GENDER GAP: A TREND ANALYSIS FROM LOW TO HIGH SECONDARY SCHOOL

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Invalsi

V Seminar
"INVALSI data: a tool for teaching and scientific research"
ROME, February 25th – 28th, 2021

"Achieving gender equality, for the empowerment of all women and girls"

Theoretical framework

- In the field of educational research, the studies conducted so far agree that males achieve better school performance in the mathematical-scientific field, while females in the linguistic sphere (Sammons, 1995; Fryer Jr. & Levitt, 2009; Stoet & Geary, 2013);

- male pupils show a greater self-control in dealing with particularly stressful and unexpected situations: an interpretation is that boys achieve higher scores in standardized tests because they have always been more used to competitions (Steele, 1997);

- the influence of socio-economic-cultural status (ESCS) appears more marked in a positive sense for males than females, because males are more sensitive to resources present in the family and learning context. This gap tends to decrease for lower ESCS levels (Legewie and Di Prete, 2012).

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International framework

The PISA survey shows the specificity of the patterns deriving from the gender effect in Mathematics and Reading-results:

- according to PISA 2018, in 36 over 36 OECD countries females scores better than males in Reading, with 34 differences statistically significant, while males scores better than females in Mathematics in 31 OECD countries over 37, but with only 8 of those differences are statistically significant (*our elaboration of PISA data*).

- in Italy these gaps between females and males were all statistically significant, both in Reading and Mathematics, in the last three PISA editions. The situation is similar for Science, where about two out of three top performer students are boys (INVALSI, 2016c).

Our HP:

gender differences in the segment related to the first cycle of education see <u>girls ahead of men in the comprehension tests; this advantage tends to decrease with the progress of the school path</u> up to almost zero at the end of the second cycle of education (high school);

<u>the situation partly changes when considering Mathematics tests</u>: differences are moderate in the first cycle of education, which sees males slightly ahead of females, then diverge in favor of males reaching important differences at the end of the school course.

Aim of the work:

<u>verify gender differences in competences at the second cycle of the school curriculum (high school) for the s.y. 2018-19</u>

Considering all the students' data we can dispose by Invalsi Tests:

- Info from 2019 13th grade tests (competence levels)
- Info from 2016 10th grade tests
- Info from 2014 8th grade tests

It's a longitudinal approach permitted by the SIDI univocal code

Longitudinal approach: dependent (DV) and independent (IV) variables

G08 2014	G10 2016	G13 2019
Ita test score (IV) Mat test score (IV) Repeating (IV)	Desired qualification (IV) ESCS (IV)	**Ita competence level (DV)** **Mat competence level (DV)** Gender (IV) Immigrant background (IV) Geographical area (IV)

In this process there's a data loss

Longitudinal approach: data loss

G08		G10		G13
2014	→	2016	→	2019
≅ 516.000		≅ 380.000		≅ 460.000

Our db consists of: 242.042.

Reasons of mismatch:

- repeating pupils between grade 9 and grade 12;
- dropout pupils;
- pupils who did not take the G10 test;
- pupils enrolled in vocational training.

Resume of the data used:

Population:

242.042 pupils, not repeating between grade 8 and 13, who attended G08 2014, G10 2016 and G13 2019 tests (**47**% of the G08 cohort)

Outcome variables (DV):

- Y_Suff_G13_Ita
- Y_Suff_G13_Mat

'1' if competence level >=3
'0' if < 3

- Y_Top_G13_Ita
- Y_Top_G13_Mat

'1' if competence level >=4
'0' if < 4

Independent variables (IV):

ITA and MAT results at the 8th grade (end of 1st cycle)
Repeating student at lower sec. school
Desired qualification
ESCS
Gender
Immigrant background
Geographical area

Methods:

1. Descriptive approach:

Descriptive statistics:

- Characteristics (IV) by gender
- (Female) Odds ratio by DV “Y_Suff_G13” (**ITA** & **MAT**)
- (Female) Odds ratio by DV “Y_Top_G13” (**ITA** & **MAT**)

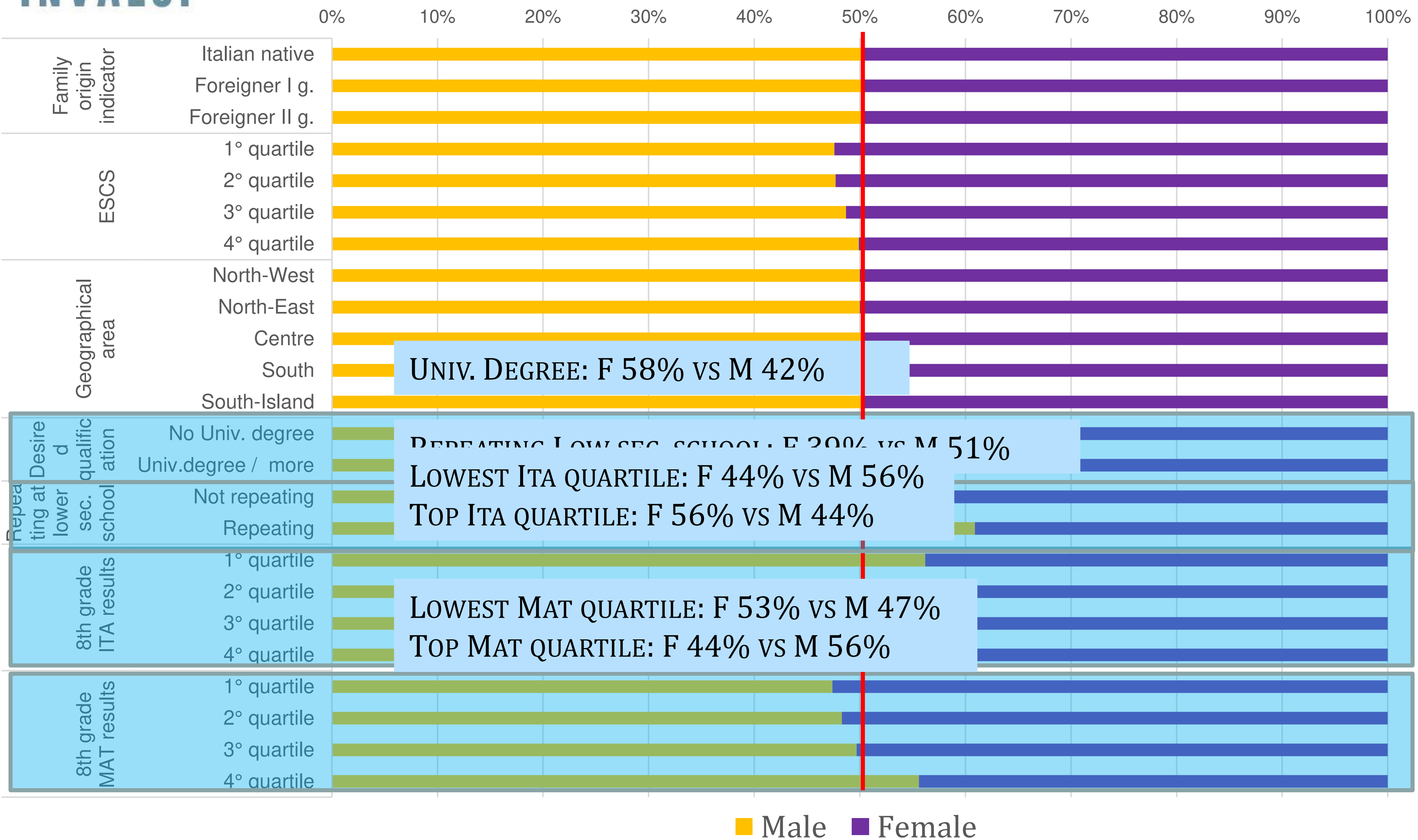
2. Modeling approach:

Logistic model:

- (Female) Odds ratio net of the other IV by DV “Y_Suff_G13” (**ITA** & **MAT**)
- (Female) Odds ratio net of the other IV by DV “Y_Top_G13” (**ITA** & **MAT**)

3. Comparison and conclusions

1. Descriptive approach: Descriptives (IV) by gender:



1. Descriptive approach: Odds ratio by G13 competences

	Y_Suff_G13_Ita		Y_Suff_G13_Mat	
	< '3'	>= '3'	< '3'	>= '3'
Male	33.2%	66.8%	28.6%	71.4%
Female	26.6%	73.4%	38.9%	61.1%
Female odds ratio	**1.37**		**0.63**	

	Y_Top_G13_Ita		Y_Top_G13_Mat	
	< '4'	>= '4'	< '4'	>= '4'
Male	61.6%	38.4%	48.1%	51.9%
Female	57.0%	43.0%	62.1%	37.9%
Female odds ratio	**1.21**		**0.57**	

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2. Modeling approach:
Categorical variables coding in the logistic model

Variable	Categories
Geographical area	North-West
	North-East
	Centre
	South
	South-Islands
2014 8th grade INVALSI test score	**1° quartile**
	2° quartile
	3° quartile
	4° quartile
ESCS	**1° quartile**
	2° quartile
	3° quartile
	4° quartile
Immigrant background	**Italian native**
	Foreigner I g.
	Foreigner II g.
Desired qualification (10th Grade Qst)	**No Univ. degree**
	Univ. degree / more
Repeating student at lower sec. school	**Not repeating**
	Repeating
Gender	**Male**
	Female

In bold the reference categories

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2. Modeling approach: logistic models

The response variables are dichotomous variable:
“Y_Suff_G13” (**ITA** & **MAT**)
“Y_Top_G13” (**ITA** & **MAT**).

The data used for the models meet the requirements for the use of logistic regression.

The pseudo R-squares are higher than 0.3, considered a threshold of acceptability of these measures in logistic regression.

Several coefficients of the models present odds-ratios very different from '1', a signal of strong association with the response variable.

2. Modeling approach:
Model summary

		Model summary	
		Italian language	**Mathematics**
Model 1 **(Y1: G13 2019 Sufficient competence level)** (above/below '3' out of 5)	-2 Log likelihood	203.256,5	222.533,1
	Cox & Snell Pseudo R-square	0.26	0.26
	Nagelkerke Pseudo R-square	0.38	0.36
Model 2 **(Y2: G13 2019 Good competence level)** (above/below '4' out of 5)	-2 Log likelihood	249.878,1	253.052,2
	Cox & Snell Pseudo R-square	0.29	0,29
	Nagelkerke Pseudo R-square	0.39	0.39

Pseudo R-Squares tell us that the 2 models can fit the data

(*note: no interpretation about variability explained can be made*)

2. Modeling approach:
Classification tables

Although the approach of this work is not of a predictive type, the classification tables can be used to check the goodness of fit of the models:

Model proposed:		**% correct**	
		Italian language	**Mathematics**
Model 1 **(Y1: G13 2019 Sufficient competence level)** (above/below '3' out of 5)	Competence level 1, 2	46.4%	48.8%
	Competence level 3, 4, 5	91.9%	89.2%
	Average	80.3%	77.4%
Model 2 **(Y2: G13 2019 Good competence level)** (above/below '4' out of 5)	Competence level 1, 2, 3	79.4%	67.8%
	Competence level 4, 5	69.5%	84.5%
	Average	75.0%	77.8%

In the 2nd model the % correct are more consistent

(*note: the 1st model would provide many "over estimated" competence level for not sufficient students*)

2. Modeling approach: logistic model using 'sufficient' competence as response (level >=3 out of 5)

Variable	Categories	Italian lan.	Mathematics
		Exp(B)=oddsratio	
Constant		0.33	0.45
Geographical area	North-West	1.87	1.95
	North-East	1.84	2.07
	Centre	1.00	1.00
	South	0.63	0.70
	South-Islands	0.50	0.52
2014 8th grade INVALSI test score	**1° quartile**	1.00	1.00
	2° quartile	**1.89**	**1.90**
	3° quartile	**5.10**	**4.51**
	4° quartile	**16.20**	**15.66**
ESCS	**1° quartile**	1.00	1.00
	2° quartile	1.22	1.19
	3° quartile	1.36	1.32
	4° quartile	1.70	1.46
Immigrant background	**Italian native**	1.00	1.00
	Foreigner I g.	0.85	1.04
	Foreigner II g.	0.88	0.99
Desired qualification (10th Grade Qst)	**No Univ. degree**	1.00	1.00
	Univ. degree or more	**2.80**	**2.28**
Repeating student at lower secondary school	Not repeating	1.00	1.00
	Repeating*	0.45	0.46
Gender	Male	1.00	1.00
	Female	**1.11**	**0.54**

2. Modeling approach: logistic model using 'good' competence as response (level >=4 out of 5)

Variable	Categories	Italian lan.	Mathematics
		Exp(B)=oddsratio	
Constant		0.09	0.16
Geographical area	North-West	1.73	1.74
	North-East	1.72	1.83
	Centre	1.00	1.00
	South	0.67	0.70
	South-Islands	0.55	0.53
2014 8th grade INVALSI test score	**1° quartile**	1.00	1.00
	2° quartile	1.12	1.53
	3° quartile	**3.04**	**3.72**
	4° quartile	**11.52**	**14.15**
ESCS	**1° quartile**	1.00	1.00
	2° quartile	1.25	1.18
	3° quartile	1.42	1.31
	4° quartile	1.80	1.47
Immigrant background	**Italian native**	1.00	1.00
	Foreigner I g.	0.79	0.99
	Foreigner II g.	0.86	1.01
Desired qualification (10th Grade Qst)	**No Univ. degree**	1.00	1.00
	Univ. degree or more	**2.64**	**2.30**
Repeating student at lower secondary school	Not repeating	1.00	1.00
	Repeating*	0.50	0.49
Gender	Male	1.00	1.00
	Female	**0.97**	**0.48**

3. Comparison and conclusions

Odds ratio comparison

	Dependent variable	(female) **Odds ratio** Descriptive approach	Modelling approach	Conclusions from the models
Y1: G13 2019 Sufficient competence (above/below ‘3’ out of 5)	**Italian language**	1.37	1.11	Decrease to a slight positive gap in favour of females
	Mathematics	0.63	0.54	Increase of the positive gap in favour of males
Y2: G13 2019 Good competence (above/below ‘4’ out of 5)	**Italian language**	1.21	0.97	Decrease to a no difference between males and females
	Mathematics	0.57	0.48	Increase of the positive gap in favour of males

3. Comparison and conclusions

Discussion

The important conclusion that emerges from this work with respect to gender is the following:

starting from the descriptive statistics that confirm the best performance of females in Italian language and of males in Maths, when we get into the model to check the effect controlling for other variables, <u>the higher effect of females in Italian language almost disappears, while that in favour of males in Mathematics remains strong</u>:

although we are controlling for some important characteristics which are related to gender, it seems they reduced the better performance only for females in Italian

3. Comparison and conclusions

<u>Limits and doubts</u>

1) we can talk only about <u>242.042 pupils</u> (only 47% of the G08 initial cohort)

2) this sub-population can be in some way "<u>selected</u>" for different reasons:

- grade 10 tests are more participated by lyceum students and less by technical and vocational schools
- vocational training and repeating pupils between grade 9 and grade 12, not included, are less proficient (and maybe are more males?)

3) the '<u>top perfomer' model</u> maybe works better because in some way we 'selected' our population excluding weak pupils and/or lyceums are over represented?

4) why the '<u>desired qualification</u>' has so much effect, considering that

- it's the only 'perception variable' (not structural)
- it's much associated with gender (Degree: F 58% vs M 42%)
- it's for sure associated with lyceum pupils which are over represented

3. Comparison and conclusions

Next steps

1) we can now use 2021 INVALSI data, and we know that G10 2018 tests (in CBT) were much more participated than 2016 (so our match will increase)

2) separate the analysis by school track

3) Consider other models, using the outcome variable in all its 5 levels of competence or considering the original continuous score

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Thanks

…and enjoy INVALSI data !!!

https://invalsi-serviziostatistico.cineca.it/