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Learning Loss and Students' Social Origins During the Covid-19 Pandemic in Italy

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Abstract

The aim of this paper is twofold. First, it is intended to establish the intensity of learning loss in reading and mathematics experienced in Italy by fifth, eighth and thirteenth graders because of school closures owing to the Covid-19 pandemic. Second, it aims to demonstrate whether school closures have or have not affected the educational inequalities associated with the social position of the students' families, their geographic area of residence, their migrant status and their high school track. To estimate these two possible effects, we exploit INVALSI data collected in school years 2018/2019 and 2020/2021 and rely on a counterfactual approach based on coarsened exact matching, where students belonging to the 2020/21 cohort represent the treated group and those of the 2018/19 cohort make up the control group. Our results indicate that the learning loss is definitely severe among students attending grade thirteen and eight, while it is less pronounced and involves only mathematics among fifth graders. Moreover, according to our hypotheses, the intensity of the learning loss turns out to be substantially the same across social strata of students' origins and their remaining ascriptive traits.

JEL-Code: I21, I24

Key words: Learning loss; social inequalities; Covid-19; Italy.

1 Introduction

As is well known, during the school years 2019/20 and 2020/21, the governments of many countries, in the attempt to limit the spread the of Covid-19 virus, decided to close schools temporarily, suspend face-to-face teaching, and replace it with on-line learning. Epidemiologists considered this decision a very effective measure to fight the pandemic. However, among social researchers, school closure raised strong concerns regarding its possible negative effects on students' academic performance and the extent of educational inequalities. Therefore, as a recent review (Hammerstein et al. 2021) has shown, many surveys on those topics were conducted in 2020 and 2021. Unfortunately, this same review documents that the number of sound analyses – that is to say, those based on data models for longitudinal data or counterfactual impact evaluations – is rather limited[1]. Moreover, such surveys focused only on primary and lower secondary schools or, even, exclusively on one of them. Therefore, the educational consequences of the Covid-19 pandemic have not yet been fully documented. This paper intends to increase the available information on these consequences. More precisely, its main purpose is to verify whether or not the closure of the entire Italian school system has effectively deepened previously existing educational inequalities.

Quite obviously, the studies referred to above have already addressed this issue, and two of them (Contini et al. 2021; Borgonovi & Ferrara 2022) were specifically devoted to the Italian situation. However, they too ignored high school students. Moreover, all the previous analyses on this topic have paid closer attention to students' pre-pandemic school performance than to their families' social positions, and their analysis of the latter does not appear entirely convincing. Furthermore, the conclusions they have reached about the relative roles played by each of these two factors are rather mixed.

With respect to the uncertainty of the conclusions regarding variations in disparities associated with previous levels of student achievement, it must be stressed that, while several studies have found a decline in their intensity (Kuhfeld et al. 2020; Contini et al., 2021; Engzell et al., 2021; Spitzer & Musslick, 2021; Tomasik et al. 2021; Schult et al., 2022), others have observed: i) an opposite trend (Clark et al. 2020); ii) a mixed trend, with reduced inequality in one subject and

[1] Quite obviously, we have updated to March 2022 the list of the researches considered by Hammerstein and her associates, adding three more surveys.

increased inequality in another , (Borgonovi & Ferrara, 2022), and iii) even no variation (Depping et al. 2021; Gore et al. 2021).

On the other hand, the results obtained by those studies that have considered variations of inequalities associated with students' social origins present three problematic aspects. The first refers, once again, to the uncertainty surrounding their intensity. The studies we have examined found, in a very similar proportion, either an increase (Engzell et al. 2021; Gore et al. 2021; Meeter et al., 2021; Sass & Goldring, 2021; Maldonado & De Witte, 2022) or, conversely, stable, and even reduced disparities (Kuhfeld et al. 2020; Birkelund et. al, 2021; Contini et al. 2021; Depping et al. 2021; Borgonovi & Ferrara 2022). The second problematic aspect lies in the risk of ecological fallacy faced by studies that infer an increase, or a decrease, of educational inequalities associated with students' social origins from comparisons of schools with different incidences of students from disadvantaged socio-economic-backgrounds (Kuhfeld et al. 2020; Meeter et al., 2021; Sass & Goldring, 2021; Maldonado & Devitt, 2022; Schult et al., 2022).[2] The third, and more general problem affecting several analyses of the learning consequences of school closures in light of students' social origins is represented by the variables adopted for expressing those origins. Quite often, the distribution of the selected characteristics (disposable family income, eligibility for free school lunch, parents' position in the labour market, parents' level of schooling, number of books owned by a family, and the like) appears to be rather weak proxies of the social stratification system of contemporary societies. Furthermore, the variable considered is usually partitioned quite sharply into a dichotomy or very few categories. As a consequence, these analyses are based on the comparison of small groups of families with all the other families in a society (Kuhfeld et al., 2020; Birkelund et al. 2021; Engzell et al., 2021; Gore et al., 2021; Meeter 2021; Sass & Goldring, 2021), rather than on the examination of the relative situations of the different social strata or classes. Sometimes, however, the social standing of students' families is represented more accurately through scores derived from factorial analyses (or similar techniques) carried out using information regarding several aspects of their socio-economic conditions (Gore et al., 2021; Maldonado *et al.*, 2021; Borgonovi & Ferrara, 2022). Yet, these scores are either treated as continuous variables or split into conventional statistical quantiles. As a consequence, in the first

[2] For the sake of correctness, it must be recognised that the researchers mentioned in the main text clearly maintain that their conclusions refer to schools and not to individuals. Nonetheless, they also add, at least implicitly, that those results can be considered indicators of the effect (or lack of effect) of individuals' socio-economic conditions.

case, no real social group can be identified, while in the second case, it might happen that families sharing very close social positions are, nonetheless, placed in different categories or, conversely, that families with a very diverse social standing are situated in the same group.

It seems, then, that there is still room for further clarification of the relationship between students' social origins and their reactions to school closures. This is precisely the main goal of our study. It is intended to capture the main traits of possible variations by social origins (and condition) in the effects of the Covid-19 pandemic on the reading and mathematics skills achieved by Italian students who were attending primary, lower secondary, and higher secondary schools at the time of the school closures. The research questions and the hypotheses we have tried, respectively, to answer and test, are described in the next section. The remainder of the article is arranged as follows. Section three illustrates data, variables, and methods used in the analysis. Section four presents the results of our study and section five sets out the main conclusions we have reached and their possible policy implications.

2 Research questions and hypotheses

The queries we addressed and their associated hypotheses were formulated in reference to the analytical framework briefly described below.

In accordance with the remarks presented in the previous section, we have tried to classify students' social origins with specific reference to the features of the Italian social stratification system as represented by the standard occupational scale developed in 1985 by De Lillo and Schizzerotto (henceforth: DLS scale). Subsequently, we decided to study the variations in the strength of educational inequalities generated by the Covid-19 pandemic only with reference to students' social origins, and to ignore students' previous school performance. Actually, according to the seminal contribution of Boudon (1974) and subsequent studies (see, for instance, Erikson & Jonsson, 1996; Jackson et al. 2007), both previous achievement and current learning skills represent the so-called "primary effects" of students' social origins. As the outbreak of the pandemic cannot be equated with a transition between two educational levels (such as, for instance, the transition from lower secondary school to one of the high school tracks), there is no analytical need to separate out the effect of students' previous attainments from the effect of their social origins. In other words, the influence of parental social standing on the current level of students' learning, net of their former school performance, does not represent a "secondary effect" of their

social origins. Finally, we would stress that the inclusion of high school students in the analyses of Covid-19 effects on learning is necessary because, while possible learning losses occurred during the attendance of primary or lower secondary school can be remedied during subsequent educational cycles, the same result is more difficult to achieve for higher level secondary school students.

Having illustrated the basic analytical premises of our study, we now turn to its underlying queries and hypotheses. In line with most surveys of the effects of school closures, we think that those effects basically have been negative. Moreover, considering the unexpected character of the pandemic and the widespread organisational dysfunctions affecting the national school system, we assume that in Italy the negative influence of the shift to on-line teaching has been quite pronounced. We also expect that learning loss has been increasingly intense moving from primary to higher secondary schools. The reasons underlying this hypothesis are quite simple. Usually, primary school is more inclusive than lower and higher secondary school. Moreover, the number of subjects taught and the associated learning difficulties are higher moving from primary to subsequent school cycles. Finally, it must be stressed that the duration of school closures at the various levels was almost identical in school year 2019/20 (practically its entire scheduled length), while in the following year online teaching lasted less in the primary than in lower secondary schools and even less than in high schools.[3] Our third hypothesis assumes that the loss of math skills has been more pronounced in primary and lower secondary schools than in high schools. The opposite should be observed in reading. Because of its technical and formal aspects, mathematics is a complex and unfamiliar subject, for beginners. Distance learning and the lack of direct teacher support widen these learning difficulties. At the same time, however, mathematical contents, precisely because of their level of formalisation, are easier to teach online to individuals whose previously achieved competence is relatively ample. The reading situation is very different because the skills that have to be achieved by high school students (possession of an evolved vocabulary, reasonable familiarity with literary works, decent capability of producing clear and

[3] Detailed information on the duration of school closures during the school year 2020/21 is not available because it was different from region to region, from locality to locality and, within the same locality, from school to school. However, besides anecdotal widespread news, there are some reliable data regarding eight regional county seats (Milan, Turin, Florence, Rome, Naples, Bari, Reggio Calabria, and Palermo). On their basis, it can be estimated that, on average, primary schools remained closed for 30 days, lower secondary for 44 days and higher secondary for 79 days.

fluid written texts) are definitely more difficult to transmit *via* internet than those required of primary and lower secondary school students.

The issues illustrated heretofore constitute the background for the central query of the paper, namely the variations, causally attributable to the Covid-19 pandemic, in the intensity of learning inequalities associated with students' social origins. Our hypothesis about this question is straightforward. We expect that the amount of the learning loss owing to school closures has been largely the same among students belonging to the various social strata we will describe in the next section. The argument underlying this hypothesis is as follows. The pandemic was a sudden, large-scale, exogenous shock that has negatively affected the overall workings of society. Therefore, no one could really escape its consequences. These negative effects were even more generalized in the educational sphere because all students were forced to undergo distance learning and to study in complete isolation from teachers and peers. At least in Italy, the occurrence of unforeseen, exogenously generated large-scale events displaying homogeneously distributed negative consequences on the whole population, is not a completely new experience. Actually, according to Brandolini (2014), the reduction of personal and family incomes, generated by the 2008 worldwide financial crisis, was largely similar, in proportional terms, across all socio-economic categories. A similar finding was made by Egidi and Demuru (2018), who showed that the risks of experiencing poor health conditions after the 2008 economic recession was largely independent of individuals' school qualifications. It is also worth noting that the 2008 economic big chill produced a wide negative educational effect that, apparently, did not increase the educational disparities associated with social origins. From that year onwards, the transition rates from high school to university strongly declined (Schizzerotto *et al.*, 2018) following a similar pattern across social classes[4].

Quite obviously, social origin is not the only factor affecting inequalities of educational performance and opportunities in Italy (and elsewhere). Indeed, other studies have already shown that students' geographic area of residence (Bratti *et al*. 2007; Azzolini and Barone 2012; Argentin *et al*. 2017), their migration status (Azzolini & Barone 2012; Ministero dell'Istruzione, 2021), and their high school track (Panichella and Triventi 2014; Guetto and Vergolini 2017) are traits that,

[4] We are referring to the results of preliminary analyses carried out by the authors on data deriving from waves 2011 and 2014 of the *Indagine sui percorsi di studio e di lavoro dei diplomati* (Survey on education and work careers of upper-secondary diploma holders) conducted by Istat.

in a normal situation, quite strongly influence their learning outcomes. However, if the hypothesis is correct that school closures have produced similar learning loss among students from different social origins, we should also observe the same result when attention is focused on disparities in the school performance associated with the above-mentioned inequality factors.

Contrary to the research expectations just elucidated, many Italian observers and educators have maintained that the effects of the pandemic should have been stronger among students from disadvantaged social backgrounds because of the lack of effective devices for connecting online with their schools and teachers; the poor quality of the schools they attend; overcrowded housing; their parents' inability to support them in learning from home, and the like. We cannot exclude that some very underprivileged groups of students had to face dramatic obstacles in keeping in touch with their schools and teachers. However, this was most likely a rather uncommon experience, not involving the great majority of students belonging to lower social strata. After all, electronic devices to access the internet are not very costly. On the other hand, possible connectedness problems deriving from the technical characteristics of the available IT infrastructures are cross-sectional and affect everybody in a given geographic area. Something similar holds for the disparities between schools in their endowments of teaching devices and the quality of their teachers.[5] Moreover, current family size in Italy is definitely small (on average 2.3 individuals per family) and almost half of families are composed of the two spouses and just one child. Therefore, the proportion of students living in overcrowded housing should be very limited. It also seems implausible that the pandemic has strongly reduced the already very limited attention usually paid by lower class parents to the learning of their sons and daughters. Finally, one should consider that, because of floor effects, declines in school performance during the pandemic should be less likely among the usually underperforming students, most of whom come from lower social strata families, belong to migrant families and/or reside in southern regions and islands than among their scholarly more capable counterparts who have parents with mid and high-level social positions, were born to native couples, and live in the north and central regions.

[5] This argument does not hold when one considers the geographic area in which an Italian school is settled. As already noted, schools located in southern regions and islands display lower pupils' performances than schools of north and central regions. However, as argued in the next lines of the main text, another mechanism exists that can account for the hypothesised similarity of learning loss suffered by students residing in the two geographic areas.

3 Data, variables and methods

3.1 Data and variables

To test our hypotheses, we compared the scores in reading and mathematics recorded by the Italian National Institute for the Evaluation of Education System (INVALSI) among students attending grades five, eight and thirteen in the school year 2018/2019 to the corresponding scores of their counterparts enrolled in the same grades during the school year 2020/2021[6]. More precisely, in order to get information that was more reliable and less prone to cheating factors, we resorted to the scores collected by INVALSI among national random samples[7] of school classes supervised by external observers during the test sessions. The variables expressing the students' reading and math skills used in the analyses consist in a linear transformation of the original INVALSI Rasch scores. Concretely, we jointly considered the scores of the two students' cohorts mentioned above and standardised them (i.e., converted them into *z* scores) within each grade and each subject. To clarify further the features of our analyses, it has to be stressed that the test scores of the 2018/19 cohort are perfectly comparable with those of the 2020/21 cohort. This comparability is made possible by INVALSI's development of a system for anchoring the results of tests administered to different school cohorts. For grade five and thirteen the benchmark cohort is 2018/2019, while for grade eight the anchoring cohort is 2017/2018.[8] Besides transforming INVALSI test scores into the above-mentioned *z* scores, we included in our analyses a set of students' personal characteristics, selected among those collected by INVALSI, that were treated either as factors of educational inequalities or as simple covariates to be controlled for.

The most important variable for testing the validity our main hypothesis is, quite obviously, the social position of students' families. For measuring it INVALSI developed an index named ESCS (Economic, Social and Cultural Status)[9]. Unfortunately, ESCS is hampered by two problems.

The first concerns the definitely large proportion of missing cases among the attendants of grade thirteen in both the 2018/19 school year (around 27%) and the 2020/21 school year (around 13%).

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[6] Due to the Covid-19 pandemic, the test was not administered in the school year 2019/2020.

[7] The 2018/2019 samples were composed by 24781 students for grade five, 29,675 students for grade eight and 36,589 students for grade thirteen; while 2020/2021 samples were composed by 16,631 students for grade five, 9,708 students for grade eight and 20,281 students for grade thirteen. Further information on the sizes of samples used in the analyses are given in the Appendix D.

[8] The mean value of the scores' distribution of the reference cohort, that is to say of that serving as a baseline for the subsequent ones, was set by INVALSI to 200 and its standard deviation to 40.

[9] ESCS scores derive from a principal component analysis carried out on three variables: i) parents' occupational status; ii) parental level of schooling; and iii) families' possessions of a set of material items.

To check whether this trait has caused a systematic sample bias, we carried out three different sets of comparisons (see Appendix A). First, we resorted to an overlapping test between the two distributions of the ESCS scores. The value of the Bhattacharyya coefficient obtained from this comparison is widely satisfactory.[10] Second, considering that ESCS is constructed following the same procedures and variables used to develop the PISA index of socio-economic conditions of students' families, we compared the two distributions of ESCS to that of the PISA index that emerged from the Italian section of the PISA 2018 survey. This comparison turned out to be very satisfying, as the three distributions almost entirely overlap.[11] Therefore, it can be maintained that the ESCS distributions among both the 2018/19 and the 2020/21 thirteenth graders cohorts are largely unbiased, despite their high number of missing cases.

The second problem affecting ESCS consists in the impossibility of using it for identifying specific social groups. For example, this index obviously supports a finding that children of families with a low ESCS score have suffered a greater, or a lesser, learning loss during the Covid-19 pandemic than their peers belonging to families recording a higher score. However, it does not allow stating, for example, whether, and to what extent, the sons and daughters of unskilled manual workers have performed worse, or better, than their counterparts from white-collar families.

In order to overcome this limitation of ESCS, we considered that it is based on occupational, educational and material assets possessed by families. Therefore, it should bear some substantive similarities with standard occupational stratification scales, as the latter take into account the advantages and disadvantages, both material and symbolic, associated with the performance of different jobs. Consequently, occupational scales scores, at least in principle, could be used in place of ESCS scores for determining the social position of students' families. For our research purposes, occupational scales are more advantageous than the ESCS index because they associate specific scores to specific occupational strata. We, then, decided to compare the distribution of ESCS scores with that of the scores, previously transformed into a standardised z variable, of the above-mentioned DLS scale. More specifically (see Appendix B), we took account of the distribution of these occupational scale scores among the Italian parents of children aged 9 to 15

[10] The Bhattacharyya coefficient regarding the similarity between the ESCS distributions in 2018/19 and in 2020/21 is 0.994.

[11] The Bhattacharyya coefficients between the distribution of the ESCS detected by the 2018 PISA survey and the two corresponding distributions (one for each subject) of ESCS supplied by INVALSI in 2018/2019 are, respectively, equal to 0.981 and 0.982. The same values were obtained from the comparison of the ESCS distribution in PISA 2018 to the distributions of ESCS in INVALSI 2020/21 (See Appendix A).

and among those of boys and girls aged 16 to 20.[12] Then, we carried out three different sets of comparisons between the DLS scores, on one side, and, on the other side, the ESCS scores recorded by the 2018/19 and the 2020/21 cohorts, taken together, among, respectively, fifth, eighth and thirteenth grade attendants. As within each grade the number of students having a test score in reading is slightly different from the number of students with a test score in mathematics, we conducted a separate comparison for each subject. All these exercises have demonstrated that the shapes of the six ESCS distributions and those of the DLS scale are largely overlapping.[13]

Exploiting this result, we, first, identified seven macro-strata within the above-mentioned parental distribution of scores on the DLS scale.[14] Second, we partitioned the six ESCS scores distributions into seven intervals, sorted in ascending order, and assigned to each of them a width equal to the incidence of the corresponding macro stratum previously identified on the overall parental distribution of DLS scores (see Appendix B). In this way, the social position of the families of students tested by INVALSI can be represented by means of a sevenfold discrete variable that approximates the shape of the Italian system of social stratification better than can be done by splitting ESCS distribution according to standard quantiles of identical proportional weight. In substantive terms, the seven macro-occupational strata we identified are as follows: 1) large and mid-size employers, higher and mid-level managers of private companies and public administrations, and professionals; 2) lower level managers of private companies and public administrations, white collars supervisors, higher level technicians, higher level routine non manual employees; 3) small employers with 4-14 employees from every economic sector; 4) self-employed (small business owners in every economic sector), mid-level technicians and mid-level routine non-manual employees; 5) lower level technicians and highly skilled manual workers, including foremen; 6) unskilled non-manual occupations in the tertiary sector and low skilled manual workers in the primary and secondary sectors; 7) marginal manual workers (such as miners, dockers, shepherds, street cleaners, and the like).

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[12] This information is based on data collected by the Italian Households Longitudinal Survey, a prospective panel study, with a retrospective component, made up by five biennial waves that began in 1997 and ended in 2005.

[13] See Appendix B Tab. B1 for the relevant coefficients.

[14] The decision of resorting to a rather reduced number of macro-strata can be justified considering that a high number of social strata risks of generating several empty combinations of individual traits and, as a consequence, a reduction of the robustness of the identification strategy.

Besides the parental occupational macro stratum, we also took into account, as stressed in the previous section, student's geographic area of residence (north and central regions vs southern regions and islands), their migrant status (native, first generation migrant, second generation migrant) and the high school track attended (traditional academic, new academic, technical, and vocational). Moreover, we controlled for the following student traits: i) sex (male *vs* female); ii) age (correct age, i.e. corresponding to that legally required for attending the relevant grade, *vs* older age); iii) if a student is repeating (no *vs* yes); iv) pre-primary school attendance (no vs yes); v) scheduled school hours per week; and vi) school of enrolment fixed effect (only for fifth and eighth graders).

3.2 Identification strategy

As stated in sections 1 and 2, to test our hypotheses we followed a counterfactual approach. The identification strategy adopted for implementing this approach was based on a before-after comparison. More precisely, we estimated the learning variations, in reading and mathematics, causally produced by the school closures during the Covid-19 pandemic, by comparing the scores achieved in the relevant test by fifth, eighth, and thirteenth graders in the school year 2020/2021 (the treated group) with those arrived at by their counterparts attending the same grades in 2018/2019 (the control group). Although the two cohorts are very close, we could not exclude the presence of compositional differences between them. To overcome this issue, we relied on a matching procedure that assured the equivalence between treated and control group with regard to the observed characteristics listed in the previous subsection. We used the coarsened exact matching (CEM) which is based on a three steps sequence (Blackwell et al. 2009). First, the CEM algorithm creates as many strata as all the possible combinations of the relevant covariates and then it classifies each treated and control unit in one of these strata. Second, the empty strata, either among treated or control subjects, are pruned in order to consider only observations lying on the common support area. Third, a weight is assigned to the control units considered in the analysis, in order to guarantee the correct balancing of treated and control groups.[15] The weights created by the CEM procedure are, then, included in the regression models specified for estimating the causal

[15] Appendix C reports additional information about the number of strata pruned and about the goodness of the matching procedure.

effect of the examined event, which, in our case, was the closing of schools during the Covid-19 pandemic.

To estimate the impact of this occurrence on the school performances of Italian students, we specified two sets of models. The first set is intended to measure, for each school grade and for each subject, the overall learning loss. The relevant models can be expressed by the following equation:

$$Y = \alpha + \beta POST + \gamma X + \theta SCHOOL + \varepsilon \quad (1)$$

where Y is the test score, either for reading or mathematics, attained by students of a given grade; POST is a dummy variable that is equal to 1 for the treated cohort and 0 otherwise, X represents the relevant observed covariates used in the matching procedure[16] and SCHOOL as stated earlier, is a schools' fixed effects in the models regarding fifth and eighth graders, while it expresses the influence of the school tracks among thirteenth grade attendants.[17]

The second set of models measures the influence on possible variations in the intensity of learning loss exerted by: i) family social position (S); ii) geographic area of residence (G); iii) migration background (M) and iv) the school track attended by thirteenth graders (T). Therefore, we added to the above equation (1) four interaction terms between the school closures indicator and the three social inequality factors just listed. The new regression equation (2) is as follows:

$$Y = \alpha + \beta POST + \delta_1 S + \lambda_1 POST * S + \delta_2 G + \lambda_2 POST * G + \delta_3 M + \lambda_3 POST * M + \delta_4 T + \lambda_4 POST * T + \gamma X + \theta SCHOOL + \varepsilon \quad (2)$$

Two more technical details have to be added to the description of our identification strategy. Besides CEM weights, we resorted to sampling weights[18] and clustered the standard errors at school level.

[16] In the matching procedure we dichotomised two variables: age and scheduled school hours per week (see Appendix C). According to Blackwell *et al.* (2009, 537), this procedure might leave some imbalance in the matched data. The solution they propose and that we have adopted consists in the inclusion of the original covariates in the regression model.

[17] The school fixed effects are included only in the models regarding five and eight grades. In those referred to grade thirteen we ignored them because of multicollinearity issue with the school track.

[18] To jointly consider sampling weights and the weights computed by the CEM procedure, we follow Ridgeway et al. (2015) that suggest multiplying the two weights.

4 School closures, students' level of learning and social inequalities

The empirical results obtained from the first specification of the models adopted in our analyses largely support our three simple initial hypotheses. Actually, with the exception of reading among fifth grade students, the Covid-19 pandemic has generated impressive learning losses among the attendants of every school grade in both subjects tested by INVALSI (Tab.1). And, as expected, i) the intensity of these skill reductions increases monotonically moving from primary to lower secondary to higher secondary school (Tab.1); and ii) it is more pronounced in mathematics among fifth and eighth graders, while among thirteenth graders it is definitely higher in reading (Tab.1).

Table 1. Learning loss effects of school closures by grade and school subject.

Grade	Subject	
	Reading	Mathematics
Five	0.057**	-0.142***
Eight	-0.020***	-0.291***
Thirteen	-0.316***	-0.273***

Sources: INVALSI 2018/2019 and 2020/2021 (authors own estimates). Notes: all models control for gender, age, geographic area of residence, migrant status, family social position, school hours per week, class retention, pre-primary school attendance, school (grade 5 and 8), and school track (grade 13). See Table D1 in the Appendix for the complete model.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Also, our central hypothesis appears to have been widely confirmed. Leaving aside reading skills in primary school, students of every social origin have deeply suffered the negative effect of school closures in both tested subjects (Tab. 2). However, the amount of their learning losses, whatever the grade and the subject, does not follow a linear trend moving from the descendants of large and mid-size employers, top and mid-level managers and professionals to the sons and daughters of marginal manual workers (Tab. 2), In other words, our data do not provide any sound evidence that the Covid-19 pandemic has worsened the school performances of students from lower occupational strata more strongly than those of their counterparts from mid-level and higher social conditions. In any case, it is worth noting that, with regard to the absolute amount of their learning losses emerging from table 2, almost all the differences between social strata are not statistically significant.

Table 2. Learning loss effects of school closures by grade, school subject and social position of students' families.

Family's social position	Grade and Subject					
	Five		Eight		Thirteen	
	Reading	Mathematics	Reading	Mathematics	Reading	Mathematics
Stratum 1	0.079*	-0.126***	-0.065	-0.214***	-0.294***	-0.225***
Stratum 2	0.316***	0.054	-0.102**	-0.180***	-0.191***	-0.319***
Stratum 3	-0.008	-0.150***	-0.115***	-0.178***	-0.340***	-0.220***
Stratum 4	0.104***	-0.099***	-0.097***	-0.198***	-0.319***	-0.277***
Stratum 5	0.060	-0.133**	-0.148***	-0.218***	-0.343***	-0.284***
Stratum 6	0.103*	-0.111*	-0.101**	-0.273***	-0.329***	-0.286***
Stratum 7	0.173***	-0.091	-0.177***	-0.323***	-0.353***	-0.253***

Sources: INVALSI 2018/2019 and 2020/2021 (authors own estimates). Notes: all models control for gender, age, geographic area of residence, migrant status, school hours per week, class retention, pre-primary school attendance, school (grade 5 and 8), and school track (grade 13). See Table D2 in the Appendix for the complete model.
Strata legend: 1) large and mid-size employers, higher and mid-level managers of private companies and public administrations, and professionals; 2) lower level managers of private companies and public administrations, white collar supervisors, higher level technicians, higher level routine non-manual employees; 3) small employers with 4-14 employees from every economic sector; 4) self-employed, mid-level technicians and mid-levl routine non-manual employees; 5) lower level technicians and highly skilled manual workers, including foremen; 6) unskilled non-manual occupations in the tertiary sector and low skilled manual workers in the primary and secondary sectors; 7) marginal manual workers.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Interaction parameters expressing the variation of the school closure effects according to the social position of students' families by grade and subject.

Family's social position	Grade and Subject					
	Five		Eight		Thirteen	
	Reading	Mathematics	Reading	Mathematics	Reading	Mathematics
Stratum 1 (ref.)	-	-	-	-	-	-
Stratum 2	0.237***	0.180***	0.037	0.034	0.103*	-0.095**
Stratum 3	-0.088*	-0.024	0.015	0.036	-0.046	0.005
Stratum 4	0.025	0.027	0.012	0.016	-0.026	-0.052
Stratum 5	-0.020	-0.007	0.008	-0.004	-0.049	-0.060
Stratum 6	0.024	0.015	0.015	-0.059	-0.035	-0.061
Stratum 7	0.094	0.035	0.012	-0.109	-0.059	-0.029

Sources: INVALSI 2018/2019 and 2020/2021 (authors own estimates). Notes: all models control for gender, age, geographic area of residence, migrant status, school hours per week, class retention, pre-primary school attendance, school (grade 5 and 8), and school track (grade 13). See Table D2 in the Appendix for the complete model.
Strata legend as given in Table 2.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This statement finds immediate confirmation in the parameters of the interaction between students' social origins and the experience of distance learning. Only six out of the thirty-six parameters of interest are statistically significant and they can be reduced to three if one would ignore those significant only at the 10% level. This means that, on most occasions, students of all

social origins have experienced the negative effects of the school closures on their level of learning with the very same absolute intensity.[19]

To complete the description of the results of our study, it must be stressed that our hypothesis about the wide similarity, across factors of social inequality, of the learning loss causally attributable to school closure is further confirmed by the analysis regarding students' area of residence, their migrant status and the high school track they attended.

Table 4. Interaction parameters expressing the variation of the school closure effects according to some ascriptive characteristics of Italian students by grade and subject.

Ascriptive characteristics	Grade and Subject					
	Five		Eight		Thirteen	
	Reading	Mathematics	Reading	Mathematics	Reading	Mathematics
Area of residence						
North & center regions (ref.)	-	-	-	-	-	-
South regions & islands	0.054	0.121	-0.080	-0.099	-0.062	-0.072
Migrant status						
Native (ref.)	-	-	-	-	-	-
First generation migrant	0.150	0.083	-0.084	-0.204**	-0.025	0.036
Second generation migrant	0.098	0.021	-0.030	0.057	0.020	0.056
High school track						
Traditional academic (ref.)	n.r.	n.r.	n.r.	n.r.	-	-
New academic	n.r.	n.r.	n.r.	n.r.	0.023	0.086
Technical	n.r.	n.r.	n.r.	n.r.	0.054	0.025
Vocational	n.r.	n.r.	n.r.	n.r.	0.148**	0.135*

Sources: INVALSI 2018/2019 and 2020/2021 (authors own estimates). Notes: all models control for gender, age, geographic area of residence, migrant status, school hours per week, class retention, pre-primary school attendance, school (grade 5 and 8), and school track (grade 13). See Table D2 in the Appendix for the complete model.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Starting with area of residence, it must be noted that the interaction parameters of this variable with that expressing the occurrence of the school closures are statistically not significant for all grades and all subjects, proving the cross-country homogeneity of the intensity of the learning loss (Tab. 4). The same holds for migrant status. Being a native, or a second-generation migrant student,

[19] A further proof of what is claimed in the main text can be found in the Fig D1 of the Appendix D showing the values appearing in table 2 and their largely overlapping 95% confidence intervals.

or a first-generation migrant student does not generate any systematic variation of the influence of the Covid-19 pandemic on the academic performances in both reading and mathematics among fifth, eighth and thirteenth graders (Tab. 4). Similarly, it can be maintained that the intensity of the learning loss in reading and mathematics is not affected by the school track attended (Tab. 4). The partial exception represented by students enrolled in vocational schools further supports our basic hypothesis, as, after school closures, these students record a reduction, rather than an extension, of their distances from the level of learning level of their more privileged counterparts attending technical and academic tracks (Tab.4).

5 Summary and conclusions

School closures during the lockdown induced by the Covid-19 pandemic have opened the debate on two questions important from both an analytical and a policy point of view. Did the lockdown induced learning loss among students who experienced the on-line teaching? Is there any evidence that this learning loss has increased the educational inequalities associated to students' social origins?

To answer these questions, we exploited a recent feature of the INVALSI data – the most appropriate data available for the Italian case – that allows a direct comparison of reading and math skills achieved by two different cohorts of students attending grade five, eight and thirteen, respectively, immediately before the pandemic and during it. We exploited this feature of the INVALSI data to carry out a causal evaluation of the school closures' impacts on the Italian students' level of learning. More precisely, our strategy for identifying school closure effects relies on a before-after comparison developed by means of a matching procedure based on CEM.

Our analyses confirm the presence of a pronounced learning loss in reading and mathematics, particularly severe among students attending grade thirteen and eight. Fifth graders also display a significant skill reduction, but it turns out to be less intense than that suffered by their peers attending lower and higher secondary schools and involves only mathematics. Despite the troubling size of these learning losses, the negative effects of school closures have not deepened the educational inequalities previously associated with students' social origins and family conditions. After adopting an analytical procedure that allowed us to classify the Italian fifth, eighth and thirteenth graders into seven different social strata, we have shown that the incidence of the learning loss due to school closures was substantially the same moving from the descendants

of large and mid-size employers to the children of unskilled non-manual and manual workers. Besides the position held by their families in the structure of social stratification, other important ascriptive characteristics of students – namely: geographic area of residence, migrant status and high school track attended – do not cause any variation in the amount of the learning loss. In other words, we have proved that the widespread supposition, whereby students from the most disadvantaged social groups should have experienced the highest level of learning loss, is not corroborated by the empirical evidence.

Rather paradoxically, it can be maintained that the lack of socially structured effects of school closures on the learning disparities raises social and policy concerns that are even wider than those generated by previous features of educational inequalities associated with individuals' social origins and conditions.

From a social perspective, the problem is that the severe reduction of competences transmitted by the school system, owing to the shift from in-presence to online teaching, has affected an entire generation of Italian students. This means that educational disadvantages are potentially added to those already suffered by Italian young people in several aspects of their personal lives, such as employment stability, work career perspectives, income levels, duration of the economic dependence on parents, chances of assuming conjugal and parental roles, and the like. In other words, there is a risk that generation will become the most effective social divide in the Italian society, even more important than family of origin.

From a policy perspective, the issue is the need to avoid the above-described possible negative effect of generation-based learning loss. In order to do that, a close attention should be paid, first, to the educational needs of the 2019/20 and 2020/21 cohorts of thirteen graders, as they do not have enough time to recover their learning loss before entering the labour market or enrolling in tertiary education. Therefore, universities should implement a set of initiatives (e.g., pre-courses, tutoring or coaching) to limit the drop-out risk for these students, a risk that is really high in Italy during the first year of university. On the other hand, students who decide to enter the labour market after high school should be supported by an extensive and articulated program of vocational (and non-vocational) training courses as part of a life-long learning framework. The risk of not recovering from their skill reduction should be lower among fifth and eighth graders, since almost all of them will continue their school attendance for an additional eight or five years, respectively. However, these students too need to be supported by some specific education measures, such as

specially designed remedial classes, in order to avoid risks of persisting poor school performances or, even worse, future grade retention. Eighth graders should also be supported by educational orientation initiatives aimed at reducing the risks of choosing an inappropriate high school track, owing either to an underestimation or, on the contrary, an overestimation, by students and their families, of the learning loss consequences for future school performance.

As stressed earlier, in the absence of effective educational measures, one cannot exclude the risk of long-lasting negative consequences of the learning loss for intergenerational inequalities and economic growth. A non-recovered learning loss could become a structural disadvantage of the generation affected by school closures and a factor reducing the future availability of well-trained and highly skilled workforce.

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Appendices

Appendix A

As mentioned in the main text, the ESCS (Economic, Social and Cultural Status) index, used for measuring the social conditions of students' families by INVALSI, is hampered by a large number of missing cases among the thirteenth graders tested in both 2018/2019 and in 2020/2021 (Tab. A1). Therefore, one cannot exclude that the distribution of this characteristic in these two samples is biased. This appendix illustrates how we have faced this issue.

Table A1. Percentage of ESCS index missing cases by grade and subject in INVALSI 2018/2019 and 2020/2021.

INVALSI survey	Grade and Subject					
	Five		Eight		Thirteen	
	Reading	Mathematics	Reading	Mathematics	Reading	Mathematics
2018/2019	0.65	0.15	2.96	2.94	27.03	27.14
2020/2021	0.95	0.18	1.32	1.34	13.54	13.53

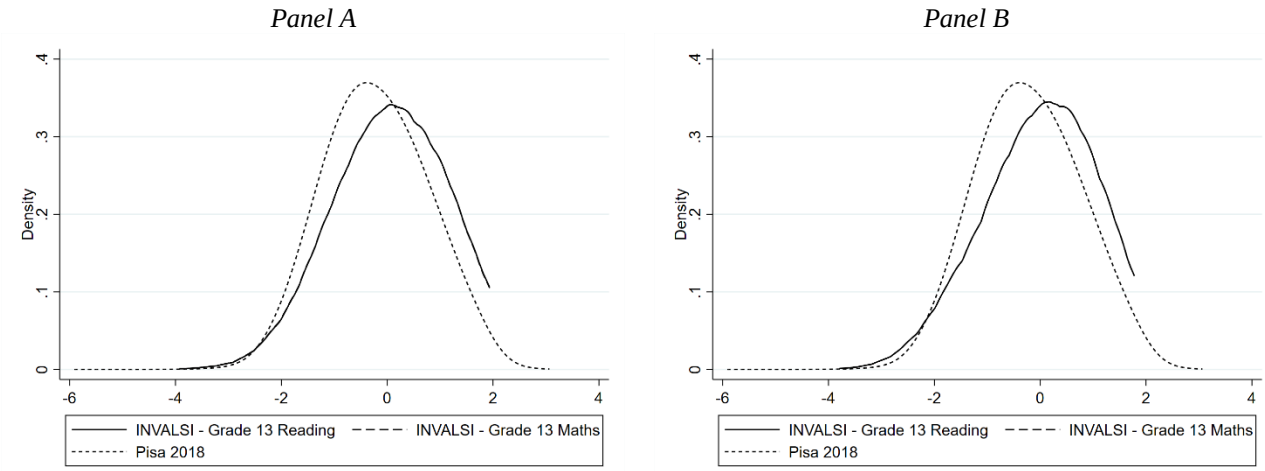
Sources: INVALSI 2018/2019 and 2020/2021 (authors own estimates).

First, we compared the distributions of the ESCS index among thirteenth graders of both INVALSI surveys between themselves. Subsequently, considering that the INVALSI index is based on the same variables and computing procedures adopted by PISA (Programme for International Student Assessment) to develop its own ESCS, we compared the two INVALSI distributions to that of the Italian section[20] of the PISA 2018 survey. We chose the PISA 2018 survey for three reasons. First, it is temporally very close to the two INVALSI surveys. Second, PISA's ESCS is not affected by a significant amount of missing cases. Third, PISA evaluates the school performance of 15-year-olds. Therefore, its reference population is very similar to that of grade thirteen students (18-year-olds).

Even the simple graph reported here below demonstrates quite convincingly that the shape of the ESCS distribution in PISA is very close to those of the ESCS distributions in INVALSI (Fig A1).

[20] The sample size is 11,785.

Figure A1. Kernel distributions of ESCS index in INVALSI grade thirteen and PISA 2018 surveys by subject.



Sources: INVALSI 2018/2019, 2020/2021 and PISA 2018 (Italian sample) (authors own estimates). Note: we have applied a bandwidth parameter equal to 0.5 to all distributions.

However, to demonstrate this similarity analytically we resorted to the Bhattacharyya coefficient (Bhattacharyya, 1943). As is well known, this coefficient measures the overlap between the distributions of a given characteristic in two different samples or populations. It ranges from 0 (no overlap between the distributions) to 1 (perfect overlap). The values of Bhattacharyya coefficient (Tab A2) resulting from all our comparisons are definitely high and support the conclusion that, despite the high incidence of missing cases, the two distributions of the ESCS index by INVALSI are not severely biased.

Table A2. Bhattacharyya test of equality of ESCS in INVALSI 2018/2019, 2020/2021 and PISA 2018 kernel distributions.

	Bhattacharyya test (n=10)	Bhattacharyya test (n=20)
ESCS 13th grade reading INVALSI 2018/2019 vs 2020/2021	0.994	0.985
ESCS 13th grade reading INVALSI 2018/2019 vs PISA 2018	0.982	0.973
ESCS 13th grade reading INVALSI 2020/2021 vs PISA 2018	0.981	0.972
ESCS 13th grade maths INVALSI 2018/2019 vs 2020/2021	0.994	0.985
ESCS 13th grade maths INVALSI 2018/2019 vs PISA 2018	0.982	0.973
ESCS 13th grade maths INVALSI 2020/2021 vs PISA 2018	0.981	0.972

Sources: INVALSI 2018/2019, 2020/2021 and PISA 2018 (authors own estimates).

As it should be clear from what said in the main text, our analyses were carried out only on the subsample of students tested by INVALSI who possess an ESCS score. This necessary selection could raise a problem regarding possible heterogeneity of the school performances of the subsample of thirteen graders considered in our study and, therefore, a possible bias in our estimates. To exclude this risk, we checked whether there were significant differences between students with an ESEC score and those without this information in the size of their respective learning loss in reading and mathematics.

Table A3. Estimated learning loss owing to school closures by school subject and between students who have (non-missing) and students who do not have (missing) information about ESCS index.

ESCS index	Subject	
	Reading	Mathematics
Non-missing	-0.321***	-0.276***
Missing	-0.409***	-0.289***

Sources: INVALSI 2018/2019 and 2020/2021 (authors own estimates). Notes: all models control for gender, age, geographic area of residence, migrant status, school hours per week, class retention, pre-primary school attendance, and school track.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To this purpose, we resorted to a statistical model similar to that used for testing our main hypotheses. Its specification is given in the following equation:

$$Y=\alpha+\beta POST+1Missing+1POST\cdot Missing+\gamma X+\theta SCHOOL+\varepsilon$$

As shown in Tab. A3, this model indicates that the learning loss of the two groups of students is almost identical in mathematics, while in reading it turns out to be statistically significantly greater among pupils without ESCS score. However, it appears rather difficult to explain why the latter underperform only in reading. Moreover, both groups have reduced their competences in reading more than in mathematics. Therefore, one can reasonably argue that the dissimilarity existing between the overall school performances of the two groups is really limited and that the subsample of thirteen graders considered in our analyses is largely reliable.

Appendix B

In the main text of the paper, we briefly described how we partitioned ESCS score distributions by using the Italian scale of occupational stratification developed in 1985 by de Lillo and Schizzerotto (henceforth DLS). This appendix contains a more detailed description of the procedures we followed in carrying out that task. In this perspective, it will be useful to describe briefly the DLS and the data source from which we derived the distribution of its scores among parents of Italian students in the appropriate school age.

The DLS scale is based on the judgments regarding the overall degree of social desirability of 540 different occupations made by a sample of 792 employed Italian people between the ages of 25 and 55.[21] The occupations are representative of over 11,000 titles recorded by the Italian census office (ISTAT)

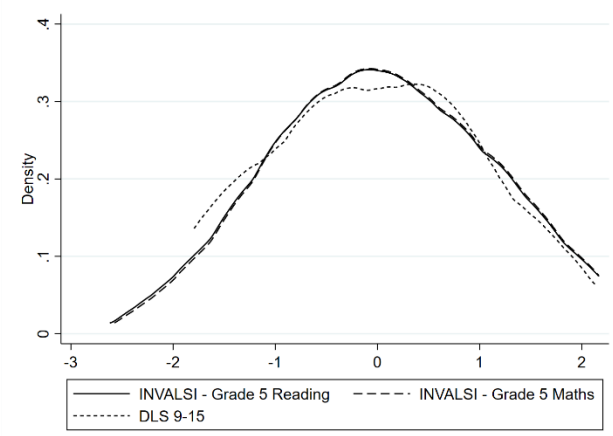
[21] Although developed in 1985, the DLS scale can still be considered reliable today. As is well known, a lot of empirical evidence suggests that there is a strong stability over time and across countries in the collective images of occupational stratification, despite the changes that have taken place in the composition of the actual occupational structure (Treiman 1977; Nakao and Treas 1994; Sarti and Terraneo 2007). Moreover, the DLS scale is very strongly correlated to the much more recent Italian scale developed by Meraviglia (2012).

during the 1981 census. After collecting the above-mentioned judgments, the 540 occupations were grouped into 93 categories, each of which has a specific score that ranges from 90.20 to 9.97.

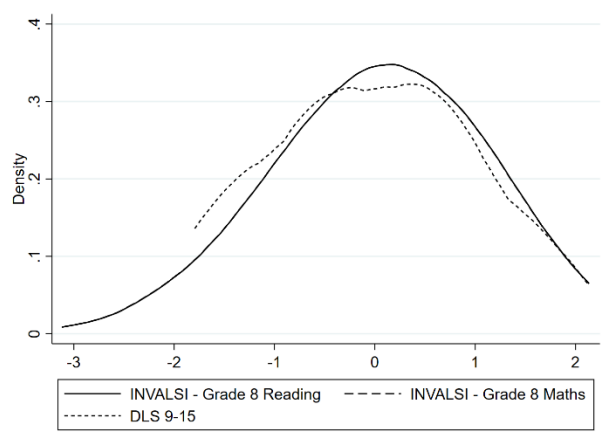
We looked at the distribution of these scores among the 1,005 families with children aged 9 to 20, whose adult members playing a parental role were interviewed during the last wave, carried out in 2005, of the Italian Households Longitudinal Survey (ILFI). ILFI is a prospective panel study, with a retrospective first wave, based on five biennial occasions starting in 1997 and ending, as stated, in 2005. Its national representative sample is composed of 9,970 adult (i.e. aged 18 or older) individuals, members of 4,714 families.

After assigning a DLS scale score to each of the above families [22], we divided them into two different groups: i) families with children aged 9 to 15 (N=593); and ii) families with children aged 16 to 20 (N=462). Then we standardised the two resulting distributions and compared that of the first group of families to the distribution of the ESCS scores of pupils attending either the fifth or the eighth grade. More precisely, we carried out two comparisons for each grade: one for reading and one for mathematics. The same comparisons, using the DLS standardised scores of the second group of families, was repeated for the thirteenth graders. For the sake of clarity, it must be recalled that, in the above comparisons, the ESCS score distributions refer to the two cohorts of students taken together.

Panel A



Panel B



Panel C

[22] To assign a DLS score to families in which both parents were employed but performed occupations with different scores, we resorted to the dominance criterion. In other words, we attributed to the family the highest of the two relevant scores.

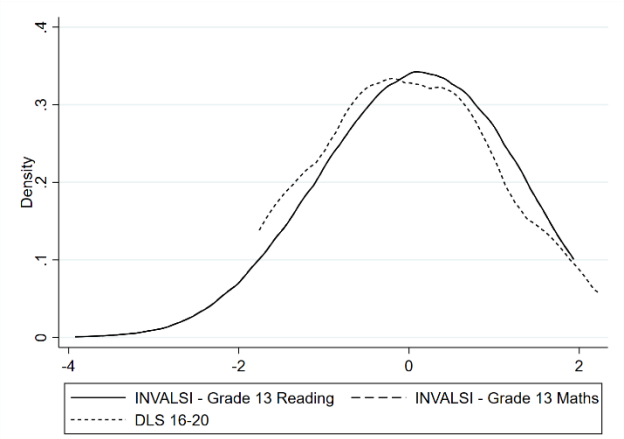


Figure B1. Kernel distributions of DLS score in ILFI subsample and ESCS index in INVALSI by grade and subject.

Sources: INVALSI 2018/2019, 2020/2021 and ILFI 2005 (authors own estimates). Note: we have applied a bandwidth parameter equal to 0.5 to all distributions.

As clearly emerges from figure B1 above, the shape of the three distributions involved in each set of comparisons is largely similar. We have reported in the main text the reasons why, even if one cannot prove that the two indices refer to exactly the same concept, it can nevertheless be assumed that they refer to very similar, not to say identical, aspects of the social inequalities existing in contemporary societies and that they represent this aspect resorting to very close indicators. Just to recall those reasons briefly, we have stressed that both DLS scale and ESCS index have occupation as a key component and that the ESCS composite score is a weighted average of three indices, one of which is parental employment status determined through the International Socio-Economic Index (ISEI) scale (Ganzeboom, 2010), which, in turn, can be considered a standard scale of occupational stratification.[23]

Table B1. Bhattacharyya test of equality of ESCS and DLS kernel distributions.

	Bhattacharyya test (n=10)	Bhattacharyya test (n=20)
ESCS 5th grade reading vs DLS pupils aged 9-14	0.965	0.907
ESCS 5th grade maths vs DLS pupils aged 9-14	0.979	0.922
ESCS 8th grade reading vs DLS pupils aged 9-14	0.974	0.935
ESCS 8th grade maths vs DLS pupils aged 9-14	0.974	0.935
ESCS 13th grade reading vs DLS pupils aged 15-20	0.960	0.932
ESCS 13th grade maths vs DLS pupils aged 15-20	0.959	0.931

Sources: INVALSI 2018/2019, 2020/2021 and ILFI 2005 (authors own estimates).

The large similarity between the distributions of ESCS and DLS scores is demonstrated further by the Bhattacharyya coefficient, the value of which, for each comparison, is given above (Table B1).

[23] The other two components are parental educational attainment (in years) and a measure of "household possessions".

Table B2. Occupational strata based on DLS score.

Stratum	DLS Rank order interval	DLS scores interval	% parents of pupils aged 9-15	% parents of pupils aged 16-20
1. Large and mid-size employers, higher and mid-level managers of private companies and public administration, and professionals	1-18	68.8-90.2	11.1	10.6
2. Lower-level managers of private companies and public administration, white collars supervisors, higher level technicians, higher level routine non-manual employees	19-27	59.6-68.7	12.1	10.4
3. Small employers with 4-14 employees from every economic sector	28-44	50.6-59.5	10.8	6.9
4. Self-employed (small business owners in every economic sector), mid-level technicians and mid-level routine non-manual employees	45-68	34.4-50.5	34.9	39.8
5. Lower level technicians and highly skilled manual workers (including foremen)	69-80	23.7-34.3	13.3	16.7
6. Low skilled workers (including unskilled non-manual occupations in the tertiary sector and low skilled manual workers in primary and secondary sectors)	81-88	17.1-23.6	8.4	7.1
7. Marginal manual workers (such as miners, dockers, shepherds, street cleaners, and the like)	89-93	9.97-17.0	9.3	8.4

Source: ILFI 2005 (authors own estimates).

This broad similarity was exploited to identify on the ESCS score distributions a set of intervals corresponding to specific positions in the Italian occupational stratification. To reach this goal, we, first, identified on the DLS scale seven macro-strata, each of them grouping some of the original occupational categories of the scale. The list of these seven occupational macro-strata is provided in the main text and in the above Table B2, which also shows the extensions of the intervals, in terms of both score and rank on the original scale, over which each of them extends. After defining these macro strata, we computed the proportion of families with children ages 9 to 15 and 16 to 20, respectively, which, according to the previously mentioned ILFI data, fell into each of the seven macro strata. Finally, we projected these seven proportions onto the relevant ESCS score distributions. So, for instance, students from 9 to 15 years old, making up the first 9.3% of the ESCS scores distribution, have been assigned to the lowest stratum, those constituting the next 8.4% were placed into the sixth stratum, and so on, until those making up the last 11.1%, who were placed in the top macro-stratum.

Appendix C

This appendix provides some additional information about the matching procedure. First, it must be stressed that, in the matching procedure, we coarsen two of the variables used in comparing the treated group (students tested by INVALSI in 2021) with the control group (students tested by INVALSI in 2019). These variables are age and scheduled school hours per week. They have been coarsened (i.e., recoded) as dummy variables in order to reduce the number of the strata.

Table C1. Matching summary statistics regarding the common support area.

	Number of strata	Number of matched strata	Control case matched	Control case unmatched	Treated cases matched
5th grade, reading	296	227	24,562	69	16,158
5th grade, mathematics	286	219	24,713	68	16,315
8th grade, reading	307	238	29,582	291	9,610
8th grade, mathematics	308	239	29,415	260	9,653
13th grade, reading	423	293	35,356	979	20,397
13th grade, mathematics	429	291	35,500	1,089	20,209

Sources: INVALSI 2018/2019, 2020/2021 (authors own estimates).

The second important aspect of our matching procedure regards the number of strata pruned by CEM and the resulting final sample size. Tab. C1 reports both items of information for the three grades and the two subjects.

Table C2. Multivariate distance before and after the matching.

	Multivariate distance before matching	Multivariate distance after matching
5th grade, reading	0.21808171	0.21660198
5th grade, mathematics	0.22537335	0.21375832
8th grade, reading	0.20529303	0.20271456
8th grade, mathematics	0.20320696	0.20231284
13th grade, reading	0.25266901	0.19908467
13th grade, mathematics	0.25696127	0.21105915

Sources: INVALSI 2018/2019, 2020/2021 (authors own estimates).

The third technical aspect of our matching procedure that seems useful to mention refers to its goodness. This can be measured by comparing the multivariate distance between treated and control group before and after matching. This distance is computed as the difference between the multidimensional histogram of all pre-treatment covariates in the treated group and the same in the control group (see Iacus et al. 2012 for the details). This indicator of the goodness of the matching procedure can vary between 0 (perfect global balance) and 1 (complete separation). A satisfactory matching solution has to be close to 0 and produce a reduction of the original multivariate distance between treated and control group. This seems to be our case.

Appendix D

This appendix shows the complete models underlying all the results described in the main text of the paper.

Table D1. Complete models for the overall learning loss due to school closures by grade and school subjects.

	Grade and Subject					
	Five		Eight		Thirteen	
	Reading	Mathematics	Reading	Mathematics	Reading	Mathematics
INVALSI survey						
Pre Covid-19 (ref.)						
Post Covid-19	0.057	-0.142	-0.020	-0.291	-0.316	-0.273
	(0.027)	(0.033)	(0.065)	(0.068)	(0.023)	(0.029)
Family's social position						
Stratum 1 (ref.)	-	-	-	-	-	-
Stratum 2	-0.200	-0.184	-0.188	-0.173	-0.014	-0.032
	(0.026)	(0.027)	(0.027)	(0.028)	(0.028)	(0.021)
Stratum 3	-0.239	-0.163	-0.262	-0.241	-0.026	-0.119
	(0.025)	(0.026)	(0.027)	(0.030)	(0.024)	(0.031)
Stratum 4	-0.458	-0.407	-0.421	-0.382	-0.082	-0.099
	(0.023)	(0.024)	(0.023)	(0.025)	(0.024)	(0.018)
Stratum 5	-0.638	-0.588	-0.649	-0.601	-0.116	-0.116
	(0.027)	(0.029)	(0.029)	(0.029)	(0.028)	(0.022)
Stratum 6	-0.695	-0.619	-0.808	-0.748	-0.113	-0.138
	(0.030)	(0.029)	(0.029)	(0.033)	(0.029)	(0.026)
Stratum 7	-0.809	-0.801	-1.011	-0.961	-0.197	-0.203
	(0.031)	(0.033)	(0.033)	(0.034)	(0.029)	(0.026)
Area of residence						
North & center regions (ref.)						
South regions & islands	-0.035	-0.003	-0.290	-0.375	-0.598	-0.670
	(0.055)	(0.072)	(0.210)	(0.194)	(0.024)	(0.029)
Migrant status						
Native (ref.)						
First generation migrant	-0.437	-0.339	-0.431	-0.217	-0.287	-0.066
	(0.051)	(0.051)	(0.047)	(0.050)	(0.029)	(0.028)
Second generation migrant	-0.353	-0.245	-0.314	-0.111	-0.244	-0.136
	(0.025)	(0.024)	(0.031)	(0.035)	(0.025)	(0.025)
Sex						
Male (ref.)						
Female	0.199	-0.166	0.227	-0.125	0.043	-0.259
	(0.013)	(0.013)	(0.013)	(0.016)	(0.015)	(0.014)
Grade retention						
No (ref.)						
Yes	-0.435	-0.131	-1.127	-0.964	-0.385	-0.391
	(0.432)	(1.194)	(0.148)	(0.228)	(0.077)	(0.071)
Age						
Correct age (ref.)						
1 year older	-0.056	-0.283	0.567	0.336	0.189	0.091
	(0.457)	(1.200)	(0.165)	(0.215)	(0.082)	(0.072)
2 year older	0.163	-0.132	0.665	0.494	0.107	0.060
	(0.439)	(1.194)	(0.146)	(0.222)	(0.075)	(0.070)
+3 or year older	0.065	0.019	-0.014	-0.056	-0.028	-0.011
	(0.024)	(0.024)	(0.025)	(0.026)	(0.019)	(0.017)
Pre-primary school attendance						
Yes (ref.)						
No	-0.153	-0.118	-0.188	-0.149	n.r.	n.r.
	(0.054)	(0.057)	(0.032)	(0.035)		

Scheduled school hours per week						
20-24 hours (ref.)						
25-29 hours	-0.048	-0.344	0.134	0.124	0.310	-0.011
	(0.138)	(0.197)	(0.037)	(0.049)	(0.251)	(0.160)
30-34 hours	-0.074	-0.353	-0.146	-0.035	0.238	-0.065
	(0.140)	(0.193)	(0.260)	(0.180)	(0.237)	(0.107)
35-39 hours	-0.116	-0.488	-0.022	0.104	0.165	-0.186
	(0.170)	(0.252)	(0.048)	(0.058)	(0.240)	(0.115)
More than 40 hours	-0.043	-0.281	0.257	0.259	0.038	-0.206
	(0.138)	(0.192)	(0.130)	(0.116)	(0.254)	(0.171)
High school track						
Traditional academic (ref.)						
New academic	n.r.	n.r.	n.r.	n.r.	-0.425	-0.836
					(0.032)	(0.040)
Technical	n.r.	n.r.	n.r.	n.r.	-0.643	-0.725
					(0.029)	(0.040)
Vocational	n.r.	n.r.	n.r.	n.r.	-1.191	-1.389
					(0.032)	(0.039)
Constant	0.386	0.888	0.629	0.819	0.727	1.474
	(0.139)	(0.194)	(0.101)	(0.098)	(0.240)	(0.114)
N	33695	34022	31338	31200	39554	39434

Sources: INVALSI 2018/2019 and 2020/2021 (authors own estimates). Notes: all models control for: school (grade 5 and 8), and school track (grade 13). Standard error in parenthesis.
Strata legend as given in Table 2 of the main text.

Table D2. Complete model for the variations in the intensity of learning loss due to school closures by grade and school subjects.

	Grade and Subject					
	Five		Eight		Thirteen	
	Reading	Mathematics	Reading	Mathematics	Reading	Mathematics
INVALSI survey						
Pre Covid-19 (ref.)						
Post Covid-19	0.050	-0.168	-0.032	-0.178	-0.315	-0.25
	(0.047)	(0.050)	(0.048)	(0.057)	(0.066)	(0.074)
Family's social position						
Stratum 1 (ref.)						
Stratum 2	-0.339	-0.294	-0.198	-0.212	-0.056	-0.339
	(0.037)	(0.040)	(0.028)	(0.030)	(0.036)	(0.037)
Stratum 3	-0.199	-0.168	-0.291	-0.309	-0.002	-0.199
	(0.033)	(0.032)	(0.030)	(0.031)	(0.026)	(0.033)
Stratum 4	-0.481	-0.440	-0.471	-0.459	-0.069**	-0.481
	(0.028)	(0.032)	(0.026)	(0.028)	(0.027)	(0.028)
Stratum 5	-0.634	-0.573	-0.701	-0.692	-0.091	-0.634
	(0.039)	(0.045)	(0.030)	(0.033)	(0.030)	(0.039)
Stratum 6	-0.721	-0.638	-0.871	-0.809	-0.113	-0.721
	(0.048)	(0.046)	(0.035)	(0.039)	(0.033)	(0.048)
Stratum 7	-0.872	-0.865	-1.058	-1.026	-0.168	-0.872
	(0.039)	(0.043)	(0.036)	(0.037)	(0.034)	(0.039)
Stratum 2*POST	0.237	0.180	-0.037	0.034	0.103	-0.095
	(0.055)	(0.057)	(0.058)	(0.062)	(0.059)	(0.042)
Stratum 3*POST	-0.088	-0.024	-0.050	0.036	-0.046	-0.088
	(0.053)	(0.054)	(0.056)	(0.063)	(0.055)	(0.053)
Stratum 4*POST	0.025	0.027	-0.032	0.016	-0.026	0.025
	(0.045)	(0.051)	(0.048)	(0.055)	(0.056)	(0.045)
Stratum 5*POST	-0.020	-0.007	-0.083	-0.004	-0.049	-0.020
	(0.060)	(0.070)	(0.060)	(0.062)	(0.064)	(0.060)
Stratum 6*POST	0.024	0.015	-0.036	-0.059	-0.035	0.024
	(0.066)	(0.068)	(0.061)	(0.070)	(0.066)	(0.066)
Stratum 7*POST	0.094	0.035	-0.112	-0.109	-0.059	0.094
	(0.068)	(0.083)	(0.066)	(0.074)	(0.066)	(0.068)
Area of residence						
North & center regions (ref.)						
South regions & islands	-0.188	-0.235	-0.311	-0.430	-0.566	-0.632
	(0.035)	(0.043)	(0.024)	(0.028)	(0.030)	(0.036)
South regions & islands*POST	0.054	0.121	-0.080	-0.099	-0.062	-0.072
	(0.050)	(0.071)	(0.051)	(0.058)	(0.047)	(0.056)
Migrant status						
Native (ref.)						
First generation migrant	-0.541	-0.392	-0.392	-0.102	-0.274	-0.080
	(0.075)	(0.084)	(0.046)	(0.054)	(0.037)	(0.035)
Second generation migrant	-0.418	-0.275	-0.306	-0.113	-0.254	-0.163
	(0.033)	(0.034)	(0.030)	(0.034)	(0.034)	(0.035)
First generation migrant*POST	0.150	0.083	-0.084	-0.204	-0.025	0.036
	(0.100)	(0.108)	(0.087)	(0.092)	(0.057)	(0.057)
Second generation migrant*POST	0.098	0.021	-0.030	0.057	0.020	0.056
	(0.051)	(0.051)	(0.060)	(0.064)	(0.050)	(0.050)
Sex						
Male (ref.)						
Female	0.201	-0.164	0.227	-0.121	0.044	-0.259
	(0.014)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)
Grade retention						
No (ref.)						

Yes	0.098	0.786	-1.159	-0.907	-0.378	-0.384
	(0.813)	(1.329)	(0.205)	(0.236)	(0.076)	(0.071)
Age						
Correct age (ref.)						
1 year older	-0.644	-1.229	0.588	0.297	0.184	0.083
	(0.826)	(1.343)	(0.214)	(0.229)	(0.082)	(0.072)
2 year older	-0.376	-1.062	0.705	0.448	0.101	0.052
	(0.821)	(1.336)	(0.205)	(0.230)	(0.074)	(0.070)
+3 or year older	0.062	0.014	-0.009	-0.040	-0.027	-0.011
	(0.024)	(0.027)	(0.027)	(0.029)	(0.019)	(0.017)
Pre-primary school attendance						
Yes (ref.)						
No	-0.078	-0.075	-0.172	-0.132	n.r.	n.r.
	(0.050)	(0.058)	(0.031)	(0.037)		
Scheduled school hours per week						
20-24 hours (ref.)						
25-29 hours	-0.043	-0.337	0.064	0.070	0.286	-0.027
	(0.076)	(0.139)	(0.032)	(0.040)	(0.248)	(0.161)
30-34 hours	-0.011	-0.305	-0.315	-0.222	0.221	-0.074
	(0.078)	(0.140)	(0.264)	(0.212)	(0.233)	(0.112)
35-39 hours	-0.065	-0.344	-0.005	0.064	0.150	-0.194
	(0.116)	(0.226)	(0.034)	(0.040)	(0.236)	(0.119)
More than 40 hours	-0.019	-0.269	-0.011	-0.023	0.015	-0.211
	(0.076)	(0.137)	(0.065)	(0.066)	(0.251)	(0.174)
High school track						
Traditional academic (ref.)						
New academic	n.r.	n.r.	n.r.	n.r.	-0.440	-0.878
					(0.042)	(0.050)
Technical	n.r.	n.r.	n.r.	n.r.	-0.671	-0.735
					(0.036)	(0.051)
Vocational	n.r.	n.r.	n.r.	n.r.	-1.261	-1.451
					(0.042)	(0.049)
New academic*POST	n.r.	n.r.	n.r.	n.r.	0.023	0.086
					(0.058)	(0.079)
Technical*POST	n.r.	n.r.	n.r.	n.r.	0.054	0.025
					(0.056)	(0.078)
Vocational*POST	n.r.	n.r.	n.r.	n.r.	0.148	0.135
					(0.060)	(0.078)
Constant	0.409	0.949	0.631	0.857	0.744	1.475
	(0.080)	(0.145)	(0.037)	(0.040)	(0.236)	(0.120)
N	33695	34022	31338	31200	39554	39434

Sources: INVALSI 2018/2019 and 2020/2021 (authors own estimates). Notes: all models control for: school (grade 5 and 8), and school track (grade 13). Standard error in parenthesis.
Strata legend as given in Table 2 of the main text.

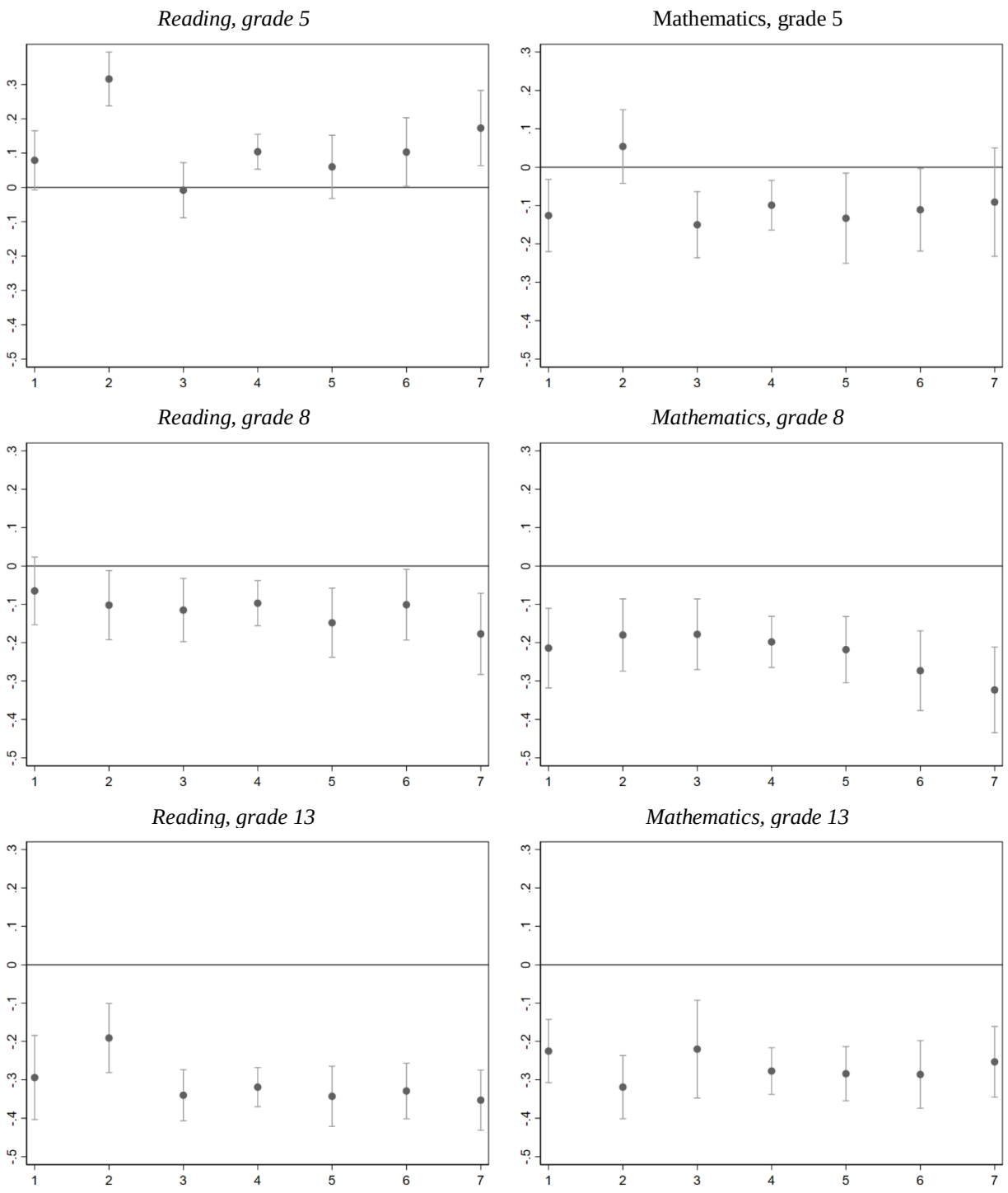


Figure D1. Estimated interaction effects and confidence interval at 95% by grade, school subject and social position of students' families.

Sources: INVALSI 2018/2019 and 2020/2021 data sets (authors own estimates). Note: all models control for: gender, age, geographic area of residence, migrant status, school hours per week, class retention, pre-primary school attendance, school (grade 5 and 8), and school track (grade 13). Strata legend as given in Table 2 of the main text.
These estimates have been derived from the model displayed in Table D2.

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