EVALUATING SOCIAL TRACKING IN THE PRIMARY SCHOOL: EVIDENCE FROM THE LOMBARDY REGION (ITALY)[1]

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Abstract

Recently, the Italian schools were deeply affected by the "social tracking" phenomenon, intended as the process of segregating students into socio-economic classes. Typically, this phenomenon occurs within the lower secondary school. In such a perspective, the study reported in the paper is innovative, since addressed to investigate the actual presence of the social tracking phenomenon as an event starting from the primary school. For this purpose, we considered data provided by Invalsi (Istituto Nazionale per la Valutazione del Sistema di Istruzione e Formazione) with regard to students of the fifth grade of primary schools in the Lombardy region (Italy). The study was carried out following two different approaches. First, a preliminary descriptive analysis of the segregation phenomenon was carried out by computing the Gini coefficient of the the socio-economic status average at class level. Second, due to the usual hierarchical structure of educational data, multilevel models were considered with the aim of partitioning the pupils' socio-economic status variability within the student, class and school level. In this way, school and class social segregation indicators were obtained. Subsequently, a conditional multilevel model including school and class social segregation indicators as explanatory variables was built. Results underline that even though in general social tracking is not an actual threat for the Lombardy primary schools, a remarkable socio-economic heterogeneity among classes appears especially in some provinces of the Lombardy region.

Key words: social tracking phenomenon, class heterogeneity, Gini coefficient, segregation indices, multi-level modeling, Invalsi data

1. Introduction

Interest in evaluating the Italian education systems is manifest in a large number of recent publications and in the diffusion of standardized tests (e.g., Haladyna, 1991; Ballard and Bates, 2008). Typically, the content of these contributions focuses on the main pupils and schools' determinants affecting the learning levels of students. If on one hand the educational research field stresses the impact of such factors on the students' attainments, on the other hand only a few works addressed the issue of equal opportunity in education (i.e. each state must provide the same opportunities for everyone who attends school regardless of gender, race or nationality). Even though the Italian law imposes the "equity principle" which should be preserved by composing the most possible heterogeneous classes, recent studies highlight that the practice of segregating students with similar features is particularly widespread, especially in the lower secondary schools (e.g. Ferrer-Esteban, 2011). Such a sociological issue falls under the name of "formal tracking" phenomenon. In some cases, school staff may generate a great deal of selection by assigning children with similar achievement to the same classroom, in order to minimize teaching difficulty, or by placing all of the "problematic" students in a certain teacher's class because he is good at dealing with them. However, the segregation phenomenon can be generated in several ways and at different levels. Specifically, the increasing participation of the pupils' parents to the dynamics of the school is leading to a kind of "informal tracking" phenomenon, allowing families to influence the classroom composition in order to better respond to their social features, such as for instance their socio-economic status (e.g. Dupriez et al., 2008).

Social tracking gives rise to homogeneity within classes (social segregation) that in turn may come out in inequality of education opportunities (e.g., Checchi and Flabbi, 2007; Hindriks et al., 2010). Children with different family background, race and ability will have different access to knowledge. It was proven (for example, Loveless, 1999) that whether the curriculum is adjusted to better match ability level of students, while high ability students may receive a boosted achievement, low ability students may suffer from assignment to lower tracks. Thus, homogeneity within classes negatively affects disadvantages students. Classroom environment is then really important for student achievement, as stated by Hill and Rowe (1996): *"How much a student learns depends on the identity of the classroom on which the student is assigned"*. Indeed, a student's innate ability can affect his peers, not only through knowledge spillovers but also through his behavior. On the contrary, a student who has not learned self-discipline at home may bother the classroom.

The study presented in this paper is innovative since it attempts to explore the actual presence of the social segregation phenomenon in Italy as an event starting from the primary schools. Indeed, to the best of our knowledge, no research contributions illustrating the existence of an informal tracking phenomenon in the Italian primary schools are currently provided in literature. More precisely, our research question is the following. Since primary schools represent the first education compulsory stage after the kindergarten, the segregation process of kids can probably be encouraged by parents on the basis of their socio-economic features. Kindergarten has a relevant role in the process of contact among the families of kids. Thus, the pupils' families may wish that their children were kept together with their kindergarten friends, when accessing to the primary school.

The analysis was carried out on data provided by the National Evaluation Committee (Istituto Nazionale per la Valutazione del Sistema di Istruzione e Formazione, henceforth Invalsi). In Italy the National Evaluation Committee has been established with the specific aim of evaluating the Italian schools through the analysis of the students' achievement at different levels of education; second and fifth year of the primary school (age 7 and 10, respectively), first and third of the lower-secondary (age 11 and 13), second and fifth of the upper-secondary (age 15 and 18). The collection of such data started from the school year 2008-2009 and represents the first time that a law imposes a national evaluation by using standardized tests in all students population. Here, we considered a unique dataset that tracks the performance in Reading of students of the fifth grade of primary schools in the Lombardy region for the school year 2009-2010.

On the statistical point of view, our proposal was pursued through two different approaches. First, a preliminary investigation of the social tracking phenomenon was provided by resorting to a descriptive inequality index, the Gini coefficient, which is widely used for studying inequality in education attainments (e.g., Leckie et al., 2012). The Gini coefficient was computed by taking into account the class average value of the variable representing the socio-economic status (henceforth denoted by SES) over all the classes in every province of the Lombardy region. Second, to shed light on how the heterogeneity of the students' performance and SES are portioned out between school and class level, different multilevel models were considered both to properly take into account the hierarchical structure of data with pupils nested in classes and schools (e.g., Snijders and Bosker, 1999) and to define social segregation indices at school and class level. Finally, a conditional multilevel model with even the social segregation indices is performed.

The remainder of the paper is organized as follows. In Section 2 the examined Invalsi dataset is illustrated and some descriptive statistics provided. In Section 3 a preliminary analysis of the social tracking phenomenon is introduced by resorting to a descriptive approach based on the Gini coefficient. In Section 4 an overview of the proposed multilevel methodology is presented. In Section 5 school and class level social segregation indices are computed and commented. Section 6 is devoted to the discussion of the obtained results. Finally, Section 7 concludes.

2. Data

Our proposal is based on data coming from the survey led by Invalsi at the end of the school year 2009-2010 and referring to students of the fifth grade (students of about 11 years old). Coherently with our research scope, the variable under study is here detected by the pupils school achievement in Reading, expressed as the proportion of correct answers provided in the administered test by each student. Such data cover the whole population (it is not a sample) made up of 77.200 students belonging to 4.488 classes that in turn belong to 1.050 primary schools located in different provinces of the Lombardy region. The administered test is built on 41 multiple-choice items and is composed by two parts: the former is related to the comprehension of two texts and the latter is related to the grammar issues. The testing time is of one hour. The test reserves even a set of questions concerning the students' personal information (e.g. gender, ethnicity, grade retention and so on). Further information about the social, economic and cultural conditions of students are collected through additional questionnaires filled by the School Principals and students' parents. Variables considered for the analysis are enlisted below and include:

- demographic variables: i.e. gender, ethnicity, year of birth;

- sociocultural variables: in this case, a synthetic index, named SES is made directly available by Invalsi. It is computed analogously to the OECD's procedure, that is by considering the parents' occupation and education, possession of some kinds of goods such as, for instance, the availability of an encyclopedia or an Internet connection, the number of books at home and so on (Campodifiori et al., 2010);
- school variables: school size (number of students), type of school administration (private or public), number of female students, number of students repeating one or more grades and number of students belonging to ethnic minorities;
- geographical area of the school, specified in the provinces of the Lombardy region: Bergamo (BG), Como (CO), Lecco (LC), Lodi (LO), Milano (MI), Pavia (PV), Varese (VA), Brescia (BS), Cremona (CR), Mantova (MN) and Sondrio (SO).

A note about the type of school administration (private or public) is needed. For private school we mean schools with private involvement in managing and funding. Here, we only focused on private schools following the ministerial program and thus considered equivalent to the public ones.

Before proceeding to the construction of the statistical model, an analysis of missing data was done for all the variables that potentially may be included in it. The reference dataset is characterized by variables which present missing values at random. However, the main trouble appears with the pre-school (i.e. kindergarten attendance) variable whose lack of information is consistent, since missing values amount to the 10.4%. In such a context, the problem of missing data was easily solved by directly deleting the pre-school variable from the model. This is because, the ejection of the pre-school variable from the model found reason in its low contribution in explaining the Reading scores variability.

In order to provide more interpretable parameters, all the variables were standardized and a reference level was defined (e.g., Snijder and Bosker, 1999). Furthermore, to better clarify the role of the categorical variables included into the model and concerning the demographic characteristics of pupils (i.e. gender, ethnicity, and grade retention) and the school features (public or private status), a related description is presented in Table 1, where the corresponding reference categories are reported.

Table 1. Description of the pupil and school categorical variables

Variables	**Description**
Demographic	
Gender	Male (reference category); Female
Ethnicity	Italian (reference category); Ethnic minorities of first or second generation
Grade Repetition	Student that has not repeated a year (reference category, pupils born in 1998); Student that has reapeated at least a year (grade repetition)
Educational	
School Administration	Public (reference category); Private

With regard to class and school level, we considered variables representing the proportion of students being female, repeating one or more grades and belonging to ethnic minorities. These variables were already available in the dataset at school level and relate to students belonging to all grades in the school. On the contrary, variables at class level were derived as aggregation of individual covariates at class level. Thus, the latter are related only to students participating to the survey of the fifth grade. Moreover, the school and class average of the students' SES index were computed as aggregation of individual SES index.

The main key statistics about variables at class and school level are displayed in Table 2. It is worth noting that variables at school level were centered on the grand mean and variables at student level were centered on the school average. As shown in Table 2, the average score[4] amounts to 73.20 with a standard deviation equal to 16.63, the average percentage of female is the 49% at class level and the student SES average is 0.03 at class level and 0.04 at school level. In addition, almost the 9% of schools are private, the average percentage of ethnic minority students amounts to the 13% both at class and school level, while the average percentage of students repeating the year is the 3% at class level and smaller than the 1% at school level.

Table 2. Descriptive Statistics

		Number of units	Mean	St Dev	Min	Max
Class	Score in Reading	77,200	73.20	16.63	0.00	100.00
	% Ethnic Minorities	4,466	0.13	0.55	0.00	1.00
	Class mean SES	4,487	0.03	2.17	-2.05	2.16
	% Females	4,485	0.49	0.51	0.00	1.00
	% Student Repeating the year	4,487	0.03	0.23	0.00	1.00
	Class size	4,488	20.00	10.00	6.00	28.00
School	% Ethnic Minorities	1,050	0.13	0.18	0.00	0.83
	School mean SES	1,050	0.04	0.86	-1.28	2.04
	% Females	1,050	0.48	0.07	0.00	1.00
	% Student Repeating the year	1,050	0.003	0.01	0.00	0.03
	School size	1,050	532.00	428.00	28.00	1,338
	School Administration: Public	74,265	91.17			
	School Administration: Private	7,191	8.83			
	Province: BG	10,020	12.30			
	Province: BS	11,401	14.00			
	Province: CO	4,869	5.98			
	Province: CR	2,833	3.48			
	Province: LC	2,867	3.52			
	Province: LO	1,923	2.36			
	Province: MN	3,477	4.27			
	Province: PV	3,991	4.90			
	Province: SO	1,558	1.91			
	Province: VA	7,412	9.10			
	Province: MI	31,105	38.19			

3. Preliminary Analysis: the Gini coefficient

In the literature, a wide range of indices are proposed for assessing the actual presence of the social tracking phenomenon. As deeply discussed by Leckie et al. (2012), Hutchens (2004) and Reardon and Firebaugh (2002), researchers typically resort to descriptive indices such as, for instance dissimilarity and square root indices (e.g., Duncan and Duncan, 1955; Jenkins et al., 2008), in order to detect possible scenarios of inequality in education opportunity. Since our aim is not limited to detect the presence of inequality in opportunity but to measure its extent, within the large set of available descriptive indices, the Gini coefficient was considered (e.g., Gini, 1921). More in detail, the idea here is to provide a measure of the heterogeneity between classes in term of the socio economic status of students. For this purpose, we propose to consider as variable of interest the average SES at class level. For all the classes within each school and each province of the Lombardy region, we computed the average value of the students' SES index. We remark that for every single student, the SES index ranges between -3 and +3. Thus, it is reasonable to believe that the average SES at class level may take even negative values. In such a context, the reliability of the classical Gini coefficient may come less since requiring the considered variable to be characterized by non-negative values. Indeed, in case of negative values, the Gini coefficient may violate the normalization principle and thus take values greater than one. A solution to this problem was recently provided by Raffinetti et al. (2014), who introduced a new Gini coefficient adjusted for the presence of negative values. The new Gini coefficient, expressed as the ratio between the absolute mean difference $(1/N^2)\sum_{i=1}^{N}\sum_{j=1}^{N}|Y_i - Y_j|$ and $(2/N)\sum_{i=1}^{N}|Y_i|$, fulfills the normalization principle. This allows us to provide a measure of inequality in opportunity which can occur as a consequence of the class composition process conditioned to the pupils' socio-economic status. Indeed, if the Italian schools actually respected the legislative principle of "equal-heterogeneity" in the composition of classes, the Gini coefficient should be close to zero. This does not happen, as shown by results in Table 3, where the Gini coefficient of the average SES at class is reported for every province.

Table 3. Gini coefficient of the average SES at class level per province

Province	BG	BS	CO	CR	LC	LO	MI	MN	PV	SO	VA
Gini coefficient	0.65	0.67	0.71	0.69	0.72	0.71	0.72	0.63	0.73	0.69	0.70

The Gini coefficient is greater than 0.60 in all the provinces. More precisely, over the 50% of the provinces presents a Gini coefficient greater than 0.70. The province of PV has the higher heterogeneity between classes with a Gini coefficient equal to 0.73. Such findings are made more evident by the boxplots in Figure 1 which show a remarkable variability of the average SES at class level in every province of the Lombardy region.

Even though these descriptive statistics seem to confirm the presence of the social tracking phenomenon, they are obtained without taking into account the hierarchical structure of classes nested in schools. Thus, the high heterogeneity between classes at province level may reflect the high heterogeneity between schools within the province. For this reason, one may assume this variability to be explained by the gaps across the territorial areas where schools are located. Indeed, schools located in more disadvantaged areas catch more disadvantaged students. Further investigations were carried out by distinctly computing the Gini coefficient of the SES average at class level within each school across all the provinces. Also in this case, the Gini coefficient reaches very high values, leading us to believe that heterogeneity between classes is a real threat for the equality in opportunity in the Italian primary schools. In order to validate such a conclusion, the multilevel modeling approach (e.g., Goldstein, 2011) was considered to take into account the complexity of the educational systems organized in school and class level. First, we assessed how the variability of SES portions out among the different considered levels in order to define segregation status indicators at class and school level, as suggested by Ferrer-Esteban (2011). Subsequently, we analyzed the partition of the variability of the scores in the Reading test among the different levels. Finally, a conditional multilevel model was built in order to evaluate the effects of both the SES index and segregation status indicators, after controlling for the aforementioned variables, with the purpose of detecting the actual presence of the social tracking phenomenon across the Lombardy primary schools.

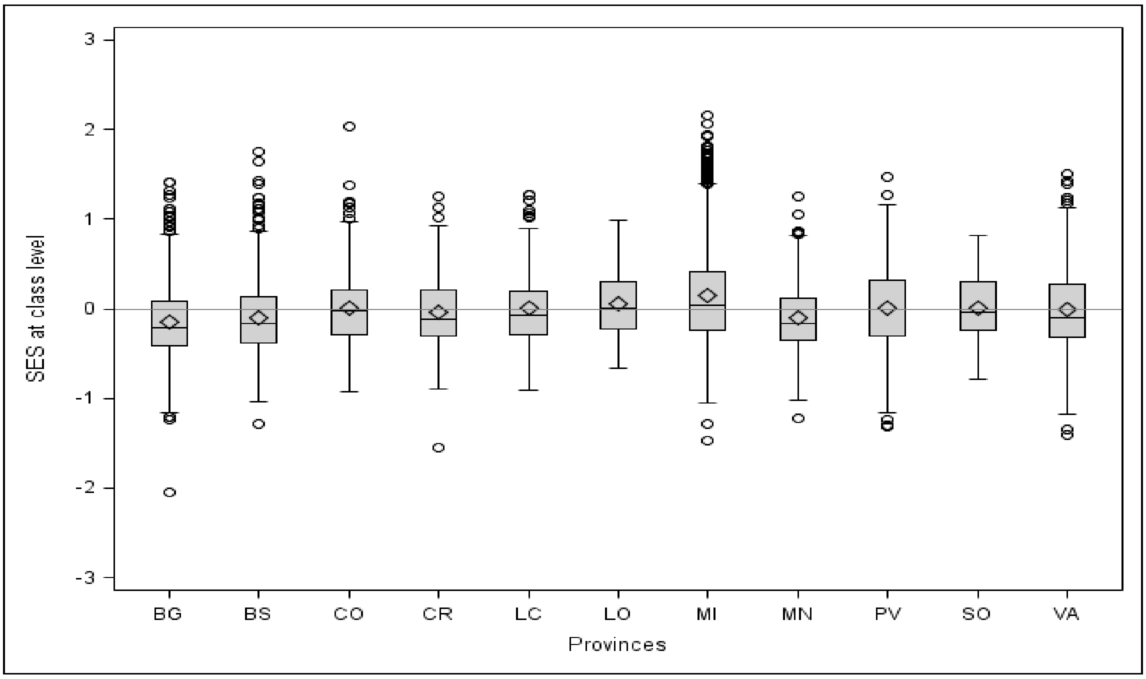

Figure 1. Boxplots of the average SES at class in every province of the Lombardy region

4. An overview about three-level models

As mentioned above, models suitable in treating hierarchical data are the multilevel models since they allow relationships to be simultaneously assessed at several levels (e.g., Snijders and Bosker, 1999), represented by pupils, classes and schools. Some details about the multilevel algebraic specification are briefly provided below.

Let us consider a three-level multilevel model in educational context, where level 1 is represented by students, level 2 by classes and level 3 by schools. The relationship between the i-th student's achievement, belonging to the j-th class, which in turn belongs to the k-th school, is expressed by:

$$y_{ijk} = \beta_{0ijk} + \beta_1 x_{ijk} \,, \tag{1}$$

$$\beta_{0ijk} = \beta_0 + v_{0k} + u_{0jk} + e_{0ijk} \,, \tag{2}$$

where: v_{0k} is the random effect at school level, an allowed-to-vary departure from the grand mean, u_{0jk} is the random effect at student level, a departure from the school effect and e_{0ijk} is the random effect at student level, a departure from the class effect within a school. The variance components at each level are defined as follows: variance between schools, $Var(v_{0k}) = \sigma_{v0}^2$; variance between students within classes within schools $Var(u_{0jk}) = \sigma_{u0}^2$; variance between students within classes within schools $Var(e_{ijk}) = \sigma_e^2$; and variance between classes $\sigma_{v0}^2 + \sigma_{u0}^2$. Different forms of variance shares are derived: the share of variance due to gaps between schools, corresponding to the intra-school correlation (level 3)

$ISC = \frac{\sigma_{v0}^2}{\sigma_{v0}^2+\sigma_{u0}^2+\sigma_e^2}$, and the share of variance due to differences between classes, corresponding to the intra-class correlation (level 2) $ICC = \frac{\sigma_{v0}^2+\sigma_{u0}^2}{\sigma_{v0}^2+\sigma_{u0}^2+\sigma_e^2}$.

Since multilevel models allow to decompose the variability of a specific phenomenon among the different involved levels, they provide information about the heterogeneity associated to each considered level. To have an idea of such heterogeneity, first the intra-class correlation coefficient (ICC) was computed. Indeed, through such a coefficient, the extent of the outcome variation related to gaps between units of each considered level was obtained. Secondly, a model with variables described in Section 2 was built to show both covariates really affecting the students' achievement and their impact. Furthermore, also segregation status indicators at class and school level were considered. The latter is identified as the between classes and schools variance, when an unconditional multilevel model for the SES variable is fitted. Finally, a comparison between the unconditional model (empty) and the conditional (full) model was introduced to show the contribution of the same model in explaining the performance variability at each level of the analysis. The residual variance located at different levels was interpreted as the result of unobserved factors, as discussed in more detail in Section 6.

5. Segregation indices

As suggested by Ferrer-Esteban (2011), social segregation at class and school level are typically measured trough the between-class variance and the the between-school variance, respectively.

A fully unconditional three-level model for the SES index allows to portion the SES variability among the considered level: within classes, between classes within schools and between schools. A high variability of SES between classes underlines more heterogeneity among different classes within the same school, meaning that classes are more homogeneous in respect of their social background. Conversely, a high SES variability between schools underlines more heterogeneity among schools, implying aggregation of students with similar social background within the school. These indicators give an idea of the extent both schools and classes within schools are socially dissimilar. Ferrer-Esteban (2011) analyzed the Italian secondary schools and found out that the SES variability at school level reaches a value of 32% in some Italian provinces, while the SES variability at class level reaches a value of 12%. Furthermore, they stressed that while the SES variability at school level is connected with the presence of metropolitan areas, the SES variability at class level has a clear pattern of territorial distribution that responds to a north-south gradient, with higher values of class segregation in the South of Italy.

For what concerns the primary schools we expected a remarkable SES variability between schools, given that this kind of school is particularly widespread across the Italian territory. For this reason, primary schools usually catch students of the area in which they are located. So, schools located in areas with more disadvantaged families will catch disadvantaged students. Furthermore, the high diffusion of the primary schools involves schools to be composed by one or few classes for each grade, leading to expect a low SES variability between classes. In Table 4 the segregation indicators at province and regional level for the Lombardy primary schools are reported.

Table 4. Social segregation indicators

Province	Between class variance (in %)	Between school variance (in %)
BG	2.24%	15.28%
BS	2.71%	14.85%
CO	5.33%	11.03%
CR	2.88%	11.76%
LC	2.20%	17.53%
LO	3.80%	12.36%
MI	3.46%	25.20%
MN	3.12%	7.06%
PV	4.47%	17.49%
SO	2.49%	8.53%
VA	3.67%	16.53%
Lombardy	3.23%	19.58%

In the Lombardy region, the variability of SES between schools is equal to 19.6%, while between classes it is equal to 3.2%. In particular, the Lombardy provinces highlight a SES variability at school level ranging between the 7.1% of Mantova and the 25.2% of Milano, and a SES variability at class level ranging between the 2.2% of Bergamo and Lecco and the 5.3% of Como and Pavia. These values, compared to the findings illustrated by Ferrer-Esteban (2011) across the whole Italy and for the lower secondary schools, are to be considered non-low. Indeed, it is well-known that the social segregation is a phenomenon appearing more marked in the lower secondary school and in the South of Italy. As expected, the metropolitan area of Milan presents a high variability of SES between schools. The SES variability between classes is low on average, but with non-low values for some provinces. To evaluate if such heterogeneity between schools and classes provides an actual impact on the students' achievement, a multilevel model built on the Reading score was considered. The related results are discussed in the following section.

6. Multilevel model results

The content of this section is focused on both the analysis of the partition of the test performance variability at individual and group level and identifying the presence of social segregation. Typically, in the education literature the study of variability in achievements is based on two-level models characterized by student and school level. Our aim is a little bit wider since addressed to identify the share of variability attached both to school and class level. The need of including the class level is supported by our research question, that is investigating the actual presence of social tracking within the Italian primary school. For this reason, a three-level model was applied to account for the class level.

In order to define the performance variability partition among the three involved levels, an empty model without explanatory variables was applied. The related results in terms of variance decomposition and intra-class correlation coefficient (ICC) are reported in Table 5.

Table 5. Variance decomposition of the implemented multilevel model – fifth grade of primary school

	Three level - School-Class-Student	
	Empty model	*ICC (%)*
Var. Between Schools	13.0	4.7
Var. Between Classes	21.3	7.7
Var. Within Classes	243.0	87.6
Total Var.	277.3	100.0

According to such findings, in primary school the well known prevailing variability in performance depends on the students' characteristics ($\sigma_e^2 = 243.0$). In addition, variability between classes is greater than variability between schools, in line with the evidence gathered from several studies (e.g., Hill and Rowe, 1996). Indeed, the former ($\sigma_{v0}^2 = 21.3$) is almost double with respect to the latter ($\sigma_{u0}^2 = 13.0$). Despite we expected a low variability between classes when only a grade is considered, we found a high percentage of this variability equal to more than the 7% of the total one. Variability between classes appears as the consequence of several factors which may be strictly related to grade, teacher effect and unobservable variables as well as peer effect.

To shed light on individual, class and school variables really impacting on the students' achievement, a conditional multilevel model was considered. Results about variables significance are displayed in Table 6. Variables marked by three asterisks in Table 6 are significant at a confidence level $\alpha = 0.01$, variables marked by two asterisks at a confidence level $\alpha = 0.05$ and finally, variables marked by only an asterisk at a confidence level $\alpha = 0.1$. Variables representing the percentage of female students, the percentage of students repeating a year, the size of class and school are non-significant in the analysis at both school and class level. The intercept value represents the Reading score for an "average" student who is defined as an Italian male student, with no grade retention, a SES index equal to the average value of all the students, and whose class presents a percentage of students belonging to ethnic minorities and an average SES index corresponding to the mean value of all the classes. Furthermore, his attended school is public, located in Milan and characterized by a percentage of students belonging to ethnic minorities and an average SES index equal to the mean value of all the schools. Such a student achieves a performance in Reading equivalent to 77.21 (i.e. an "average" student correctly answers to the 77% of the test). To be a male implies a reduction in Reading score equal to 1.64. As it is trivial to believe, when focusing on individual student variables, the consistent decrease of the Reading score is related to students belonging to ethnic minorities of first generation (-11 points). Student belonging to ethnic minorities of second generation provides a smaller decrease in Reading achievements, corresponding to 7.80 points. Definition of ethnic minorities of first and second generation is needed. Ethnic minorities of first generation are students born in their origin country from parents belonging to ethnic minorities, while ethnic minorities of second generation are students born in Italy from parents belonging to ethnic minorities. The same negative results on the Reading performance are associated to class and school variables concerning the percentage of students belonging to ethnic minorities. Obviously, also the grade retention involves a worsening of -7.43 points. Conversely, a positive trend in Reading performance is associated to the SES index. Indeed, an unitary increment in the SES index value provides an increase of 4.38 points in the Reading score. This happens also for the school and class SES index variable. Students attending a school in the province of Lodi, Mantova and Brescia reach worse results with respect to those attending a school in the province of Milan.

Table 6. Three-level Multilevel model Effects

Levels	Variables	Estimate
Student	Intercept	77.21***
	Gender (Female)	-1.64***
	Ethnic minority - First Generation (Ref. Italian)	-10.99***
	Ethnic minority - Second Generation (Ref. Italian)	-7.80***
	Grade Repetition	-7.43***
	Student SES	4.38***
Class	% Ethnic minority in class	-0.05**
	Class mean SES	0.98***
	% Female students in class	0.00
	% Repeating the year in class	0.03
	Class size	-0.04
School	% Ethnic minority at school	-0.08***
	School mean SES	3.18***
	% Female students in school	-0.01
	% Repeating the year in school	0.16
	School size	0.05
	Private school (Ref. Public)	-0.98
	School Segregation	-8.83*
	Class Segregation	-53.03
	Province: BG (Ref. MI)	0.26
	Province: BS (Ref. MI)	-0.93*
	Province: CO (Ref. MI)	1.37
	Province: CR (Ref. MI)	-1.31
	Province: LC (Ref. MI)	0.09
	Province: LO (Ref. MI)	-2.44**
	Province: MN (Ref. MI)	-2.75***
	Province: PV (Ref. MI)	0.24
	Province: SO (Ref. MI)	0
	Province: VA (Ref. MI)	0

Both school and class segregation indicators, computed in Section 5, were considered for every province and included as explanatory variables into the model. While the school segregation indicator is significant in the model, the class segregation indicator does not. This finding involves the presence of school segregation and the absence of class segregation in the Lombardy primary schools. Such a conclusion arises as the consequence of the widespread of the primary schools across the Italian territory. Indeed, since the primary schools usually receive students living in the area where the schools are located, the socio-economic status of the area strongly affects the socio-economic status of the school. The consistent SES variability between schools is in general an expected result which further stands out for the metropolitan area of Milan. In particular, it is worth noting that the effect of segregation on achievement is negative causing a reduction of over 8 points on the Reading performance.

To clarify the contribution of such variables in explaining the students' achievement variability in the Reading test, an analysis on the variance reduction at school and class level was carried out. As shown in Table 7, the full multilevel model provides a contribution of about only the 33.7% of the students' performance variability at school level, about the 17.7% at class level and about the 15% within class level. These outcomes have not to be considered as a failure of our proposed approach, since typically in the primary school the main share of variability in achievement is the consequence of non-observable students' characteristics such as, for instance, hours working on homework and/or students' interest in school matters.

Table 7. Decomposition of Variance

Variance	Empty Model	Conditional Model		Factors
	ICC	Reduction	ICC	
Between Schools	4.7%	33.7%	1.3%	Observed school factors
			2.5%	Other unobserved factors
Between Classes	7.7%	17.7%	1.3%	Observed class factors (class composition)
			6.2%	Teacher effect and other unobserved factors
Within Classes	87.6%	15.0%	13.3%	Observed individual factors
			75.5%	Other unobserved individual factors
Total	100.0%	16.1%	100.0%	

The explained variance has to be ascribable to the presence of observed factors at different levels, while the residual variance can be ascribable to the presence of unobserved factors. For instance, at class level the residual variance may include the impact of teacher and/or other unobserved factor. Definitely, observed school factors explain only the 1.3% of the performance variability. Unobserved school level factors account for the largest differences in variability in school performances, but in this case they capture just the 2.5% of the overall variability in achievements. Compositional factors at class level account for the 1.3% of the overall performance variability. Thus, it is reasonable to believe that, the impact of unobservable variables between classes (within schools) on gaps in achievement, is much more marked amounting to the 6.2%. Finally, the unobserved individual factors account for the 75.5% of the overall variability highlighting that the unobservable student's characteristics represent the largest differences in the non-explained variability.

7. Conclusions

In this paper we investigated the presence of the social segregation phenomenon by analyzing education data provided by Invalsi and concerning the achievement in the Reading test, obtained in the school year 2009-2010, by students attending the fifth grade of the primary schools in the Lombardy region (Italy). From this point of view, our study is innovative since it attempted to detect the social segregation phenomenon as an event starting from the primary schools. For this purpose, two different approaches were considered. First, a preliminary investigation of the social tracking phenomenon was provided by resorting to the Gini coefficient computed by taking into account the class average value of the SES variable over all the classes in every province of the Lombardy region. Results show a high heterogeneity between classes and would seem to validate the hypothesis of social tracking inside the primary schools. However, to account for the hierarchical data structure, a multilevel model was carried out. First of all, segregation indices at class and school level through a fully unconditional three-level model for the SES index were found out. Such indices are defined in terms of the SES index (representing the pupils' socio-economic background) variability among the considered levels (i.e. within classes, between classes within schools and between schools). Findings highlight that even though the SES index presents a low variability on average, such variability is consistent in value across some provinces. Then, a conditional multilevel model including both indicators of between class and school segregation as explanatory variables for every province was built. While the school segregation index is significant in the model, the class segregation index does not. These results suggest that the segregation phenomenon mainly occurs at school level, neglecting the actual threat of the social tracking phenomenon in the primary schools of the Lombardy region. However, from a descriptive point of view the presence of a consistent class heterogeneity is an evidence especially in some provinces of the Lombardy region. This issue encourages us to believe that such a phenomenon may represent an actual event in early education in the areas of Italy (South and Islands), where inequality in households' socio-economic status is known from the literature to be more marked.

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[4] The score on Reading test corresponds to the total percentage of correct answers provided by the students. Thus, it lies between 0 and 100.