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Three Essays in Economics of Gender

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Introduction

During recent decades, economists' interest in gender-related issues has risen. Researchers aim to show how economic theory can be applied to gender related topics such as peer effect, labor market outcomes, marriage and divorce, and education. This dissertation aims to contribute to our understandings of the interaction, inequality and sources of differences across genders, and it consists of three empirical papers in the research area of gender economics.

The aim of the first paper ("Separating gender composition effect from peer effects in education") is to demonstrate the importance of considering endogenous peer effects in order to identify gender composition effect. This fact is analytically illustrated by employing Manski's (1993) linear-in-means model. The paper derives an innovative solution to the simultaneous identification of endogenous and exogenous peer effects: gender composition effect of interest is estimated from auxiliary reduced-form estimates after identifying the endogenous peer effect by using Graham (2008) variance restriction method. The paper applies this methodology to two different data sets in order to identify both endogenous and pure gender composition effects in American and Italian schools.

The motivation of the second paper ("Gender differences in vulnerability to an economic crisis") is to analyze the different effect of recent economic crisis on the labor market outcome of men and women. Using triple differences method (before-after crisis, harder-milder hit sectors, men-women) the paper used British data at the occupation level and shows that men suffer more than women in terms of probability of losing their job. Several explanations for the findings are proposed.

The third paper ("Gender gap in educational outcome") is concerned with a controversial academic debate on the existence, degree and origin of the gender gap in test scores. The existence of a gap both in mean scores and the variability around the mean is documented and analyzed. The origins of the gap are investigated by looking at wide range of possible explanations (namely, parental expectation, differences in measures of local social capital, cultural differences between natives and immigrants, and differences in response to the school resources)

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To my parents and my brother whom I love and appreciate forever.

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Chapter 1

Separating Gender Composition Effect from Peer Effect in Education

ABSTRACT

This paper aims to highlight the importance of considering endogenous peer effects, as defined by Manski (1993), in order to identify gender composition effect on education outcome appropriately. Using Manski (1993) linear-in-means model, this paper illustrates that the gender composition effect that is currently estimated in education function is the function of three parameters: social multiplier, gender differences in outcome and gender composition effect (known as a gender peer effect). The appropriate gender peer effect is identified after using Graham's variance restriction method to identify and rule out a social multiplier effect. The findings suggest that a social multiplier plays a crucial role in learning process for Italian secondary and US primary students, although a gender peer effect is not as important as highlighted in previous literatures (Hoxby, 2000; Whitmore, 2005; Lavy and Schlosser, 2011) .

Keywords: Social interaction, social multiplier, gender peer effect, INVALSI, Project STAR.

JEL Classification Numbers: I21, J16

I Introduction

Pupils attending school may develop their skills and abilities by receiving inputs coming from a variety of sources: teachers, school facilities, parental investments, environment and neighborhood, as well as their peers at school. The relationship between peers' interaction at school and educational outcome has attracted researchers' interest since the Coleman report (Coleman et al., 1966), which was the first empirical study on peer effects at school. Subsequently, a large and multidisciplinary literature has focused on pupil's schoolmate's background characteristics and abilities and their achievement at school. Several years after Manski (1993) formally discussed the difficulties in the identification of social interaction, which are potentially relevant to the study of the peer effect in education (Epple and Romano, 2011). In his seminal paper, Manski (1993) expressed three hypotheses [1] that are often used to explain the conformity of individual behavior with that of the group to which they belong. He pointed to the simultaneity problem that arises when there are both endogenous and exogenous social interactions.

Since Manski (1993), the identification of social interaction among schoolmates, commonly referred to as peer effects, has emerged as a controversial topic among socio-economic scholars. On one hand, theoretical researchers have proposed methods for the identification of social interaction (Graham, 2008; Brock and Durlauf, 2001); on the other hand, the empirical scholars (Zimmerman, 2003; Kremer and Levy, 2008; Hoxby, 2000; Whitmore, 2005; Lavy and Schlosser, 2011; Angrist and Lang, 2004; Ammermueller and Pischke, 2006; Vigdor and Nechyba, 2004; Graham, 2008) have employed either experimental or quasi-experimental research design to determine peer effect.

Only few empirical studies focus on social interaction among schoolmates of a different

[1] He separated peer effect to three parts as following: endogenous effect is the propensity of individual to behave in some ways varies with the prevalence of that behavior in the individual's group, exogenous effect is the propensity of individual to behave in some way varies with the characteristics of the individual's group and correlated effect is when individuals in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments (Epple and Romano, 2011).

gender, referred to as 'gender peer effects' and is commonly proxied by gender composition effect (Hoxby, 2000; Whitmore, 2005; Kang, 2007; Lavy and Schlosser, 2011). One such study is that of Hoxby (2000), who identifies idiosyncratic variation in the number of girls and achievement of students by comparing adjacent cohorts' gender and racial groups' shares. She estimated gender and race peer effects in Texas elementary schools, finding that boys and girls have higher test scores when classrooms have a larger number of female students.

Whitmore (2005) studies the share of female students on academic achievements; however, unlike Hoxby (2000) her findings are mixed (positive in kindergarten and second grade, zero in first grade and negative in third grade). In her studies Tennessee's Project STAR's randomized experiment in which gender variation generated by the random assignment of students into classrooms is exploited.

Most recently, Lavy and Schlosser (2011) estimated the effects of classroom gender composition on the scholastic achievements of boys and girls in Israeli primary, middle and high schools. Following Hoxby (2000), the authors relied on idiosyncratic variations in the proportion of female students across adjacent cohorts within the same school. They found that the proportion of girls in a class has a positive and significant effect on the academic achievements of both girls and boys in high school, with the size of the estimated effects being similar for both genders. Furthermore, their exploration of the gender peer effect mechanism indicates that a higher proportion of females in a class lead to a better classroom and learning environment.

My study contributes to different strands of literature. First, it supplements existing literature on the identification of a gender peer effect (Hoxby, 2000; Whitmore, 2005; Lavy and Schlosser, 2011). However, my approach departs from other literature mentioned above by distinguishing between the gender peer effect (i.e. the variable that was aimed to be identified initially) and other determinants of the gender composition's coefficient in regression function (i.e. the gender differences in outcome and social multiplier)[2]. Hoxby (2000) claims that "when the groups are males and females (unlike racial group), there is no neat test of whether a group's peer effects all operate through peer achievement". Within Manski's framework, this means one cannot separate the exogenous effect of having more females in the classroom from the fact that females might be better peers and have higher scores. Lavy and Schlosser (2011) do not consider the spillover effects of pupils' achievements in investigating the overall payoff from all the possible mechanisms through which gender peer effects might be at play; instead, their analysis is limited to the few channels through which a gender peer effect might be at work. Whitmore (2005) mentions that having a predominately female class in the second grade substantially increases students' test scores, which can only be partly explained by being exposed to higher quality peers (as girls' scores are higher than those of boys). Therefore, she claims that there should be something further about having a predominately female class per se, although her study does not precisely distinguish between different possible effects.

Second, I contribute to the parts of the literature on social interaction that aim to overcome the 'reflection problem' [3] in order to estimate the effects of the endogenous social multiplier in a quasi-experimental framework. Finally, to my knowledge this is the first paper to estimate a social multiplier in an Italian school.

The remainder of this paper is organized as follows. Section 2 presents the theoretical concept to show the problem of identification based on Manski's linear-in-means model. Section 3 suggests the empirical strategies to solve the identification problems, while section 4 presents the data set. Section 5 presents the results, before section 6 summarizes the findings and provides a brief conclusion.

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[2] Other determinants can be derived from applying Manski's linear-in-means model to the gender peer effect framework, as further described in Chapter 2.

[3] The term "reflection problem" is used to characterize the simultaneity problem that arises when there are both endogenous and exogenous social interaction Epple and Romano (2011)

II Gender peer effect in linear-in-means form

In order to show the identification problem of estimating a gender peer effect, I assume that a social interaction takes the linear-in-means form as in Manski (1993). Assume:

$$y_{ci} = \alpha_0 + \alpha_1 x_i + \alpha_2 x_c + \beta \bar{y}_c + \epsilon_{ci} \tag{1.1}$$

Where; In each grade, denote classes with c and individual with i. y is individual achievement in school, x_i is a dummy variable denoting the gender of individual i, which is equal to 1 if i is a girl. x_c is the proportion of girls in each class (i.e. $E(x_i|c)$), $\bar{y}_c$ is the average achievement of individual i in the class, ϵ_{ci} are unobserved attributes that directly affect y. Following Manski (1993), I assume $E(\epsilon_{ci}|c, x_i) = c'\sigma$, which captures the correlated effect.

One should note the two important restrictions associated with the specification introduced above. Firstly, it is implicitly assumed that the gender composition effect is identical across gender, and secondly, the endogenous effect is homogenous across gender, meaning that the average achievement of an individual affects all the students identically, regardless of their gender. The first assumption is verified by looking at the results of previous literature in the field (Whitmore, 2005; Lavy and Schlosser, 2011). Both Hoxby (2000) and Lavy and Schlosser (2011) findings show that the proportion of girls in the classroom affect both genders virtually identical, while the second assumption is logical given that the gender composition effect is internalized in the model as an exogenous peer effect.

Average achievement within a class leads to:

$$\bar{y}_c = \alpha_0/(1-\beta) + 1/(1-\beta)(\alpha_1 + \alpha_2)x_c + 1/(1-\beta)c'\sigma \tag{1.2}$$

A reduced form is obtained by replacing Eq. (1.2) into Eq. (1.1):

$$y_{ci} = \gamma\alpha_0 + \alpha_1 x_i + ((\gamma - 1)\alpha_1 + \gamma\alpha_2)x_c + \gamma c'\sigma \tag{1.3}$$

Where; $\gamma = 1/(1-\beta)$ is a social multiplier, namely the ratio between the average cumulative response and the individual response following an exogenous shock. From Eq. (1.3), one can clearly see the identification problem that arises in the study of peer effect, as discussed by Manski (1993): by OLS regression of individual achievement on gender composition in the classroom, only the composite parameters $\alpha_0\gamma$, α_1, $((\gamma-1)\alpha_1 + \gamma\alpha_2)$ and $\gamma\sigma$ are identified. Moreover, identification of the composite parameters does not enable us to distinguish between the two social effects (endogenous and exogenous ones). As one can see from Eq. (1.3), based on Manski's linear-in-means model the coefficient that are estimated so far by regressing gender composition on educational outcome (i.e $((\gamma-1)\alpha_1 + \gamma\alpha_2)$) is formed by three separate elements: the effect of having more girls in the classroom (α_2) , the difference between girls and boys in educational outcome (α_1) and the social multiplier (γ).

III Empirical strategy

In order to solve the identification problem mentioned in chapter 2, the social multiplier (γ) is estimated first, which allows driving a gender peer effect that is solely due to the existence of more girls in the class (α_2) by estimating Eq. (1.3).

A Identification of social multiplier

Graham (2008) proposed a method for the identification of a social multiplier (γ in equation 1.3), by exploiting differences in variances across groups. For a linear form of social interaction, he defined the unconditional between-group variance of means outcome as the sum of the variance of any group level heterogeneity (classroom certain characteristics such as teacher quality), between-group variance of any individual-level heterogeneity (variability in average student ability) and the strength of any social interaction (peer effect). Therefore, in the presence of social interaction, between-group variation in outcome should reflex between-group variation in 'peer quality'. Following Galbiati and Zanella (2012), we can rewrite the reduced form model from equations (1.2) and (1.3) in variance components. The transformation of group-level heterogeneity (α_c=α_2 girls + $\sigma c'$), individual-level heterogeneity (ϵ_{ci}=α_1 gender) and the group level average of individual-level heterogeneity ($\bar{\epsilon_c}$= $\alpha_1 girls$) yields the following behavioral equations:

$$y_{ci} = \gamma\alpha_c + \epsilon_{ci} + (\gamma - 1)\bar{\epsilon}_c \tag{1.4}$$

$$\bar{y_c} = \gamma(\alpha_c + \bar{\epsilon_c}) \tag{1.5}$$

Graham (2008) proved that under some specific assumptions discussed below, γ^2 can be identified by using the following conditional and unconditional restrictions:

$$E[G_c^b - \theta W_{2c} - \gamma^2 G_c^w | W_{1c}, W_{2c}] = 0 \tag{1.6}$$

$$E[\begin{pmatrix} W_{1c} \\ W_{2c} \end{pmatrix} (G_c^b - \theta W_{2c} - \gamma^2 G_c^w)] = 0 \tag{1.7}$$

Where; W_{1c} and W_{2c} are two vectors containing observable classroom-level information, W_{1c} denotes class size (small vs. large) and W_{2c} denotes other classroom-level information such as the share of educated parents, share of immigrants in the classroom, etc. G_c^w and G_c^b are within- and between- group statistics, respectively. (For more details, see supplement part of Graham (2008) and Galbiati and Zanella (2012)).

Eq.(1.7) delivers the appropriate specification to estimate (i.e. by GMM) the social multiplier, γ^2, using W_{1c} as an instrumental variable.

The three primitive assumptions that guarantee identification are as follows:

- Independent Random Assignment: Teacher and students' assignment to classroom must be random.
- Stochastic Separability: The population variance of small and large classroom teacher effectiveness must be the same.
- Peer Quality Variation: This is a rank restriction, which requires that the variance of peer quality differs between the two types of classrooms.

B Identification of composite parameters

The model based on Eq. (1.3) suggests that regression of "gender composition" on educational outcome delivers the coefficient of the following form:

$$\delta = (\gamma - 1)\alpha_1 + \gamma\alpha_2 \qquad (1.8)$$

δ is estimated for two case studies, namely the US and Italy. The first case study is based on a randomized experiment, while, for the second case study, idiosyncratic variation in gender composition across adjacent cohort is employed in order to gain a clean estimate of δ.

C Identification of gender peer effect

In order to recover a gender peer effect and its standard deviation, a bootstrapping method is used to approximate the distribution of a statistic by a Monte Carlo simulation.

IV Data

The empirical analysis is based on two case studies: elementary school students in the US and secondary students in Italy. The reasons for including two different case studies are threefold. Firstly, in order to investigate the gender peer effect in both primary and secondary schools. Secondly, in order to gain a better understanding of the importance of endogenous effects by comparing my results with those from Hoxby (2000) and Whitmore (2005), two main contributions to existing literature on gender peer effect. And finally, the Italian case study is very applicable in order to introduce a method for investigating social multiplier in a non-experimental framework.

A US

The assessment of gender peer effect in the learning process is conducted by using data from the class size reduction experiment Project STAR. According to Word et al. (1990), Project STAR was started in the fall of 1985, whereby kindergarten students were randomly assigned to one of three class types within their school: small, regular and regular with a full-time teacher's aide. Thereafter, teachers were randomly assigned to one of these three class types.

The within-school randomization was implemented in 79 schools and ultimately included 11,600 students. In the experiment, a single cohort of children was assigned to small or regular classes from kindergarten through to third grade, before all students returned to regular sized classes in fourth grade.

B Italy

For the Italian primary students, the data requirements are fulfilled by the INVALSI data set for the universe of Italian primary and secondary schools in the academic years 2009-10 and 2010-2011. INVALSI (the National Institute for the Evaluation of the Education

System) is in charge of designing and administering standardized education tests in Italy. Since 2008, the tests have been administered on an annual basis.

The recent waves of this data set collected data for the population of primary and lower secondary students in their second, fifth, sixth and eighth Italian grades. For each student, the data set contains information on class size and grade in the school, immigrant status based on citizenship and language spoken at home, test scores in Italian and Math, gender, age and family background information.

Tables 1.1, 1.2 and 1.3 present the number of observations, the mean, the standard deviation, and the minimum and the maximum values of math and reading scores of boys, girls and the overall population for second, fifth and eighth graders, respectively. For example, the fifth graders standardized reading test had a mean of around 0.7 points and a standard deviation of around 0.17 points in 2009-2010. The average female scored 0.02 points – around a 0.12 standard deviation – higher than the average male.

V Results

A Social multiplier and gender peer effect in US primary schools

Full details on the validity of identification assumptions one need to identify social multiplier with experiment Project STAR are provided by Graham (2008). However, he limited his analysis to kindergarten students. Table 1.4 reports Graham (2008) findings for kindergarten students as well as the social multipliers that I assess for second and third graders using Tennessee's Project STAR experiment. The estimations of social multipliers for second graders are 2.23 and 2.14 for math and reading, respectively, and the standard errors of parameter recovered by using the delta method. These are almost the same as estimated for kindergarten students. Third graders' social multipliers are 1.5 and 2 for math and reading, respectively, which suggests that a social multiplier might be less determinant for upper graders. The first graders are ruled out from the analysis, given that, according to Whitmore (2005), kindergarten was not required in Tennessee at the time of Project STAR, and consequently there was a large influx of new entrants in first grade of significantly lower quality than kindergarten entrants who might have disrupted classrooms.

The estimations of gender peer effects are presented in table 1.5. After accounting for the roles of a social multiplier and the differences between gender in outcome, gender peer effects lost most of their initial magnitude. However, one should note that, in the cases where social multipliers are not significantly different from one, social interactions are not at place, and the female share coefficient (δ) reflects the gender peer effect coefficient (α_2).

It is important to highlight that a bootstrapping method is used to approximate the distribution of a statistic by a Monte Carlo simulation in order to recover the gender peer effect and its standard deviation.

B Social multiplier and gender peer effect in Italy primary and secondary schools

In order to identify the social multiplier among Italian students, the discontinuity in the relationship between enrollment and class size at an enrollment multiple of 25, which is induced by the so-called "Maimonides' rule"[4], is employed. This discontinuity induced classes of different sizes, prompting the need to employ Graham's method. Tables 1.6 and 1.7 and panel B of table 1.3 show descriptive statistics for the grades with enrollments in a range close to the points of discontinuity. These are the grades with enrollment in the set of intervals $\{[22, 30], [47, 55], [72, 80], [97, 105], [122, 130], [147, 155], [172, 180], [197, 205], [222, 230],$ $, [247, 255], [272, 280], [297, 305], [322, 330], [347, 355], [372, 380], [397, 404]\}$. Around 17 percent of the total grades are in these intervals after accounting for a $+10\%$ margin of flexi-

[4] This term was first used by Angrist and Lavy (1999).

bility [5]. As is shown in the tables, the average characteristics of classes in the discontinuity sample are remarkably similar to those for the full sample.

Assumptions verification

In this section, I assess the three required assumptions in order to identify social multiplier: peer quality variation, independent random assignment and stochastic separability. The approach adopted here is based on non-experimental methods in evaluation research (Campbell, 1969): regression discontinuity design. This method utilizes verifying the necessary assumptions in order to estimate social multiplier appropriately.

1. Peer Quality Variation The idea of using RDD to identify class size effect comes from what Angrist and Lavy (1999) termed Maimonides' rule, in which they exploit the fact that class size is partly determined by a known discontinuity function of observed covariates (enrollment in a grade). For my purpose, the importance of Maimonides' rule is that it has been used to determine the division of enrollment grades into classes in Italian public schools. Based on Italian law, class size cannot be larger than 25, with a margin of flexibility of +10 percent. Moreover, it cannot be smaller than 10, with a margin of flexibility of -10%. Let Z be the total enrollment in a grade and C the number of classes; subsequently, the rule for class size disregarding the margins of flexibility is:

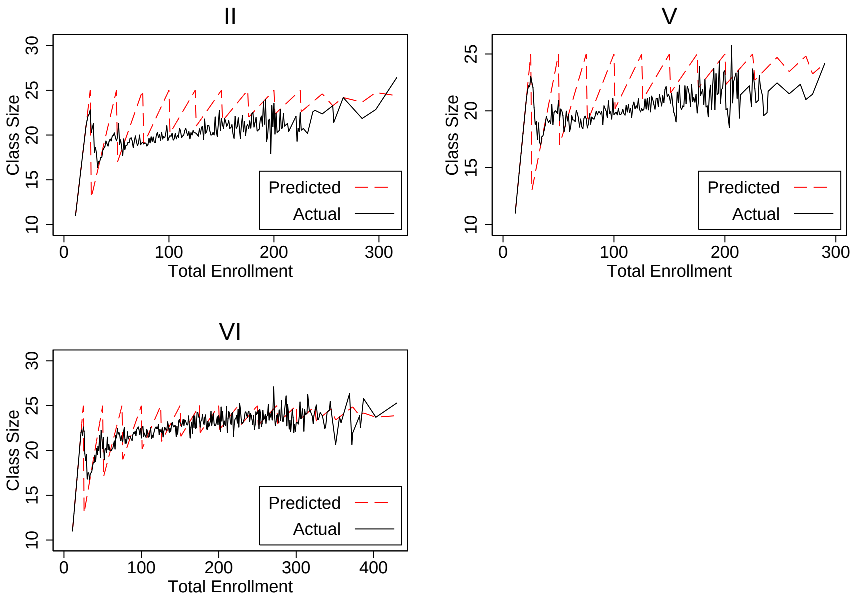
$$\bar{S} = \frac{Z}{Int(\frac{Z-1}{25}) + 1} \tag{1.9}$$

   Where $lnt(x)$ is the largest integer smaller or equal to x. Based on equation (1.9), the theoretical class size is a function of grade (in a particular school) enrollment, which displays discontinuities at multiples of 25. We can see the predicted and actual class size in Italian elementary school in figure 2.1 (taken from Ballatore

[5] For example, for the first interval enrollment that contains 25 and 26 students is excluded

et al. (2012)).

Figure 1.1: Predicted and actual class size in Italy



Note: Each graph shows the predicted (red line) and actual (black line) class size in different grades

On the left of each threshold, the theoretical class size is larger than on the right, with this feature of the rule offering a source of variation in peer equality. As I will show in the next section, the variance of peer quality indeed differs between two types of the classroom. Therefore, one of the three assumptions is required for identification to be verified (i.e. rank condition is satisfied).

2. Independent Random Assignment [6]

The attractive feature of RDD is the fact that it allows testing the validity of its identification condition, which is parallel to the assumption of independent random assignment. The condition for identification based on RDD requires that no discontinuity takes place at the threshold for selection in the counterfactual world. This is called the orthogonality condition, which is as follows:

[6] this assumption is also called double randomization assumption, which means students and teachers should independently and randomly assigned to the classroom

$$(Y1, Y0) \perp I|S = s \tag{1.10}$$

Where (Y_1, Y_0) are the two potential outcomes. I is the binary variable that denotes treatment status, with $I = 1$ for small classroom and $I = 0$ for larger ones. Treatment status depends on an observable unit characteristic S (enrollment), and there exists a known point in the support of S where the probability of participation changes discontinuously (enrollment equal to 25).

Tables 1.8 and 1.9 present the test for this assumption based on the idea of comparing units marginally above and below the threshold with respect to variables whereby:

- cannot be affected by the treatment;
- are affected by the same unobservable that is relevant for the outcome.

With few exceptions, the evidences in tables 1.8 and 1.9 suggest that the existence of discontinuities in pre-treatment variables is unlikely to be correlated with potential outcomes. To confirm this result and ensure that the exceptions in tables 1.8 and 1.9 are only a spurious correlations, table 1.10 indicates the Pearson's chi-squared Test for the random assignment of girls in the classroom. This test was first used by Ammermueller and Pischke (2006). The results of the test suggest that girls are randomly spread across the classes of different size, which provides further evidence in support of an "Independent Random Assignment" (for eighth graders, only a Pearson's chi- squared Test for all the country is measurable due to limitations in the data set).

The evidences in tables 1.8, 1.9 and 1.10 allow one to reject the presence of discontinuities in pre-treatment variables that are likely to be correlated with potential outcomes. In other words, the schools below and above the threshold are comparable.

3. Stochastic separability

   This assumption states that the teacher effectiveness variation across two types of classroom must be equal, and is not valid if the distribution of teacher characteristics is not similar across classrooms of different sizes. As we compare classes with different size across different schools, it is very unlikely that teachers are sorted across classes. However, to further test this assumption, a sensitivity analysis test suggested by Graham (2008) is performed. The results of the sensitivity analysis test suggest that the typical difference in effectiveness across a pair of teachers would have to be implausibly large in small versus large classrooms to produce social multiplier estimates of the size reported in table 1.11, if, in fact, there were no peer effects. (For details of sensitivity analysis, see supplement to Graham (2008))

Results

Table 1.11 reports the estimate of γ^2 using 2009-2010 wave of INVALSI dataset for the second, fifth and eighth graders by estimating equation 1.7. The first, third and fifth columns report the results for math and the second, fourth and sixth for reading (Italian). The estimates of a social multiplier are 2.8, 1.88 and 3.24 for math and 1.52, 3.03 and 3.85 for reading in the second, fifth and eighth grades, respectively. These findings suggest that social interaction plays an important role in the learning process. In contrast to the fifth and eighth graders, the null hypothesis that $\gamma^2 = 1$ is not rejected at the 90% confidence level for second graders; therefore, one cannot reject the hypothesis of no peer interaction for second graders.

Panel B of table 1.11 shows the first stage results of the estimate. The coefficient of variable "small" is statistically significant, which supports the first assumption of peer quality variation. The first stage F- statistics is large, suggesting that the instrument is not weak. In order to check the robustness of the results, table 1.12 presents the social multiplier calculated for the first two thresholds (enrollments less than 60), with the results proving robust across the two different samples.

Following the empirical method employed by Hoxby (2000) and Lavy and Schlosser (2011), gender peer effects for Italian 8th graders (Eq. (1.3)) are estimated by relying on idiosyncratic variation in gender composition across adjacent cohorts within the same grade in the same school (eighth grade is the only grade whereby one can match cohorts of adjacent years by using the Invalsi data set). This approach proposes a persuasive solution for the two possible sources of confounding factors: self-selection of students into the schools and correlation between school characteristics and gender composition.

The estimations of gender peer effects for Italian students are presented in Table 1.13. After considering the role of a social multiplier and the differences between genders in terms of outcome, the gender peer effect is relatively large and negatively significant in math and approximately zero and not significant in reading. This is consistent with the findings from Whitmore (2005)empirical study indicating that a peer effect in school deteriorates educational outcomes for upper grade females.

VI Conclusion

In this paper, I empirically measure the extent of gender peer effects in Italian secondary and US primary schools on students' academic achievements. Using Manski (1993) linear-in-means model, I was able to disentangle two different mechanisms through which a higher proportion of females in the class might affect students' academic achievements: a social multiplier and a gender composition effect. It is shown that the two mentioned mechanisms, along with gender differences in outcome, form the gender composition coefficient estimated to date by researchers in order to find gender peer effect in school on academic achievement.

The project STAR experiment allows identifying a gender peer effect for US primary students, while this is identified for Italian secondary students by using idiosyncratic variation in gender composition across an adjacent cohort within the same school. In order to disentangle the multiplier's effect Graham (2008) conditional variance restriction method is employed.

With one exception, the evidence provided in this paper suggests that a social interaction plays a crucial role in the learning process for primary pupils in the US and secondary pupils in Italy. However, the gender composition effect is not as important as previously thought, after accounting for a social multiplier and gender gap in the outcome. The general implication of these findings is that in contrast to gender mix of class, the spillover effects of pupils' achievements should be taken into account in inter- and intra-school resource allocation in elementary schools. Furthermore, findings show that higher proportions of females in the math classroom deteriorate the educational outcome of upper grade male pupils. Indeed, this is consistent with the findings from Whitmore (2005) empirical study.

This study does not control for a heterogeneous social multiplier effect across gender and is unable to rule out the possibility that the female proportion in the classroom might differ in importance for education outcome between the two genders. However, the results provide important insight towards understanding the relative role of a social multiplier and gender composition effect.

VII Tables chapter 1

Table 1.1: Discriptive statistics - grade 2

	mean	sd	min	p25	p50	p75	max	var
A. 2009-2010								
Grade 2: 5969 schools,22745 classes								
All score math	.62	.2	0	.46	.6	.78	1	.04
All score ita	.66	.23	0	.5	.69	.85	1	.053
boy score math	.63	.2	0	.46	.61	.79	1	.04
boy score ita	.64	.23	0	.46	.69	.85	1	.054
girl score math	.62	.2	0	.46	.61	.79	1	.04
girl score ita	.67	.23	0	.5	.73	.85	1	.051
class size	20.6	3.6	11	18	21	23	35	13
disadvantaged								
B.2010-2011								
Grade 2: 7337 schools, 26628 classes								
All score math	.66	.19	0	.53	.68	.78	1	.037
All score ita	.72	.19	0	.6	.76	.86	1	.035
boy score math	.66	.19	0	.53	.68	.82	1	.037
boy score ita	.71	.19	0	.6	.76	.87	1	.035
girl score math	.65	.19	0	.53	.64	.78	1	.037
girl score ita	.73	.18	0	.63	.76	.87	1	.03
class size	19	3.8	11	17	20	22	35	14.7

Source: Invalsi data for academic years 2009-10 and 2010-2011. Performance in a test is measured as the fraction of correct answers.

Table 1.2: Discriptive Statistics - grade 5

	mean	sd	min	p25	p50	p75	max	var
A. 2009-2010								
Grade 5: 5937 schools, 22846 class								
All score math	.65	.18	0	.52	.66	.79	1	.034
All score ita	.7	.17	0	.59	.74	.84	1	.03
boy score math	.66	.19	0	.52	.68	.82	1	.035
boy score ita	.69	.18	0	.58	.72	.83	1	.031
girl score math	.64	.18	0	.5	.64	.77	1	.033
girl score ita	.71	.17	0	.61	.74	.84	1	.03
class size	20.8	3.7	11	18	21	24	35	13.8
B. 2010-2011								
Grade 5: 7374 schools, 27303 classes								
All score math	0.69	.17	0	.59	.72	.83	1	.028
All score ita	.74	.14	0	.65	.75	.85	1	.02
boy score math	.7	.16	0	.59	.72	.83	1	.02
boy score ita	.73	.15	0	.65	.75	.84	1	.02
girl score math	.69	.17	0	.57	.7	.83	1	.028
girl score ita	.74	.14	0	.65	.77	.85	1	.02
class size	19	3.8	11	17	19	22	35	14.4

Source: Invalsi data for academic years 2009-10 and 2010-2011. Performance in a test is measured as the fraction of correct answers.

Table 1.3: Discriptive statistics - grade 8

	mean	sd	min	p25	p50	p75	max	var
A. 2009-2010 full sample								
Grade 8: 3760 schools, 21577 classes								
All score math	.49	.18	0	.36	.47	.62	1	.03
All score ita	.68	.17	0	.57	.71	.81	1	.03
boy score math	.51	.19	0	.38	.5	.66	1	.035
boy score ita	.65	.18	0	.55	.69	.79	1	.033
girl score math	.46	.17	0	.34	.45	.58	1	.029
girl score ita	.7	.16	0	.61	.73	.82	1	.026
class size	20	4.3	11	17	21	24	33	18.7
B. 2009-2010 discontinuity sample								
Grade 5: 613 schools, 3604 classes								
All score math	.48	.18	0	.36	.47	.62	1	.03
All score ita	.68	.18	0	.57	.71	.81	1	.032
boy score math	.51	.19	0	.36	.5	.64	1	.035
boy score ita	.65	.19	0	.54	.67	.79	1	.035
girl score math	.46	.17	0	.34	.45	.58	1	.03
girl score ita	.7	.16	0	.61	.74	.82	1	.027
class size	20	4.4	11	17	21	24	32	19.3

Source: Invalsi data for academic years 2009-10 and 2010-2011. Performance in a test is measured as the fraction of correct answers.

Table 1.4: Social Multiplier in US

	Kindergarten		2nd grade		3rd grade	
	Math	Re	Math	Re	Math	Re
G_c^w (coefficient: γ^2)	3.47	5.28	5	4.58	2.26	4.05
	(1.03)	(2.48)	(1.8)	(2.1)	(1.3)	(1.04)
Social multiplier (γ)	1.86***	2.3***	2.23***	2.14***	1.5***	2.01***
(delta method)	(0.27)	(0.54)	(0.4)	(0.49)	(0.44)	(0.26)
p-value H_0*:* $\gamma^2 = 1$	0.018	0.086	0.02	0.09	0.34	0.004
B: *First stage*						
F-stat.	46.8	19.0	57.08	38.88	45.58	56.7
Number of classroom	317	317	331	331	330	325
School fixed effects	yes	yes	yes	yes	yes	yes

Notes. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1.5: Gender peer effect in US

	Kindergarten		2nd grade		3rd grade	
	Math	Re	Math	Re	Math	Re
Female Share(δ_1)	0.42**	0.35**	0.24	0.503**	-0.303	-0.33
	(0.186)	(0.17)	(0.281)	(0.250)	(0.252)	(0.26)
Gender peer effect*	0.17***	0.066***	0.09***	0.13***	-0.2***	-0.27***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.005)	(0.003)
Control						
School fixed effects	yes	yes	yes	yes	yes	yes
Classroom type	yes	yes	yes	yes	yes	yes
Socio-economic statues	yes	yes	yes	yes	yes	yes
race	yes	yes	yes	yes	yes	yes
Observations	5707	5629	5723	5731	5829	5751
R-squared	0.264	0.263	0.256	0.254	0.228	0.2

Notes. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.
* a bootstrapping method is utilized to approximate the distribution of a statistic by a Monte Carlo simulation.

Table 1.6: Discriptive statistics - discontinuity sample grade 2

	mean	sd	min	p25	p50	p75	max	var
A. 2009-2010								
Grade 2: 986 schools, 3632 classes								
All score math	.62	.2	0	.46	.6	.78	1	.04
All score ita	.65	.23	0	.5	.69	.85	1	.05
boy score math	.62	.2	0	.46	.61	.78	1	.04
boy score ita	.64	.23	0	.46	.6	.78	1	.04
girl score math	.62	.2	0	.46	.6	.75	1	.04
girl score ita	.67	.23	0	.5	.73	.85	1	.05
class size	21	3.8	11	18	21	24	32	15
B. 2010-2011								
Grade 2: 1162 schools, 4228 classes								
All score math	.66	.19	0	.53	.68	.82	1	.04
All score ita	.72	.19	0	.6	.76	.87	1	.035
boy score math	.66	.19	0	.53	.68	.82	1	.038
boy score ita	.72	.19	0	.6	.76	.87	1	.035
girl score math	.65	.19	0	.53	.68	.78	1	.037
girl score ita	.73	.18	0	.63	.76	.87	1	.03
class size	19.6	4	11	17	20	23	30	16

Source: Invalsi data for academic years 2009-10 and 2010-2011. Performance in a test is measured as the fraction of correct answers.

Table 1.7: Discriptive Statistics - discontinuity sample grade 5

	mean	sd	min	p25	p50	p75	max	var
A. 2009-2010								
Grade 5: 1021 schools, 3791 classes								
All score math	.65	.18	0	.52	.66	.79	1	.34
All score ita	.7	.17	0	.59	.74	.84	1	.03
boy score math	.66	.19	0	.52	.68	.82	1	.35
boy score ita	.69	.17	0	.58	.72	.84	1	.03
girl score math	.64	.18	0	.5	.64	.79	1	.03
girl score ita	.71	.17	0	.6	.75	.84	1	.03
class size	21	3.9	11	18	21	24	29	15.3
B. 2010-2011								
Grade 5: 1185 schools, 4371 classes								
All score math	.7	.17	0	.59	.72	.83	1	.028
All score ita	.74	.14	0	.65	.77	.85	1	.02
boy score math	.71	.17	0	.59	.72	.82	1	.03
boy score ita	.74	.14	0	.65	.75	.85	1	.02
girl score math	.69	.17	0	.59	.72	.83	1	.028
girl score ita	.75	.14	0	.67	.77	.85	1	.019
class size	19	4	11	17	19	23	29	16

Source: Invalsi data for academic years 2009-10 and 2010-2011. Performance in a test is measured as the fraction of correct answers.

Table 1.8: Random Allocation Test - discontinuity sample grade 2

VARIABLES	Share with high educated parents	Share with low skilled parents	Share with num of imigrants	share of girls
gap at the threshold	-0.008***	0.001*	-0.001	-0.006*
	(0.001)	(0.001)	(0.001)	(0.0035)
Observations	69067	69067	69067	68417
R-squared	0.002	0	0	0

Notes. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1.9: Random allocation test-discontinuity sample grade 5

VARIABLES	Share with high educated parents	Share with low books at home	Share with num of imigrants	share of girls
gap at the threshold	0	-0.009	0	-0.003
	(0.001)	(0.006)	(0.001)	(0.004)
Observations	73822	73822	73822	73181
R-squared	0	0	0	0

Notes. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1.10: Pearson's chi-squared Test for random assignment of girls in the classroom

	Grade 2	Grade 5	Grade 8
All the Country			
Pearson's test statistics	1995.873	2424.859	313.6128
degree of freedom	2644	2770	2961
p-value	1	1	1
North			
Pearson's test statistics	940	928	
degree of freedom	1220	1130	
p-value	1	1	
Center			
Pearson's test statistics	372	439	
degree of freedom	477	492	
p-value	1	0.96	
South			
Pearson's test statistics	682	911	
degree of freedom	947	1148	
p-value	1	1	

Notes. The degrees of freedom are $\sum_s^S (n_{class} - 1)/J - 1$. S is the total number of schools for a given grade and J is the number of possible values taken by the characteristic one wants to test the random assignment.

Table 1.11: Social multiplier - Italy

	2nd grade		5th grade		8th grade	
	Math	Re	Math	Re	Math	Re
G_c^w (coefficient: γ^2)	7.86	2.33	3.55	9.21	10.5	14.8
	(5)	(0.9)	(1.4)	(1.3)	(4.13)	(2.9)
Social multiplier (γ)	2.8***	1.52***	1.88***	3.03***	3.24***	3.85***
(delta method)	(0.89)	(0.29)	(0.38)	(0.22)	(0.63)	(0.38)
p-value H_0: $\gamma^2 = 1$	0.17	0.14	0.07	0	0.02	0
B: *First stage*						
F-stat.	10.44	19.11	49.93	11.36	4.1e+10	1.2e+10
p-value	0.0012	0	0	0.0008	0	0
Number of classroom	3627	3623	3791	3791	3812	3811
School fixed effects	yes	yes	yes	yes	yes	yes

Notes. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1.12: Social Multiplier-Italy first two threshold

	2nd grade		5th grade		8th grade	
	Math	Re	Math	Re	Math	Re
G_c^w (coefficient: γ^2)	7.86	2.33	3.55	9.21	7.77	10.84
	(6.6)	(1.2)	(1.88)	(1.76)	(6.13)	(4.05)
Social multiplier (γ)	2.8***	1.52***	1.88***	3.03***	2.78***	3.29***
(delta method)	(1.19)	(0.39)	(0.5)	(0.29)	(1.1)	(0.6)
p-value H_0: $\gamma^2 = 1$	0.3	0.26	0.17	0	0.27	0.01
B: *First stage*						
F-stat.	5.97	10.95	27.59	6.45	1.4e+12	8.3e+10
p-value	0.015	0.001	0	0.01	0	
Number of classroom	785	788	817	817	281	282
School fixed effects	yes	yes	yes	yes	yes	yes

Notes. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1.13: Gender peer effect eighth Italian graders

	Math	Re
Female Share(δ)	-0.025	-0.22***
	(0.08)	(0.1)
Gender peer effect*	-0.56***	-0.003
	(0.005)	(0.003)
Control		
School fixed effects	yes	yes
Time fixed effect	yes	yes
Observations	15102	15102
R-squared	0.8	0.7

Notes. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
* a bootstrapping method is utilized to approximate the distribution of a statistic by a Monte Carlo simulation.

Chapter 2

Gender Differences in Vulnerability to Economic Crisis

ABSTRACT

This paper investigates the different effects of recent economic crisis on the unemployment rate of women and men. The aim of the study is to determine the vulnerable part of the society that appropriate labor market policy should target during the crisis. UK Labor Force Survey (LFS) data is used to examine both the level and the channels of the crisis effect. The fact that the crisis hit various sectors with considerably different degree is exploited in order to use triple difference method to measure the extent of the overall different effect. Findings reveal that men are more vulnerable to the economic crisis when compared to women. One explanation for our findings is that men are dominating the lowest level occupational category of the most vulnerable sectors, and, that household labor supply behavior does not explain the gap.

Keywords: great recession, unemployment rate, household supply behavior.

JEL Classification Numbers: J21, J22, J78

I Introduction

Understanding changes in the labor market during the most recent downturn is the initial step in creating pertinent policies to respond to future crisis. Female has traditionally been the main victims of worse working conditions in comparison with male. Therefore, it is important to understand if their conditions are hardening during the economic downturn in order to take appropriate actions.

Whether economic crisis emphasizes or modifies gender imbalances, is ambiguous. Current literature mostly considers partial effect rather than the overall effect. One strand of the literature emphasizes gender differences in providing labor supply during the economic crisis (Mitchell, 1971; Bruegel, 1979; Rubery, 2010). The other strands study the firm discriminatory behavior (Seguino et al., 2009; Verick and Islam, 2010) or occupational segregation (Milkman, 1976; Johnson, 1983; Miller, 1990). The former group either supports "added worker effect" hypothesis (Bruegel, 1979; Rubery, 2010), or "discouraged-worker effect" (Mitchell, 1971). And, The latter one pointed to the role of occupational segregation, for example, by considering a severe job losses in male dominated sectors, or the firm's incentive to alter their discriminatory behavior, for example, by shedding more female workers because they are less attached to the labor market.

The studies findings are inconculsive. They stress on merely one of the mechanism through which crisis might lead to gender imbalance in labor market outcome. Moreover, the findings are contradictory and ambiguous. Therefore, the vulnerability of gender to the economic downturn is questionable, and current policies in response to the crisis were typically based on ad-hoc or institutional considerations (Cho and Newhouse, 2013).

In this paper, I aim to analyze the overall different effects of current economic crisis on genders in terms of labour supply outcome (i.e. unemployment rate). My study supplements existing literature on the gender effects of economic crisis in different ways. Firstly, it can be considered as a bridge between various strands of literature. The overall result from the contribution of all the possible channels through them crisis might hit gender unevenly is measured. The fact that the crisis hit various sectors with considerably different level is exploited in order to use triple difference strategy to measure the extent of the overall effects. Secondly, for investigation of possible explanations all the channels and mechanisms which have been offered by preceding literature are presented and this paper studies the gender differences in job loosing at both occupational and industrial level. Finally, Lundberg (1985) interpretation of added worker effect components is employed in order to compare the labor supply response of a married woman at the time of crisis and before that as one of the potential explanations.

For the purpose of this study, present economic crisis in the UK is considered. According to Sabarwal et al. (2010), the present economic crisis appears to be altering the predictions and the gendered behaviors common to previous crisis as a result of the recent increase in women's attachment to the workforce and the contraction of the global demand. UK is among those countries which hit the hardest and, therefore, is a good target for the purpose of this study. The result indicates that men are more vulnerable to the economic crisis than female. Males occupations within the sectors that hit harder by the crisis are more vulnerable than their females' counterparts, and findings are not driven by household labor supply response to the crisis.

The remainder of this paper is organized as follows. Section 2 presents the origins of the gender gap during the crisis. Section 3 presents the data set, while Section 4 suggests the empirical strategies to solve the identification problems. Section 5 presents the results, before section 6 summarizes the findings and provides a brief conclusion.

II Why crisis might affect gender differently?

The literature offers several explanations for the fact that the gender response to the economic crisis is different.

A Gender preferences in choosing job sectors and occupations are different

Gender differences in investigating on human capital explain the discrepancies across preferences to work in a particular sector and choose particular occupation. There are some evidences that men are over-represented in sectors vulnerable to the crisis such as manufacturing, construction, and financial services (Elsby et al., 2010; Elder et al., 2010), therefore, there are more vulnerable to the reductions in employment during the current crisis. The gender proportion differences across occupations, however, receive less attention by scholars. As it is shown in table 2.2 and 2.10 respectively, both differences are remarkable regarding LFS dataset.

B Firms' discriminatory behavior

The second mechanism that can explain the gender differences in response to the economic crisis is firm discriminatory action. The theory of statistical discrimination (Phelps, 1972; Arrow, 1973) provides an explanation for firm behavior during a crisis. Based on this theory firms as a decision-maker use observable characteristics of individual as a proxy for unobservable, but outcome relevant, characteristics (Fang and Moro, 2010). For example, during the crisis firms might shed female workers first because they believe that females are less attached to the labor market, due to child-rearing career disruptions, or because they are less likely to be bread winners. This might make female more vulnerable to the economic downturn in comparison with the male.

C Household labor supply decisions

According to Mincer (1962), a change in one individual's income may result in other family members change in their labor market status If negative income effect due to the reduction in family earning power outweighs the positive substitution effect the added worker might enter to the labor market. Lundberg (1985), demonstrates the added worker effect in terms of transition probabilities from non-participation to participation and from unemployment to employment due to change in two reservation wages: one that controls the participation decision and one that defines acceptable employment offers. Therefore, to understand how crisis might affect household labor supply decisions one should study both components of the added worker effect. If the married women's transition from non-participation to employment outweighs the one from non-participation to unemployment (but participation), one could conclude that household labor supply response to the crisis is countercyclical.

III Data and descriptive statistics

The data used are from the Labour Force Survey [1] (LFS) which is managed by the Social and Vital Statistics division of the Office for National Statistics (ONS) in Great Britain.

For the purpose of the main analysis of the paper the individual version of this data set pooled over 8 years to form a no-crisis period (2004-2007) and crisis period (2008-2011); while, the household version of LFS is utilized in order to investigate the possible channels through which crisis might differently hit genders. Both versions of the data set cover demographic factors as well as labor market outcome of the sample of individuals and households. For the purpose of this study, I disregard inactive individual and the one who are under 16 years of ages in my main analysis. Moreover, I distinguish between the sectors that hit harder (hard_ hit from here) by the crisis and other sectors (others from here). Figure 2.1 shows the trend in percentage growth of yearly annual value added in industrial sectors in comparison with services for the four major European countries.

[1] The Labour Force Survey is a survey of households living at private addresses in the UK. Its purpose is to provide information on the UK labour market which can then be used to develop, manage, evaluate and report on labour market policies. The survey is managed by the Social and Vital Statistics division of the Office for National Statistics (ONS) in Great Britain and by the Central Survey Unit of the Department of Finance and Personnel in Northern Ireland on behalf of the Department of Enterprise, Trade & Investment (DETINI).

As the graph suggests, manufacturing sectors are hit much harder by the crisis. Table 1 shows ILO unemployment rates for those sub sectors which will be considered in the subsequent analysis [2]. Columns one and three of this table illustrate ILO unemployment rate at no-crisis time for women and men respectively and columns two and four illustrate that, at a crisis time. The last two columns suggest overall unemployment rate across crisis time. Table 2.1 suggests that jobs at industrial sectors are more vulnerable to the recent economic downturn in comparison with the job at service sectors.

Table 2.2 shows unweighted descriptive statistics for a sample of individuals described above. As one can see there are not many striking differences across the group of sectors in term of demographic factors; however, there are differences in terms of job characteristics (working in private or public sectors) and percentage of female that is considered and discussed in the forthcoming analysis.

IV Identification strategy

A DDD estimation

The goal of the empirical work is to analyze how recent economic crisis hit genders differently. The fact that the crisis hit specific sectors the most is utilized to control for any systematic shocks to the labor market outcomes of both genders in the hard_hit sectors that are correlated with, but not because of the crisis. Using the strategy analogy to "differences_in_differences_in_differences" one can control for other heterogeneities. I compare the female unemployment rate in the hard_hit sectors to a male unemployment rate in those same sectors and measure the change in the female's relative outcome, relative to other sectors. Empirically this exercise is plausible by including year effects, to capture any trends in the earning of the female, sector effects to control for secu-

[2] Following Bureau of Labor Statistics the previous job sectors of the people who are currently unemployed considered in order to explore the unemployment by industry

lar earning differences in the hard_hit sectors and those from other sectors, and finally sector_by_year effect, to control for sector specific shocks that are correlated with the passage of crisis over the same period.

The identification of this "differences_in_differences_in_differences" (DDD) estimator requires that there be no contemporaneous shock (rather than crisis) that affects the relative outcomes of the gender in hard_hit sectors in crisis time differently than others. The validity of this assumption is verified by no-crisis period placebo analysis in the following section.

The overall differences_in_differences_in_differences can be written as the outcome of two differences_in_differences (DD). The first one indicates the unemployment rate differences between genders in hard_hit sectors:

$$DD_{hard\_hit} = \{E(w|group = women, yr = after\} - \{E(w|group = men, yr = after\}$$
$$- \{\{E(w|group = wemon, yr = before\} - \{E(w|group = men, yr = before\}\} \tag{2.1}$$

And, the second one is the corresponding DD in other sectors:

$$DD_{other} = \{E(w|group = women, yr = after\} - \{E(w|group = men, yr = after\}$$
$$- \{\{E(w|group = women, yr = before\} - \{E(w|group = men, yr = before\}\} \tag{2.2}$$

And, triple-difference estimator is the difference between the double differences:

$$DDD = DD_{hard\_hit} - DD_{other} \tag{2.3}$$

B Regression framework for DDD estimation

Regression below is the analogy to the equation (2.3).

$$e_{ijt} = \alpha + \beta_1 X_{ijt} + \beta_2 \tau_t + \beta_3 \delta_j + \beta_4 gender_i \\ + \beta_5(\tau_t * \delta_j) + \beta_6(\tau_t * gender_i) + \beta_7(\delta_j * gender_i) + \beta_8(\tau_t * gender_i * \delta_j) \tag{2.4}$$

The main advantages of regression framework in this context is that it firstly allows to control for other observables that affect the outcome variable of interest, and, secondly one can easily extend the analysis to subsamples of young (age less than 25) and single. (Gruber, 1994)

As it is explained by Gruber (1994) the analogy of this regression to equation 2.3 is straightforward. the fixed effects control for the time-series changes in employment rate (β_2), the time-invariant characteristics of the hard_hit sectors (β_3), and the time invariant characteristics of the treatment group (β_4). The second-level interactions control for changes over time in the hard_hit sectors (β_5), changes over time for the treatment group sector wide (β_6), and time-invariant characteristics of the treatment group in the hard_hit sectors (β_7). The third-level interaction (β_8) captures all the variation in unemployment rate specific to the treatment (relative to the control) in the hard_hit sectors (relative to the others) in the crisis period (relative to the year prior to crisis).

V Results

A Gender gap during the downturn

Table 2.3 and 2.4 illustrate a variation in the gender gap across crisis time, in each sector after controlling for the time trend. They suggest that, in contrast to other sectors, female unemployment rate in comparison to male unemployment rate dropped at crisis time in the hard_ hit sectors with the exception of real estate. These preliminary evidences suggest that the male might be more vulnerable to the current economic downturn compare to female. Table 2.5 illustrates DDD estimation of the effect of the crisis on the unemployment rate by gender. The top panel compares the changes in gender unemployment rate in hard_hit sectors across the crisis time. Each cell contains the unemployment rate for the group labeled on the axes, along with the standard errors and the number of observations. There was a 2.6% fall in the unemployment rate of men in the hard_hit sectors over this period, compared to a 1.3% fall in the unemployment rate of women. Thus, there was a significant 1.24% relative fall in the female unemployment rate in comparison with male in the hard_hit sectors. This is the differences_in_differences estimate of the crisis effect. However, without considering the sectors that were not hit or hit with much lower magnitude by crisis, there is a risk to lose control over any distinct labor market shock to the hard_hit sectors over mentioned periods. Bottom panel of table 1 illustrates the same exercise for the control group (sectors are defined in table 1). For this group, a relative fall in the unemployment rate of 0.24% was computed. The difference between the two panels indicates that there is a 1% fall in the relative unemployment rate in the hard_hit sectors, compared to the change in other sectors this, however, might be considered as a lower bound of the true effect as other sectors hit slightly by crisis. This statistically significant DDD estimate provides some evidence that the crisis hit female to a lower degree than male.

Table 2.6 presents the estimates of the third level interaction from regression 1 (β_8). The raw estimates of β_8 are presented in columns one, three and five indicate that the relative unemployment rates of female are dropped across all the demographic groups. The second, fourth and sixth columns of this table present the estimates of β_8 for all, youth and the single individuals in the sample after controlling for the set of demographic covariates including age and its squares, nationality, education, and, marital status. The fact that introducing the other covariates did not have a sizeable impact on the coefficients estimated in the raw specification is comforting, given the experimental interpretation of the estimate.

As it is discussed in chapter IV the results which are presented in table 2.6 are informative if the required identification assumption [3] holds. The validity of such assumption is verified in table 2.7 where it is shown that 3 years prior to crisis (years 2004 and 2005) there were no gender differences in terms of unemployment rate in hard_hit sectors in comparison with other sectors over time.

B Mechanisms and channels

As it is discussed in the theoretical chapter the fact that the crisis hit gender differently can explain through three main Mechanisms: differences in gender preferences in choosing a job; firm's discriminatory behavior; and workers' labour market behavior in response to household income. Investigating the contribution of firm's behavior is beyond the scope of this paper; however, analysis of the other two channels will provide some insights in understanding the mechanisms behind the findings.

Household labour market behavior

In order to investigate workers' labor market behavior in response to household income, I test, the "added worker effect" hypotheses following Lundberg (1985) classification of the added worker effect components. As it is stated in the theoretical chapter in order to understand how crisis might affect household labor supply decisions, one should consider wives transition from non-participation to participation as well as from unemployment to employment. Only if the transition from non-participation to employment outweighs the one from non-participation to unemployment the household labor supply behavior during the crisis is countercyclical.

[3] that there is no contemporaneous shock (rather than crisis) that affects the relative outcomes of the treatment group (women in hard_hit sectors after crisis) differently than others.

The cross-tabulation in table 2.8 reveals that married women are less likely to be employed in the labor force when their husbands are unemployed both at the crisis time and before that.

Table 2.9 illustrates the linear probability model for both types of transitions. The dependent variables in column one and column two are dichotomous variables taking the value of 1 if the wife is employed and if she is in labor force participation respectively. The findings suggest that at the crisis time the probability of wife participation is 3.8 percent more, however, this does not contribute to their employment rate as the interaction variable (interaction between two indicator variables crisis and husband unemployment) in column one is not statistically significant. Therefore, one cannot conclude that the household labor supply behavior during the crisis is countercyclical.

Gender occupations within industry

Table 2.10 indicates the proportion of male and female in each major occupation groups across crisis period for "hard_hit" versus "others" sectors. The major occupations are divided to 9 from managers and senior level to elementary ones. There are fundamental differences between the distributions of occupation across genders in hard_hit sectors in comparison with other sectors. This table suggests that the proportion of male workers within hard_hit sectors are far more than female ones in the both extreme part of occupational distribution.

Table 2.11 shows the estimation of coefficient β_8 from estimating equation 2.4 within each major occupation group. The findings suggest that the crisis might hit lowest part of occupation distribution the most and previous results is mostly driven from the lowest occupational category.

VI Conclusion

In this paper, I analyze the different effects of current economic crisis on the unemployment rate of men and women for the sample of working age group in the UK. Using triple difference technique by considering the fact that sectors are hit differently by crisis, I compare the female unemployment rate in the sectors which are hit harder with the male unemployment rate in those same sectors. This helps measuring changes in the female's outcome relative to other sectors. This unique set up allows controlling for any heterogeneity that may affect the results other than economic crisis. The evidences provided in this paper suggest that men are more vulnerable to the crisis when comparet to women.

Furthermore, examining the explanations provided in literature, this paper studies the mechanisms through which economic crisis might affect genders differently with respect to labor market outcome. Findings suggest that men occupy the most vulnerable occupations within the sectors which are hit hardest by the crisis and that family supply response to the crisis does not explain the findings.

My study suggests that appropriate labor market policy during the crisis should target the individuals (mostly males) who occupy the lowest level occupation in the sectors that hit hardest by the crisis.

VII Tables chapter 2

Table 2.1: Industrial unemployment rate by gender.

	Women		Men		All	
	No Crisis	Crisis	No Crisis	Crisis	No Crisis	Crisis
A: Industry						
Manufacturing	4.2 (0.001) [32712]	5.2 (0.001) [24720]	4.3 (0.0007) [91454]	6.5 (0) [70312]	4.3 (0) [124166]	6.2 (0) [95032]
Construction	2.4 (0.001) [7782]	4.2 (0.002) [6835]	3.7 (0) [66521]	7.8 (0.001) [58935]	3.6 (0) [74303]	7.4 (0.001) [65770]
Real estate	3.3 (0) [45254]	4.8 (0.001) [44099]	3.4 (0) [59943]	5.1 (0) [60481]	3.36 (0) [105197]	5 (0) [104580]
B: Services						
Public administrate	1.55 (0) [33574]	2.67 (0) [29109]	1.84 (0) [31806]	2.1 (0) [27842]	1.7 (0) [65380]	2.4 (0) [56951]
Education	1.67 (0) [63345]	2.37 (0) [62142]	2.07 (0) [22599]	2.87 (0.001) [21750]	1.77 (0) [85944]	2.5 (0) [83892]
Health&social work	2.1 (0) [93616]	2.68 (0) [89960]	2.4 (0.001) [22454]	3.3 (0.001) [22806]	2.16 (0.) [116070]	2.81 (0) [112766]

Notes. Cells contain ILO unemployment rate of those previously employed in the industry for the group identified. Standard errors are given in parentfeses; sample sizes are given in square brackets. crisis periods are defined in the text.

Table 2.2: Descriptive statistics

	Hard_hit sectors		Other sectors	
	After	Before	After	Before
(1) Female	0.32	0.32	0.72	0.72
	(0.47)	(0.47)	(0.45)	(0.45)
(2) British	0.41	0.39	0.46	0.42
	(0.49)	(0.49)	(0.5)	(0.49)
(3) Age	41.8	40.8	43.5	42.8
	(12.3)	(12.1)	(11.6)	(11.3)
(4) Public	0.036	0.035	0.69	0.72
	(0.46)	(0.44)	(0.19)	(0.18)
(5) Full time	0.86	0.87	0.66	0.66
	(0.34)	(0.33)	(0.47)	(0.47)
(6) Single	0.273	.0278	0.272	0.267
	(0.44)	(0.45)	(0.44)	(0.44)
(7) Log hourpay	2.46	2.33	2.4	2.3
	(0.58)	(0.57)	(0.53)	(0.53)
Number of observations	70429	66607	75940	75827

Notes. Cells contain proportion of the observations for the each group. Standard errors are given in parentfeses. Years before/after crisis, and hard hit/other sectors, are defined in the text.

Table 2.3: Regression analysis unemployment rate by sectors (hard_hit)

A: Manufacturing	
Crisis	0.02**
	(0.002)
gender	-0.0012
	(0.001)
Interaction*	-0.011**
	(0.003)
Controls	
Time trend	yes
Number of observations	219198
Pseudo R_Squared	0.002
B: Construction	
Crisis	0.041**
	(0.002)
gender	-0.013**
	(0.002)
Interaction	-0.023**
	(0.003)
Controls	
Time trend	yes
Number of observations	140073
Pseudo R_Squared	0.009
C: Real state	
Crisis	0.021**
	(0.002)
gender	-0.0008
	(0.001)
Interaction	-0.002
	(0.002)
Controls	
Time trend	yes
Number of observations	209777
Pseudo R_Squared	0.003

Notes. Dependant variable is a dummy variable for being in employment.
* "Interaction" is the interaction between variables Crisis and Gender

Table 2.4: Regression analysis unemployment rate by sectors (others)

A: Public Administration	
Crisis	0.017**
	(0.002)
gender	-0.003**
	(0.001)
Interaction	-0.002
	(0.002)
Controls	
Time trend	yes
Number of observations	122331
Pseudo R_Squared	0.001
B: Education	
Crisis	0.014**
	(0.002)
gender	-0.004**
	(0.001)
Interaction	-0.0009
	(0.001)
Controls	
Time trend	yes
Number of observations	169836
Pseudo R_Squared	0.0012
C: Health	
Crisis	0.015
	(0.002)
gender	-0.003
	(0.001)
Interaction	-0.003*
	(0.0017)
Controls	
Time trend	yes
Number of observations	228836
Pseudo R_Squared	0.001

Notes. Dependant variable is a dummy variable for being in employment.

Table 2.5: DDD estimates of the impact of crisis on unemployment rate

	Before crisis		After crisis	Time difference for gender
A: Hard_hit sectors				
Male	0.039 (0) [217918]		0.065 (0) [189728]	-0.026 (0)
Female	0.036 (0) [85748]		0.049 (0) [75654]	-0.013 (0)
Gender differences at a point in time	0.0032 (0.0007)		0.015 (0.001)	
Dif_in_Dif		-0.0124 (0.001)		
B: Other sectors				
Male	0.021 (0) [76859]		0.029 (0) [72398]	-0.0087 (0)
Female	0.019 (0) [190535]		0.025 (0) [181211]	-0.0063 (0)
Gender differences at a point in time	0.002 (0.0005)		0.0044 (0.0007)	
Dif_in_Dif		-0.0024 (0.0009)		
DDD		**-0.01** (0.001)		

Notes. Cells contain unemployment rate for the group identified. Standard errors are given in parentfeses; sample sizes are given in square brackets. Years before/after crisis, and hard hit/other sectors, are defined in the text. Difference-in-difference-in-differen(DDD) is the difference-in-difference in the upper panel minus that in the lower panel.

Table 2.6: DDD estimates across demographic groups

	All		Youth		Single	
	1	2	3	4	5	6
β_8 **(DDD)**	-0.01**	-0.008**	-0.025**	-0.021**	-0.028**	-0.022**
	(0.001)	(0.002)	(0.007)	(0.007)	(0.004)	(0.004)
Female	-0.002**	-0.005**	-0.017**	-0.015**	-0.017**	-0.018**
	(0.0006)	(0.0006)	(0.003)	(0.003)	(0.002)	(0.001)
Crisis	0.009**	0.009**	0.016**	0.019**	0.01**	0.014**
	(0.0008)	(0.0008)	(0.004)	(0.004)	(0.002)	(0.002)
Sector	0.018**	0.008**	0.029**	0.012**	0.03**	0.014**
	(0.0007)	(0.0007)	(0.003)	(0.003)	(0.002)	(0.002)
Female*sector	-0.001	0.002**	0.003	0.014**	-0.005**	0.003
	(0.001)	(0.001)	(0.004)	(0.005)	(0.002)	(0.002)
Female*crisis	-0.002**	-0.002**	-0.0008	0.001**	0.002	0.0006
	(0.0009)	(0.001)	(0.005)	(0.005)	(0.002)	(0.002)
Sector*crisis	0.017**	0.017**	0.024**	0.02**	0.03**	0.03**
	(0.001)	(0.001)	(0.005)	(0.005)	(0.003)	(0.003)
Demographic Controls		yes		yes		yes
Observations	1090051	892033	107707	88476	308634	253566
R-squared	0.007	0.02	0.01	0.02	0.02	0

Notes. Standard errors are given in parentheses. Controls are demographic factors including age and age^2 as a proxy for experiences, education which is the highest level of education each individual obtained, whether they are British and single.

Table 2.7: Placebo Analysis 2004-2005

	(1)	(2)	(3)
VARIABLES	All	Youth	single
DDD	-0.002	-0.002	0
	(0.003)	(0.01)	(0.006)
Observations	289122	30700	79203
R-squared	0.004	0.006	0.008

Notes. Cells contain unemployment rate for the group identified. Standard errors are given in parentheses.

Table 2.8: Added worker effect comparison across crisis period

	No Crisis 2006-2007			Crisis 2008-2009		
	Employment %	Unemployment %	Inactive %	Employment %	Unemployment %	Inactive %
All Wives	55.83	1.43	42.39	55.39	1.5	43.11
Husband employed	63.44	1.57	34.56	62.95	1.60	35.45
H unemployed	55.67	1.56	42.09	55.82	1.49	42.70
H not participate	46.16	1.21	52.1	46.3	1.1	52.6

Table 2.9: Added worker effect regression analysis

	Dependant variable Wife employment	Dependent variable Wife participation
Husband unemployed	-0.09**	-0.09**
	(0.01)	(0.01)
Crisis	-0.002**	-0.028**
	(0.001)	(0.002)
Interaction*	0.018	0.038**
	(0.014)	(0.017)
Controls		
British	0.002**	0.01
	(0.001)	(0.002)
Age	0.0005**	-0.006**
	(0)	(0)
Num children under 4	-0.0003	-0.13**
	(0.001)	(0.003)
Num dependent children	-0-004**	-0.03**
	(0.0006)	(0.001)
Ethnicity	yes	yes
Highest Education	yes	yes
Number of observations	88393	108048
Pseudo R_Squared	0.02	0.08

Notes. the table shows the linear probability model on the labor supply probability of women.

* "Interaction" is the interaction between variables Crisis and Husband unemployed.

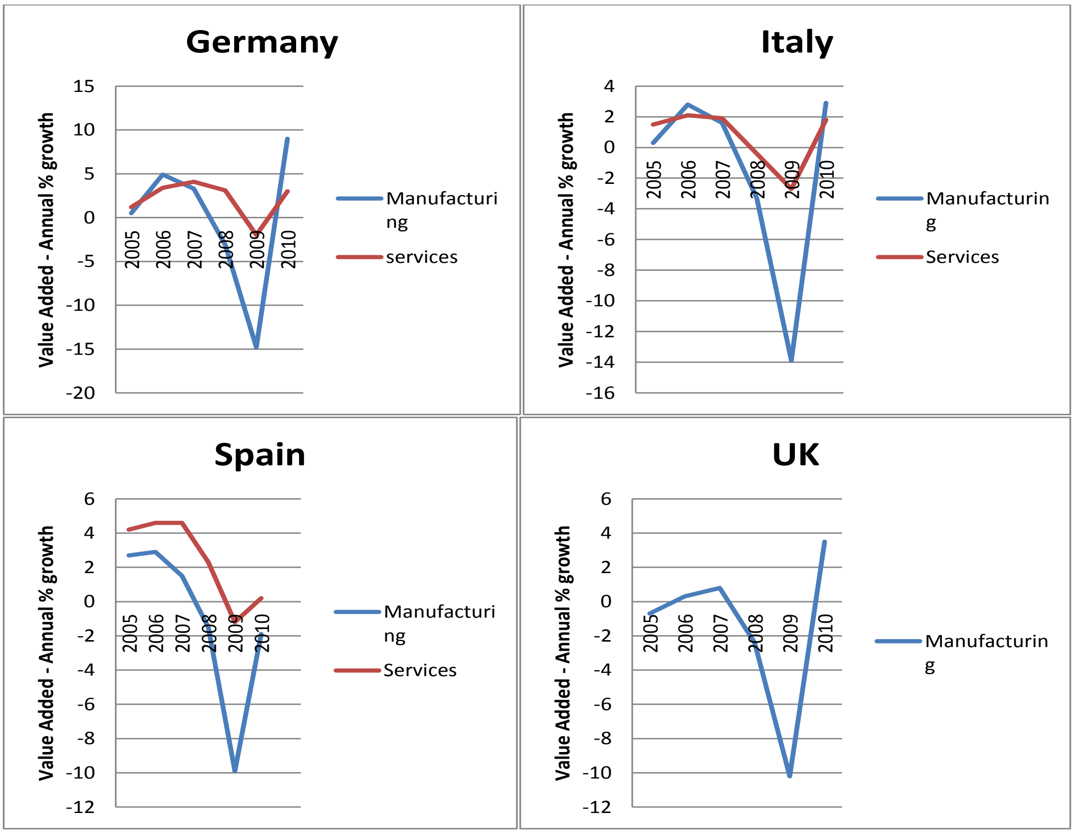
Table 2.10: Distribution of occupations by gender before and after crisis

	No Crisis 2004-2007		Crisis 2008-2011	
	Male %	female %	Male %	Female %
A: Hard hit				
Managers and Senior Officials	74.73	25.27	73.26	26.74
Professional occupations	80.72	19.28	79.69	20.31
Associate Professional and Technical	61.69	38.31	60.38	39.62
Administrative and Secretarial	17.12	82.88	16.88	83.12
Skilled Trades Occupations	96.45	3.55	96.60	3.40
Personal Service Occupations	39.2	60.8	43.99	56.01
Sales and Customer Service Occupations	37.74	62.26	39	61
Process, Plant and Machine Operatives	80.75	19.25	83	17
Elementary Occupations	70.40	29.60	67.65	32.35
B: Others				
Managers and Senior Officials	43.15	56.85	41.98	58.02
Professional occupations	37.79	62.21	36.18	63.82
Associate Professional and Technical	35.42	64.58	34.36	65.64
Administrative and Secretarial	17.04	82.96	18.08	81.92
Skilled Trades Occupations	60.24	39.76	62.27	37.73
Personal Service Occupations	11.34	88.66	12.35	87.65
Sales and Customer Service Occupations	20.99	79.01	25.47	74.53
Process, Plant and Machine Operatives	78.92	21.08	79.1	20.9
Elementary Occupations	23.15	76.85	25.75	74.25

Table 2.11: DDD estimates by oocupational groups

	1	2	3	4	5	6	7	8	9
β_8 **(DDD)**	0.002**	0.008	0.0015	-0.004	-0.046**	0.026	0.029	-0.02	-0.06**
	(0.004)	(0.004)	(0.001)	(0.007)	(0.012)	(0.018)	(0.026)	(0.014)	(0.008)
Observations	126697	175282	160448	124059	119332	102593	14738	64118	86429
R-squared	0.003	0.004	0.009	0.008	0.012	0.004	0.015	0.012	0.03

Figure 2.1: Industry vs. Services - Annual % growth of value added



Note. Each graph shows the Annual % growth of Value Added for services (red line) and manufacturing (blue line) in different countries. Source: World Bank.

Chapter 3

Gender Gap in Scholastic Outcome

ABSTRACT

The existence, origin and degree of gender gap has been the matter of concern in academic debates. This paper analysed the emergence of a gender gap in "mathematics" and "reading" test scores among second, fifth and sixth Italian graders. I use INVALSI dataset for the universe of Italian primary and secondary school in the academic year 2009-10. The findings suggest that girls loose the ground to boys in mathematics but not in reading, and that the variability is stronger among boys when compared to that among girls. Boys predominate in three of the four extreme scoring categories (low reading, low mathematics and high mathematics) while girls predominate in high reading. A wide range of possible explanations are explored including social differences (low parental expectation, provincial differences in culture and social capital) and innate differences (difference in reaction to school resources as a proxy for innate differences). However, little evidence is found to support any of these arguments.

Keywords: Gender gap, Education, INVALSI.

JEL Classification Numbers: I21, J16.

I Introduction

The fact that genders are different in schooling achievements in terms of average performance and variability around the average have raised considerable debate. researchers study the mean differences, in educational outcome, suggest that boys outperform girls in mathematics, while, girls are dominant in languages (Machin and Pekkarinen, 2008; Guiso et al., 2008; Fryer Jr and Levitt, 2009). Their findings are more striking when one considers that female systematically outperform males on many other educational dimensions. The variability differences across genders, however, attracted less consideration even if the idea that males are intellectually and educationally more variable than females dates back to late 19th century texts from Ellis (1894) and Galton (1952). (Machin and Pekkarinen, 2008). The recent example for the concept that there are always more males at the upper end of the distributions of educational and professional success is that there being more male than female Nobel Prize winners (Machin and Pekkarinen, 2008)

Some recent studies focus on the origins of the gender gap. One strand of the literature investigates the biological differences between the two genders. They consider brain composition differences (Cahill, 2005; Gallagher and Kaufman, 2005), difference in hormone levels (Davison and Susman, 2001) and, differences in spatial ability (Lawton and Hatcher, 2005). The other strand, however, emphasize on societal factors by investigating the differences in the level of competitivity (Gneezy et al., 2003; Gneezy and Rustichini, 2004; Gneezy et al., 2009; Niederle and Vesterlund, 2007, 2010) in the parental expectation (Eccles and Jacobs, 1986; Bhanot and Jovanovic, 2005; Bouffard and Hill, 2005; Muller, 1998; Parsons et al., 1982), deferential treatment by teachers (Dee, 2005) and stereotype threat (O'Brien and Crandall, 2003; Spencer et al., 1999; Brown and Josephs, 1999). Empirical evidences suggest that the determinants of the gender achievement gaps have not yet been very well understood, and there is scope for further research.

In this paper, the INVALSI [1] data set is utilized to document the gender gap in terms of mean and variability among Italian second, fifth and sixth graders. The origin of the gap is investigated by examining some of the societal forces (i.e. the parental expectation, provincial differences in social capital, cultural differences between natives' and immigrants' pupils) and innate differences which is proxied by gender gap in reaction to change in school resources.

The rest of the paper is organized as follows: Section 2, presents the existence of the gender gap in Italy. Section 3, presents the potential origin of this gap and finally, Section 4, summarizes the findings and provide the conclusion.

II Gender gap in Italy

A Data

The primary dataset used in this paper is the Istituto Nazionale per la Valutazione del Sistema Dell'Istruzione (INVALSI). INVALSI is the National Institute for the Evaluation of the Education System which is in charge of design and administration of standardized education tests in Italy. The tests have been administered every year since 2008. The recent waves of INVALSI collect data for the entire population of Italian primary students (second and fifth graders), and lower secondary ones. For each student in grades 2, 5 and 6 the dataset contains information on class size and grade in the school, immigrant status based on citizenship and language spoken at home, test scores in reading and mathematics, sex, age and family background information. Performance in reading and mathematics test is measured as the fraction of correct answers.

Table 3.1 illustrates summary statistics for the variables in the core specification of the paper. Students who are missing data in test scores or gender are dropped from the

[1] INVALSI is the National Institute for the Evaluation of the Education System, in charge of design and administration of standardized education tests in Italy

sample. The primary outcome variables are standardized test scores in mathematics and reading. Both mathematics and reading test are evaluated based on the fraction of correct answers. As one can see from this table, female students are outperformed by males in mathematics, in both second and fifth grades, and the gap between them is enlarging over time. However, in reading females performance are better than males. Regarding demographic variables (e.g. socio-economic status of the family, whether parents are highly educated or skilled), mean differences across genders are small because children's gender is approximately randomly assigned across households.

B Mean differences

Research studies compromised the differences across genders in terms of average mathematics and reading test score (Machin and Pekkarinen, 2008; Guiso et al., 2008b; Fryer Jr and Levitt, 2009). Findings across Italian graders are similar. Table 3.2 presents the gender gap in mathematics and reading for second Italian graders. Gender gap is measured in total as well as by geographical areas across northern, center and southern part of Italy. Evidences suggest that on average boys, score approximately 0.01 points more than girls in mathematics, yielding a trivial achievement gap in favor of boys. In reading, girls start 0.028 points ahead of boys. Regional analysis suggests that the gender gap in mathematics be surprisingly higher in north and center when compared to the south. However, there is no gap in reading test score.

The gender gaps in mathematics, and reading test score for fifth graders are displayed in table 3.3. The fifth graders' male students score 0.025 points in average more than female students in mathematics, which is noticeably higher than the gap when compared to the second grade.

Table 3.4 and 3.5 present a series of the estimation of the gender gap for the second and fifth graders. The estimated equations are of the following form:

$$y_i = \alpha + \beta Gender_i + \gamma x_i + \epsilon \tag{3.1}$$

Where, i indexes students and *Gender* is an indicator variable. In the most fully parameterized models, the vector of other covariates denoted x_i are includes. The estimates are done using ordinary least square.

The first two columns of table 3.4 and 3.5 report the raw gender gap for the second and fifth graders in mathematics and reading respectively. These numbers parallel those found in tables 3.1, 3.2 and 3.3. As mentioned earlier, the gender gap in mathematics is statistically different from zero and by the end of the fifth grade the gap increases to 0.024 standard deviation and is marginally significant.

The gender gaps change little when the covariates are added. As it is shown in the last two columns of table 3.4 the magnitude of the gender gap after controlling for other factors is slightly larger than the raw gap in mathematics. The magnitude and sign of the other covariates appear plausible. First and second generations of immigrant students perform significantly worse than Italian; second generation, however, do better than the first generation. Furthermore, children with lower family background do worth than their counterparts.

Table 3.5 provides a parallel analysis on reading achievement. Female students are performing better in reading, and these differences persist over time and after controlling for the set of controls. As it was the case for mathematics analysis, the inclusion of the controls slightly improve the performance of boys relative to that of girls, and the magnitude and sign of the other covariates are in line with the expectation.

C Variability differences

The other interesting phenomenon which is highly debated in the literature (Machin and Pekkarinen, 2008; Guiso et al., 2008a; Fryer Jr and Levitt, 2009), is the scores variability differences between girls and boys. If girls were equally represented throughout the achievement distribution, one would expect any cut of the distribution to have the boys to girls' ratio of approximately 1.016 which is the corresponding ratio for the second graders in the overall population.

The last three rows of table 3.2 display the ratio of boys to girls for the second graders in different parts of the raw test score distribution over various geographical areas in Italy (i.e. South, Centre, and North). The variance ratio of boys to girls in mathematics test score is significantly more than one in all the areas with the exception of south, where, the variance ratio is not significantly different from one. The ratio of boys to girls in the top and bottom ten percent of the distribution in mathematics is in favor of the boys. Considering reading test scores, the overall variance ratio has remained in favor of boys regardless of the regions they are living in. However, The ratio of boys to girls in the top ten percent is in favor of the girls.

The last three rows of table 3.3 report the variance ratio, top and bottom ten percent of mathematics and reading distribution for the fifth Italian graders. The trend is the same when compared to the second graders with the higher magnitude in mathematics, and, the lower one for reading test scores. Moreover, the ratio of the boys to girls in the top 10 percent of a mathematics distribution are more for the fifth graders when compared to the second graders. This suggests that gender gap is increasing notably in mathematics while decreasing in reading when children become older. In both grades Boys predominate in three of the four extreme scoring categories (low reading, low mathematics, and high mathematics), while, girls predominate in top reading category.

III Origins of the gender gap

This section examines some of the potential driving forces of gender differences in educational outcomes. The two main categories in explaining this phenomena are social environment and biological differences (innate differences). Differences in the social conditions across genders can be determined by the differences in the stereotype threat, parental expectation, cultural and social capital and teacher treatment. In this chapter differences in parental expectations and differences in social capital across Italian regions are examined as a proxy for social environment. However, biological differences can be measured by the factors such as brain composition, hormone levels and spatial ability. Investigating the biological differences is beyond the scope of this paper, since the dataset provides no information related to biological factors. However, reaction of the gender to the changes in the class resources (i.e. class size) assumed to be a potential measure for innate gender differences under certain conditions (for example if gender peer effect is constant across classes with different sizes).

A Parental expectation and stereotype threat

The negative stereotype that women are weaker in mathematics performance may cause an apprehension that disrupts women's mathematics performance (Spencer et al., 1999). Parents' math-related gender stereotypes (e.g. if daughters' parents thought their child had to work harder to do well in math in comparison with their son) might create a wide range of stereotype threat that might affect girls' math ability perceptions and her confidence. Therefore, children's attitude may be influenced by their parent's attitudes about their abilities. According to Jacob 1986, parental expectation and beliefs are formed children's perception of their parents' beliefs and that altered children's self confidence which might have a greater influence on students' attitudes when compared to their past performances. Following (Fryer Jr and Levitt, 2009) I assume that lack of impact on parental expectations is consistent with the absence of an impact of being in a family where the mother has more education than the father. Moreover, the gender gap between families whose father has more education than the mother as well as the one that both parents are highly educated in comparison with the one who are not educated are examined. To do this analysis, equations of the following form are estimated:

$$y_{isc} = \alpha_{ics} + Gender_{isc}\beta + motherdomination_{isc}\gamma + Gender_{ics} * motherdomination_{ics}\delta + \epsilon_{isc} \tag{3.2}$$

Where y_{isc} is pupil is score, *Gender* is dummy variable equal to one if is girl, mother-domination is dummy variable equal to one if mother is dominating father in terms of education and δ is a coefficient of primary interest capturing the gender differences in mother's dominated families in comparison with other families. ϵ is error component specific to pupils.

The evidences in tables 3.11, 3.12 and 3.13 do not support the idea that parental expectation might influence children's performance in mathematics.

As parental expectation and beliefs might be influenced by media, the gender gap in the families with the high number of books at home when compared to other families is investigated. Therefore, the higher number of books at home is taken as a proxy for not being exposed to media, or less affected by them. However, the findings in table 3.14 suggest that there be no significant differences among those different kinds of families.

B Social capital, culture and gender differences

Studies suggest that in countries with more gender equal culture, the gender gap that is usually in favor of boys, in average mathematics and reading test scores, is erased or even reversed in favor of girls (Machin and Pekkarinen, 2008). Considering gender equality perception as a good value, one of the mechanisms through which social capital might affect the gender gap is by enhancing the prevailing level of good values in children.

Cultural transmission of value cooperation modeled by Tabellini (2008) based on the previous work on value transmission framework by (Bisin and Verdier, 2000, 2001; Bisin et al., 2004), shows that parents optimize the level of the values they choose to pass onto their children. Based on Tabellini's model the payoff from cooperation increases when more people cooperate, and this expands the scope of cooperation. Therefore, an expansion in the scope of cooperation makes it easier for the parents to transmit good values to their children.

In this section the link between the level of social capital which is defined as a good culture [2] (Guiso et al., 2008a) in provincial level in Italy and the size of the gender gap is examined to see whether the provincial differences in the size of the gender gap are associated to the differences in the level of social capital each region endowed with.

To investigate the effect of social capital on the gender gap two different methods are utilized. The first method uses the measures of social capital which are defined by Guiso et al. (2008). In their seminal paper the causal effect of social capital on financial development is investigated by determining two measures for social capital at the provincial level. The first one is the number of blood donations per million inhabitants in 1995 and the second one is the average electoral participation in the referenda held in Italy between 1946 and 1987. In the second method, the gender gap among natives is compared with the one among different generations of immigrants in Italy. In the first method, the gender gap in mathematics and reading are interacted with the two measures of social capital to examine the differences in the gender gap between regions with a higher level of social capital when compared to others. As social capital is strongly correlated with local economic conditions I also control for provincial GDP per capita. To do this

[2] In Guiso et al. (2008a) social capital is defined as âĂIJgoodâĂİ culture, which means a set of beliefs and values that facilitate cooperation among the members of a community

analysis equations of the following form are estimated:

$$y_{isc} = \alpha_{ics} + Gender_{isc}\beta + socialcapital_p\gamma + Gender_{ics} * socialcapital_p\delta + \epsilon_{isc} \quad (3.3)$$

Where y_{isc} is pupil i's score in logarithm form, Gender is dummy variable equal to one if is girl, $socialcapital_p$ is measured by two different indices as I explained above and p denotes province, δ is a coefficient allowing for the return to social capital to be different among genders. ϵ is error component.

Table 3.11 shows the result for the second graders' mathematics score. Considering turnover at referenda as a proxy for social capital (column 3 and 5) return to social capitals are economically and statistically significantly different for boys and girls. Social capital is highly correlated with provincial GDP, thereby potential omitted variable bias that might arise if a gender gap differ systematically by provincial economic conditions is addressed by controlling for the GDP per province (Columns 4 and 5). However, controlling for provincial economic condition make no differences in to the estimated coefficient on the gender gap relative to raw estimation (columns 2 and 3). The estimated score return on social capital in the fifth specification (column 5) is -40.7 % for each extra percentage voter turnout at referenda for boys (as a measure for social capital) and -49 % (=-0.407+(-0.083)), in percent) for girls. Since, the regression function for boys and girls have different slope, the gender gap depends on the voter turnout for the referenda at the province level. For 0.8 percent turnout at referenda the gender gap is estimated to be -0.0154 % (=-0.083 * 0.8 + 0.051); for 0.85 percent turnout, the gender gap is more in percentage terms, -0.0195 %.

Table 3.12 shows the result for the second graders' reading score. Return to social capitals are economically and statistically significantly different for boys and girls in the 90 percent interval if social capital is proxied by turnover at referenda (columns3 and 5). Controlling for the GDP per province to address potential omitted variable bias does not change estimated coefficients. The estimated score return on social capital is -12.5 % for each extra percentage voter turnout at referenda for boys (as a measure for social capital) and -8.6% (= -0.125+ 0.039), in percent) for girls (based on fifth regression specification). Since, the regression function for boys and girls have different slope, the gender gap depends on the voter turnout for the referenda at the province level. For 0.8 percent turnout at referenda the gender gap is estimated to be 0.052 % (= 0.039* 0.8 + 0.022); for 85 % percent turnout, the gender gap is more in percentage terms, 0.055 %. The results for the fifth graders are consistent with the one for the second graders but the magnitudes of the coefficients are bigger in the latter one.

The second approach is based on the fact that, the behaviors of the movers is affected by the level of social capital of the province (country) where they were born (Guiso et al., 2008). Based on this approach, if social capital are matter, the social capital and cultural differences between natives and immigrants might lead to the differences in the gender gap among two cohorts.

The findings in table 3.14 suggests that for the second graders there are no differences in the gender gap between first generation immigrants and native Italians. However, the gender gap between the two groups is statistically significant in their fifth grades. The coefficient in reading test score is in line with the expectations and the gap in gender gap is more among immigrants than natives. However, the result is reverse considering mathematics score, where, surprisingly the gender gap is less for immigrants.

Based on the results for the second generation of immigrants which is shown in table 3.15 there are no evidences on the gap in gender gap between natives and immigrants with the exception of reading test score for the second graders that is in the expected direction.

C Gender differences in response to the class size effect

This chapter examines the gender differences in response to the changes in school resources (i.e. class size). I assume that, under certain assumptions (e.g. changes in peer effect is the same for both genders across classes of different size), gender differences in response to the class size cannot be explained by any societal factors, therefore; it might be a proxy for genders' innate differences.

Following Angrist and Lavy (1999), I exploit Maimonides [3] rule that can be used to evaluate the effect of the class size on the performance of Italian pupils based on their genders by providing a potentially exogenous source of variation in class size.

Based on Italian law, class size cannot be larger than 25 with a margin of flexibility of +10 percent, and it cannot be smaller than 10 with a margin of flexibility of -10% (Ballatore et al., 2012). Therefore, class size increases with enrollment until 25 pupils are enrolled, when another extra student is enrolled, there will be a sharp drop in class size, to an average of 13 pupils. Similarly, when 50 pupils are enrolled, the average class size become 25 students per class, but when 51 are enrolled the average class sizes drop to 25,5.

Let Z be the total enrollment in a school and C the number of classes, the rule for class size disregarding the margins of flexibility is:

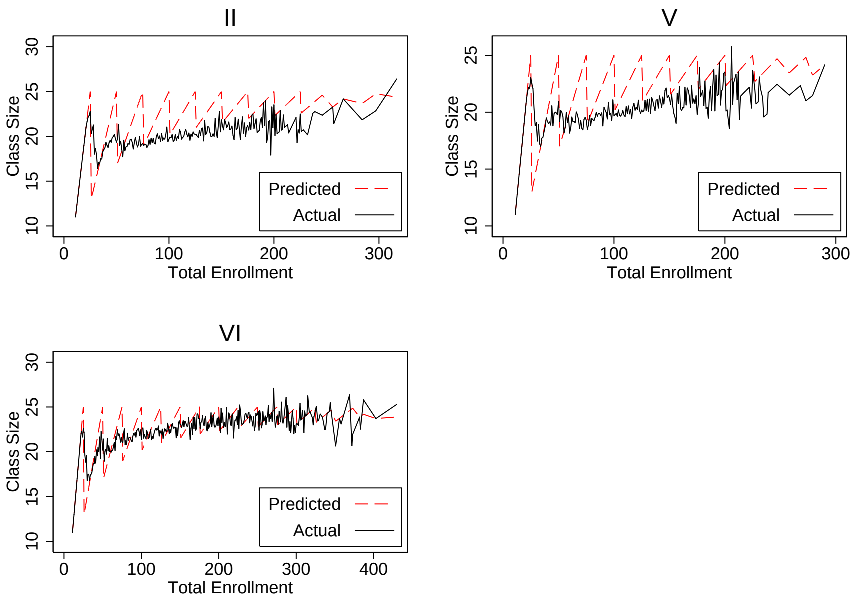
$$\bar{S} = \frac{Z}{Int(\frac{Z-1}{25}) + 1} \tag{3.4}$$

Where $lnt(x)$ is the largest integer smaller or equal to x. Based on equation (3.4) theoretical class size is a function of school enrollment that displays discontinuities at multiples of 25. The predicted and actual class size in Italian elementary and early secondary schools

[3] Twelfth century Rabbinic scholar who first interprets the Talmud's (who discuss rules for the determination of class size and pupil teacher ratio in bible around the beginning of the sixth century) discussion of class size: one teacher might assign to the class with up to twenty five students; an assistant should add to a class of twenty five to forty students and if there are more than forty students two teacher must be appointed.

are plotted in figure 3.1 (Ballatore et al., 2012).

Figure 3.1: Predicted and actual class size in Italy



Note: Each graph shows the predicted (red line) and actual (black line) class size in different grades

Figure 3.1 plots the average class size by enrollment size for second, fifth and sixth grade pupils along with the predicted class size. It is shown that, at enrollment levels that are not integers multiples of 25, class size increases approximately linearly with enrollment size. But average class size drops sharply at integers multiples of 25. Therefore, on the left of each threshold theoretical class size is larger than on the right, and this feature of the rule offers a source of variation for class size. For the relative analysis the first threshold (enrollment from 10 to 40) is considered, Since, this threshold is more compatible with class size rule.

Table 3.17 reports descriptive statistics, including average class size, enrollment, test scores and average of the number of girls and boys in classes in the entire population as well as in the discontinuity sample (first threshold: enrollment between 10 to 40). As it is shown in panel A of the table, the average elementary school's class in the data set has about 20 pupils, and there are nearly 117 pupils per grade.

Panel B of the table shows descriptive statistics for the discontinuity sample defined to include only schools with enrollments in the set of interval 10 to 40. As it is shown in the table, slightly more than one-quarter of classes come from schools with enrollments in this range. Average class size is marginally smaller in this discontinuity sample when compared to the overall population. And, the average characteristics of classes in the discontinuity sample (e.g. test scores) are slightly higher when compared to the average in the population.

Figure 3.2 shows the change in class size by enrollment for the first threshold for each gender. Enrollment between 26 to 28 is dropped from the analysis to respect the margin of flexibility in class size rule. As one can see from this figure, there is a jump in real class size when enrollment passes the threshold.

In addition to exhibiting a strong compliance with the class size rule, the real class size is expected to be correlated with the average test scores of second and fifth graders. This can be seen in Figures 3.3 and 3.4 which plot average scores and average values of class size by enrollment size in enrollment intervals of 10. The figures show that average mathematics scores by enrollment exhibit an up-and-down pattern that is the mirror image of the class size rule. However, the pattern is not as clear in reading scores.

The figures suggest a link between the variation in the class size induced by Maimonides' rule and pupil achievements for both genders, but they do not provide a framework for formal statistical inference. Therefore, a model for individual pupils test scores is used to describe the causal relationship between class size and performance for each gender and to verify whether there is any difference in the gender reaction to class size. For the ith student in class c and school s,the following equation is estimated:

$$y_{isc} = X_s\beta + Gender_{isc}\alpha + Lowsize_{sc}\gamma + Gender * Lowsize_{ics}\delta + \epsilon_{isc} \tag{3.5}$$

Where y_{isc} is pupil is score, X_s is a vector of school characteristics including functions of enrollment, Gender is dummy variable equal to one if is the girl, Lowsize is dummy variable equal to one if enrollment is more than 28 and δ is a coefficient of primary interest capturing the gender differences in response to class size. ϵ is error component specific to pupils. Applying Campbell (1969) [4] suggestion to the class size equation first used by Angrist and Lavy (1999), I identify the causal effect of class size on test scores for each gender in Italian school by using discontinuities or nonlinearities in the relationship between enrollment and class size for each gender. Following Angrist and Lavy (1999) I control for confounding factors by adding smooth functions of enrollment in the vector of covariates.

The identifying assumptions behind this approach are as following:

- Continuity assumption at the threshold for both kinds of schools must hold. This means, the smooth functions included in the equation must capture all the potential relation between nonclass-size effects on test scores and enrollment. Like all the other identification assumption, this assumption is not directly testable.

- Parents do not exploit the class size rule to send their children to the schools with small classes. According to Italian law transferring children from one school to another one is solely possible if parents move from one place to another, therefore, this assumption is plausible.

The evidences in table 3.17 suggest that the identification assumptions are indeed plausible, for instance, the classes before and after the threshold have the same characteristics in terms of share of pupils with uneducated parents in the class. Table 3.18 and 3.19 illustrates the findings for the second and fifth graders respectively. The results are partially in line with what have been observed by the figures. However, there are no significant differences between genders in response to the class size effect.

[4] In his seminal paper "Nonexperimental methods, in evaluation research" he discussed, how to identify the causal effect of treatment that is assigned as a deterministic function of the observed covariate that is also related to the outcome of interest

IV Conclusion

In this paper, I employ a nationally representative data set for Italian second, fifth and sixth graders in order to document and analyse the emergence of the gender gap in mathematics and reading. Consistent with the findings of current studies, I illustrate that genders are indeed different in their average achievement in mathematics and reading and the variability around the average, and, the differences are sharper when they become older (second grade compared to the fifth one). Moreover, findings illustrate that boys predominate girls in three extreme categories of mathematics and reading distribution: low reading, low mathematics, and high mathematics. The origins of the gender gap are investigated by exploring the wide range of possible explanations, including parental expectation, social capital and cultural differences, as well as responses to class size effect as a potential measure for innate gender differences. However little supports for any of those arguments were found.

V Tables chapter 3

Table 3.1: Summary statistics by gender

Variable	Male	Female	Difference	Mean Difference Significant
Mathematics test score				
Grade 2	0.627	0.617	0.009	**
	(0.0004)	(0.0004)	(0.0006)	
Grade 5	0.662	0.637	0.247	**
	(0.0004)	(0.0004)	(0.0005)	
Reading test score				
Grade 2	0.643	0.671	-0.027	**
	(0.0005)	(0.0005)	(0.0007)	
Grade 5	0.694	0.708	-0.013	**
	(0.0003)	(0.0004)	(0.0005)	
Grade 6	0.607	0.6228	-0.0148	**
	(0.0003)	(0.0003)	(0.0004)	
Gender proportions	0.48	0.46	0.022	**
	(0.0004)	(0.0004)	(0.0008)	
Italian ratio	0.43	0.41	0.018	**
	(0.0004)	(0.0004)	(0.0007)	
1st immigrant generation	0.025	0.022	0.002	**
	(0.0001)	(0.0001)	(0.0002)	
2nd immigrant generation	0.21	0,19	0.001	**
	(0.0001)	(0.0001)	(0.00017)	
Low educated share of parents	0.134	0.13	0.004	**
	(0.0003)	(0.0003)	(0.0005)	
Low skilled share of parents	0.037	0.035	0.001	**
	(0.0002)	(0.0002)	(0.0002)	
Frequency of Missing Values:				
Citizenship	0.0027	0.0027	0	
	(0.00006)	(0.00006)	(0.00008)	
Parents skills	0.016	0.015	0.001	**
	(0.0001)	(0.0001)	(0.0001)	
Number of Observations	683730	652188		

Source: Invalsi data for academic years 2009-10 and 2010-2011. Performance in a test is measured as the fraction of correct answers.

Table 3.2: Gender Gap in Italy-Grade 2

	Itally	North	Center	South
Mathematics				
Mean M_F gap	.0094**	.014**	.013**	.0024*
	(0.0006)	(0.0009)	(0.001)	(0.001)
M_F Variance Ratio	1.017**	1.065**	1.031**	0.99
M_F Ratio in top 10%	1.11	1.36	1.17	1.02
M_F Ratio in bottom 10%	1.33	1.13	1.24	1.57
Reading				
Mean M_F gap	-.027**	-.029**	-.027**	-.025**
	(0.0007)	(0.001)	(0.0016)	(0.0012)
M_F Variance Ratio	1.056**	1.053**	1.069**	1.054**
M_F Ratio in top 10%	0.87	0.85	0.86	0.89
M_F Ratio in bottom 10%	1.35	1.4	1.49	1.27

Notes. Significance levels: ** p<0.01, * p<0.05

Table 3.3: Gender gap in Italy-Grade 5

	Itally	North	Center	South
Mathematics				
Mean M_F gap	.025**	.033**	.033**	.009**
	(0.0005)	(0.0008)	(0.001)	(0.001)
M_F Variance Ratio	1.041**	1.113**	1.058**	1
M_F Ratio in top 10%	1.33	1.73	1.5	1.06
M_F Ratio in bottom 10%	1.25	1.17	1.06	1.40
Reading				
Mean M_F gap	-.013**	-.016**	-.009**	-.012**
	(0.0005)	(0.0008)	(0.001)	(0.001)
M_F Variance Ratio	1.03**	1.055**	1.024**	1.014*
M_F Ratio in top 10%	0.92	0.92	0.95	0.9
M_F Ratio in bottom 10%	1.13	1.06	1.27	1.20

Notes. Significance levels: ** p<0.01, * p<0.05

Table 3.4: Estimation of gender gap in mathematics

	Grade2	Grade5	Grade2	Grade5
(1) Female	-0.009***	-0.024***	-0.01***	-0.026***
	(0.0006)	(0.0005)	(0.0007)	(0.0007)
(2) ForeignI			-0.09***	-0.09***
			(0.002)	(0.002)
(3) ForeignII			-0.077***	-0.06***
			(0.001)	(0.002)
Controls				
(4) Low educate parents			-0.046***	-0.06***
			(0.0009)	(0.0007)
(5)Low skilled parents			-0.036***	-0.03***
			(0.001)	(0.001)
(5) Constant	0.63***	0.66***	0.65***	0.69***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Observations	406023	406216	288182	291304
R-squared	0.0005	0.004	0.028	0.046

Notes.The dependent variable is mathematics score, Standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 3.5: Estimation of gender gap in reading

	Grade2	Grade5	Grade2	Grade5
(1) Female	0.028***	0.014***	0.027***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
(2) ForeignI			-0.151***	-0.124***
			(0.003)	(0.002)
(3) ForeignII			-0.120***	-0.076***
			(0.002)	(0.002)
Controls				
(4) Low educated parents			-0.098***	-0.080***
			(0.001)	(0.001)
(5)Low skilled parents			-0.029***	-0.014***
			(0.002)	(0.001)
(5) Constant	0.643***	0.694***	0.690***	0.733***
	(0.001)	(0.000)	(0.001)	(0.000)
Observations	409325	412164	290790	295627
R-squared	0.004	0.002	0.068	0.073

Notes.The dependent variable is reading score, Standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Parental expectation and gender gap-high educated parents

	Math		Reading	
VARIABLES	Grade 2	Grade 5	Grade 2	Grade 5
female	-0.015***	-0.038***	0.053***	0.020***
	(0.001)	(0.001)	(0.002)	(0.001)
high educated parents	0.1***	0.127***	0.170***	0.118***
	(0.003)	(0.002)	(0.003)	(0.002)
female * high educate parents	-0.007	-0.014***	-0.007	0.002
	(0.004)	(0.004)	(0.005)	(0.003)
Constant	-0.525***	-0.458***	-0.530***	-0.403***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	305137	307983	307707	312463
R-squared	0.007	0.015	0.008	0.016

Notes. The dependent variables are log of reading and mathematics scores, robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1. "female" is a dummy variable equall to 1 if is female, "high educate parents" is a dummy variable equall to 1 if parents hold university degree.

Table 3.7: Parental expectation and gender gap-Mother dominated in terms of education

	Math		Reading	
VARIABLES	Grade 2	Grade 5	Grade 2	Grade 5
female	-0.016***	-0.039***	0.051***	0.020***
	(0.001)	(0.001)	(0.002)	(0.001)
mother dominate	0.003	0.020***	0.025***	0.022***
	(0.007)	(0.007)	(0.009)	(0.007)
female * mother dominate	0.004	-0.012	0.021*	0.009
	(0.010)	(0.009)	(0.012)	(0.009)
Constant	-0.515***	-0.448***	-0.514 ***	-0.394***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	405839	406172	408775	411882
R-squared	0	0.003	0.003	0.001

Notes. The dependent variables are log of reading and mathematics scores, robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1. "female" is a dummy variable equall to 1 if is female, "mother dominate" is a dummy variable equall to 1 if mother dominate father in terms of acquired years of education.

Table 3.8: Parental expectation and gender gap-father dominated in education

	Math		Reading	
VARIABLES	Grade 2	Grade 5	Grade 2	Grade 5
female	-0.015***	-0.036***	0.053***	0.023***
	(0.001)	(0.001)	(0.001)	(0.001)
father dominate	-0.040***	-0.016	-0.030*	-0.004
	(0.011)	(0.010)	(0.016)	(0.009)
female * father dominate	-0.012	0.018	-0.010	0.001
	(0.016)	(0.014)	(0.021)	(0.013)
Constant	-0.527***	-0.461***	-0.534***	-0.408***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	405839	406172	408775	411882
R-squared	0	0.003	0.003	0.001

Notes. The dependent variables are log of reading and mathematics scores, robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1. "female" is a dummy variable equall to 1 if is female, "father dominate" is a dummy variable equall to 1 if father dominate mother in terms of acquired years of education.

Table 3.9: Parental expectation and gender gap: number of books at home

	Math	Reading	
VARIABLES	Grade 5	Grade 5	Grade 6
female=1	-0.039***	0.020***	0.028***
	(0.001)	(0.001)	(0.001)
# books at home	0.078***	0.085***	0.115***
	(0.002)	(0.002)	(0.002)
female * # books at home	-0.005	0.006**	0.005**
	(0.003)	(0.003)	(0.002)
Constant	-0.462***	-0.407***	-0.544***
	(0.001)	(0.001)	(0.001)
Observations	390190	378768	476705
R-squared	0.011	0.010	0.024

Notes. The dependent variables are log of reading and mathematics scores, robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1, "female" is a dummy variable equall to 1 if is female, "# books at home" is a dummy variable for high number of books at home.

Table 3.10: Social capital and gender gap-provincial analysis for second graders in mathematics

VARIABLES	1	2	3	4	5
female	-0.015***	-0.011***	0.051***	-0.011***	0.051***
	(0.002)	(0.003)	(0.019)	(0.019)	(0.019)
Blood Donation		-1.468***		-1.146***	
		(0.289)		(0.249)	
Female interacted with BD		-0.163**		-0.159*	
		(0.080)		(0.080)	
Turnover at Referenda			-0.464***		-0.407***
			(0.066)		(0.086)
Female interacted with TR			-0.083***		-0.083***
			(0.024)		(0.024)
GDP per province				-0.002**	-0.001
				(0.001)	(0.001)
Constant	-0.527***	-0.489***	-0.153***	-0.460***	-0.184***
	(0.009)	(0.013)	(0.055)	(0.016)	(0.064)
Observations	405839	404250	380747	404250	380747
R-squared	0	0.009	0.014	0.011	0.014

Notes. Robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1. "female" is a dummy variable equall to 1 if is female, the rest of the variables are defined in the text.

Table 3.11: Social capital and gender gap-provincial analysis for second graders in reading

VARIABLES	1	2	3	4	5
female	0.053***	0.049***	0.022	0.049***	0.022
	(0.002)	(0.003)	(0.018)	(0.003)	(0.018)
Blood Donation		-0.727***		-0.651***	
		(0.218)		(0.233)	
Female interacted with BD		0.153*		0.154*	
		(0.081)		(0.081)	
Turnover at Referenda			-0.153**		-0.125*
			(0.058)		(0.075)
Female interacted with TR			0.039*		0.039*
			(0.022)		(0.022)
GDP per province				-0.001	0
				(0.001)	(0.001)
Constant	-0.534	-0.515***	-0.409***	-0.508***	-0.424***
	(0.005)	(0.007)	(0.048)	(0.0100)	(0.056)
Observations	408775	407184	383458	407184	383458
R-squared	0.003	0.004	0.004	.0.004	0.004

Notes. Robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1 "female" is a dummy variable equall to 1 if is female, the rest of the variables are defined in the text.

Table 3.12: Social capital and gender gap-provincial analysis for fifth graders in math

VARIABLES	1	2	3	4	5
female	-0.036***	-0.023***	0.122***	-0.023***	0.122***
	(0.004)	(0.005)	(0.017)	(0.005)	(0.017)
Blood Donation		-0.583***		-0.478***	
		(0.156)		(0.163)	
Female interacted with BD		-0.516***		-0.516***	
		(0.117)		(0.117)	
Turnover at Referenda			-0.121***		-0.107***
			(0.038)		(0.045)
Female interacted with TR			-0.198***		-0.198***
			(0.021)		(0.021)
GDP per province				-0.001	-0.000
				(0)	(0)
Constant	-0.461***	-0.446***	-0.362***	-0.437***	-0.370***
	(0.004)	(0.006)	(0.032)	(0.008)	(0.034)
Observations	406172	404770	380284	404770	380284
R-squared	0.003	0.006	0.007	0.007	0.007

Notes. Robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1. "female" is a dummy variable equall to 1 if is female, the rest of the variables are defined in the text.

Table 3.13: Social capital and gender gap-provincial analysis for fifth graders in reading

VARIABLES	1	2	3	4	5
female	0.023***	0.018***	0.005	0.018***	0.005
	(0.002)	(0.002)	(0.017)	(0.002)	(0.017)
Blood Donation		-0.207		-0.257	
		(0.157)		(0.162)	
Female interacted with BD		170**		0.170**	
		(0.072)		(0.072)	
Turnover at Referenda			0.022		0.020
			(0.034)		(0.040)
Female interacted with TR			0.021		0.021
			(0.020)		(0.020)
GDP per province				0	0
				(0)	(0)
Constant	-0.408***	-0.402***	-0.423***	-0.407***	-0.422***
	(0.004)	(0.006)	(0.029)	(0.007)	(0.031)
Observations	411882	410468	385691	410468	385691
R-squared	0.001	0.001	0.001	0.001	0.001

Notes. Robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1. "female" is a dummy variable equall to 1 if is female, the rest of the variables are defined in the text.

Table 3.14: gap in gender gap 1st generation immigrants vs. native

	Math		Reading	
VARIABLES	Grade 2	Grade 5	Grade 2	Grade 5
female	-0.015***	-0.038***	0.053***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)
1st gen immigrants	-0.193***	-0.201***	-0.363***	-0.264***
	(0.005)	(0.0040)	(0.008)	(0.004)
female interacted with 1st gen immigrants	0.006	0.025***	0.020*	0.021***
	(0.007)	(0.006)	(0.011)	(0.007)
Constant	-0.521***	-0.451***	-0.522***	-0.395***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	405839	406172	408775	411882
R-squared	0.009	0.019	0.020	0.029

Notes. Robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1. "female" is a dummy variable equall to 1 if is female, "1st gen immigrants" is a dummy indicated first generation of immigrants.

Table 3.15: gap in gender gap 2nd generation immigrants vs. native

	Math		Reading	
VARIABLES	Grade 2	Grade 5	Grade 2	Grade 5
female	-0.015***	-0.036***	0.051***	0.023***
	(0.001)	(0.001)	(0.002)	(0.001)
2nd gen immigrants	-0.163***	-0.110***	-0.284***	-0.132***
	(0.004)	(0.004)	(0.005)	(0.004)
female interacted with 2nd gen immigrants	0.008	-0.004	0.034***	0
	(0.005)	(0.005)	(0.008)	(0.006)
Constant	-0.518***	-0.457***	-0.518***	-0.402***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	405839	406172	408775	411882
R-squared	0.010	0.007	0.020	0.007

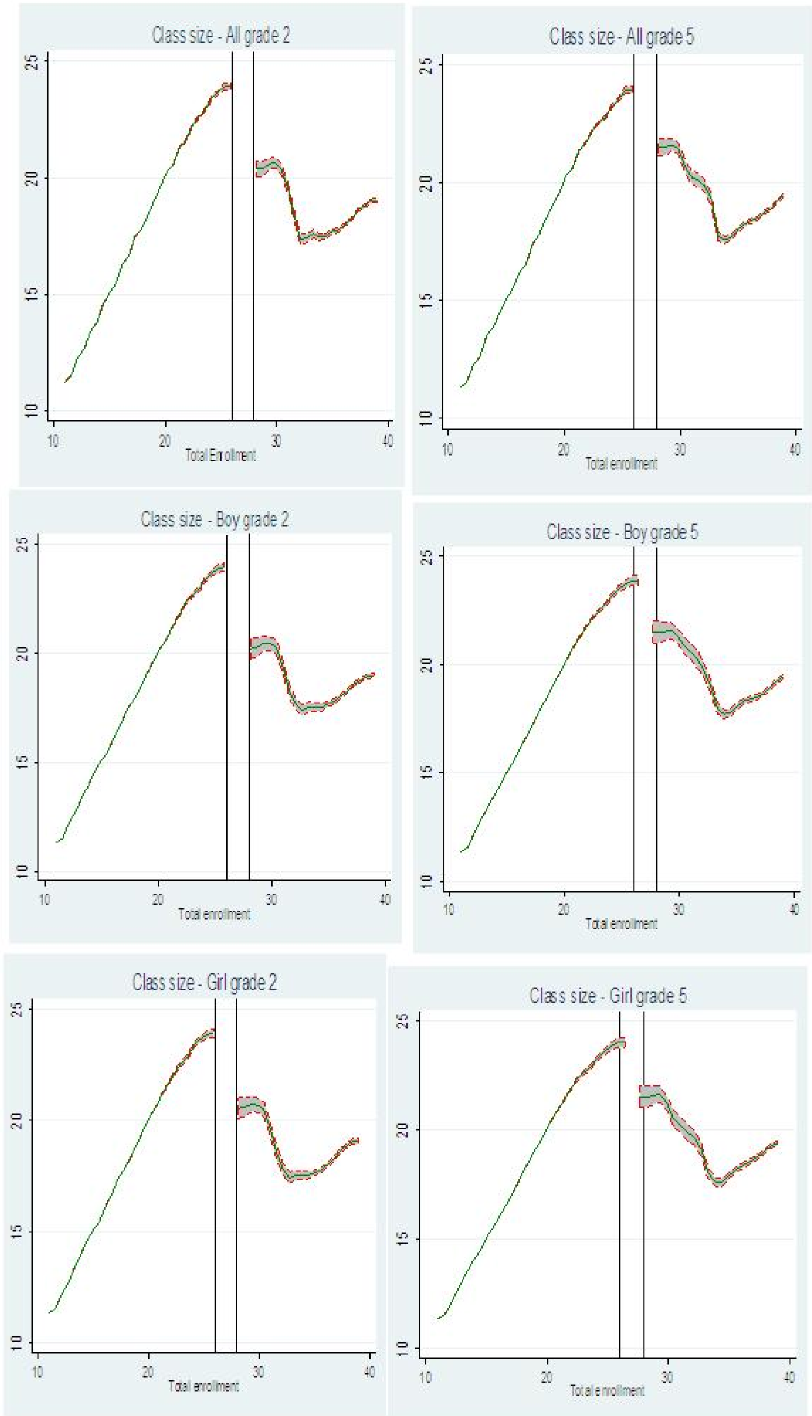
Notes. Robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1. "female" is a dummy variable equall to 1 if is female, "2nd gen immigrants" is a dummy indicated second generation of immigrants.

Table 3.16: Discriptive statistics-Full sample vs. Discontinuity sample

	mean	sd	min	p25	p50	p75	max	N Class
A: Full sample								
Grade 2: 5969 schools								
Class size	20	3.7	11	17	20	23	35	22745
Enrollment	103	46	11	70	101	131	317	22745
Average reading	0.66	0.23	0	0.5	0.70	0.85	1	22745
Average math	0.62	0.2	0	0.46	0.6	0.78	1	22745
N girls	9.5	2.8	0	8	9	11	21	22745
N boys	9.9	2.8	0	8	10	12	23	22745
Grade 5: 5937 schools								
Class size	20	3.8	11	17	20	23	35	22846
Enrollment	103	46	11	72	102	132	290	22846
Average reading	0.7	0.17	0	0.6	0.7	0.84	1	22846
Average math	0.65	0.18	0	0.52	0.66	0.79	1	22846
N girls	9.5	2.9	0	8	10	11	28	22846
N boys	9.8	2.9	0	8	10	12	27	22846
Grade 6: 5368 schools								
Class size	22	36	11	20	23	25	35	25288
Enrollment	145	77	11	84	130	198	430	25288
Average reading	0.61	0.15	0	0.52	0.64	0.72	1	25288
N girls	9.8	3	0	8	10	12	22	25288
N boys	10.5	3	0	9	11	12	24	25288
B: Discontinuity sample (enrollment 10-40)								
Grade 2: 1491 schools								
Class size	19	4.6	11	16	18	22	33	1988
Enrollment	27	7	15	22	27	33	39	1988
Average reading	0.7	0.23	0	0.54	0.73	0.88	1	22745
Average math	0.68	0.21	0	0.5	0.68	0.85	1	22745
N girls	9.2	3.5	0	7	9	11	21	1988
N boys	9.6	3.3	0	7	9	12	20	1988
Grade 5:1440 schools								
Class size	19	4.7	11	16	19	23	35	1901
Enrollment	27	6.8	15	22	27	33	39	1901
Average reading	0.72	0.18	0	0.6	0.75	0.85	1	1901
Average math	0.68	0.19	0	0.54	0.7	0.84	1	1901
N girls	9.4	3.6	0	7	9	12	28	1901
N boys	9.6	3.6	0	7	9	12	27	1901
Grade 6: 761 schools								
Class size	19	4.4	11	16	18	21	34	1113
Enrollment	29	6.7	15	24	31	35	39	1113
Average reading	0.6	0.15	0	0.52	0.62	0.72	0.98	1113
N girls	8.5	3.5	0	6	8	11	22	1113
N boys	9.2	3.3	0	7	9	11	24	1113

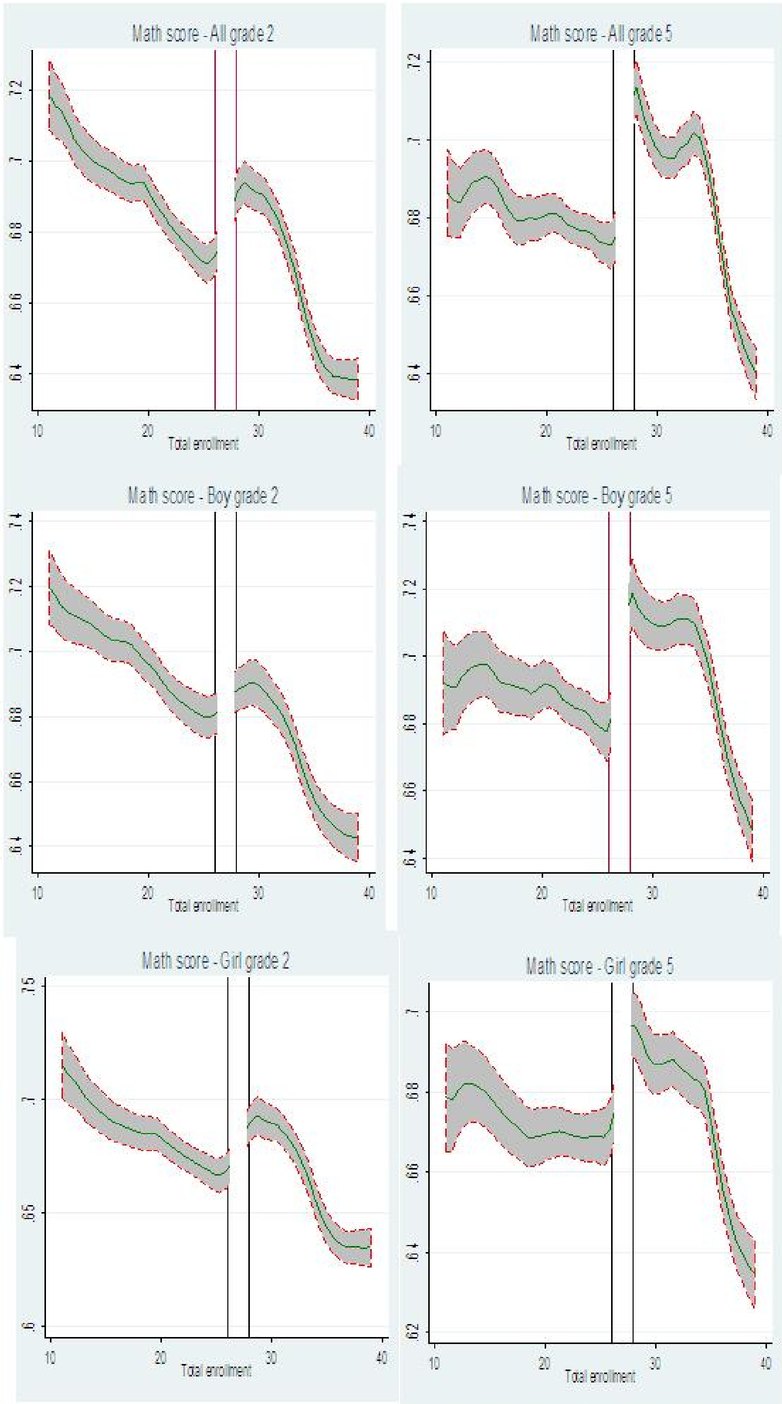
Source: Invalsi data for academic year 2009-10. Note that performance in a test for first two grades is measured as the fraction of correct answers.

Figure 3.2: Class size by enrollment



Note: Class Size in 2009-2010 by Enrollment

Figure 3.3: Math test score by enrollment



Note: Average Math Test Scores in 2009-2010 by Enrollment

Table 3.17: Discontinuity assumption-uneducated parents

	All	Boys	Girls
Grade2			
Gap at the threshold	-0.000	0.002	-0.003**
	(0.001)	(0.001)	(0.001)
Observations	25192	12837	12251
R-squared	0	0	0
Grade5			
Gap at the threshold	0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)
Observations	24075	12147	11928
R-squared	0	0	0

Notes. Robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 3.18: Gender difference in reaction to class size results: grade 2

VARIABLES	Math	Reading
Low class size	0.097***	-0.041
	(0.026)	(0.031)
female	-0.022***	0.040***
	(0.006)	(0.008)
female inteeracted with Low size	0.014	0.019*
	(0.009)	(0.011)
Constant	0.552	-2.256***
	(0.963)	(1.146)
Observations	28418	28559
R-squared	0.010	0.008

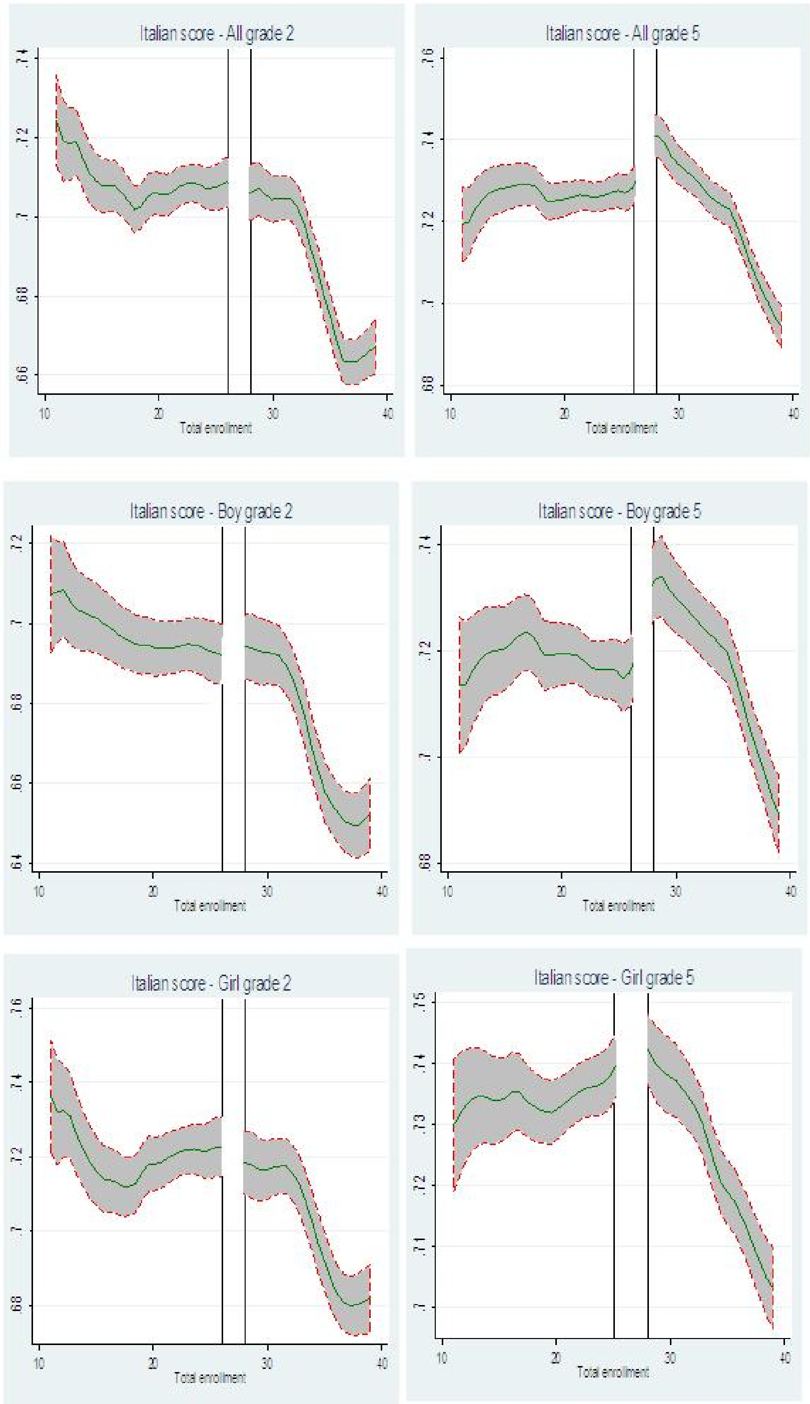
Notes. Robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 3.19: Gender difference in reaction to class size results: grade 5

VARIABLES	Math	Reading
Low class size	0.023	0.028
	(0.024)	(0.023)
female	-0.026***	0.022***
	(0.006)	(0.005)
female inteeracted with Low size	-0.008	-0.015*
	(0.008)	(0.008)
Constant	-1.430	-0.177
	(0.913)	(0.855)
Observations	26543	26543
R-squared	0.009	0.004

Notes. Robust standard errors in parentheses and significance levels: *** p<0.01, ** p<0.05, * p<0.1

Figure 3.4: reading test score by enrollment



Note: Average reading Test Scores in 2009-2010 by Enrollment

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