly disagree	(%)
Disagree	6.14
Agree	27.4
Strongly agree	51.49
Missing	14.33
	0.60
I need to understand Maths in order to learn other subjects at school	
Strongly disagree	
Disagree	10.68
Agree	35.48
Strongly agree	42.01
Missing	11.20
	0.63
I need to be good at Maths in order to choose what to do after school	
Strongly disagree	
Disagree	18.65
Agree	34.77
Strongly agree	33.41
Missing	12.49
	0.69
I need to be good at Maths in order to get a good job	
Strongly disagree	18.78
Disagree	31.87
Agree	32.93
Strongly agree	15.71
Missing	0.72

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