Economics of Education Review 58 (2017) 32–42

Contents lists available at ScienceDirect

Economics of Education Review

journal homepage: www.elsevier.com/locate/econedurev

The gender gap in mathematics achievement: Evidence from Italian data

Dalit Contini[a], Maria Laura Di Tommaso[b], Silvia Mendolia[c,*]

[a] Department of Economics and Statistics Cognetti de Martiis, University of Turin, Torino, Italy
[b] Department of Economics and Statistics Cognetti de Martiis, University of Turin and Collegio Carlo Alberto, Moncalieri, Italy
[c] School of Accounting, Economics and Finance Room 40.215, University of Wollongong North Wollongong, NSW 2522, Australia

ARTICLE INFO

Article history:
Received 5 July 2016
Revised 28 January 2017
Accepted 1 March 2017
Available online 16 March 2017

JEL classification:
J16
I24
C31

Keywords:
Math gender gap
Education
School achievement
Inequalities
Pseudo panel estimation
Quantile regression

ABSTRACT

Gender differences in the STEM (Science Technology Engineering and Mathematics) disciplines are widespread in most OECD countries and mathematics is the only subject where girls tend to underperform with respect to boys. This paper analyses the gender gap in math test scores in Italy, which is one of the countries displaying the largest differential between boys and girls, according to the latest Programme for International Student Assessment (PISA). We use data from an Italian national level learning assessment, involving children in selected grades from second to tenth, and analyse the gender gap in mathematics test scores using OLS, school fixed effects, quantile regression, metric free and dynamic pseudo-panel models. Our results show that girls systematically underperform boys, even after controlling for an array of individual and family background characteristics. The average gender gap increases with children's age, is larger among top performing children, and girls keep losing ground relative to boys when progressing in the education system.

1. Introduction

The traditional gender gap in educational outcomes advantaging boys has been completely filled up in most industrialized countries, and has now reversed in favour of girls. Girls tend to do better than boys in reading test scores, in grades completion and repetition at school, in the propensity to choose academic educational programs in upper secondary school, in tertiary education attendance and graduation rates. In this perspective, there is now an extensive literature addressing the underperformance of boys (Department for Education and Skills, 2007; Legewie & Di Prete, 2012).

However, boys keep doing better than girls in math tests. According to the last available PISA (Programme for International Students Assessment) data set, Italy is one of the countries with the highest gender gap in mathematics for 15 years-old students. While the Italian mean test scores in mathematics are similar to the OECD average, the gender differences in mathematics are much higher in Italy than the OECD average (a 20 points difference in Italy against an average difference of 9 points in the OECD). This difference is the second highest among OECD countries with only Austria displaying a larger difference (OECD, 2016). In addition, TIMMS 2015 (Trends in International Mathematics and Science Study) shows that Italy has the highest gender gap in mathematics for children in fourth grade among all the 57 countries included in the survey (Mullis, Martin, Foy, & Hooper, 2016). The presence of a substantial females' disadvantage in math is of particular importance, because it is likely to be a cause of the critically low share of women choosing STEM (Science Technology Engineering and Mathematics) disciplines at university, of gender segregation in the labour market, and gender pay gaps (European Commission, 2006, 2012, 2015; National Academy of Science, 2007).

Several explanations have been proposed for the existence of the gender gap in mathematics. Some scholars refer to biological factors (Baron-Cohen, Wheelwright, Skinner, Martin, & Clubley, 2001). However, as shown by international assessments (Mullis et al, 2016, OECD, 2016) the gender gap in math differs

* Corresponding author.
E-mail addresses: dalit.contini@unito.it (D. Contini), marialaura.ditommaso@unito.it (M.L.D. Tommaso), smendoli@uow.edu.au (S. Mendolia).

http://dx.doi.org/10.1016/j.econedurev.2017.03.001

substantially across countries and some contributions (Guiso, Monte, Sapienza, & Zingales, 2008, De San Roman & De La Rica, 2012; OECD, 2015) provide evidence that the gender gap in math in the PISA survey is negatively related to country level indexes of gender equality. The literature also emphasizes the importance of parents and teachers' beliefs about boys and girls capacities (Cornwell & Mustard, 2013; Fryer & Levitt, 2010; Robinson-Cimpian, Lubienski, Ganley, & Copur-Gencturk, 2014; Bhanot & Jovanovic, 2009; Jacobs & Bleeker, 2004). Girls display less math self-efficacy (self-confidence in solving math related problems) and math self-concept (beliefs in their own abilities), and more anxiety and stress in doing math related activities (OECD, 2015, Heckman & Kautz, 2012, 2014; Lubienski, Robinson, Crane, & Ganley, 2013, Twenge and Campbell, 2001). As demonstrated by the recent work by Heckman and colleagues (e.g. Heckman & Kautz, 2012, 2014; Heckman & Mosso, 2014), non-cognitive abilities including motivation and self-esteem are important predictors of success in life and in the labour market. There is also empirical evidence that girls with mothers working in math-related occupations lag behind boys as much as those whose mothers are not in math-related occupations (Fryer & Levitt, 2010; OECD, 2015). Schools and educational methods and practices also seem to matter. Problem solving, class-discussions and investigative work and cognitive activation strategies have been found to improve girls' performances (Boaler, 2002; Zohar & Sela, 2003; OECD, 2015). In addition, Boaler, Altendorff, and Kent (2011) and Good, Woodzicka, and Wingfield (2010) show that girls' proficiency increases by using counter-stereotypic pictures with female scientists.

From a policy perspective, it is important to describe when the gap first shows up. Tackling the gender gap in mathematics at an early stage is more cost-efficient and it can address the inequality at the beginning of the educational journey, before girls choose high schools or university degrees. Research about the evolution of the gender gap in mathematics from an early age is mainly based on the US dataset "Early Childhood Longitudinal Study, Kindergarten Class of 1998–1999" (ECLS-K) following students from kindergarten through eighth grade. The main finding from these data is that the math gender gap starts as early as in kindergarten and increases with the age of the child (Robinson & Lubiensky, 2011; Fryer & Levitt, 2010; Penner & Paret, 2008). Another relevant result is that the math gender gap is higher for top performing students. Initially boys appear to do better than girls among well performers and worse at the bottom of the distribution; however, by third grade, the gender gap, while still larger at the top, appears throughout the distribution. Moreover, the male advantage among high performers is largest among families with high parental education. Girls appear to lose ground in math over time in every family structure, ethnic group, and level of the socio-economic distribution (Fryer & Levitt, 2010).

Differently from the US, in Europe there are not many studies about the evolution of the gender gap in mathematics during childhood. Cross sectional data sets show that the gender gap in mathematics exists in 4° and 8° grade (in TIMMS data[1]) and in 10° grade (in PISA data, OECD, 2016) in many European countries but not much has been done to study its evolution from an early stage. One obvious reason is the lack of longitudinal data, but even where these data exists, not much research has been done. Longitudinal studies in UK (LSYPE and the Millennium Cohort Study) report limited evidence of a substantial gender gap in math (Department for Education and Skills, 2007), and the National Education Panel Study (NEPS) in Germany does not focus on gender inequalities (Blossfeld, von Maurice, & Schneider, 2011). However, according to the PISA assessment (OECD, 2016), both countries display a significant math gender gap in favour of boys at age 15.

This lack of attention to the study of the evolution of the gender gap in mathematics in European countries is also mirrored by a lack of policies to re-address it at an early age. Many policies and campaigns have focused on high school students, women and STEM subjects at university, or on gender inequality in research and innovation,[2] but there has been a lack of policies focusing on the early stages of the educational systems.

As for Italy, there are currently no systematic contributions on the evolution of the gender differentials in mathematics over childhood. Many contributions have provided evidence about inequalities in students' achievements across Italian regions, between migrant and native children, and across different income and socio-economic groups (Montanaro, 2008; Checchi, Fiorio, & Leonardi, 2013; Mocetti, 2011; Carlana, La Ferrara, & Pinotti, 2016). Excluding international reports (OECD, 2016, Mullis et al., 2016) the only contribution that has been looking at the gender gap in mathematics in Italy (De Simone, 2013) analyses inequalities in mathematics and science of Italian students at the end of the lower secondary school, using TIMMS data for 4° and 8° grades. This paper investigates the determinants of learning gaps in maths and science, including gender, socio-economic status and country of birth, and uses a pseudo panel technique showing that the gender gap in math does not widen between grades 4 and 8.

Our 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 favouring boys over girls at age 15 (OECD, 2016; Mullis et al., 2016). We exploit the data of the National Assessment carried out by INVALSI[3] from 2010 until 2015, testing the entire population of Italian children in school years 2, 5, 8 and 10, and analyse gender differences in math achievement throughout childhood in different cohorts. Secondly, by focusing on differentials along the entire test score distribution, we analyse the gender gap at different points of the test scores' distribution with quantile regression.

Thirdly, we apply a metric free method to analyse the girls' disadvantage along the entire performance distribution, but focusing on rankings rather than on the specific values of the test scores. The advantage of this method is that it does not rely on stringent psychometric assumptions and hence delivers robust findings also when comparing results across different assessments.

Lastly, we estimate dynamic models relating math performance at two consecutive assessments. Since there is no suitable longitudinal dataset on Italian students, we use a pseudo-panel regression technique, to identify the "new" gender effect operating between the two surveys and disentangling it from carryover effects of previously established inequalities.

Altogether, this body of evidence confirms the general findings on gender inequalities in math test scores observed in US data and in particular, that the math gender gap starts at an early age, is larger among well performing than among low performing children and widens as children grow older.

[1] For a detailed description of the gender gap in Math and Science across OECD countries in TIMMS data, see Bedard and Cho (2010).

[2] Science It's a girl things (http://science-girl-thing.eu/en/splash). Female Empowerment in Science and Technology, FESTA (http://www.festa-europa.eu/site-content/news). Hypathia (http://www.expecteverything.eu/hypatia/). Gendered Innovation in Science, Health & Medicine, Engeenering, Environment. (http://ec.europa.eu/research/swafs/gendered-innovations/index_en.cfm?pg=home). See also the Gender Summit 2016 on "Gender-based research, innovation and development for sustainable economies and societal wellbeing" Brussels, 8-9 Nov 2016.

[3] 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).

2. Italian education system and data

The Italian education system is organised in three stages. Students attend primary school from the age of 6 until the age of 11 years old. At the end of primary school, they enrol in middle school, and remain within the same institution (and in the same class) from the age of 11 until the age of 14 years old. High school begins at the age of 14 and lasts for five years, but compulsory education terminates at 16 years old, so a relevant share of children does not attain the upper secondary school qualifications.

At the end of middle school, students choose among different kinds of high schools, with significant differences in the curriculum. These educational programs are broadly classified into three main types: 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 offer some compulsory subjects (Italian, Mathematics, Sciences, History, one or two foreign languages and Physical Education). However, there are significant differences in terms of the time allocated to each subject, and the specialised field of studies. Lyceums generally provide higher-level academic education, with a specialisation in the humanities, sciences, languages or arts. Technical institutes usually provide students with both a general 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.[4]

Previous research (Checchi & Flabbi, 2007, Contini & Scagni, 2013) has shown that family background plays a big role in the choice of the upper secondary track in Italy. Gender is also relevant, as girls are overrepresented in school types with an emphasis on humanities (classical, linguistic, social sciences, art lyceums) and underrepresented in other school types (scientific lyceum, technical and vocational schools), some of which delivering educational programs with a stronger mathematical content.

This study uses data from the National Test INVALSI from 2010 until 2015, assessing the reading and mathematical skills of Italian pupils. Since 2010, all Italian children have been tested by the INVALSI in grades 2, 5, 6, 8 and 10. More than half a million students in each grade sit this test each year. The tests for grade 6 were discontinued in year 2014. Therefore the last available figure for 6th grade is in year 2013.

INVALSI assesses the overall population of students enrolled in Italian schools but a subsample of schools and students takes the tests under the supervision of an external inspector. To ensure better data quality in our analysis, we only use the subsample of children whose test was supervised by an external inspector.[5]

We restrict the sample to native children, mostly because recent migrants may be enrolled in classes that 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.

In addition to test scores, INVALSI data includes information about parental characteristics and family background, collected from a students' survey and from school board records. In selected years, INVALSI provides a synthetic indicator of economic and socio-cultural status (ESCS) similar to that the one available in PISA. The ESCS index is calculated by taking into consideration parental educational background, employment and occupation, and home possessions. The complete set of descriptive statistics for the variables used in the estimation is provided in Table A1.

3. Modelling strategies

3.1. Cross-sectional regression models

Since test scores are not measured on the same scale at different school years, 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.

First, we focus on the total effect of gender on average math achievement. We estimate an OLS model with standardized test scores as dependent variables, gender as the independent variable of interest, and a set of control variables describing maternal and paternal education, socio-economic status of the family, and macro-area. Further, we include province fixed effects, in order to control for the geographical area at a smaller scale.

Second, if school characteristics influence children's learning, the effect of gender might operate both indirectly via school choices and directly net of school characteristics. The existence of an indirect effect could play a role in particular after tracking into different educational programs has taken place (see Section 2), but it might also apply at earlier stages of schooling. Students attending the same school are exposed to a similar environment in the student body composition (in terms of gender, socioeconomic status, and immigrant background), learning targets, educational practices, and gender stereotypes, that might affect the performance of girls and boys differently. For these reasons, we estimate the direct effect of gender on math achievement estimating a model including school fixed effects, which exploit within-school variability, and deliver valid estimates of the gender gap given individual controls and (observed and unobserved) school characteristics.

Third, we shift the focus from the expected value of test scores to the entire test score distributions of girls and boys and analyse gender differentials at different points of the ability distribution. To this aim, we estimate quantile regression models (Koenker & Basset, 1978). In essence, with these models we inspect the gender gap at different percentiles of the grade distribution, and assess whether female's disadvantage in math exists throughout the distribution, or instead is stronger among low performing or top performing children. In the simplest case where gender is the only explanatory variables, 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.

3.2. Metric-free analysis of the entire performance distribution

A weakness of the methods described so far is that test scores are measured on the interval scale. The interval scale assumes that there is the same difference in cognitive ability between pairs of children with the same absolute difference in test scores (for example between children scoring +1.0 and +1.5 and between children scoring -1.5 and -1.0). However, this assumption implicitly relies on stringent psychometric assumptions that are not likely to hold (see De Simone and Gavosto, 2013 and Jacob and Rothstein, 2016 for a similar discussion). This issue is particularly relevant when comparing different surveys, because in this case we must also assume that a given difference in test scores at the first assessment implies the same distance at later assessments.

To overcome this limitation we use *metric-free* methods that treat the test score as an ordinal variable, analyzing rankings rather than on the specific values of the test scores. The focus is on the

[4] For a general account of the Italian education system, see Ichino and Tabellini (2014).

[5] For a detailed explanation of the problem of "cheating" in Invalsi data see Angrist et al. (2015), Bertoni et al. (2013), Lucifora and Tonello (2015), Paccagnelli and Sestito (2014).

entire test score distribution, by analyzing the relative position that girls and boys occupy in each percentile within the overall ranking.

Following Robinson and Lubienski (2011), we analyze the gender gap throughout the performance distribution by estimating at specific percentiles θ the following:

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

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 for $\theta < 50$ indicate the share of *boys below* percentile θ, if girls and boys were equally represented in the sample, while values of λ_θ for $\theta \geq 50$ indicate the share of *girls above* percentile θ. Hence, values of λ_θ below 0.5 indicate a girls' disadvantage throughout the entire distribution.

For example, $\varphi_F(20)$ is the share of females below the 20th percentile of the overall performance distribution including both girls and boys and $\varphi_M(20)$ is the share of males below the overall 20th percentile. If $\varphi_F(20) > \varphi_M(20)$, more girls than boys perform below the 20th percentile and thus $\lambda_{20}.<0.50$. Instead, $1-\varphi_F(80)$ is the percentage of females above 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 boys, and $\lambda_{80} < 0.50$. The larger the distance of λ_θ from 0.5, the stronger the gender inequality in favor of boys.

3.3. Dynamic regression models

Cross-sectional analyses do not allow exploring the mechanisms underlying the *development* of inequalities as children grow. Cross-sectional regression coefficients at age *t* represent the effects accumulated up to age *t* and do not allow distinguishing new effects operating between two successive assessments and carryover effects of pre-existing achievement gaps between girls and boys. Further, coefficients based on standardized test scores also depend on the achievement variability at each assessment.[6] Hence, if this variability increases between two surveys for reasons not related to gender (for example, due to increasing differences across socioeconomic levels), we might observe a diminishing gender gap even if there are no forces at work making girls catching up the previous disadvantage (Contini & Grand, 2015).

In this perspective, we aim at estimating a simple dynamic model, relating achievement at a given time point (t=2) to previous achievement (at t=1) and individual characteristics, including gender. In the absence of longitudinal data, we use pseudo-panel techniques proposed by De Simone (2013) and Contini and Grand (2015), allowing to estimate simple dynamic models with repeated cross-sectional data.[7] The basic idea is that the unobserved lagged dependent variable can be replaced by a predicted value from an auxiliary regression using individuals observed in previous cross-sections. This strategy delivers consistent estimates under quite restrictive conditions – for example, if there are no time-varying exogenous variables, or if the time-varying exogenous variables are not auto-correlated (Verbeek & Vella, 2005). Despite being restrictive, these conditions apply to our case study, because the explanatory variable of main interest is gender and the other control variables are time-invariant sociodemographic variables.[8]

In this paper, we apply the method adopted in Contini and Grand (2015). To illustrate its rationale, consider two cross sectional assessments using a single scale to measure achievement (i.e. "vertically equated" scores). Subsequent scores follow the relation:

$$y_{i2} = y_{i1} + \delta_i \quad (2)$$

where δ_i is achievement growth, that may vary across individuals and depend linearly on individual characteristics x_i and previous achievement:

$$\delta_i = \Delta + \beta x_i + \theta y_{i1} + \varepsilon_{i2} \quad (3)$$

Under these assumptions, the dynamic model relating achievement at the two occasions is:

$$y_{i2} = \Delta + (1+\theta)y_{i1} + \beta x_i + \varepsilon_{i2} \quad (4)$$

The parameter of interest is β, representing the difference between test scores at t=2 of a boy and a girl with identical performance at t=1. Hence, β captures gender inequalities developed between the two surveys, whereas θ are carry-over effects of inequalities already existing at t=1. Notice that β is expressed in the scale of y_{i2}, so in this analysis there are no issues of metrics comparability.

When achievement scores are not equated, the relation between subsequent scores is:

$$y_{i2} = \tilde{y}_{i1} + \delta_i \quad (5)$$

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

$$y_{i2} = \varphi(1+\theta) + \Delta + \tau(1+\theta)y_{i1} + \beta x_i + \varepsilon_{i2} \quad (6)$$

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

The analysis is conducted in two steps. In the first step, we estimate the cross sectional model for test scores at t=1:

$$y_{i1} = \mu_1 + \rho x_i + \delta w_i + \varepsilon_{1i} \quad (7)$$

where w is an appropriate instrumental variable affecting achievement at t=1 but not affecting achievement at t=2 given achievement at t=1

In the second step, we substitute y_1 with its OLS estimate $\hat{y}_1$ and plug it in model (6). 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 $\hat{y}_1$.The final model is:

$$y_{i2} = \mu_2 + \gamma \hat{y}_{1i} + \beta x_i + u_{2i} \quad (8)$$

Model (8) will deliver consistent estimates of β. The major drawback of this approach is that the standard errors will be largely inflated, and therefore the sample size is critical in order to obtain reliable estimation coefficients.

Following Contini and Grand (2015), as an instrumental variable we use the month of birth, since there is widespread evidence that younger children generally underperform their older peers, in particular at early school stages (see for example Crawford, Dearden, & Meghir, 2007; Robertson, 2011; Crawford, Dearden, & Greaves, 2014 among many others). Further, younger children are also more likely to have negative emotional and social experiences, such as, for example, being bullied on the playground

[6] Ignoring other control variables, the standardized gender gap at age/year j is: $(\bar{Y}_{j,B} - \bar{Y}_{j,G})/\sigma_{Yj}$. Clearly, the score variability σ_{Yj} may vary over time as a result of multiple driving forces, including increasing differences across social backgrounds or ethnic status.

[7] Recent applications of this methodology can be found in Choi et al. (2016a,b).

[8] Note that the inclusion of school characteristics in the model would invalidate the estimation, because school features are typically correlated to the error term (that incorporates innate ability), because higher ability children usually choose schools with more favorable characteristics (see Contini and Grand, 2015, pg. 14). Similar conclusion would apply if we were to include other endogenous variables capturing behavior and attitudes.

Table 1
Average gender gaps (G-B) in Maths, standardised test scores, Invalsi data from 2010 to 2015, by cohorts of children starting school in different years.

	2°	5°	8°	10°
Year 1 in 2003-04			**−0.176**	**−0.298**
Year 1 in 2004-05			**−0.142**	**−0.189**
Year 1 in 2005-06		**−0.152**	**−0.181**	**−0.341**
Year 1 in 2006-07		**−0.079**	**−0.152**	
Year 1 in 2007-08		**−0.172**	**−0.119**	
Year 1 in 2008-09	**−0.088**	**−0.186**		
Year 1 in 2009-10	**−0.070**	**−0.126**		
Year 1 in 2010-11	**−0.095**	**−0.197**		

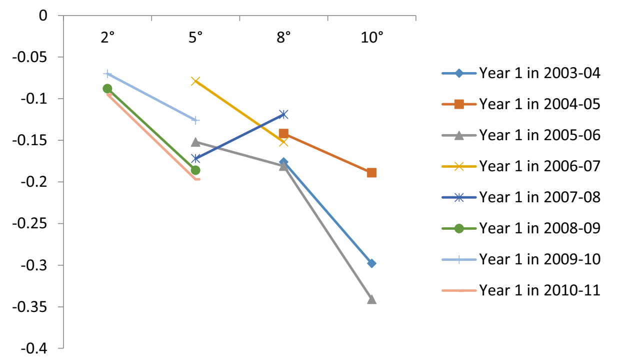


Fig. 1. Average gender gaps (G-B) in Maths, standardised test scores, Invalsi data from 2010 to 2015, by cohorts of children starting school in different years.

(Ballatore, Paccagnella, & Tonello, 2015), that might also affect their schooling outcomes. However, these differences substantially decrease over time. For example, Robertson (2011) showed that differences between children born at the beginning and at the end of the academic year are eliminated by eighth grade (age 12–13). Our data confirm these findings (see the coefficient of the month of birth in Table 4).

For these reasons, the underlying assumption in our model is that age of the child does not affect achievement at one particular grade, *given* previous achievement, i.e. once we control for differences in achievements early in life, the impact of month of birth on later achievements is not relevant to later outcomes[9].

4. Results

4.1. Cross sectional regression results

As outlined in Section 2, we utilise INVALSI cross sectional data from 2010 until 2015 for children in year 2, 5, 8, 10. Unfortunately, there are no longitudinal data available, therefore we analyse the data by cohort relying on repeated assessments of the same cohort of students (although not the same specific students). We are able to identify 8 cohorts of students who started school from school year 2003-04 until school year 2010-11. Given that INVALSI data is available from 2010 until 2015, we only have data for some grades for each cohort.

Table 1 and Fig. 1 show descriptive evidence of the average gender gap in standardised test scores in mathematics by cohort, for all the available data for each grade by cohorts. Since tests at different age are not equated (i.e. measured on the same scale), comparing the difference of raw scores across school years is not meaningful, and therefore we use the standardized achievements. Looking at each cohort, we see that the gap always increases as children age, with the exception of the cohort in year 1 in 2007-08 , where the gap decreases between years 5 and 8.

The gender gap in favour of boys varies between -0.07 and -0.09 in grade 2, implying that girls obtain test scores that are on average 0.07 and 0.09 standard deviations (s.d.) below those of boys. In grade 5, the gap varies between 0.08 and 0.19 s.d. In grade 8, the gap varies between 0.12 and 0.18 s.d., while in grade 10, it varies between 0.19 and 0.34 s.d..

[9] The use of the season of birth as an instrumental variable to account for the endogeneity of children's age on later outcomes has recently been questioned by Buckles and Hungerman (2013). They argue that, contrary to common belief, the season of birth is not totally idiosyncratic; in fact in USA winter births are disproportionally represented by teenagers and unmarried mothers. However, in this paper we use 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 consistently estimate the effects of socio-demographic variables net of previous achievement.

Table 2
The gender gap (G-B) in math test scores for two selected cohorts.

COHORT 1	Year 2	Year 5	Year 8	Year 10
Raw gap		−0.152	−0.181	−0.341
		(0.011)***	(0.013)***	(0.012)***
OLS		−0.152	−0.184	−0.322
		(0.011)***	(0.012)***	(0.012)***
Province FE		−0.153	−0.184	−0.311
		(0.011)***	(0.012)***	(0.011)***
School FE		−0.166	−0.191	−0.282
		(0.009)***	(0.011)***	(0.011)***
N		31,134	25,111	22,943
COHORT 2				
Raw gap	−0.088	−0.186		
	(0.011)***	(0.013)***		
OLS	−0.088	−0.186		
	(0.011)***	(0.013)***		
Province FE	−0.090	−0.184		
	(0.010)***	(0.013)***		
School FE	−0.087	−0.192		
	(0.009)***	(0.012)***		
N	31,330	21,207		

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 5% level, ** at 1% and ***0.1%. All models include area of residence. Models for year 2, year 5, and year 8 also include maternal and paternal education. Model for year 5, cohort 2 and model for year 10 include the ESCS index (not available for other years).

In the subsequent analysis, we focus on two cohorts of students. The first one is the cohort of students who started school in year 2005-06 (from now on Cohort 1) and the second one is the cohort of students who started school in year 2008-09 (from now on Cohort 2). We choose these two specific cohorts because they are the closest in time from each other, they cover all school grades from 2 to 10, and data is available for at least two grades for each cohort. [10]

Table 2 shows the raw gender gaps in math achievements (including standard errors), as well as the estimates of the gender gap calculated using OLS, OLS with school fixed effects, and OLS with province fixed effects[11]. Gender has a significant and sizable effect on test scores in mathematics at all ages. The absolute values of the estimates are higher for higher grades, similarly to the raw gender gap. Results remain unchanged when adding province or school fixed-effects up to year 8. In year 10 we observe a small de-

[10] Analysis for the other cohorts are available from the authors upon request.

[11] The descriptive statistics of all the variables used in the estimates and the full set of parameters for the OLS estimation are reported in Appendix A, Tables A1 and A2.

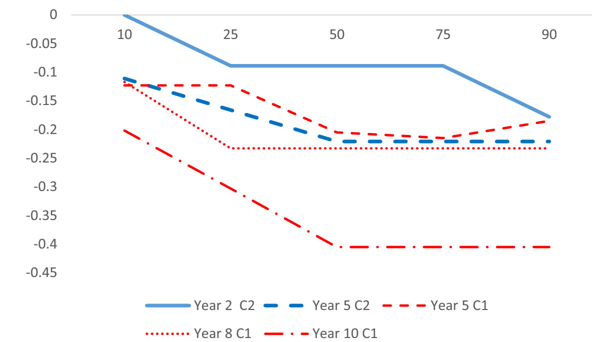
Table 3
The gender gap (G-B) in math test scores. OLS by region, parental education and ESCS.

	Year 2	Year 5	Year 8	Year 10
By Region				
North				
Cohort 1		−0.195***	−0.247***	−0.345***
Cohort 2	−0.119***	−0.204***		
Centre				
Cohort 1		−0.207***	−0.241***	−0.395***
Cohort 2	−0.090***	−0.193***		
South				
Cohort 1		−0.093***	−0.101***	−0.262***
Cohort 2	−0.059***	−0.159***		
By Maternal education				
Middle school				
Cohort 1		−0.128***	−0.153***	n.a.
Cohort 2	−0.079***	−0.136***		
High school				
Cohort 1		−0.177***	−0.222***	n.a.
Cohort 2	−0.069***	−0.214***		
University				
Cohort 1		−0.230***	−0.198***	n.a.
Cohort 2	−0.087***	−0.194***		
By Paternal education				
Middle school				
Cohort 1		−0.141***	−0.147***	n.a.
Cohort 2	−0.066***	−0.161***		
High school				
Cohort 1		−0.210***	−0.211***	n.a.
Cohort 2	−0.097***	−0.213***		
University				
Cohort 1		−0.147***	−0.234***	n.a.
Cohort 2	−0.070**	−0.193***		
By ESCS				
First quartile				
Cohort 1		n.a.	n.a.	0.400***
Cohort 2	n.a.	−0.133***		
Second quartile				
Cohort 1		n.a.	n.a.	0.305***
Cohort 2	n.a.	−0.183***		
Third quartile				
Cohort 1		n.a.	n.a.	0.300***
Cohort 2	n.a.	−0.252***		
Fourth quartile				
Cohort 1		n.a.	n.a.	0.285***
Cohort 2	n.a.	−0.168***		

Notes. * indicates that the underlying coefficient is significant at 5% level, ** at 1% and ***0.1%. Each regression is performed by including area of residence, maternal and paternal education (only years 2, 5 and 8), ESCS (only year 10 and year 5-cohort 2), with the exception of the variable in the stratification.

cline in the gender gap when controlling for province fixed-effects and a slightly larger reduction when controlling for school fixed–effects. Hence, there is evidence of a (small) indirect effect of gender via school characteristics, possibly related to the tracking into different educational high school programs. In fact, as mentioned in Section 2, girls tend to choose high schools with a lower content of mathematics with respect to boys.

We further explored our results by analysing the gender gap in mathematics in different subsamples, following Fryer and Levitt (2010). In particular, the results presented in Table 3 show that the gender gap is persistent at all ages, in most geographical areas, as well as across different socio-economic groups. These results also show that girls appear to fall further behind where their mother is a university or high school graduate. All these results are consistent in terms of size and significance with findings presented in Fryer and Levitt (2010), who show that girls lose grounds in every subsample and, "if anything, the gap is greatest at the top of the SES/educational distribution" (Fryer & Levitt, 2010, p. 224) .



Note:C2 stands for cohort 2 and C1 stands for Cohort 1

Fig. 2. Quantile regression. Gender coefficients at different percentiles of the distribution.

Results presented in Table 3 do not show a clear path when we analyse differences in the gender gap by macro geographical area. Some previous studies (Guiso et al., 2008) have shown that there is a positive correlation between gender equality (measured with indicators like, for instance, female labour force participation) and the gender gap in math. In our data, we do not see a positive correlation between areas with higher gender inequality (especially South of Italy) and the gender gap in math test scores. Interestingly, results in Table 3 show that the South region is the one with the lowest gender gap.

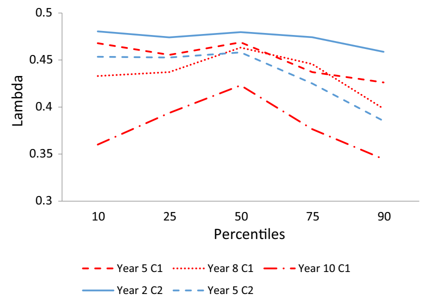
Finally, we report the results of the quantile regression analysis, for the two cohorts analysed (Fig. 2). The gender gap in achievements increases throughout the grade distribution. For example, consider students in year 2 in cohort 1. At the 10° percentile, there are no difference between girls and boys, whereas at the 90° percentile the gender gap is 0.18 s.d. In other words, considering gender specific rankings we find that girls at the 90° percentile score much less than boys at the 90° percentile. Moreover, the difference between the performance of girls and boys increases substantially as we move from year 2 to year 10. By year 10, girls at the first quartile underperform boys by 0.19 standard deviations, whereas the gap between students in the top 10% of the distribution is 0.4 standard deviations.[12] Our results confirm the finding for the US, showing that the girls' disadvantage increases as children age and is larger at the top of the distribution (Robinson & Lubiensky, 2011; Fryer & Levitt, 2010).

4.2. Results of the metric-free analysis of the entire performance distribution

As described in Section 3.2, we compute the metric-free gender gap at different points in the achievement distribution, in order to investigate whether the gap is higher (lower) for top (bottom) performing students relative to low performing students. Fig. 3 present metric-free measures of the math gender gap throughout the test scores distribution in years 2, 5, 8 and 10. Values of λ below 0.5 indicate a boys' advantage, while values above 0.5 indicate a girl's advantage. Fig. 3 show that the gap favours males at all percentiles in all school years.

Girls are always over-represented at the bottom of the distribution and under-represented at the top of the distribution. For instance, consider Cohort 1-year 5. λ_{10} is equal to 0.45, meaning that if girls and boys where equal in number, the bottom 10% of the distribution would be composed by 45% of boys and 55% of

[12] OECD (2015) reports similar results for Italian children in PISA data at age 15.



Note: λ equal to 0.5 means that boys' and girls' test scores are aligned. λ>0.5 benefit boys while values>0.5 favour girls. C2 stands for cohort 2 and C1 stands for Cohort 1

Fig. 3. Metric-free gender gap in Maths achievement throughout the distribution

girls. Instead, λ_{90} is equal to 0.38: hence, with an equal share of boys and girls, the top 10% of the distribution would be composed by 38% of girls and 62% of boys.

In years 2 and 5 the girls' disadvantage is moderate at low percentiles and increases at high percentiles (meaning that the top performing children are mostly boys). Instead, the difference is very strong at both the bottom and the top of the distribution in years 8 and 10, indicating that as we move further from the median, bottom performers are increasingly composed by girls, and top performers are increasingly composed by boys.[13] Hence, this analysis shows that girls are over-represented among the bottom performers while boys are over-represented among top performers.

How does the gender gap evolve as children grow older? The relative position of girls over boys deteriorates substantially between years 2 and 5 (i.e. throughout elementary school). Instead, there is only a small change between years 5 and 8 (middle school), while the girls' disadvantage sharply increases again between years 8 and 10 (after tracking, in the first two years of high school). These results are not dissimilar from the findings from the regression models on test scores, and as we will see below, are highly consistent with the results of the dynamic model estimation.

4.3. Dynamic model estimation

As shown in Table 1, we only have data for a limited number of school years within each cohort. For the estimation of the dynamic model with the pseudo-panel strategy described in Section 3.3, there is an additional limitation, because the month of birth – the instrumental variable necessary for model identification – is not available for all assessments. Hence, we have little leeway in the choice of the cohorts: (i) for the analysis of the evolution between years 2 and 5 we use the cohort attending year 1 in 2010-11; (ii) for the analysis of the evolution between years 5 and 8 we use the cohort attending year 1 in 2007-08; (iii) for the analysis of the evolution between years 8 and 10 we use the cohort attending year 1 in 2005-06.

Table 4 summarizes the results for the gender coefficient.[14] Columns labelled "CS" include the estimates of the gender coefficient from cross-sectional models, while columns labelled "Dyn" report the corresponding coefficients for dynamic models.

In the dynamic models, the coefficients represent the extent to which the achievement growth between two consecutive assessments differs between girls and boys, given test scores at the previous assessment (in other words, the difference between girls and boys in the second assessment when comparing a girl and boy displaying the same performance in the previous assessment).

We observe a widening gap between girls and boys between years 2 and 5. When comparing a boy and a girl with the same individual characteristics and same performance in second grade, by the end of fifth grade the boy will score on average 0.145 standard deviations more than the girl.

The gap keeps increasing between years 5 and 8 (the coefficient estimate is -0.029, implying that the girls would lose on average an additional thirtieth of a standard deviation), but the estimate is not statistically significant. Thus, we conclude that the gap does not evolve much in middle school. Interestingly, if we had interpreted the evolution based on the comparison of the corresponding cross-sectional coefficients (-0.180 in year 5 vs. -0.145 in year 8), we would have inferred a reduction of the gender gap (see Section 3.3 for a discussion on this point). Notice that this result is consistent with the results shown by De Simone (2013) and based on the TIMSS assessment, who finds that the gender gap in math in Italy does not widen between years 4 and 8.[15]

Once we analyse the evolution between years 8 and 10, we find another substantial deterioration of girls' achievements (girls lose -0.151 points relative to equally performing boys in year 8). However, the coefficient of the month of birth decreases substantially as children grow older, and appears much lower at year 8 than in earlier grades. Since the reliability of the estimates depends on the predictive power of the instrument, caution should be used when interpreting this estimate.[16]

Overall, dynamic modelling shows that the distance between girls and boys widens substantially in elementary school, remains basically stable during middle school and starts widening again in high school. Interestingly, these results are fully consistent with our robust findings from the metric-free analyses.

5. Summary and conclusions

In this paper, we conduct a detailed analysis of the gender gap in math test scores in Italy, one of the countries in the OECD displaying the largest differential between boys and girls in the PISA assessment. We have employed cross sectional data from an Italian national learning assessment from 2010 to 2015, testing children in selected grades from second to tenth grades. Given the lack of longitudinal data, we analyse the data by cohort relying on repeated assessments of the same cohort of students (although not the same specific students).

First, we describe the gender gap in standardised test scores for all the available cohorts and we see that the gender gap is always in favour of boys. Second, we estimate the magnitude of the standardized gender gap using OLS regression, and school and province

[13] Notice that the interpretation of metric-free graphical representations is different from the interpretation of quantile regression graphs.

[14] Full estimates are in Appendix A, Table A4.

[15] Notice however that De Simone (2013) does not address the issue of the need of an instrumental variable to ensure identification, while in this paper we use the month of birth.

[16] These considerations stem from the results of an extensive simulation study in Contini and Grand (2015), who study the reliability of the estimates for different predictive power of the instrument and sample sizes.

Table 4
Results of the pseudo-panel estimation. Cross sectional and dynamic models estimates.

	Between 2° and 5° grade			Between 5° and 8° grade			Between 8° and 10° grade		
	Cohort year 1 in 2010–11			Cohort year 1 in 2007–08			Cohort year 1 in 2005–06		
	Y-2 CS	Y-5 CS	Y-5 Dyn	Y-5 CS	Y-8 CS	Y-8 Dyn	Y-8 CS	Y-10 CS	Y-10 Dyn
Female	−0.093***	−0.194***	−0.145***	−0.180***	−0.145***	−0.029	−0.222***	−0.358***	−0.151***
Month of birth	−0.031***	−0.017***		−0.016***	−0.010***		−0.005**	−0.005**	
PredictedY1_lag			0.536***			0.644***			0.932**
N	25,752	18,051	18,051	24,617	21,586	21,586	21,149	18,274	18,274

Notes. Pseudo-panel estimates are grey-shadowed.
- CS=cross-sectional model. Dyn=dynamic model. Lag y#=lagged value is the predicted scores at year #.
- * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%.
- All models include macro-area of residence, maternal and paternal education.
- Children anticipating enrolment before the regular grade and children enrolled in lower grades are not included.
- Month of birth measured as: January=1, February=2..... December=12.

fixed-effect models for two of the longest available cohorts, separately. Our results show that girls systematically underperform boys, even after controlling for individual and family background characteristics. We also find that the gap is larger for those children whose mothers have a high school or university degree.

Third, we analyse the gap throughout the test scores distribution using quantile regression, and show that the gap is generally larger at the top of the performance distribution.

Fourth, we re-analyse the gap throughout the test scores distribution using metric-free methods. As expected, girls are overrepresented among the bottom performers while boys are overrepresented among top performers. By comparing children in different school years, we observe very clearly that the gender gap widens substantially as children progress in school. In particular, inequalities rise sharply between grades 2 and 5 (elementary school), do not evolve much between grades 5 and 8 (middle school), and rise again after year 8, when students are in high school.

Finally, we estimate dynamic models relating the average math performance at two consecutive assessments, allowing estimating genuine new gender inequalities developed between two consecutive surveys. Lacking longitudinal data, we have used a pseudo-panel imputed regression technique. Our findings point to the existence of mechanisms making girls losing ground relative to boys between years 2 and 5 and between year 8 and 10, while we do not observe a widening gap between years 5 and 8. These findings are fully consistent with the metric-free results.

Overall, our findings confirm previous results from the US data, that the gender gap exists at an early age (in grade 2 for Italy) and it increases in older grades. Our paper represents the first systematic analysis of gender inequalities in math achievement in Italy.

As highlighted in the introduction, gender related stereotypes are likely to play a major role in the differences between girls and boys cognitive outcomes, both in maths and scientific subjects (where girls are disadvantaged) and reading literacy (where boys are disadvantaged). The analysis of the reasons why the gender gap in maths exists and how it can be reduced is beyond the scope of our contribution. Nevertheless, even if Italy is one of the countries with worst performances in terms of gender equality within the European union (EIGE, 2015), gender equality is not explicitly considered as a goal for the school system and it is not incorporated into official regulations for education until 2015 (Eurydice 2010a, b, Biemmi, 2015). The school reform of 2015 contains an article (Law n.107, 13 July 2015, art. 1, 16) that aimed to promote gender equality and to prevent gendered violence but this article has not been implemented yet. Our paper, providing extensive evidence of the existence of a gender gap in mathematics since an early age and of its increase during childhood, points to the need of the introduction of gender equality policies in the Italian educational system. Given that the gap is smaller in primary school respect to older grades, there is a potential for cost-effective policies interventions targeting young children.

Appendix A

Table A1
Descriptive statistics (by cohort).

	Cohort 1			Cohort 2	
Gender	Year 5	Year 8	Year 10	Year 2	Year 5
Male	0.51	0.50	0.50		
Female	0.49	0.50	0.50	0.51	0.50
Missing				0.49	0.50
ESCS index					
Mean	n.a.	n.a.	0.07	n.a.	0.06
Standard deviation			0.95		1.01
Area of residence					
North-West	0.18	0.19	0.27	0.18	0.17
North-East	0.20	0.20	0.30	0.21	0.20
Centre	0.21	0.19	0.22	0.21	0.17
South	0.22	0.23	0.13	0.21	0.26
Islands	0.19	0.19	0.08	0.19	0.20
Maternal education			n.a.		
Degree	0.13	0.13		0.15	0.14
High School	0.32	0.30		0.33	0.34
Middle school	0.38	0.35		0.34	0.33
Missing	0.17	0.22		0.18	0.19
Paternal education			n.a.		
Degree	0.12	0.11		0.12	0.11
High school	0.27	0.26		0.28	0.29
Middle school	0.43	0.40		0.40	0.40
Missing	0.18	0.23		0.20	0.20

Table A2
Effect of other independent variables on achievements in Mathematics (OLS by cohorts).

	COHORT 1			COHORT 2	
	Year 5	Year 8	Year10	Year 2	Year 5
Female	−0.152	−0.184	−0.324	−0.088	−0.183
	(0.011)***	(0.012)***	(0.012)***	(0.010)***	(0.013)***
Escs index	n.a.	n.a.	0.187	n.a.	0.136
			(0.008)***		(0.011)***
Escs*Fem	n.a.	n.a.	0.042	n.a.	−0.007
			(0.012)***		(0.013)
Region of residence					
(ref NW)					
NE	−0.056	0.086	−0.009	−0.105	−0.031
	(0.017)***	(0.019)***	(0.018)	(0.017)***	(0.020)
Centre	−0.125	−0.065	−0.416	−0.123	−0.139
	(0.017)***	(0.019)***	(0.018)***	(0.016)***	(0.020)***
South	−0.159	−0.215	−0.512	−0.106	−0.257
	(0.016)***	(0.018)***	(0.017)***	(0.015)***	(0.018)***
Islands	−0.305	−0.095	−0.555	−0.194	−0.388
	(0.018)***	(0.019)***	(0.018)***	(0.017)***	(0.020)***
Maternal education					
(ref University)					
Middle school	−0.369	−0.486	n.a.	−0.301	−0.296
	(0.021)***	(0.024)***		(0.020)***	(0.028)***
High school	−0.132	−0.216	n.a.	−0.088	−0.127
	(0.020)***	(0.023)***		(0.018)***	(0.023)***
Missing	−0.255	−0.277	n.a.	−0.219	−0.150
	(0.035)***	(0.035)***		(0.033)***	(0.039)***
Paternal education					
(ref University)					
Middle school	−0.296	−0.334	n.a.	−0.265	−0.132
	(0.022)***	(0.025)***		(0.021)***	(0.028)***
High school	−0.105	−0.090	n.a.	−0.088	0.001
	(0.021)***	(0.025)***		(0.020)***	(0.025)
Missing	−0.336	−0.271	n.a.	−0.290	−0.086
	(0.034)***	(0.036)***		(0.033)***	(0.040)**
N	31,134	25,111	22,943	31,330	21,271
R^2	0.068	0.081	0.156	0.048	0.102

Notes. Std errors are in brackets. * indicates that the underlying coefficient is significant at 5% level,
** at 1% and ***0.1%. Missing is a dummy variable equal 1 if the specific variable is missing; equal 0 otherwise.

Table A3
The gender gap (G-B) in math test scores. OLS using raw % scores (by cohorts).

	Year 2	Year 5	Year 8	Year 10
Cohort 1	n.a	−0.028	−0.035	−0.079
		(0.002)***	(0.002)***	(0.003)***
Cohort 2	−0.018	−0.035	n.a.	n.a
	(0.002)***	(0.002)***		

Notes. Std errors are in brackets. * indicates that the underlying coefficient is significant at 5% level, ** at 1% and ***0.1%.

Table A4
Dynamic models estimation. Complete results.

	Between 2° and 5° grade			Between 5° and 8° grade			Between 8° and 10° grade		
	Cohort year 1 in 2010–11			Cohort year 1 in 2007–08			Cohort year 1 in 2005–06		
	Y-2 CS	Y-5 CS	Y-5 Dyn	Y-5 CS	Y-8 CS	Y-8 Dyn	Y-8 CS	Y-10 CS	Y-10 Dyn
Female	−0.093	−0.194	−0.145	−0180	−0.145	−0.029	−0.222	−0.358	−0.151
	(0.011)***	(0.014)***	(0.015)***	(0.012)***	(0.013)***	(0.026)	(0.013)***	(0.013)***	(0.091)***
Month of birth	−0.031	−0.017		−0.016	−0.010		−0.005	−0.005	
	(0.002)***	(0.002)***		(0.002)***	(0.002)***		(0.002)**	(0.002)**	
PredictedY1_lag			0.536			0.644			0.932
			(0.068)***			(0.126)***			(0.404)**
Macro area NW omitted									
NE	0.004	0.053	0.051	0.031	−0.010	−0.030	0.081	0.020	−0.056
	(0.017)	(0.021)**	(0.021)**	(0.018)*	(0.019)	(0.020)	(0.020)***	(0.020)	0.038)
Centre	0.043	−0.118	−0.141	−0.036	−0.159	−0.136	−0.102	−0.419	−0.323
	(0.018)**	(0.021)***	(0.021)***	(0.018)**	(0.020)***	(0.020)***	(0.020)***	(0.020)***	(0.046)***
South	0.081	−0.240	−0.283	−0.007	−0.279	−0.274	−0.255	−0.583	−0.345
	(0.017)***	(0.020)***	(0.021)***	(0.017)	(0.019)***	(0.019)***	(0.019)***	(0.019)***	(0.106)***
Islands	−0.022	−0.226	−0.214	−0.163	−0.237	−0.132	−0.121	−0.620	−0.508
	(0.018)	(0.023)***	(0.023)***	(0.018)***	(0.021)***	(0.030)***	(0.021)***	(0.021)***	(0.054)***
Paternal educ (University omitted)									
High school	−0.125	−0.115	−0.048	−0.121	−0.149	0.071	−0.081	−0.033	0.042
	(0.021)***	(0.024)***	(0.026)*	(0.023)***	(0.024)***	(0.028)**	(0.026)***	(0.020)	(0.038)
Middle school	−0.276	−0.296	−0.148	−0.327	−0.388	−0.178	−0.319	−0.216	0.081
	(0.022)***	(0.026)***	(0.032)***	(0.023)***	(0.025)***	0.048)***	(0.027)***	(0.021)***	(0.130)
Missing	−0.342	−0.254	−0.070	−0.325	−0.317	−0.107	−0.273	−0.359	−0.104
	(0.038)***	(0.041)***	(0.047)	(0.038)***	(0.036)***	(0.054)**	(0.039)***	(0.031)***	(0.114)
Maternal educ (University omitted)									
High school	−0.130	−0.179	−0.110	−0.140	−0.199	−0.108	−0.207	−0.101	0.092
	(0.019)***	(0.022)***	(0.024)***	(0.021)***	(0.022)***	(0.029)***	(0.025)***	(0.019)***	(0.085)
Middle school	−0.362	−0.444	−0.250	−0.401	−0.476	−0.218	−0.437	−0.275	0.133
	(0.021)***	(0.025)***	(0.034)***	(0.022)***	(0.024)***	(0.056)***	(0.026)***	(0.021)***	(0.177)
Missing	−0.168	0.206	−0.116	−0.243	−0.303	−0.147	−0.217	−0.278	−0.075
	(0.037)***	(0.040)***	(0.042)***	(0.038)***	(0.036)***	(0.047)***	(0.039)***	(0.033)***	(0.093)
N	25,752	18,051	18,051	24,617	21,586	21,586	21,149	18,274	18,274
$\mathbf{R^2}$	0.059	0.085	0.085	0.076	0.098	0.098	0.083	0.173	0.173

Notes. Std errors are in brackets. Pseudo-panel estimates are grey-shadowed.
-CS=cross-sectional model. Dyn=dynamic model. Lag y#=lagged value is the predicted scores at year #.
-* indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%.
-Children anticipating enrolment before the regular grade and children enrolled in lower grades are not included.
-Month of birth measured as: January=1, February=2.... December=12.
-Missing is a dummy variable equal 1 if the specific variable is missing; equal 0 otherwise.

References

Angrist, J., Battistin, E., & Vuri, D. (2015). *In a small moment: Class size and moral hazard in the Mezzogiorno* IZA Discussion Paper No. 8959.

Ballatore, R., Paccagnella, M., & Tonello, M. (2015). Bullied because younger than my mates? 635 The effect of age rank on victimization at school*. Bank of Italy Working pa- 636 per. Available at: https://www.bancaditalia.it/pubblicazioni/altri-atti-convegni/2016-human-capital/Ballatore_Paccagnella_Tonello.pdf.

Baron-Cohen, S., Wheelwright, S., Skinner, R., Martin, J., & Clubley, E. (2001). The autism-spectrum quotient (AQ): Evidence from Asperger syndrome/high-functioning autism, males and females, scientists and mathematicians. *Journal of Autism and Developmental Disorders, 31*(1), 5–17.

Bedard, K., & Cho, I. (2010). Early gender test score gaps across OECD countries. *Economics of Education Review, 29*, 348–363.

Bertoni, M., Brunello, G., & Rocco, L. (2013). When the cat is near the mice won't play: The effect of external examiners in Italian schools. *Journal of Public Economics, 104*, 65–77.

Bhanot, R. T., & Jovanovic, J. (2009). The links between parent behaviors and boys' and girls' science achievement beliefs. *Applied Developmental Science, 13*(1), 42–59.

Biemmi, I. (2015). Gender in schools and culture: Taking stock of education in Italy, gender and education, 27:7, 812–827, doi: 10.1080/09540253.2015.1103841.

Boaler, J. (2002). Paying the price for 'sugar and spice': Shifting the analytical lens in equity research. *Mathematical Thinking and Learning, 4*(2&3), 127–144.

Boaler, J., Altendorff, L. &, & Kent, G. (2011). Mathematics and science inequalities in the United Kingdom: When elitism, sexism and culture collide. *Oxford Review of Education, 37*(4), 457–484.

Blossfeld, H.-P., von Maurice, J., & Schneider, T. (2011). The national educational panel study: Need, main features, and research potential. In H.-P. Blossfeld, H.-G. Roßbach, & J. von Maurice (Eds.), *Education as a lifelong process - the German national educational panel study (NEPS)* (pp. 5–17). Heidelberg: VS Verlag für Sozialwissenschaften. (Zeitschrift für Erziehungswissenschaft; Special Issue 14).

Buckles, K. S., & Hungerman, D. M. (2013). Season of birth and later outcomes: Old questions, new answers. *The Review of Economics and Statistics, 95*(3), 711–724.

Carlana, M., La Ferrara, E., & Pinotti, P. (2016). *Shaping educational careers of immigrant children: Aspirations, cognitive skills and teachers' beliefs*. Mimeo: Bocconi University.

Checchi, Daniele, & Flabbi, Luca (2007). *Intergenerational mobility and schooling decisions in Germany and Italy: The impact of secondary school tracks*. Institute for the Study of Labor (IZA) IZA Discussion Papers 2876.

Checchi, D., Fiorio, C. V., & Leonardi, M. (2013). Intergenerational persistence of educational attainment in Italy. *Economics Letters, 118*, 229–232.

Choi, Á, Gil, M., Mediavilla, M, & Valbuena, J. (2016a). Double toil and trouble: grade reten- 674 tion and academic performance (March 9, 2016) IEB Working Paper N. 2016/07. 675 Available at SSRN:https://ssrn.com/abstract=2745970

Choi, Á, Gil, M.. Mediavilla, M.& . and Valbuena, J. (2016b). The evolution of educational inequalities in Spain: Dynamic evidence from repeated cross-sections, IEB Working Paper N. 2016/25.

Cornwell, C., & Mustard, D. (2013). Non-cognitive skills and the gender disparities in test scores and teacher assessments: Evidence from primary school. *The Journal of Human Resources, 48*, 236–264.

Contini, Dalit, & Scagni, Andrea (2013). Social origin inequalities in educational careers in Italy. Performance or decision effects? In Jackson Michelle (Ed.), *Determined to succeed? Performance, choice and education*. Stanford University Press.

Contini, D., & Grand, E. (2015). On estimating achievement dynamic models from repeated cross-sections. *Sociological Methods and Research*. doi:10.1177/0049124115613773.

Crawford, C., Dearden, L., & Meghir, C. (2007). When you are born matters: The impact of date of birth on child cognitive outcomes in England. Report. Centre for the Economics of Education, London.

Crawford, C., Dearden, L., & Greaves, E. (2014). The drivers of month-of-birth differences in children's cognitive and non-cognitive skills. *Journal of Royal Statistical Society, 177*, 829–860.

Department for Education and Skills (2007).. *Gender and education: The evidence on pupils in England* http://webarchive.nationalarchives.gov.uk/20090108131525/http:/Dcsf.gov.uk/research/data/uploadfiles/rtp01-07.pdf.

De San Román, A. G., & de La Rica Goiricelaya, S. (2012). Gender gaps in PISA test scores: The impact of social norms and the mother's transmission of role attitudes. *IZA Discussion Paper* 6338.'

De Simone, G. (2013). Render unto primary the things which are primary's: Inherited and fresh learning divides in Italian lower secondary education. *Economics of Education Review, 35*(C), 12–23.

De Simone, G., & Gavosto, A. (2013)., "Patterns of value-added creation in the transition from primary to lower secondary education in Italy", FGA Working Paper n. 47/2013.

EIGE. (2015). *Gender equality index 2015- Italy*. Vilnius: European Institute for Gender Equality.

Eurydice. (2010a). *Gender differences in educational outcomes: A study on the measures taken and the current situation in Europe*. Brussels: Education, Audiovisual and Culture Executive Agency.

Eurydice. (2010b). *Gender differences in educational outcomes: A study on the measures taken and the current situation in Europe – Italy*. Brussels: Education, Audiovisual and Culture Executive Agency.

European Commission. (2006). *Women in science and technology- the business perspective*. Luxembourg: Office for Official Publication of the European Communities.

European Commission. (2012). *Enhancing excellence, gender equality and efficiency in research and innovation*. Luxembourg: Office for Official Publication of the European Communities.

European Commission (2015).. *Science is a girls' thing* Newsletter Nov. 2015 http://science-girl-thing.eu/newsletters/november-2015.html.

Fryer, R. G., & Levitt, S. D. (2010). An empirical analysis of the gender gap in mathematics. *American Economic Journal: Applied Economics, 2*(2), 210–240.

Good, J. J., Woodzicka, J. A., & Wingfield, L. C. (2010). The effects of gender stereotypic and counter-stereotypic textbook images on science performance. *Journal of Social Psychology, 150*(2), 132–147.

Guiso, L., Monte, F., Sapienza, P., & Zingales, L. (2008). Culture, gender, and math. *Science, 320*(5880), 1164–1165.

Heckman, J. J., & Mosso, S. (2014). The economics of human development and social mobility. *Annual Review of Economics, 6*, 689–733.

Heckman, J. J., & Kautz, T. (2012). Hard evidence on soft skills. *Labour Economics, 19*, 451–464.

Heckman, J. J., & Kautz, T. (2014). Fostering and measuring skills interventions that improve character and cognition. In J. J. Heckman, J. E. Humphries, & T. Kautz (Eds.), *The GED myth: education, achievement tests, and the role of character in American life*. Chicago, IL: University of Chicago Press Chapter 9.

Ichino, A., & Tabellini, G. (2014). Freeing the Italian school system. *Labour Economics, 30*, 113–128.

Jacob, B., & Rothstein, J. (2016). The measurement of student ability in modern assessment systems. *Journal of Economic Perspectives, 30*(3), 85–108.

Jacobs, J. E., & Bleeker, M. M. (2004). Girls' and boys' developing interests in math and science: Do parents matter. *New Directions for Child and Adolescent Development, 106*, 5–21.

Koenker, R., & Basset, G. (1978). Regression quantiles. *Econometrica, 46*(1), 33–50.

Legewie, J., & DiPrete, T. A. (2012). School context and the gender gap in educational achievement. *American Sociological Review, 77*(3), 463–485.

Lubienski, S., Robinson, J., Crane, C., & Ganley, C. (2013). Girls' and boys' mathematics achievem*ent, affect, and experiences: Findings from ECLS-K. Journal for Research in Mathematics Education, 44*, 634–645.

Lucifora, C., & Tonello, M. (2015). Cheating and social interactions. Evidence from a randomized experiment in a national evaluation program. *Journal of Economic Behavior & Organization, 115*, 45–66.

Mocetti, S. (2011). Educational choices and the selection process: Before and after compulsory schooling. *Education Economics, 20*(2), 189–209.

Montanaro, P. (2008). Learning divides across the Italian regions: Some evidence from national and international surveys. Bank of Italy Questioni di Economia e Finanza (Occasional Papers) No. 12.

Mullis, I. V. S., Martin, M. O., Foy, P., & Hooper, M. (2016). *TIMSS 2015 international results in mathematics*. Retrieved from Boston College, TIMSS & PIRLS International Study Center.

National Academy of Science (2007). Beyond bias and barriers: Fulfilling the potential of women in academic science and engineering (2007).

OECD. (2015). *The ABC of gender equality in education: aptitude, behavior, confidence*. PISA Paris: OECD.

OECD. (2016). *PISA 2015 results (Volume I): Excellence and equity in education*. Paris: OECD Publishing.

Paccagnella, M., & Sestito, P. (2014). School cheating and social capital. *Education Economics, 22*(4), 367–388.

Penner, A. M., & Parer, M. (2008). Gender differences in mathematics achievement: Exploring the early grades and the extremes Social Science Research 37 (1), 239–253.

Robertson, E. (2011). The effects of quarter of birth on academic outcomes at the elementary school level. *Economics of Education Review, 30*, 300–331.

Robinson, J. P., & Lubiensky, S. A. (2011). The development of gender achievement gaps in mathematics and reading during elementary and middle school examining direct cognitive assessments and teacher ratings. *American Educational Resources Journal, 48*, 2268–2302.

Robinson-Cimpian, J. P., Lubienski, S. T., Ganley, C. M., & Copur-Gencturk, Y. (2014). Teachers' perceptions of students' mathematics proficiency may exacerbate early gender gaps in achievement. *Development Psychology, 50*(4), 1262–1281. doi:10.1037/a0035073.

Twenge, J. M., & Campbell, W. K. (2001). Age and birth cohort differences in self-esteem: A cross-temporal meta-analysis. *Personality and Social Psychology Review, 5*(4), 735–748.

Verbeek, M., & Vella, F. (2005). Estimating dynamic models from repeated cross–sections. *Journal of Econometrics, 127*, 83–102.

Zohar, A., & Sela, D. (2003). Her physics, his physics: Gender issues in Israeli advanced placement physics classes. *International Journal of Science Education, 25*(2), 245–268.