The Best in the Class

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Abstract

I propose a novel methodology to identify how being the *best in the class* at the beginning of one's school life shapes future academic performance. My methodology exploits that some students are the *best in the class* because better students in their school were assigned to other classes and the random component of this allocation is a well-known function of students ranking in the school and the number of classes. I find a negative impact of being the *best in the class* on future performance: being the best in second grade reduces test scores by 0.34 standard deviation in fifth grade while being the best in fifth grade reduces test scores by 0.43 standard deviation in eighth grade.

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1 Introduction

Top-performing students are likely to hold the leading positions in future society. However, little research is devoted to them.[1] The National Association for Gifted Students regrets the absence of a uniform federal policy for "gifted services". This lack of regulation results in a variety of State policies which go from "Accommodations in the regular classroom" to "Full-time grouping with students of similar abilities".[2] The adopted policy may have relevant consequences for talented students' future outcomes. In this paper, I address the implications of being the best student in the class for future academic performance.

Previous literature shows that students' position in the school-cohort ranking positively influences future academic performance. However, the average ranking effect may not apply to the top performer in the class: First, *the best* is a more salient position. This may imply more social responsibility which may harm those students with low capacity to cope with pressure. However, it may also imply social approval which boosts self-confidence and therefore future performance (Ferkany [2008]). Second, the best student in each class may be demotivated from lack of competition. Demotivation may result in worse future performance. Third, the best in the class does not receive positive influences from better peers which would have improved performance.[3]

In this paper, I propose a novel methodology to estimate the impact of being the best in the class on future performance that does not require experimental data. I exploit the allocation of students to classes within a school. In practice, this allocation may not be random. For this reason, I use the theoretical probability of being the best in the class under random assignment of students to classes within a school as an instrument for being best of the class. My identification strategy relies on two facts: First, a given student becomes the first of the class if those students in the school-cohort who are better than the

[1] Some exceptions are Griffith and Rask [2007] and Horstschräer [2012] studies of talented children's school choice and Figlio and Lucas [2004] analysis of the impact of high grading standards on high ability students.

[2] See https://www.nagc.org/ for more detailed information.

[3] The peer effects literature shows the positive influence of high ability students on their peers: Sacerdote [2001], Whitmore [2005], Carrell, Fullerton, and West [2009], Black, Devereux, and Salvanes [2013], and Booij, Leuven, and Oosterbeek [2017].

student are allocated to a different class. Second, if the allocation of students to classes within a school was random, the probability of being the best of the class would be a deterministic function of students' ranking in the school cohort and the number of classes in the school-cohort. For example, for the second student in a school-cohort with two classes, the probability of being the first student in the class equals the probability that the first student in the school-cohort is assigned to the other class (one half). If the second student in the school-cohort attends a school with three classes this probability goes up to two thirds. Finally, the third student in the school-cohort has a probability of being the first in the class in a school with two classes equal to the probability that both the first and the second student in the school cohort are in the other class (0.5^2=0.25). I use these theoretical probabilities of being the best of the class given the student's ranking position and the number of classes in the school-cohort as an instrument for being the best in the class.

My objective is to compare future performance of individuals with the same ability but one is the best in the class and the other one is not. To make these individuals comparable, I control for ranking position in the school-cohort using dummies. As it is standard in the literature on ranking effects, I also take into account individuals' ability by including their own test scores in the list of controls. Current test scores also include contemporaneous effects of being best in the class and hence my estimation of effects on future performance is net of those contemporaneous effects. I also account for selection into schools and its variation over time by including school-cohort fixed effects in my regressions. Finally, being the best in the class may have different implications in big and small classes. I take this into account by including class size fixed effects.

I use data on standardized tests administered to all students in Italy. These tests cover two subjects (Italian and mathematics), are designed by an agency of the Italian Government (the National Institute for the Evaluation of the School System - INVALSI), and are mandatory for all students. Students are tested in second, fifth, eight and tenth grades of compulsory schooling. In my analysis I use information on mathematics test scores for second, fifth and eighth grades. I use data on ranking, student and school characteristics in second and fifth grades for the academic years 2012–13 to 2013–14 and data on performance three years later (fifth and eighth grades in the academic years 2015–16 to 2016–17).

My empirical design works best in contexts where assignment of students to classes within a school is closer to random allocation. I test this in my data using both a regression of being best in the school-cohort on a vector of dummies for individuals in other ranking positions being in the same class and the test proposed in Guryan, Kroft, and Notowidigdo [2009]. Both tests indicate that there is small positive correlation between students' ability within classes in my data. Hence, allocation of students to classes within a school is not random, which justifies the use of my instrument. On the other hand, the small magnitude of the correlation indicates that there is enough random variation to be extracted through my instrument. As a result, my instrument is strong and the estimated effect is arguably representative of the population.

Results show that being the best in the class reduces future students' performance. Being the best in second grade decreases test scores by 0.34 standard deviation in fifth grade while being the best in fifth grade decreases test scores by 0.43 standard deviation in eighth grade. This effect is stronger for girls and individuals at lower positions of the school ranking. The effect is also negative in the estimation of the effect of being best in the class in eighth grade on performance in tenth grade. Results are robust to the inclusion of a fourth order polynomial in test scores. These negative effects are in line with the findings in Genakos and Pagliero [2012] for sport tournaments. In contrast, the effect of being second in the class on future performance is positive.

1.1 Related Literature

This paper relates to the literature on the impact of relative position in the school ranking on future educational outcomes. Recent papers on this argument include Murphy and Weinhardt [2013], Elsner and Isphording [2017], and Denning, Murphy, and Weinhardt [2018]. Murphy and Weinhardt [2013] find that being ranked highly during primary school has large effects on secondary school achievement, with the impact of rank being more important for boys than girls. They exploit variation in the dispersion of ability within a school and grade and thus, they rely on their measure of ranking position being comparable across school and grades with different degrees of dispersion. In other words, their methodology requires that being in a given position of the ranking has the same implications in a context with compressed test scores than in one with dispersed test scores.

Elsner and Isphording [2017] find that if two students with the same ability have a different rank in their respective cohort, the higher- ranked student is significantly more likely to finish high school, attend college, and complete a 4-year college degree. Their identification strategy exploits variation across cohorts within the same school. This implies that they rely on the school quality, including the quality of peers and teachers, stay stable over time.

Denning, Murphy, and Weinhardt [2018] find that a student's rank in third grade impacts grade retention, test scores, high school graduation, college enrollment, and earnings up to 19 years later. Their methodology is similar to Elsner and Isphording [2017] but they also exploit across subjects variation. Differently from the three papers mentioned above which study the effect of school ranking on performance, my paper refers to relative position within the class controlling for the schooling ranking.

The closest paper to mine is Cicala, Fryer, and Spenkuch [2017]. They find that, in the context of 61 Kenyan primary schools, increasing a student's rank by fifty percentiles boosts test scores at end-line by about 0.2 standard deviation. They make use of random allocation of students to classes within the same school and assume that ability is well accounted for using a quadratic polynomial of test scores. In my paper, I focus on the best student rather than the average effect of ranking positions and my methodology does not require experimental data. Bertoni and Nisticò [2018] exploit a similar experiment implemented in the University of Amsterdam where first year students in Economics were randomly allocated to tutorial groups. They show that students with higher ordinal ability rank within groups have better academic outcomes. In their setup, moving from the bottom to the top of the within-group ability distribution increases the number of credits achieved by about half of a standard deviation.

Given that *the best in the class* is a very salient position, my paper closely relates to the literature on ranking concerns. There is evidence suggesting that students care about their achievement rank even in the absence of specific rank incentives (Tran and Zeckhauser [2012], Azmat and Iriberri [2010]). Rank concerns have been studied also in various fields outside of education, for example, in the study of well-being at work and job satisfaction (Brown, Gardner, Oswald, and Qian [2008], Card, Mas, Moretti, and Saez [2012]), of performance in sport tournaments (Genakos and Pagliero [2012]) and of labor market productivity (Vidal and Nossol [2011]), among others. Tincani [2017] points at ranking concerns as one of the mechanisms behind the heterogeneity of peer effects.

The remainder of this paper is organized as follows. I present the data and institutional background in Section 2. In Section 3 I describe my methodology and in Section 4 I present my results. Section 5 discusses several extensions and robustness checks. I conclude in Section 6.

2 Data and Institutional Framework

Education is compulsory in Italy between ages 6 and 16. Admission to Italian schools is based on a point system in which distance from home to school, having attended a kindergarten under the same school administration and number of siblings (specially if they already attend the same school) increase the likelihood of admission. The education system is divided in elementary school (five years), middle school (three years) and secondary school (five years).

I use standardized test score data from the National Institute for the Evaluation of the School System (INVALSI) which cover the universe of Italian students. Students take standardized tests in the second and fifth year of elementary school, then three years later in the third year of middle school and finally two years later in the second year of secondary school. INVALSI provides data from academic years 2009–10 to 2016–17.

Individual identifiers are available for the academic years 2013–14 to 2016–17. This allows me to link individuals in two consecutive tests taken three years apart. This is crucial for my identification strategy because I can study the impact of being the best in the class in a given grade on performance three years latter: performance in fifth grade of the best of the class in second grade and performance in eighth grade of the best of the class in fifth grade.[4] From second to fifth grade most students remain in the same school, with the same classmates and teachers. In contrast, from fifth to eighth grades all students change school, teachers and at least part of their classmates. These differences could potentially lead to distinct consequences of being best in the class in terms of reputation concerns, motivation and peer effects. Hence, the comparison of the effect of *best in the class* in second grade on fifth graders' performance to the effect of *best in the class* in fifth grade on eighth graders' performance provides interesting insights.

The INVALSI data contains test scores from two subjects (Italian and mathematics) and indicates the number of correct answers. I focus on mathematics tests instead of Italian because mathematics is less likely to be affected by migrant status or the use of a regional language at home (14% students declare to speak a language other than Italian at home). I standardize scores by subject, academic year, and grade to have zero mean and unit variance (as in Angrist, Battistin, and Vuri [2017]). The data set also includes students' characteristics (among them: gender, migrant status, daycare attendance and kindergarden attendance) and parental characteristics (among them: migrant status, level of education, and occupation).

I make a series of exclusions to arrive at the sample that I use for my analysis. I focus on individuals who attended fifth and eighth grades in the academic years 2015–16 to 2016–17 because those are the only ones for which information about a previous grade is available and I select students for whom there is information about the previous grade. Those are the vast majority of students as the Invalsi test is proposed to the universe of students in Italy. Still, students who moved in from abroad or those who had at-home schooling (an extremely uncommon practice in Italy) are excluded. Third, I select individuals who are in the first eighteen positions of the school ranking. I choose that threshold because for those individuals the probability of being the best in their class is at least 1%.

The resulting data set includes $235,560$ observations for the analysis of being best in the class in second grade on fifth grade performance and $251,945$ observations for the

[4] A significant fraction of non-randomly selected students drop out by tenth level. This attrition could bias my estimation of the impact of best in the class in eighth grade on performance in tenth grade. I nevertheless show these results in Section 5.3.

analysis of being best in fifth grade on eighth grade. As part of my supplementary analysis, I also estimate the impact of being best in eighth grade on tenth grade for which there are 156, 230 observations. The average student in my sample answers correctly 74% of the questions in the mathematics tests (both second and fifth graders). The corresponding percentage for eighth graders is 81%.

Table 1 presents average key characteristics of students and their parents. I describe separately the samples used in the estimations of the effect of being best in the class in second grade on fifth grade performance (first two columns), being best in the class in fifth grade on eighth grade performance (third and fourth columns) and being eighth in the class on tenth grade performance (last two columns). I first comment on the samples of second to fifth graders and fifth to eight graders which are used in my main analysis and then highlight the differences with respect to the sample of eight to tenth graders.

The average test score in the sample of second to fifth graders goes from 0.77 standard deviations in second grade to slightly below one half standard deviation in fifth grade. For the sample of fifth to eighth graders average test scores move from 0.77 standard deviations in fifth grade to 0.6 in eighth grade. The average student has an ex-ante probability of being the best in the class slightly below 0.15. On average students are in schools with 2-3 classes and 19 students per class. The average student in my sample is number 9 in the school-cohort ranking. There are slightly more males than females. Although the incidence of foreign-born is relatively low (between 2% and 3%), almost 9% of students have an immigrant father and almost 11% of mothers are immigrants. In the sample of eighth to tenth graders, average test scores are much higher (from 1.14 in eighth grade to 0.77 in tenth grade). Also the ex-ante probability of being best in the class is much higher (0.24). The latter is a consequence of the larger number of classes in the average school which is higher than 4. Demographic characteristics are comparable across the three samples.

Table 14 in Appendix A.2 provides further information for these groups; it describes daycare and kindergarden attendance and the education and labor market status of parents. The proportion of students who attended daycare was 40% and 34% among second and fifth graders, respectively. As much as 86% of students attended kindergarden. Regarding the education level of parents, 43% of mothers have a high-school degree. The proportion of university graduated mothers is 24% and 21% in second and fifth grade, respectively. Fathers are slightly less educated: less than 40% of them have a high-school degree and 18% have a university degree. The proportion of homemakers among mothers is relatively high (30% and 33% for second and fifth graders). Although the proportions of white collar workers are the same for mothers and fathers (43-44%), the proportions of self-employed and blue collar workers are low for mothers (around 10% in each category) but they are much more relevant for fathers (one fourth of fathers are self-employed and another fourth are blue collar). These characteristics are in line with those observed for the sample of eighth to tenth graders with the exception of the proportion of students who attended daycare which is lower (less than 28%).

Table 1: Descriptive Statistics. Grades 5, 8 and 10.

	Grades 2 to 5		**Grades 5 to 8**		**Grades 8 to 10**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Test score in t	0.768	0.64	0.773	0.668	1.143	0.625
Test score in t+1	0.48	0.842	0.602	0.881	0.773	0.930
Instrument	0.148	0.266	0.148	0.265	0.236	0.294
No. of classes	2.645	1.018	2.646	1.024	4.307	2.448
No. of students in class	19.088	3.821	18.36	3.887	19.615	4.017
Student ranking in grade	9.441	5.184	9.442	5.185	9.281	5.19
Male	0.531	0.499	0.534	0.499	0.544	0.498
Immigrant child	0.019	0.138	0.027	0.163	0.031	0.173
Immigrant father	0.086	0.28	0.079	0.27	0.069	0.253
Immigrant mother	0.108	0.31	0.1	0.299	0.088	0.283

Notes: This table presents averages and standard deviations (left and right column, respectively) for each sample used in the estimations.

3 Methodology

My identification strategy exploits the allocation of students to classes within a school. In this section I first explain how I test whether this allocation can be considered random. I then describe the methodology I use to estimate the impact of being the best in the class on future performance.

My first objective is to address whether students are assigned to classes depending on their ranking in the school cohort. If allocation was random, I could estimate the impact of best in the class using an OLS regression of future test score on best in the class. Otherwise, my instrument becomes useful to extract the random component of class assignment. The closer class assignment is to random allocation, the stronger my instrument will be. Also, if class assignment is similar to random allocation, my estimates are more representative of the population.

Class assignment is likely to be almost random from first to fifth grade as classes are formed in first grade when there is no comparable information on student performance (most students do not know how to write and in the vast majority of cases there are no interviews or psychological assessments) and the composition of classes is typically kept fixed up to fifth grade. New classes are formed in sixth grade and their composition is kept fixed up to eighth grade. Class assignment is also likely to be close to random in this case. Principals of the new school typically do not have access to comparable performance information when they form classes. Even if they had, there are no official indications or directives on whether homogenous or heterogeneous classes should be formed. However, principals may use other observable characteristics (students' home address, parental education, previous school, number of siblings, etc.) to proxy for student future performance and use this information to form classes. I explore this possibility by studying the probability that the first and the second (third, fourth, etc.) student in the school-cohort ranking are in the same class. I do this by regressing a dummy for best in the school-cohort on dummies for ranking positions two to eighteen as follows:

$$\begin{aligned} Best\ in\ cohort &= \beta_0 + \beta_1 D(2nd\ in\ class)_{i,t} + \beta_2 D(3rd\ in\ class)_{i,t} + ... \\ ... &+ \beta_{17} D(18th\ in\ class)_{i,t} + \beta_{18} School\text{-}cohort_{i,t} + \beta_{19} Class\text{-}size_{i,t} + u_{i,t} \end{aligned} \tag{1}$$

where *Best in cohort* is a dummy for student i being best in the school-cohort at time t and t takes values 2013-14 and 2014-15. $D(n\text{-}th\ in\ class)$ are dummies equal to one if the student in ranking position number n in the school-cohort ranking is in the same class. I also include dummies for *School-cohort* and indicators for number of students in the class, *Class-size*. Standard errors u are clustered by class. I run the regression separately for second and fifth grade.

Under random assignment, I expect the β coefficients to be small, negative and of similar magnitude. The reason is that under random assignment the probability that the second (third, fourth, etc.) of the school cohort is in the same class as the first one is negatively affected by the fact that in the class of the first student in the school-cohort one of the class slots is occupied by him/her. Hence, under random assignment, each of the β coefficients should equal one divided by the average class size. Guryan, Kroft, and Notowidigdo [2009] propose a correction to account for this negative bias in the context of a standard random assignment test. The standard test is a regression of individual test scores on the average test score of the class excluding the individual. As in the previous test, this automatically generates a negative bias. Guryan, Kroft, and Notowidigdo [2009] correct this by including the average test score of all potential class members excluding the student as a control in the regression. The resulting equation is as follows:

$$TS_{i,t} = \gamma_0 + \gamma_1 Mean\ TS\ in\ class_{-i,t} + \gamma_2 Mean\ TS\ in\ school_{-i,t} + v_{i,t} \tag{2}$$

where TS is the mathematics test score at the individual level while *Mean TS in class* and *Mean TS in grade* are the average test scores of all students excluding individual i in the class and school-cohort, respectively.

If the coefficients arising from the estimation of equations (1) and (2) indicate that class assignment is close to random, my instrument is strong and my identification strategy provides representative estimates of the effect best in the class on future performance.

After this preliminary check, I move to the estimation of the impact of being the best in the class on future performance. I do this by regressing the test score three years later on a dummy for being the best in the class as follows:

$$TS_{i,t+3} = \alpha_0 + \alpha_1 Best_{i,t} + \alpha_2 CR_{i,t} + \alpha_3 TS_{i,t} + \alpha_4 School\text{-}cohort_t + \alpha_5 Class\text{-}size_t + \varepsilon_{i,t} \tag{3}$$

where *Best* is an indicator of best student in the class and CR is a vector of dummies for school-cohort ranking position. Again, I run the regression separately for second and fifth grades.

Controlling for a vector of dummies for each position in the school-cohort ranking is crucial to take into account relative ability of the student in the school. Including students' test scores at time t accounts for students ability. Contemporaneous test scores also account for contemporaneous effects of being the best in the class on test scores. The vector of school-cohort fixed effects is necessary to account for selection of students into schools according to their ability. Finally, I allow for the possibility that being best in the class has different implications in big and small classes by including class size fixed effects.

In the context of the previous regression, some concerns on the exogeneity of best in the class may still arise. First, the assignment of students to classes may depend on factors which are revealed only as students grow older. Second, the perspective of a better performance in the future may affect students' current ranking position if teachers and parents act according to their expectations. Third, teachers characteristics could affect the performance trend of the first student in the class. For this reason, I propose an instrument that provides consistent estimates even if class allocation is not fully random or if there is reverse causality or omitted factors affecting my OLS estimates.

3.1 The Instrument

My instrument is the theoretical probability of being the best in the class under random assignment, P. To construct it, I take as given students' position in the school-cohort ranking and the number of classes in the school-cohort. Therefore, P is the theoretical probability that all those students in a school-cohort who are better than a given student are in classes different from him/her. In practice, this is a deterministic function of position in the school-cohort ranking and number of classes in the school-cohort such that:

- If the student is the *second* in the school cohort & there are *two* classes in the school, then $P = 1/2$.

- If the student is the *second* in the school cohort & there are *three* classes in the school, then $P = 2/3$.

- If the student is the *third* in the school cohort & there are *two* classes in the school, then $P = 1/2 * 1/2 = 1/4$
- If the student is the *third* in the school cohort & there are *three* classes in the school, then $P = 2/3 * 2/3 = 4/9$

The general formula for this theoretical probability is:

$$P = \left(\frac{\#classes - 1}{\#classes}\right)^{(CR-1)} \tag{4}$$

where $\#classes$ is the number of classes in the school cohort and CR is the position of the student in the school-cohort ranking.[5]

Table 2 shows the theoretical and empirical probabilities of being the best in the class for different combinations of position in the school-cohort ranking and number of classes in the school-cohort.

The instrument is a function of the school cohort ranking and the number of classes in the school. Given that I control non-parametrically by the school cohort ranking and the school, it is unlikely that the instrument is related to any omitted factor affecting students' performance or that future performance influences the instrument.

4 Results

I first present my results of the random class assignment tests. I then show the naïve OLS estimates of test scores on best in the class which constitute a reference for the causal estimates. Finally, I describe the set of regressions associated to the causal estimate of best in the class on future performance.

Table 3 shows the results of the estimation of Equation (1). For assignment to be random the estimated coefficient should equal the inverse of average class size multiplied by minus one. The average class size is 19.1 in the sample of second graders and 18.4

[5] In computing the theoretical probability of being best in the class I do not take into account that this is also affected by the number of slots available in each class. I do this to avoid that endogeneity arising from class size affects my instrument.

Table 2: Theoretical versus Actual Probabilities of Being the Best in the Class

	Theoretical probability	Actual probability
Cohort ranking=2, #classes=2	0.5	0.46
Cohort ranking=3, #classes=2	0.25	0.24
Cohort ranking=4, #classes=2	0.125	0.13
Cohort ranking=5, #classes=2	0.06	0.08
Cohort ranking=2, #classes=3	0.67	0.57
Cohort ranking=3, #classes=3	0.44	0.37
Cohort ranking=4, #classes=3	0.3	0.27
Cohort ranking=5, #classes=3	0.2	0.19
Cohort ranking=2, #classes=4	0.75	0.62
Cohort ranking=3, #classes=4	0.56	0.45
Cohort ranking=4, #classes=4	0.42	0.32
Cohort ranking=5, #classes=4	0.32	0.28
Cohort ranking=2, #classes=5	0.8	0.62
Cohort ranking=3, #classes=5	0.64	0.5
Cohort ranking=4, #classes=5	0.51	0.4
Cohort ranking=5, #classes=5	0.41	0.3
Cohort ranking=2, #classes=6	0.83	0.61
Cohort ranking=3, #classes=6	0.69	0.46
Cohort ranking=4, #classes=6	0.58	0.4
Cohort ranking=5, #classes=6	0.48	0.34

Table 3: Random Assignment Test

	Grade 2	Grade 5	Grade 8
Second in class	0.006	0.007	0.001
	(0.001)***	(0.001)***	(0.001)
Third in class	0.001	-0.0009	-0.003
	(0.001)	(0.001)	(0.001)**
Fourth in class	0.001	-0.0001	-0.004
	(0.001)	(0.001)	(0.001)***
Fifth in class	-0.0004	-0.004	-0.005
	(0.001)	(0.001)***	(0.001)***
Sixth in class	-0.001	-0.002	-0.007
	(0.001)	(0.001)**	(0.001)***
Seventh in class	-0.005	-0.005	-0.007
	(0.001)***	(0.001)***	(0.001)***
Eighth in class	-0.004	-0.004	-0.006
	(0.001)***	(0.001)***	(0.001)***
Ninth in class	-0.004	-0.005	-0.010
	(0.001)***	(0.0009)***	(0.001)***
Tenth in class	-0.004	-0.007	-0.009
	(0.001)***	(0.001)***	(0.001)***
Eleventh in class	-0.007	-0.006	-0.012
	(0.001)***	(0.001)***	(0.001)***
Twelveth in class	-0.008	-0.006	-0.010
	(0.001)***	(0.001)***	(0.001)***
Thirteenth in class	-0.008	-0.008	-0.015
	(0.001)***	(0.001)***	(0.001)***
Fourteenth in class	-0.007	-0.009	-0.014
	(0.001)***	(0.001)***	(0.001)***
Fifteenth in class	-0.008	-0.011	-0.013
	(0.001)***	(0.001)***	(0.001)***
Sixteenth in class	-0.008	-0.009	-0.010
	(0.001)***	(0.001)***	(0.001)***
Seventeenth in class	-0.007	-0.010	-0.012
	(0.001)***	(0.001)***	(0.001)***
Eighteenth in class	-0.009	-0.011	-0.014
	(0.001)***	(0.001)***	(0.001)***
Obs.	235698	251979	156289
R^2	0.002	0.003	0.005

Notes: Data is from INVALSI test for the years 2012-13 and 2013-14. All regressions include school-cohort fixed effects. Standard errors are clustered at the school level.

in the sample of fifth graders. Hence, the random assignment coefficient under random assignment should be -0.052 and -0.054, respectively. The estimated coefficients are higher than the target values and become more negative as students are ranked lower in the school-cohort ranking. This indicates that there is some positive assortative matching across classes within the same school, specially at the very top of the school ranking.

I next present the results of the test for exogeneity of assignment proposed by Guryan, Kroft, and Notowidigdo [2009]. This test incorporates a correction of the negative bias induced by the presence of the individual herself in the analyzed group. The results of this test suggest that there is a small positive correlation among students' performance within classes. This confirms that I need to use my instrument to obtain consistent estimates of the effect of being best in the class on future performance.

Table 4: Random Assignment Test with Negative Bias Correction

	Second grade	Fifth grade	Tenth grade
Mean TS class	0.014	0.011	0.015
	(0.004)***	(0.004)**	(0.006)**
Mean TS grade	-14.529	-14.528	-10.457
	(0.213)***	(0.141)***	(0.132)***
Obs.	233687	250095	148785
R^2	0.934	0.934	0.854

Notes: Data is from INVALSI test for the years 2012-13 and 2013-14. All regressions include school-cohort fixed effects and class size dummies. Standard errors are clustered at the school level.

I then move to the estimation of the causal effect of being the best in the class. As a first approximation, I estimate the OLS regression of test scores at $t + 3$ on being the best in the class at t controlling for test score at t, ranking position dummies, and number of classes in the school-cohort indicators (see Table 5). I first add school fixed effects and then individual controls to arrive to the specification in Equation (3). We find that the association between best in the class and future test scores is positive and small in all regressions. The magnitude of the estimated correlations decreases as I add controls. This suggests that there is a positive omitted variable bias in the OLS estimates.

In order to address the potential endogeneity of best in the class in the OLS regressions above, I use the instrument defined in Section 3.1. I first address whether the proposed

Table 5: Test Scores in $t+3$ on Best in the Class in t

Panel A: Test Scores in Fifth Grade on Best in the Class in Second Grade. OLS

	(1)	(2)	(3)
Best in class	0.07	0.061	0.055
	(0.006)***	(0.005)***	(0.005)***
Test score	0.449	0.433	0.411
	(0.01)***	(0.009)***	(0.009)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	235,698	235,698	235,698
R^2	0.183	0.155	0.181

Panel B: Test Scores in Eighth Grade on Best in the Class in Fifth Grade. OLS

	(1)	(2)	(3)
Best in class	0.17	0.139	0.133
	(0.006)***	(0.006)***	(0.006)***
Test score	0.322	0.543	0.522
	(0.008)***	(0.009)***	(0.009)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	251,979	251,979	251,979
R^2	0.222	0.216	0.238

Notes: Data is from INVALSI test for the years 2012-13 and 2013-14 together with test scores for years 2015-16 and 2016-17. All regressions include dummies for number of classes in the school cohort, indicators for ranking position, class size dummies, and year fixed effects. Standard errors are clustered at the school level.

instrument is strong in the context of our specifications and selected sample. The first stage estimations displayed in Table 6 show that the instrument is very strong in all three specifications. The magnitude of the coefficients indicates that more of 60% of students in my sample are compliers, i.e., for them being best in the class depends on the exogenous probability that better students are assigned to other classes.

Table 6: First Stage. Best in the Class on Theoretical Probability

Panel A: First Stage. Best in the Class in Second Grade on Theoretical Probability

	(1)	(2)	(3)
Theoretical probability	0.615	0.636	0.636
	(0.015)***	(0.015)***	(0.015)***
Test score	0.001	0.021	0.02
	(0.0005)***	(0.003)***	(0.003)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	235,698	235,698	235,698
R^2	0.499	0.494	0.495

Panel B: First Stage. Best in the Class in Fifth Grade on Theoretical Probability

	(1)	(2)	(3)
Theoretical probability	0.599	0.606	0.605
	(0.015)***	(0.015)***	(0.015)***
Test score	0.003	0.01	0.008
	(0.0005)***	(0.002)***	(0.002)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	251,979	251,979	251,979
R^2	0.496	0.491	0.492

Notes: Data is from INVALSI test for the years 2012-13 and 2013-14. All regressions include dummies for number of classes in the school cohort, indicators for ranking position, class size dummies, and year fixed effects. Standard errors are clustered at the school level.

I then estimate the impact of the theoretical probability of being the best in the class on test scores three years later. I use a reduced form specification in which I substitute the dummy for being best in the class by the theoretical probability of being the best in the class in Equation (3). The results of such exercise are displayed in Table 7. The effect of the theoretical probability of being the best in the class on future test score is negative, significant and consistent across specifications. The magnitude of the estimated causal effect shows that a change from a probability of being the best in the class from zero to one reduces test scores three years later by a magnitude between one fifth and one fourth standard deviation.

Table 7: Reduced Form. The Impact of Theoretical Probability of being Best in the Class in t on Test Scores in $t+3$

Panel A: Reduced Form. The Impact of Theoretical Probability of Being Best in the Class in Second Grade on Test Scores in Fifth Grade

	(1)	(2)	(3)
Theoretical probability	-0.188	-0.214	-0.216
	(0.031)***	(0.029)***	(0.029)***
Test score	0.447	0.418	0.396
	(0.01)***	(0.009)***	(0.009)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	235,698	235,698	235,698
R^2	0.182	0.155	0.18

Panel B: Reduced Form. The Impact of Theoretical Probability of being Best in the Class in Fifth Grade on Test Scores in Eighth Grade

	(1)	(2)	(3)
Theoretical probability	-0.482	-0.267	-0.259
	(0.033)***	(0.032)***	(0.031)***
Test score	0.317	0.522	0.501
	(0.009)***	(0.009)***	(0.009)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	251,979	251,979	251,979
R^2	0.22	0.215	0.236

Notes: Data is from INVALSI test for the years 2012-13 and 2013-14 together with test scores for years 2015-16 and 2016-17. All regressions include dummies for number of classes in the school cohort, indicators for ranking position, class size dummies, and year fixed effects. Standard errors are clustered at the school level.

I then get a sense of the magnitude of the impact of being the best in the class on future test scores instrumenting being the best in the class by the theoretical probability of being the best in the class. Results in Table 8 show that an individual who becomes the best in the class because school mates who are better than him/her are assigned to a different class worsen their fifth and eighth grade test scores by 0.34 and 0.43 standard deviation.

Table 8: The Impact of Best in the Class in t on Test Scores in $t+3$. IV

Panel A: The Impact of Best in the Class in Second Grade on Test Scores in Fifth Grade. IV

	(1)	(2)	(3)
Best in class	-0.306	-0.337	-0.340
	(0.051)***	(0.047)***	(0.046)***
Test score	0.448	0.425	0.403
	(0.01)***	(0.009)***	(0.009)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	235,698	235,560	235,560
R^2	0.17	0.133	0.159

Panel B: The Impact of Best in the Class in Fifth Grade on Test Scores in Eighth Grade. IV

	(1)	(2)	(3)
Best in class	-0.805	-0.441	-0.428
	(0.061)***	(0.055)***	(0.054)***
Test score	0.32	0.526	0.505
	(0.009)***	(0.009)***	(0.009)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	251979	251945	251945
R^2	0.145	0.18	0.203

Notes: Data is from INVALSI test for the years 2012-13 and 2013-14 together with test scores for years 2015-16 and 2016-17. All regressions include dummies for number of classes in the school cohort, indicators for ranking position, class size dummies, and year fixed effects. Best of the class is instrumented using the theoretical probability of being best of the class. Standard errors are clustered at the school level.

5 Extensions and Robustness Checks

5.1 Second in the Class

Does the negative impact of being the best in the class extend to the second in the class ranking? I estimate the impact of being the second in the class using the theoretical probabilities of being second in the class as an instrument (Table 9). The general formula for this theoretical probability is:

$$P = \left(\frac{1}{\#classes}\right) * \left(\frac{\#classes - 1}{\#classes}\right)^{(CR-2)} \tag{5}$$

I first estimate the impact of being second in the class on future performance singularly (column one) and then estimate the impact of being second in the class jointly with the impact of being best in the class in column two. All specifications show that while being best in the class has a detrimental effect on performance, being second has a positive effect. In terms of magnitude the impact of being second in the class is less than half the effect of being the best in the class in absolute value in the first sample (Panel A) and five times smaller in the second sample (Panel B). The reduction in the effect of being second in the class when it is estimated jointly with the effect of being the best indicates that both effects are correlated and thus, students may benefit from being second rather than the best. The different effects of being the best and the second in the class may be explained because the second in the class receives positive influences from the best and does not feel the pressure and demotivation effects so intensively.

5.2 Gender Differences

In my main analysis, I estimate a negative effect of best in the class on future test scores on average. This effect may differ across genders. I explore this possibility by interacting the variable best in the class with a male dummy. Results shown in Table 10 show that females are more affected by the negative influence of being best in the class on future academic performance. However, the magnitude of this gender difference is small.

Table 9: The Impact of Second in the Class in t on Test Scores in $t+3$

Panel A: The Impact of Second in the Class in Second Grade on Test Scores in Fifth Grade

	(1)	(2)
Best in class		-0.280
		(0.049)***
Second in class	0.177	0.126
	(0.036)***	(0.04)***
Test score	0.404	0.399
	(0.009)***	(0.009)***
Obs.	235,560	235,560
R^2	0.176	0.158

Panel B: The Impact of Second in the Class in Fifth Grade on Test Scores in Eighth Grade

	(1)	(2)
Best in class		-0.393
		(0.057)***
Second in class	0.157	0.076
	(0.04)***	(0.045)*
Test score	0.514	0.504
	(0.009)***	(0.009)***
Obs.	251,945	251,945
R^2	0.235	0.205

Notes: Data is from INVALSI test for the years 2012-13 and 2013-14 together with test scores for years 2015-16 and 2016-17. All regressions include dummies for number of classes in the school cohort, indicators for ranking position, class size dummies, and year fixed effects. Standard errors are clustered at the school level.

Table 10: Gender Differences in the Impact of Best in the Class in t on Test Scores in $t+3$

Panel A: Gender Differences in the Impact of Best in the Class in Second Grade on Test Scores in Fifth Grade

	(1)	(2)	(3)
Best in class	-0.336	-0.378	-0.360
	(0.052)***	(0.048)***	(0.047)***
Best in class by male	0.053	0.03	0.03
	(0.013)***	(0.011)***	(0.011)***
Male	0.123	0.116	0.117
	(0.004)***	(0.003)***	(0.003)***
Test score	0.448	0.409	0.402
	(0.01)***	(0.009)***	(0.009)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	235,698	235,560	235,560
R^2	0.176	0.138	0.158

Panel B: Gender Differences in the Impact of Best in the Class in Fifth Grade on Test Scores in Eighth Grade

	(1)	(2)	(3)
Best in class	-0.920	-0.521	-0.497
	(0.063)***	(0.057)***	(0.056)***
Best in class by male	0.174	0.1	0.101
	(0.014)***	(0.012)***	(0.011)***
Male	0.051	0.025	0.028
	(0.004)***	(0.004)***	(0.004)***
Test score	0.318	0.518	0.503
	(0.009)***	(0.009)***	(0.009)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	251,979	251,945	251,945
R^2	0.144	0.177	0.202

Notes: Data is from INVALSI test for the years 2012-13 and 2013-14 together with test scores for years 2015-16 and 2016-17. The best in the class dummy is interacted with male. All regressions include dummies for number of classes in the school cohort, indicators for ranking position, class size dummies, and year fixed effects. Standard errors are clustered at the school level.

5.3 Tenth Grade

As mentioned above, my data also allows to study the impact of best in the class in eighth grade (third grade of secondary school) on performance two years later (second grade of high-school). This transition can be compared to those from the impact of being best in the class in fifth grade on performance three years later as the transition from eight to tenth grade also implies a change in school. The estimation of best in the class effects in tenth grade is affected by attrition as some students in that grade become sixteen and can therefore legally drop out from school. I nevertheless show the results of such estimation in Table 11. Results show a negative impact of being best in the class on future performance. Point estimates are lower in absolute value as compared to those in the main analysis and indicate that being the best in the class in eighth grade reduces test scores in tenth grade by 0.125 standard deviation.

Table 11: The Impact of Best in the Class in Eighth Grade on Test Scores in Tenth Grade. IV

	(1)	(2)	(3)
Best in class	0.008	-0.097	-0.125
	(0.043)	(0.042)**	(0.042)***
Test score	0.679	0.579	0.537
	(0.01)***	(0.011)***	(0.011)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	156,289	156,230	156,230
R^2	0.267	0.184	0.206

Notes: Data is from INVALSI test for the years 2012-13 and 2013-14 together with test scores for years 2015-16 and 2016-17. All regressions include dummies for number of classes in the school cohort, indicators for ranking position, class size dummies, and year fixed effects. Standard errors are clustered at the school level.

5.4 Fourth Order Polynomial in Test Scores

Cicala, Fryer, and Spenkuch [2017] account for ability using a quadratic term while Elsner and Isphording [2017] include a fourth order polynomial of test scores in their regressions. In this section, I make sure my results are robust to the use of the most demanding specification used by previous literature by including a fourth order polynomial of test score in Equation (3). Results in Table 12 support my main conclusions. The estimated effect becomes only slightly weaker for the estimation of the effect of being best in the class in second grade on fifth grade performance (the difference is 0.09) but it remains unchanged for the estimation of the effect of best in the class in fifth grade on eighth grade. The same picture arises with lower order polynomials.

5.5 Restricting the Sample

I restrict my sample to students who are in positions from one to eighteen in the school cohort ranking. Those students have probabilities above one percent of being the best in some class. In this section I explore how my results change when I use more restrictive sample definitions. Table 13 contains the results of using three different sub-samples: Students who are in ranking positions from one to twelve, from one to fifteen and from one to eighteen (the baseline). The resulting estimates show that my main results are driven by students at lower positions of the school ranking.

6 Discussion

Being the best student in the class would be beneficial if it makes students have more self-confidence, exert effort in line with high expectations, receive more attention and better treatment by teachers and peers. In contrast, being the best in the class would be detrimental if it implies unbearable psychological pressure, if it makes students exert lower effort because they do not feel threaten or inspired by a better peer, or if a better peer would have been helpful when studying or doing homework together. Hence, the question of whether being the best in the class is beneficial or detrimental does not have an obvious answer. In this paper, I design a novel methodology to estimate the impact of being the best in the class on future performance. My methodology can be applied even when experimental data is not available.

I exploit natural exogenous variation in class assignment within schools and I find that being the best in the class has detrimental effects on future performance. This effect

Table 12: The Impact of Best in the Class in t on Test Scores in $t+3$ controlling for test scores using fourth order polynomial. IV

Panel A: The Impact of Best in the Class in Second Grade on Test Scores in Fifth Grade. IV

	(1)	(2)	(3)
Best in class	-0.077	-0.246	-0.251
	(0.05)	(0.047)***	(0.046)***
Test score	0.546	0.424	0.404
	(0.013)***	(0.011)***	(0.011)***
Test score^2	0.003	0.031	0.027
	(0.013)	(0.009)***	(0.009)***
Test score^3	-0.030	-0.026	-0.025
	(0.009)***	(0.006)***	(0.006)***
Test score^4	-0.011	-0.020	-0.019
	(0.005)**	(0.004)***	(0.004)***
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	235,698	235,560	235,560
R^2	0.183	0.144	0.169

Panel B: The Impact of Best in the Class in Fifth Grade on Test Scores in Eighth Grade. IV

	(1)	(2)	(3)
Best in class	-0.374	-0.445	-0.429
	(0.057)***	(0.055)***	(0.054)***
Test score	0.486	0.53	0.509
	(0.011)***	(0.01)***	(0.01)***
Test score^2	-0.004	0.053	0.053
	(0.01)	(0.008)***	(0.008)***
Test score^3	-0.061	-0.020	-0.020
	(0.005)***	(0.003)***	(0.003)***
Test score^4	-0.012	-0.003	-0.003
	(0.003)***	(0.002)	(0.002)
School-cohort fixed-effects	No	Yes	Yes
Individual characteristics	No	No	Yes
Obs.	251,979	251,945	251,945
R^2	0.205	0.179	0.203

Notes: Data is from INVALSI test for the years 2012-13 and 2013-14 together with test scores for years 2015-16 and 2016-17. All regressions include dummies for number of classes in the school cohort, indicators for ranking position, class size dummies, and year fixed effects. Best of the class is instrumented using the theoretical probability of being best of the class. Standard errors are clustered at the school level.

Table 13: The Impact of Best in the Class in t on Test Scores in $t+3$ restricting my sample. IV

Panel A: The Impact of Best in the Class in Second Grade on Test Scores in Fifth Grade. IV

	up to 12th	up to 15th	up to 18th
	(1)	(2)	(3)
Best in class	-0.133	-0.246	-0.340
	(0.056)**	(0.05)***	(0.046)***
Test score	0.386	0.386	0.403
	(0.011)***	(0.01)***	(0.009)***
Obs.	158,064	197,058	135,560
R^2	0.117	0.106	0.159

Panel B: The Impact of Best in the Class in Fifth Grade on Test Scores in Eighth Grade. IV

	up to 12th	up to 15th	up to 18th
	(1)	(2)	(3)
Best in class	-0.142	-0.293	-0.428
	(0.061)**	(0.055)***	(0.054)***
Test score	0.517	0.5	0.505
	(0.011)***	(0.01)***	(0.009)***
Obs.	169,096	210,679	251,945
R^2	0.151	0.188	0.203

Notes: Data is from INVALSI test for the years 2012-13 and 2013-14 together with test scores for years 2015-16 and 2016-17. All regressions include dummies for number of classes in the school cohort, indicators for ranking position, class size dummies, and year fixed effects. Best of the class is instrumented using the theoretical probability of being best of the class. Standard errors are clustered at the school level.

is stronger for female students and students who are ranked lower in the school ranking. Results are robust to the use of a sample of higher grade students and to the inclusion of a fourth order polynomial in test scores. Interestingly, the effect of being second in the class on future performance is positive, ruling out that my results are driven by a reversion to the mean of the test score process. My findings have implications in terms of the non-linearity of ranking effects at the extremes of the ability distribution. My findings also lead to some policy recommendations: The promotion of extra-curricular activities where the most talented students interact outside of their class.

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A Appendix

A.1 Institutional Background

The Italian education system is divided into elementary school (grades 1 to 5), middle school (grades 6 to 8) and high school (grades 9 to 13). Education is compulsory between the age of six (grade 1) and sixteen (grade 10). After middle school, students start high schools and follow one of three tracks (vocational school, technical school, lyceum). School year starts mid-September and finishes mid-June. Education is compulsory from September of the year the student becomes 6 up to age 16 which implies that students who have not repeated any grade can drop out from school in grade 10 (second grade of high school). Students who repeat grades can drop out in lower grades as soon as they become 16.

A.2 Other Student Characteristics

Table 14 describes daycare and kindergarden attendance and the education and labor market status of students included in the samples used in the regressions of being best in the class in second grade on fifth grade performance, being best in fifth grade on eighth grade and being best in eighth grade on tenth grade.

Table 14: Descriptive Statistics by Group. Grades 5 and 8. Both Cohorts

	Grades 2 to 5		Grades 5 to 8		Grades 8 to 10	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Attended daycare	0.393	0.488	0.336	0.472	0.276	0.447
Attended kindergarden	0.859	0.348	0.858	0.349	0.885	0.319
Mother elementary school	0.015	0.12	0.018	0.132	0.012	0.111
Mother middle school	0.215	0.411	0.244	0.429	0.228	0.42
Mother high school	0.437	0.496	0.43	0.495	0.446	0.497
Mother vocational school	0.069	0.253	0.078	0.267	0.085	0.279
Mother tertiary non-university	0.026	0.159	0.026	0.161	0.027	0.161
Mother university	0.239	0.427	0.205	0.403	0.202	0.401
Father elementary school	0.019	0.135	0.021	0.143	0.015	0.121
Father middle school	0.296	0.456	0.315	0.464	0.297	0.457
Father high school	0.4	0.49	0.388	0.487	0.397	0.489
Father vocational school	0.079	0.27	0.085	0.279	0.093	0.29
Father other tertiary	0.017	0.129	0.017	0.129	0.015	0.123
Father university	0.189	0.392	0.175	0.38	0.183	0.386
Mother unemployed	0.053	0.225	0.044	0.205	0.032	0.177
Mother homemaker	0.303	0.46	0.326	0.469	0.31	0.462
Mother white collar	0.444	0.497	0.428	0.495	0.451	0.498
Mother self-employed	0.084	0.278	0.086	0.281	0.093	0.291
Mother blue collar	0.114	0.318	0.115	0.319	0.112	0.315
Mother retired	0.001	0.032	0.001	0.034	0.001	0.037
Father unemployed	0.044	0.206	0.042	0.2	0.029	0.168
Father homemaker	0.004	0.059	0.003	0.056	0.003	0.058
Father white collar	0.443	0.497	0.44	0.496	0.456	0.498
Father self-employed	0.242	0.428	0.25	0.433	0.26	0.439
Father blue collar	0.262	0.439	0.257	0.437	0.24	0.427
Father retired	0.005	0.07	0.008	0.087	0.012	0.107
Year of the test	2013.505	0.5	2013.495	0.5	2014.521	0.5

Notes: This table presents averages and standard deviations (left and right column, respectively) for each sample used in the estimations.