A Lost Generation? Impact of COVID-19 on High School Students

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A lost generation? Impact of COVID-19 on high school students' achievements*

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Abstract

This paper estimates the effect of a full year of the Covid-19 pandemic on school performance, focusing on students at the end of upper secondary school who are about to enter the labour market or start university without having had the opportunity to recover. Using longitudinal data from standardised tests for the student population nationwide, we use difference-in-differences models to analyse the performance of two cohorts of students in Italy: a cohort that has never been exposed to the pandemic and the cohort that graduated in 2021. We find that the pandemic had a huge negative impact on students' performance in mathematics and reading (approximately 0.4 s.d. in both domains). Low-achieving students suffered the most, increasing the gap between strong and poor performers. The relative position of girls improved compared to boys. Contrary to the findings of the existing international literature, inequalities by parental education remained largely unchanged.

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1 Introduction

The Covid-19 pandemic took a toll on the lives of many children in both poor and rich countries. Children experienced intensified poverty, increased malnutrition and mortality, worse health outcomes (stemming from strained health systems), mounting risks of violence, exploitation and abuse (as a result of heightened tensions in the household) and learning loss (UNICEF, 2022).

In this paper, we concentrate on the last aspect of this long list: learning loss. Since the beginning of the pandemic, in spring 2020, many countries have imposed total school closures for weeks, sometimes months. The duration of the closures has varied considerably between countries in relation to the timing of the outbreak and the way governments chose to deal with the pandemic (UNESCO, 2023). In this context, loss of learning could have occurred through different channels: (i) weakening of relationships and cooperation with classmates, concentration difficulties, socio-emotional loss and mental health problems, triggered by isolation and social distancing; (ii) increased number of absences of children and teachers due to contagion; (iii) potential reduced effectiveness of distance learning as a substitute for school-based teaching, difficulty of access to distance learning and insufficient parental support. In particular, the last two channels are more likely to occur among disadvantaged social groups, thereby exacerbating inequalities. Measuring learning loss and disparities between children from different backgrounds is crucial because a significant reduction in skill acquisition and the widening of social gaps can have major negative repercussions on a country's social and economic development (Fuchs-Schündeln et al., 2022; Hanushek & Woessmann, 2020; UNDP, 2020).

Several empirical studies have aimed to quantify the effect of the pandemic on school learning in various countries, mostly focusing on children in primary and lower secondary school (see, among others, Blaskó et al., 2022; Engzell et al., 2021; Haelermans et al., 2022; Maldonado & De Witte, 2022; Schult et al., 2022). Few meta-analyses have processed the different findings of these empirical studies and attempted to draw general conclusions from them (Betthäuser et al., 2023; Patrinos et al., 2022). Although a sharp decline is observed in general, the loss varies greatly between countries, age groups and measures taken to contain the pandemic. Also, due to data availability, the existing studies adopt different empirical strategies, so it is difficult to make precise comparisons. Nevertheless, it seems clear that the losses were greatest when schools were closed for the longest time. Moreover, there is wide range of evidence that the pandemic increased educational inequalities by socio-economic background. In terms of initial skills, most studies have found that low-performing students lose out the most.

We contribute to the literature by analysing the learning loss suffered by students affected by the pandemic at the end of high school, a level of schooling for which there is still little research, despite being a crucial time in the life of young people. To date, only a very small number of empirical studies, from Latin America (Lichand et al., 2022; Vegas, 2022), have focused on the learning loss in late adolescence.

The impact on young individuals in their final year of high school is of particular interest because these students are about to enter the labour market or embark on a university career without having had the opportunity to recover. Without downplaying the extreme importance of early childhood development and the risk that younger children are more impaired due to the cumulative nature of human capital acquisition (e.g., Fuchs-Schündeln et al., 2022), children in the early grades do have several years of schooling ahead of them to make up for learning deficits if appropriate remedial policies are put in place. The European Union has implemented an unprecedented stimulus package, known as Next Generation EU, to support the recovery in the aftermath of the pandemic, including a budget for school renovation and dedicated projects. However, students who were in their final year of school in 2021 will not benefit from these interventions and might suffer the long-term effects of learning loss both at university and in the labour market (Hampf et al., 2017). Additionally, the severe restrictions imposed during lockdowns and school closures led to an enormous change in youngsters' social environment, resulting in feelings of social isolation that affected mental health and socio-emotional development. Medical research has shown that the prevalence of clinically elevated symptoms of depression and anxiety, that increased as the pandemic progressed, was higher in older children (Racine et al., 2021). Sandner et al. (2023) also show a large decline in the well-being of the 2021 graduation cohort.

The situation in Italy is particularly worrying because, even before the pandemic, adult literacy and numeracy levels were well below the average of OECD countries participating in the Survey of Adult Skills (PIAAC), the proportion of young individuals with tertiary education is among the lowest in Europe and the proportion of NEETs (young adults not in Employment, Formal Education or Training) is among the highest (Education GPS, 2023; Eurostat, 2023). Moreover, relative to other countries, Italy lacked digital skills and proper infrastructures for remote learning as a replacement for face-to-face teaching. Before the outbreak of the pandemic, Italy had one of the lowest scores in the Digital Economy and Society Index (DESI) in the European Union, one of the lowest shares of households with a fixed broadband subscription and one of the lowest shares of individuals with at least basic software skills (European Commission, 2020). Teachers usually have low ICT skills and little experience with blended and technology-enhanced teaching (Bertoletti et al., 2023; European Schoolnet, 2012; OECD, 2018). Moreover, Italy has one of the highest shares of children lacking individual and school learning resources among European Union countries (Blaskó et al., 2022). Considering that Italy is one of the countries that experienced the longest school closures (UNESCO, 2023), younger students were prioritized in the re-opening of schools in 2020/2021, whereas high school was closed for much longer. According to Champeaux et al. (2022), in spring 2020 Italian parents reported being worried about their children's home learning process and emotional well-being, especially when online courses were not provided.

We apply difference-in-differences techniques to examine achievements in reading and maths using a rich panel database on students' learning covering the full population of students at the national level. In Italy, national standardized assessment was suspended in 2020 due to the pandemic. Thus, we compare the results in Grade 13 (2021) of the cohort of students hit by the pandemic the previous year with those of the cohort of students attending the same grade two years before (2019), controlling for previous achievements in Grade 10. Controlling for previous achievements is fundamental because initial skills can vary among cohorts for reasons not related to the pandemic (Werner & Woessmann, 2023).

We also analyse how educational outcomes change in relation to prior performances, and inequalities related to gender, parental education, migratory background and geographical area. To address the fact that not all the assessments under consideration provide horizontally equated test - more specifically, test scores for Grade 13 are equated (i.e., linked) and therefore comparable between the two cohorts of students, while test scores for Grade 10 are not - we propose a novel strategy to analyse inequalities, consisting of estimating the model for test scores standardized within each cohort and within each grade. The problem we describe below arises for the Italian data but may also apply to other contexts where standardised assessments are repeated over time (across different cohorts) but are not horizontally equated.

In Italy, previous studies have focused on primary and lower secondary schools. Contini et al. (2022) estimated the effects of the first wave of the pandemic (February-June 2020) on the mathematics achievement of primary school children in the city of Turin and found a loss in maths achievements. Borgonovi & Ferrara (2023) examined the impact of COVID-19 on students' achievement in mathematics and reading in primary and lower secondary schools. They found a small positive effect of the pandemic on primary school children's achievements and a negative effect for lower secondary school students. Focusing on children in primary school, Aparicio Fenoll (2022) found that during the pandemic, only children with parents in non-teleworkable occupations suffered a learning loss. Two studies included high school in their analysis. Battisti & Maggio (2023) analysed data from primary, lower secondary and upper secondary schools together, without distinguishing the effect of the pandemic by school level.[1] Bazoli et al. (2022) estimated the effects of the pandemic on reading and mathematics achievement in samples of Italian students across all schooling stages, including high school. However, their study did not control for achievements in previous grades.

Our results reveal that students at the end of high school suffered huge learning losses during the pandemic, about 0.4 standard deviations in both mathematics and reading. On average, each week of school closure results in a loss of -0.013 s.d. in both mathematics and in Italian (comparable to -0.014 s.d. per week, derived in the meta-analysis by Betthäuser et al., 2023). The analysis also shows that low-achieving students suffered the most. Boys lost ground to girls both in Italian (where girls were already doing better, meaning the gap widened) and, to some extent, in mathematics (where girls typically do worse, narrowing the gap in favour of boys). When comparing students with similar performance at Grade 10, the disadvantage between migrant and native students and between southern and northern students decreased significantly. However, because of the pre-existing gap in favour of native and northern students, and the fact that low-achieving students lost the most, overall inequalities between these groups increased. In contrast, and somewhat surprisingly, there is no evidence of a widening of achievement gaps related to parental education.

The structure of the paper is as follows. Section 2 presents the Italian schooling system and details of the Italian school closure during the pandemic. Section 3 describes the data, sample and cohorts utilised in the analyses. Section 4 focuses on the empirical strategy and addresses the issue of a lack of anchoring across cohorts in prior test scores. Section 5 illustrates the results. Section 6 concludes.

2 The Italian context

2.1 The schooling system

In Italy, the school year starts in early September and finishes in mid-June in all grades. The primary and lower secondary school systems are compulsory, comprehensive and

[1] Moreover, since in Italy test scores are not comparable across school levels (they are not vertically equated), estimating pooled models for different assessments may deliver biased results.

free of charge. At the end of lower secondary school, in Grade 8, students take a national exam and choose among several different types of upper secondary schools that last 5 years (Grades 9-13).[2] Alternatively, at the end of lower secondary school, students can choose three-year regional vocational education and training. Since compulsory education lasts a total of ten years, up to age 16, it ideally includes (for students who have not repeated school years) the first two years of upper secondary school or vocational training.

Upper secondary schools can be broadly grouped into general (lyceums), technical and vocational tracks. More specifically, general programs include traditional lyceums – the most academic-oriented options, divided into the humanistic lyceum (classical) and the scientific lyceum – and other lyceums, which include schools with an emphasis on foreign languages, social sciences and arts. The aim of lyceums is to give students a strong background to pursue higher education and to prepare them in terms of competences, methodological and substantive knowledge, and critical thinking skills (Eurydice, 2023). Technical schools combine general and technical education, aimed at providing students with a strong background in technological and/or economic subjects and preparing them for skilled technical or administrative professions. Vocational schools provide students with a vocational background to access a variety of low-skilled occupations and deliver both three- and five-year programs. Upon completion of any five-year high school program and passing of a national exam, students are awarded a high school diploma that grants them access to college without proficiency requirements. Despite the formal openness of the system, the likelihood of enrolling in higher education (and even more so, the likelihood of earning a college degree) varies widely across school types (Contini & Salza, 2020).

To monitor children's skills across their schooling careers, the National Institute for the Evaluation of the School System (INVALSI) administers Italian literacy and maths standardized tests at different grades, from primary school to the end of high school. In high school, students enrolled in all tracks sit on these tests in Grade 10 and Grade 13, as described in Section 3.

2.2 The Covid-19 pandemic and school closure

Italy was the first Western country to impose strict social restrictions due to the widespread outbreak of Covid-19. During the first wave of the pandemic, in the spring of 2020, schools were closed nationwide for about 15 weeks, from the end of February

[2] Students also receive non-binding recommendations by their teachers during the final year of lower secondary school.

until the end of the school year in mid-June. Wherever possible, face-to-face teaching was replaced by distance learning, leaving teachers, students and schools largely unprepared and struggling to cope. In the same school year, the Italian government suspended the possibility of applying grade retention – the practice of holding back low-achieving students to repeat a school year – which is common in Italy, especially in high schools (Salza, 2022).[3]

Due to the new spread of Covid-19, school closures were again ordered at the beginning of the new school year. In practice, in the school year 2020/2021, schools were closed intermittently, with alternating periods of full closure, full opening and limited closure in regions with high prevalence of infection (Camera dei Deputati, 2022). Class-level closures were also based on the occurrence of cases in each class/school. Priority was given to opening primary and lower secondary schools, while high schools were closed for longer periods.[4] When schools were closed, the replacement of face-to-face teaching with distance learning was mandatory, although the actual implementation of distance learning was very uneven across schools. When high schools were open, to ensure social distancing, only 50-75% of students could attend face-to-face lessons, which they attended in turn. In the school year 2021/2022, schools of all grades were again open and face-to-face teaching was resumed, with few derogations related to exceptional circumstances.

Italy is characterized by high regional variation. The South is penalised in terms of school facilities and average test scores are lower (INVALSI, 2022). The pandemic also hit the different regions with different severity. Moreover, although the general rules on school closure were set out in national guidelines, in school year 2020/2021 regional authorities were allowed to impose stricter measures. This led to considerable variation in school closures across the country, linked to the severity of the pandemic but also to political decisions and the sensitivities of local governors, idiosyncratic motivations and preferences. Figure 1 summarizes the total weeks of school closure over school years 2019/2020 and 2020/2021 across the Italian region, which range from 23.4 (Trentino) up to 37.4 (Puglia). Puglia is the region with the longest period of school closure, almost two months longer than the Italian average.[5]

[3] The empirical implications for our results of this policy change are discussed in Section 5.4 (Robustness checks).

[4] The decision was based on the assumption that older students would be less harmed by distance learning and that they did not require parents to be present at home.

[5] The total number of weeks of school closure are calculated as the sum of the weeks of school closure in 2019/2020 and 2020/2021. In 2019/2020, schools were closed at national level for about 15 weeks (with minor differences between regions according to the regional school calendars). In 2020/2021, school closures were decided both at the national and at the regional level according to the spread of the contagion and to the political choices of the regional authorities.

[Figure 1 about here]

In terms of counter-measures, as early as March 2020, schools received funding to improve digital tools for distance learning and technical support (Camera dei Deputati, 2022). While this measure had positive effects in terms of the speed of adaptation, it also shows how unprepared schools were at the time. A budget was allocated to provide free digital equipment (PCs, tables, internet connection) to students from low socio-economic backgrounds. In the summer of 2020, a specific budget was allocated for the renovation of school buildings – to ensure physical distance in classrooms and school during the school year – and for school staff to reduce the disruption caused by teacher contagion. In terms of remedial measures to improve student learning, no measures were taken in the summer of 2020. Instead, in the 2020/2021 school year, the state funded face-to-face teaching projects aimed at reducing learning deficits, with priority given to primary and secondary schools in disadvantaged areas. Projects were submitted by schools and then approved, with wide variations between schools in what was actually implemented. Overall, there was no uniform policy across schools, provinces and regions, and only the schools that were better equipped in terms of human resources were able to access the available funding.

3 Data and descriptive statistics

This paper exploits the data from the national standardised tests administered by INVALSI. Tests are administered to the entire population of Italian students (about 500,00 students per grade) in Grades 2, 5, 8, 10 and 13 and evaluate students' reading and maths skills.[6] As mentioned above in Section 2, upper secondary schools in Italy can be classified into three broad tracks: general (lyceums), technical and vocational. The reading test in Grades 10 and 13 is the same across the different tracks, whereas the mathematics test has a common part and a specific part that varies between tracks.

The standardised tests in primary and lower secondary schools have been conducted in late spring every year since 2008/2009. The assessment in Grade 10 was first administered in 2011; students in Grade 13 were tested starting in 2019. Due to the pandemic, in 2020 the survey was suspended for all school stages and then administered again in 2021 and in 2022. However, the Grade 10 assessment resumed only in 2022. The tests are conducted between March and May, depending on the grade. Students in Grade 13 sit the test in March, students in lower secondary school

[6] Recently, standardised tests in English proficiency have also been introduced.

in April, primary school children in the beginning of May, and students in Grade 10 in mid May.

An important distinction, which is often overlooked in the economic literature, is between equated and non-equated tests. In equated tests, some items appear in both assessments, allowing their "anchoring" (Bond & Lang, 2013). This allows the scores of different assessments to be expressed in a common metric. The term *horizontally equated tests* refers to different assessments administered to students' from different cohorts in the same grade: when tests are horizontally equated, it is possible to make direct comparisons of the achievement levels of students who took the test in different years. The term *vertically equated tests* refers to assessments administered at different grade levels: when tests are vertically equated, it is possible to compare the results of children enrolled in different grades and to estimate achievement growth over time.

INVALSI tests have never been vertically equated. Instead, since 2019, the tests have been horizontally equated for all school grades, making it possible to express grade-specific scores in a common metric and to assess changes in results over time.[7] These aspects have implications for the empirical analysis, discussed below in Section 4. Taking advantage of these data, this paper compares test scores of students enrolled in Grade 13 in 2020/2021 - a cohort that experienced one full year of intermittent school closure due to the pandemic - with the test scores of students enrolled in Grade 13 in 2018/2019 - a cohort that did not experience the school closure, while controlling for prior skills. The pre-Covid cohort took the INVALSI tests in spring 2019 and the Covid cohort in spring 2021. Thanks to the longitudinal nature of the survey, it is possible to link test scores in Grade 10 at the individual level. For the pre-Covid cohort, we link the dataset for Grade 13 in 2019 with the dataset for Grade 10 in 2016 and for the Covid cohort, we link the dataset for Grade 13 in 2021 with the dataset for Grade 10 in 2018 (Figure 2).[8]

[Figure 2 about here]

Given the characteristics of the linkage, the longitudinal sample consists of all students who took the tests in both Grade 10 and Grade 13, who did not repeat a school

[7] The procedure adopted by INVALSI requires that part of the items administered in the 2019 assessment are re-administered to a sub-sample of students who carried out the test in 2021.

[8] There is some evidence of cheating in INVALSI tests (Angrist et al., 2017; Bertoni et al., 2013; Lucifora & Tonello, 2015). However, this should not be an issue of major concern here. First, because the existing evidence points to lower cheating behaviour in higher grades(Lucifora & Tonello, 2015). Second, we use test scores corrected by INVALSI for the risk of cheating. Third, the tests in Grade 13 - our outcome variable - are computer-based (CBT) since 2018 and correction is centralized, reducing the risk of cheating, in particular when stemming from teacher shirking (Angrist et al., 2017).

year in between (otherwise, it would not be possible to identify the same student in the Grade 10 archive three years earlier) nor dropped out of the school system. Robustness checks to account for the potential differential selection across cohorts are presented in Section 5.4.

The initial dataset recording all students in the Covid and pre-Covid cohorts who took the Grade 13 test consists of 879,786 students. A few students were excluded because they were absent from one of the two assessments (maths or Italian) in Grade 13, our outcome of interest. Others were excluded because it was not possible to match them with their prior test scores, due to absences in Grade 10, or because they experienced a grade retention in between. Longitudinal linkage has been possible for the majority of the students. Our final sample is composed of 618,226 individual observations, 289,938 in the pre-Covid cohort (47%) and 329,029 in the Covid cohort (53%) (see Table A1 in the Appendix for the details of the sample selection).

Table 1 reports the descriptive statistics both for the entire sample and separately for the two cohorts.[9] To facilitate comparability with other studies and the interpretation of the results, we rescaled test scores to have mean 0 and standard deviation 1 in the original full population. When horizontally anchored (as occurs in Grade 13), test scores are directly comparable (and standardized across cohorts). As prima facie evidence of a negative effect of the pandemic, we see that Grade 13 test scores are higher for the pre-Covid cohort than for the Covid cohort in both Italian and in Math.

[Table 1 about here]

Test scores for Grade 10 for 2016 and for 2018 are not horizontally anchored, and they are standardised by INVALSI within each cohort and not directly comparable over time. Note that Grade 10 test scores have a mean slightly above 0 in both cohorts; this is an indication of the existence of some positive sample selection, as mentioned above.

In addition to scores in the standardised test, INVALSI collects information on teacher's marks in Italian and mathematics at the end of the first term,[10] students' socio-demographic characteristics and family background. The set of variables includes age, gender, migratory background, parents' level of education and occupation, and geographic area. All the variables used in the analysis are described in Table A3 in the Appendix.

[9]Table A2 presents additional descriptive statistics on parental occupation and macro-area of residence.

[10]Marks range between 0 and 10 (6 is the pass mark), although in practice marks below 4 are extremely rare.

4 Identification strategy

4.1 Average effects

Our starting point is a model for achievement at a given stage of schooling based on a standard education production function, with a value-added specification (Todd & Wolpin, 2003):

$$Y_{1ij} = \alpha + \lambda X_{ij} + \gamma Y_{0ij} + \delta_j + \varepsilon_{ij} \tag{1}$$

where Y_{1ij} is a standardised test in maths or reading set by student i in school j in Grade 13; X_{ij} is a vector of controls, including the student's characteristics (age and gender) and socio-economic background measured at time 0 (Grade 10) (migratory background, parental education and occupation); Y_{0ij} is a vector of prior skills (standardised test scores and teacher's marks) measured at the time of the previous assessment, in Grade 10. δ_j are schools fixed effects and ε_{ij} are normally distributed stochastic errors.

To assess the average impact of the pandemic on children's learning, we use an extended version of a difference-in-differences model comparing achievements of children in the pandemic cohort with those of children in the pre-pandemic cohort:[11]

$$Y_{1ikj} = \alpha_0 + \alpha_1 C_k + \lambda X_{ikj} + \gamma Y_{0ikj} + \delta_j + e_{ikj} \tag{2}$$

C_k is a dummy variable equal to 1 if the child is in the Covid cohort k and 0 otherwise, and X_{ikj} and Y_{0ikj} are the explanatory variables previously defined corresponding to cohort k. α_1 is the coefficient of interest, capturing the causal effect of being in the Covid cohort rather than in the pre-Covid cohort on the test scores, given previous performance in maths and Italian and conditional on school fixed effects. The untestable identifying assumption is that, conditional on prior abilities, the performance of children in the Covid cohort would have been the same as the pre-Covid cohort had the pandemic not occurred. Such an assumption seems plausible as the two cohorts are close in time to each other and we are also conditioning on school fixed effects.

As in the canonical difference-in-differences, there is a treated and and control cohort and a pre and post period. It is worth noting that the classical difference-in-differences model is a special case of (2) when $\gamma = 1$ (see Appendix B1), which may be applied only when Y_1 and Y_0 are measured on the same scale, i.e., when test scores

[11] Due to the presence of school fixed effects, we cannot identify geographical effects, but nevertheless, geographical effects are kept under control.

corresponding to assessments administered in different grades to the same cohort of students are vertically equated. When test scores are not vertically equated - as in the present context - the classical difference-in-differences model may lead to uninformative results (see Contini & Cugnata, 2020, section 3.1).[12]

4.2 Length of school closure and regional differences

Next, we investigate the impact of the length of school closure and how it has influenced regional differences.

First, we also estimate a version of model (2) where we include the number of weeks of closure W_{rk} (varying at the regional level and equal to 0 in the pre-Covid cohort) instead of the Covid-cohort dummy. The corresponding coefficient captures the average effect of a week of closure across the country and is approximately equal to the total effect of the pandemic divided by the average number of weeks of closure.

Regional differences in the impact of the pandemic can be investigated by estimating a version of model (2), where being in the Covid cohort is interacted with regional dummies.[13] Since the duration of school closures was defined regionally and varied significantly across regions, it is also interesting to assess whether the observed regional differences could be fully explained by the duration of school closures. From this perspective, we estimate a model that additionally includes the number of weeks of school closures W_{kr}.[14] If closing weeks were entirely responsible for spatial differences, the region-specific coefficients of the Covid-cohort variable would become non-statistically significant.

4.3 The anchoring issue and heterogeneous effects

A possible limitation of the analyses described above is that for the school years of interest, the assessments in Grade 10 were not horizontally equated, thus Y_0 is not measured on the same scale in the two cohorts of students (Covid and pre-Covid cohort). This means that a given result in one cohort cannot be considered better or worse in absolute terms than that of another cohort. Instead, the comparison can be

[12] Additionally, a specification as equation (2) allows estimating the heterogeneous effects by prior skills.

[13] Building on the previous equation (2): $Y_{1ijkr} = \alpha_0 + \theta_r D_r * C_k + \lambda X_{ijkr} + \gamma Y_{0ijkr} + \delta_{jr} + e_{ijkr}$, where θ_r are the coefficients of the interaction terms between regional dummies D_r and the Covid cohort.

[14] $Y_{1ijkr} = \alpha_0 + \theta_r D_r * C_k + \beta W_{kr} + \lambda X_{ijkr} + \gamma Y_{0ijkr} + \delta_{jr} + e_{ijkr}$.

This model has one extra coefficient, so identification is obtained by setting one of the regions' D_r (in this case, Lombardy) to 0. The effect of the pandemic in Lombardy is represented by β_1 times the number of weeks of school closures in Lombardy. The remaining $\theta_r s$ represent the additional effect in region r that is not captured by $\beta_1 W_r$.

made in relative terms: two children with the same score in two different cohorts may not have the same absolute performance, but they share the same relative position within their cohort distribution. In essence, what we are actually doing in equation (2) is regressing the appropriately anchored results relative to Grade 13 (conceivable as absolute measures of performance) on within-cohort standardised test scores in Grade 10 (conceivable as relative measures of performance). This could lead to biased estimates of the impact of the pandemic. For example, if children's performance in Grade 10 had worsened on average between the two cohorts, the same relative position in the two cohorts would imply a lower absolute performance in the post-pandemic cohort, with the consequence of the negative impact of the pandemic being overestimated. Instead, the negative impact of the pandemic would be underestimated in the opposite scenario.

This issue is difficult to solve when analyzing average impact of the pandemic. A naive alternative to tackle the anchoring issue would be to compare the outcomes of the Covid and pre-Covid cohorts in a regression framework but not controlling for prior ability. However, as pointed out by Werner & Woessmann (2023), among others, the causal effect of the pandemic on student outcomes should not be estimated with cross-sectional data on different cohorts, because the two cohorts might have different abilities for reasons not attributable to the pandemic per se.

To address this point, as a sensitivity check we run simulations that provide estimates of a lower and an upper bound for the average effect. In the first, we subtract 0.1 s.d. from all individual test scores of the Covid cohort in Grade 10 (mimicking a 0.1 s.d. decrease, a quite large deterioration over two years). In the second, we add 0.1 s.d. to all test scores of the Covid cohort in Grade 10. In both cases, we estimate model (2) and take the resulting estimates as bounds.

In addition to the average effect, we are interested in assessing how inequalities between socio-demographic groups have evolved due to the pandemic, and in this perspective we address the anchoring issue by proposing a novel strategy to analyse inequalities.

In the absence of anchoring issues, one would allow coefficients and school-specific fixed effects in (2) to vary across cohorts. Naming coefficients of the pre-Covid cohort with subscript 0 and coefficients of the Covid cohort with subscript 1 we obtain the following specification:

$$\begin{aligned} Y_{1ijk} = {} & \alpha_0 + (\alpha_1 - \alpha_0)C_k + \lambda_0 X_{ijk} + (\lambda_1 - \lambda_0)C_k X_{ijk} + \gamma_0 Y_{0ijk} + \\ & + (\gamma_1 - \gamma_0)C_k Y_{0ijk} + (\delta_{jk} + \varepsilon_{ijk}) \end{aligned} \tag{3}$$

where the coefficients of interest are those of the interaction terms, capturing the extent to which the effects of individual variables and prior abilities varied before and after Covid. If only the constant term is allowed to vary across the two cohorts, this model boils down to (2).

The following strategy allows us to analyse how inequalities across social groups evolved during the pandemic. This strategy applies to all circumstances in which some (or all) assessments provide unanchored scores. Instead of focusing on absolute performance measures, we analyse the changes in the relative positions of each social group in Grade 13 before and after Covid-19 school closures, given their prior relative position.

Let us define Z_1 and Z_0 as the within-cohort standardised test scores in the two grades of interest, so that $E(Z_1) = E(Z_0) = 0$.[15] It can be shown that if we standardise scores, single cohort models have the same structure as (1):

$$Z_{1ij} = \alpha' + \lambda' X_{ij} + \gamma' Z_{0ij} + \delta'_j + \varepsilon'_{ij} \tag{4}$$

and consequently, the DiD model becomes:

$$\begin{aligned} Z_{1ijk} = \alpha'_0 + (\alpha'_1 - \alpha'_0)C_k + \lambda'_0 X_{ijk} + (\lambda'_1 - \lambda'_0)C_k X_{ijk} + \gamma'_0 Z_{0ijk} + \\ + (\gamma'_1 - \gamma'_0)C_k Z_{0ijk} + (\delta'_{jk} + \varepsilon'_{ijk}) \end{aligned} \tag{5}$$

The parameters of interest are the coefficients of the interaction terms $(\gamma'_1 - \gamma'_0)$ and $(\lambda'_1 - \lambda'_0)$, capturing the differential effects on learning in the two cohorts: the first, by prior skills, the second by gender, parents' education and migratory background.[16] The coefficient of the cohort variable has no meaningful interpretation here, as it is simply a rescaling term that ensures a 0 mean for Z. Geographical differences are not identified with school fixed effects: to analyse whether the pandemic increased territorial disparities, we also estimate a version of this model incorporating regional dummies but no school fixed effects.

The previous coefficients of the interactions between each X and the cohort variable represent how differentials across groups have changed before and after the pandemic, conditional on prior achievements and school features. We also want to answer a more descriptive but relevant question: what happened to the overall differentials be-

[15] To avoid the within-cohort stantardised scores to be affected by selection in the matched sample, we implemented the within-cohort standardisation in the original sample. We then implement the empirical analysis in the final analytical sample.

[16] Note that Contini & Cugnata (2020) make additional arguments on the identification of the different channels responsible of changes in inequalities that do not apply to our case, because we have longitudinal data at the individual level.

tween social groups? To do so, we estimate a reduced form of (5) that does not include the prior ability relative position, nor school-fixed effects:[17]

$$Z_{1ijk} = \alpha_0'' + (\alpha_1'' - \alpha_0'')C_k + \lambda_0'' X_{ijk} + (\lambda_1'' - \lambda_0'')C_k X_{ijk} + u_{ijk} \tag{6}$$

Thus, in the results' section, we will show the estimates of the interaction effects of being in the Covid cohort with the X variables, when controlling and not controlling for Z_0 (prior ability) and school fixed effects. The firsts are derived from the estimation of (5), the seconds, from the estimation of model (6).

The coefficients of the interaction terms in (6) capture the gross gain (or loss) of different social groups relative to each other that occurred in the pandemic years, which could be attributed to one of the following mechanisms: (i) 'new' inequalities developed between Grades 10 and 13 given prior abilities and school features, i.e., new social ; (ii) differences in carryover effects of prior ability; and (iii) differences in the value-added of the schools attended. Instead, the coefficients of the interaction terms in (5) capture the net changes, imputable only to channel (i) (see Appendix B.2 for a formal discussion).

Note that schools' value-added might have changed relative to each other after the pandemic because some schools were better equipped to deal with critical moments (good management, good teachers) or had more ICT knowledge, which is particularly important during school closures. Differences in the carryover effects of prior skills may have occurred because higher-achieving students probably show greater attachment to school, are more resilient to unexpected shocks in the teaching environment and may possess greater ICT skills. Differences in the relative learning between social groups, net of prior achievement and school effects, could be the result of the different resources available to different schools for facing the difficulties associated with school closures.

To assess how inequalities have developed *due* to the pandemic, it is more appropriate to analyse changes net of prior skills and school-specific effects (which across cohorts could have changed also for reasons unrelated to the pandemic). However, if the interest is also to *describe* how inequalities have changed across social groups over the time span of interest, it is important to analyse also overall changes. Foe example, new inequalities across social groups may not increase, but due to the fact that one group is more likely to have low performances, and that low performing students lose more than high performing ones, overall inequalities may increase.

[17] In this case, we include dummies to control for school track.

5 Results

5.1 Average learning loss

Table 2 reports the average learning loss related to the Covid-19 pandemic on students' performance in maths and in Italian for all students in Grade 13 and by school track. These figures derive from the estimation of equation (2), including all the available sets of controls at the individual level and school fixed effects.[18]

[Table 2 about here]

Overall, high school students suffered an average loss of 0.39 standard deviations in mathematics and 0.41 standard deviations in Italian due to the pandemic. We observe some differences across tracks; in particular, students at Scientific high schools and Technical institutes suffer the most severe losses in maths and reading, while students at Vocational institutes suffer the least.

To account for the fact that tests in Grade 10 (initial abilities) are not equated between the Covid and pre-Covid cohorts, we perform a sensitivity check by estimating upper and lower bounds for the point estimates of the average effects. Even accounting for a possible deterioration (or improvement) across cohorts as large as 0.1 s.d., results are close to the main estimates and always indicative of a large loss. The bounds are reported below each point estimates in Table 2.

As a term of comparison, in their meta-analysis Betthäuser et al. (2023) point to a learning loss of 0.14 s.d. on average across grades and subjects. This loss persists over time during the two years following the start of the pandemic. The authors report no substantial differences between primary and secondary schools, with some studies finding greater losses for younger children and other studies finding the opposite. However, of the 42 studies included in their review, only a minority concerned upper secondary school, while most research focused on primary school and, to a lesser extent, lower secondary school.

Our estimates are also much larger than the available evidence for Italy in the lower stages of schooling, where the average learning difference is estimated between -0.13 s.d. and -0.29 in maths and +0.06 s.d. and -0.08 in reading, depending on the period covered, the grade and the estimation strategy (Bazoli et al., 2022; Borgonovi & Ferrara, 2023; Contini et al., 2022). The fact that the learning loss is much larger in Grade 13 is probably due to the longer duration of school closure that high school students have been exposed to. The magnitude of the loss is so large, that students

[18] Full results are available from the authors upon request.

may have experienced not only a delay in their expected learning growth, but possibly even a loss of competences already acquired, with long-lasting effects on their future educational and working life.

To the best of our knowledge, only two existing studies have focused on students close to the end of upper secondary school, and they are both from middle-income countries. Lichand et al. (2022) estimates that in 2020 in Brazil the dropout risk more than triplicates and average learning loss in maths and reading amounted to 0.32 s.d. for students in Grades 6 through 12, with some variation by grade but no distinctive difference between lower and upper secondary school. In Colombia, Vegas (2022) estimates a learning deficit of 0.2 s.d. for students in Grade 11. Worryingly, the estimated effect for Italy is even larger and thus requires urgent action for these young adults.

5.2 Length of school closure

As discussed in Section 4.2, we take advantage of the regional variation in school closure weeks to estimate the effect of one week of school closure on mathematics and reading learning. We present two specifications in Table 3. First, instead of including a dummy variable for being in the Covid or pre-Covid cohort in equation (2), we include a continuous variable corresponding to the number of weeks of school closure in each region, equal to 0 for all students in the pre-Covid cohort (column 1). The results show an average learning loss of 0.013 s.d. per week of school closure in both mathematics and Italian. In a second specification, we include the same continuous variable but focus only on students in the Covid cohort (column 2). This specification overcomes the issue of non-horizontal-anchoring for Grade 10. The results indicate a slightly smaller loss: 0.009 in mathematics and 0.012 in Italian.

[Table 3 about here]

Figure 3 shows the heterogeneous impact of the pandemic by region, controlling and not controlling for the number of weeks of school closure. Learning losses vary significantly across regions when we do not control for school closures (blue dots and lines). Learning losses in maths vary between 0.55 s.d. (Puglia) and 0.20 s.d. (Valle d'Aosta and Molise). Reading learning losses vary between 0.58 s.d. (Puglia) and 0.22 s.d. (Valle d'Aosta). We replicated the analysis, also controlling for the number of weeks of school closures (red lines). Regional differences are reduced as expected, but only slightly; thus, we may conclude that weeks of school closure do not fully explain regional differences.

[Figure 3 about here]

5.3 Effects on inequalities

In order to analyse the impact of the pandemic on learning inequalities and to address the potential problem related to unanchored pre-test scores, we estimate models (5) and (6) in terms of z-scores, including interaction terms with all the explanatory variables for which we want to assess changes in inequalities between the pre-Covid and Covid cohorts (prior achievement, gender, parental education, migrant background, geographical area).

To begin, we focus on results relative to prior skills. In Figure 4, we report the average marginal effects of the corresponding interaction term in equation (5). Overall, for a one standard deviation increase in test scores in Grade 10, the corresponding test scores in Grade 13 increase by 0.11/0.16 s.d. (Italian/math) more in the Covid cohort than in the previous cohort. This means that previously low-performing children lost more than high-performing ones during the pandemic, and inequalities by ability have widened significantly. The results are consistent with most of the existing literature (notable exceptions are Birkelund & Karlson (2022); Contini et al. (2022)).[19] If we look at the results by school type, we can see that this trend is more pronounced in lyceums for Italian and in technical schools for mathematics. The pandemic has thus exacerbated even more the educational inequalities among students with different initial skills - amplifying the risk of increasing inequalities in the long run.

[Figure 4 about here]

Next, we describe the results on inequalities by socio-demographic dimensions. The average marginal effects of being in the Covid cohort by socio-demographic characteristics and conditional on prior abilities are reported in red (equation 5), while the unconditional effects (not controlling for prior abilities and school fixed effects) are presented in blue (equation 6). The former can be thought of as the pandemic effect when comparing students with the same relative positions of previous performance, the latter captures the variation in the overall learning gaps between socio-demographic groups. We also estimated a model in which school fixed effects are included, but the results end up being very similar to those without school fixed effects,

[19] Also some of the heterogeneous results by socio-demographic characteristics are to some extent different from Contini et al. (2022); however, a direct comparison is difficult to implement, because of multiple differences (level of schooling and Grade, period analysed and length of school closure, and geographical scope.

suggesting that the main driver of the differences between conditional and unconditional estimates are prior skills.[20]

The results for gender differences are shown in Figure 5. Overall, the relative position of girls compared to boys can be seen to improve after the pandemic, particularly in Italian, but also in mathematics in Technical and Vocational schools (no gender differences are observable in Scientific lyceums). One possible explanation for this finding is that girls are more disciplined and self-controlled than boys (Duckworth & Seligman, 2006). During school closures self-discipline is particularly important, because in an online learning environment there is less feedback and less interaction between students and teachers (De Paola et al., 2023).[21] Given the finding that better performers lose less and given that, on average, girls perform worse than boys in mathematics, it is not surprising that the relative improvement for girls found without controlling for prior achievement (and school fixed effects) is smaller than that observed when we do include prior achievement in the model.

[Figure 5 about here]

Figure 6 presents differences by parental education. Overall, these inequalities remained virtually unchanged: most of the observed effects are small and statistically insignificant. This result is in line with existing studies on lower grades in Italy (Bazoli et al., 2022; Borgonovi & Ferrara, 2023), which highlights an Italian specificity rather than a grade specificity and calls for further reflection. Why is it that, in Italy, contrary to theoretical predictions and international findings, there is no evidence that students from disadvantaged backgrounds have suffered the greatest learning losses? Unfortunately, we do not have a fully convincing explanation for this result, and more research is certainly needed. However, we can imagine a few hypotheses. It is possible that highly educated parents in highly skilled occupations were more likely to continue working during the pandemic, either physically or remotely, with even more intense work schedules than before, making it difficult for them to support their children effectively. Using data collected in Italy in spring 2020, Del Boca et al. (2020) show that both women and men spend less time with their offsprings if they continue to work away from home. In the U.S. Bansak & Starr (2021) revealed that in households experiencing a loss of employment income due to COVID-19, parents devoted more time

[20] Results are available from the authors upon request.

[21] De Paola et al. (2023) find that online teaching during Covid-19 reduced the performance of university students. However, the effects differed greatly according to the students' tendency to procrastinate costly activities such as studying. If the same is true for younger students, this could explain the overall improvement of girls compared to boys.

to help children with schoolwork than households that did not face income loss. Such an effect could have been more pronounced in Italy, where many low-skilled workers were not allowed to go to work during the first lockdown (in spring 2020) and thus remained at home. On the contrary, white-collar and high-skilled office workers were overwhelmed with the need to learn how to use ICT tools in order to continue their activities remotely. This may be an Italian peculiarity, given the low level of digital literacy that most people had before the pandemic (European Commission, 2020).

[Figure 6 about here]

Figure 7 show the results by migrant background. Children from migrant backgrounds end up improving slightly relative to natives with the same prior achievement. Indeed, this is an unexpected result. One possible explanation is that, due to the significant disadvantages that migrant students face at school, they have to work harder to achieve the same results as natives. Therefore, when we run the analyses controlling for prior achievement, migrants may do better because they are likely to be endowed with higher unobservable non-cognitive skills and/or resilience. However, since migrant pupils perform more poorly on average and the lowest-achieving students lose more, overall, they have lost further ground relative to natives. The total migrant-native gap increased on average by 0.06 standard deviations in maths and by 0.04 standard deviations in Italian during the pandemic.

[Figure 7 about here]

The effect of the pandemic on geographical achievement gaps[22] is shown in Figure 8. When comparing equally proficient students in Grade 10, students living in the South can be seen to have improved significantly over those living in the Northern regions.[23] This improvement is impressive, particularly in mathematics. It should be noted, however, that achievement gaps along the North-South divide have always been large, with southern students vastly underperforming (INVALSI, 2022).[24] Thus, as the gap between high and low achievers widened, not conditional on prior achievement the gap appears essentially unchanged.

[Figure 8 about here]

[22]Note that since these differences are not identified with school fixed effects, these results derive from the estimation of a version of also model (5) that does not include them.

[23]When we control for Z_0, students in the Centre are in between those of the North and South for maths. For Italian, they are close to the South. Unconditional on Z_0 and school fixed effects, students in the Centre of Italy are not significantly different from students in the North. Results available from the authors upon request.

[24]The reasons for these differences have been attributed to the role of contexts and school quality (Bratti et al., 2007).

5.4 Robustness checks

To confirm the validity of our results, we now perform robustness checks based on model (2).

The first issue to address is that our analytical sample consists of students who participated in assessment in Grades 10 and 13 and who did not repeat a school year between the two grades. As mentioned in Section 3, this feature implies that the analytical samples used for the difference-in-differences analysis are to some extent positively selected. By analysing the data of students in Grade 13 without controlling for prior performance, we can compare the estimates deriving from the total population of students who took the tests in Grade 13 with those of the selected population that we were able to link with the test data in Grade 10. The results are shown in Table 4. In column 1, we report the results for our final sample, while in column 2, we report those of the full sample.[25] Estimates of the learning loss are very similar in the two samples for both Italian and math. The small differences are consistent with the expectations: since in our main analyses we found a greater loss for previously poorly achieving students, a smaller learning deficit should be observed in the analytical (selected) sample rather than in the full sample. This suggests that even in the difference-in-differences analysis the level of bias should be small, and that, if anything, the learning loss is slightly underestimated. Also note that when not controlling for prior abilities, the estimated learning loss is somewhat smaller than the results when we include Grade 10 test scores in the model (-0.33 s.d. in maths and -0.36 s.d. in Italian, vs -0.39 s.d. and -0.41 s.d. in our preferred specification).

[Table 4 about here]

A second robustness check takes into consideration the fact that due to the school closure that occurred in spring 2020, the Ministry of Education suspended grade retention for the current school year (acknowledging that schools were unprepared to cope with the new situation, remote learning was not mandatory and only oral exams were allowed). This results in a lack of full comparability between the two cohorts, which were subjected to different rules: in the pre-Covid cohort, Grade 12 students with low results were exposed to the risk of being retained, whereas this was not the case for those in the Covid cohort. For this reason, the group of Grade 13 students in the Covid

[25] Since data on parental education and occupation were not available for the initial sample (because the information was retrieved from the Grade 10 assessment), we controlled for the student ESCS (Economic, Social and Cultural Status) instead. When comparing the final sample estimates derived from using ESCS with those derived from using parental education and occupation we find very similar results.

cohort could be to the same extent poorer performing than the corresponding group in the pre-Covid cohort. Consequently, the risk is to overestimate the negative effects of the pandemic on student learning. To account for this imbalance, we derived the proportion of students who were held back between Grade 12 and Grade 13 in school year 2018/2019 from the statistics of the Italian Ministry of Education: 3.33% in Scientific lyceums, 2.95% in Other lyceums, 7.15% in the Technical track and 10% in the Vocational track (Ministero dell'Istruzione, 2020). To simulate what would have happened if grade retention had been applied, we removed the corresponding proportions of retention for each track from the lowest performing students in the Covid cohort sample. The results, presented in Table 5, column 2, are very similar to the main estimates already shown in Table 2 and reported again in column 1. Again, the minimal observed differences go in the expected direction, with the new estimates being slightly smaller than the main ones.

Third, one potential additional issue with national assessments performed during the Covid-19 pandemic is attrition bias. As pointed out by Werner & Woessmann (2023) in their study on Germany, a larger fraction of students did not participate in the assessments during the pandemic than during normal times. If these students are low achievers, as one would expect, then the learning deficit is underestimated. In our data, we can measure attrition as the proportion of students who participated in the Grade 10 assessments and not in the Grade 13 ones, separately for the Covid and the pre-Covid cohort. Consistent with expectations, attrition in the Covid cohort (28%) is larger than in the pre-Covid cohort (21%), with large regional variation (Table A4 in the Appendix). Attrition bias can be reduced by controlling for prior ability, as done in our main analyses. Nevertheless, to get a sense of the possible bias that this problem introduces, we estimate the probability of taking the assessment in Grade 13 separately for the pre-Covid and Covid cohort. The sample is composed of the population of students who undertook the national assessment in maths and Italian in Grade 10, and the dependent variable is a dummy variable indicating if the student participated in the Grade 13 assessment. Columns 1 and 2 of Table A5 in the Appendix report the estimates controlling only for maths and Italian test scores in Grade 10. As expected, high achievers in Grade 10 are more likely to participate in the Grade 13 assessment and slightly more in the Covid cohort. This result is confirmed when controlling for gender, parental education and migratory background (Columns 3 and 4). Results indicate that socio-demographic variables also predict the probability of participation: girls, students with highly educated parents and natives are more likely to participate in Grade 13 assessment, conditional on their prior ability. Overall, these results suggest that non-participation could lead to a small underestimation of learning loss, in line with Werner & Woessmann (2023).

Lastly, we perform an additional robustness check, re-estimating the main model by excluding two outlier regions that experienced a much longer school closure during the pandemic (Puglia, 37.4 weeks, and Campania, 34.8 weeks, as compared to the national average 29.9; see Figure 3) and Calabria, which has a high attrition rate in the Covid cohort. Puglia also had a much larger proportion of attrition in the Covid cohort than the rest of Italy: the proportion of students present in Grade 10 who did not participate in Grade 13 assessment was 59% (Table A4 in the Appendix). There is no substantial difference with the main results (Table 5, columns 3, 4, and 5).

[Table 5 about here]

6 Discussion and conclusions

This paper focuses on the learning loss due to Covid-19 for students at the end of upper secondary school in Italy, a country that was already lagging behind other rich countries before the pandemic in terms of GDP, human capital accumulation, learning outcomes, tertiary attainment and labour market outcomes for young people.

Although the literature on the effects of Covid on learning at the primary and lower secondary levels is now quite extensive, there is still a lack of empirical evidence on the effects for older students. Using rich panel data from national standardised tests for the whole student population, repeated over different cohorts, this paper analyses the learning loss associated with the pandemic and how inequalities between socio-demographic groups have changed.

Focusing on students who were first hit by the pandemic during Grade 12, we estimate two sets of difference-in-differences models. With the first one, we estimate the average effect of the pandemic on student learning at the end of Grade 13, comparing the performance of students in the pandemic cohort (measured in spring 2021) with that of students in a pre-pandemic cohort (measured in spring 2019), while controlling for prior skills at the end of Grade 10. As the Grade 10 assessments were not horizontally equated, these estimates are based on the untestable assumption that the prior distribution of skills did not change between the two cohorts. The second set of models does not require this assumption and aims to investigate whether and how inequalities have changed during the pandemic period by analysing the relative position of the different groups, defined by prior performance, gender, parental education, migratory background and geographical area.

Our main findings can be summarized as follows. The average impact of the pandemic is extremely large in both mathematics (-0.39 s.d.) and reading (-0.41 s.d.), with no marked differences between tracks. The negative effects vary widely across regions, even after controlling for regional differences in the duration of school closures, suggesting that other contextual factors matter. Altogether, these estimates are much larger than those obtained for lower grades in Italy (Bazoli et al., 2022; Borgonovi & Ferrara, 2023; Contini et al., 2022), suggesting that the disruption was much greater in high school than in earlier grades. While the losses experienced by younger children are of great concern because of the cumulative nature of learning, the learning losses experienced by students at the end of their school careers can also be critical. These individuals are about to enter either the labour market or tertiary education, with major shortcomings compared to the past. In Italy, the situation is especially worrisome, as even before the pandemic, the level of adult maths and reading competencies according to the Survey of Adult Skills (PIAAC) was very low, and the percentage of NEET was very high.

In terms of inequalities, consistent with most of the literature, we find that previously lower achieving students experienced the largest losses. The relative position of girls compared to boys improved after the pandemic, that is, boys lost more than girls, with opposite effects in terms of inequality: the gender gap in reading (in favour of girls) increased, whereas the gender gap in mathematics (in favour of boys) decreased. Conditional on prior abilities, the learning gap between students with a migratory background (first and second generations) and natives decreased. We speculate that this result could be due to unobservable non-cognitive skills and resilience that helped the migrant students more than the natives. Note, however, that the overall inequality (unconditional on initial ability) between migrants and natives actually increased during the pandemic due to the large initial achievement gap in favour of native children.

Our results show no significant differences related to parents' education, while most of the international evidence emphasises the exacerbation of inequalities based on parents' socio-economic background. These results are in line with other results for Italy in the lower grades (Bazoli et al., 2022; Borgonovi & Ferrara, 2023). In the results' section we speculate on possible explanations, pointing to the specificity of the Italian case, where many low-skilled workers were forced to stay home (not working), while high-skilled workers who worked remotely had to learn how to use ICT tools they had no familiarity with (as already mentioned, before the pandemic Italy had very low digital skills among the adult population).

Our results strongly call for educational policies to support the formation of human capital for this generation of students, and in particular for the most fragile groups. Indeed, more research is needed to better understand the medium-term legacy of the pandemic and counteract the negative impact on the development of skills and the professional futures of boys and girls. However, it is already clear that the price paid by the younger generation for the pandemic is very high, with likely long-term consequences for this generation and for society as a whole. Urgent remedial action is needed to compensate for these losses and to support the human capital formation of students of all ages, including those in high school and university, who are entering the labour market with a very heavy burden. In the absence of education policies that effectively address these gaps, there is a high risk of an increase in university dropout, the proportion of NEETs, as well as a sharp decline in employment prospects, wages and, ultimately, national growth.

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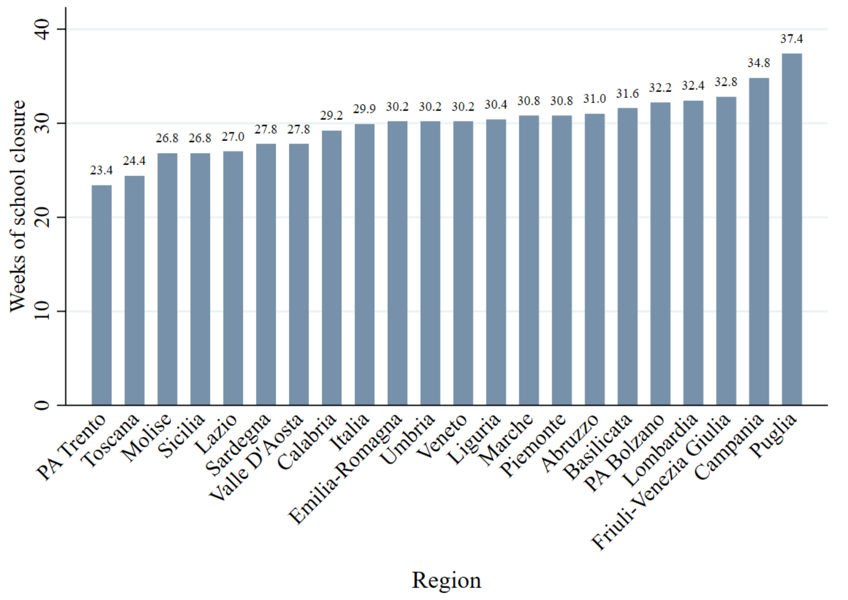
Figures

Figure 1: Length of school closure in 2019/20 and 2020/21 school years across Italian regions



Note: Total weeks of school closure across Italian regions for the 2019/20 and 2020/21 school years. For the former school year, the weeks of closure have been measured using the regional planned school calendars provided by the Ministry of Education and Research.

Figure 2: Dataset structure and timeline of the anchoring of INVALSI tests

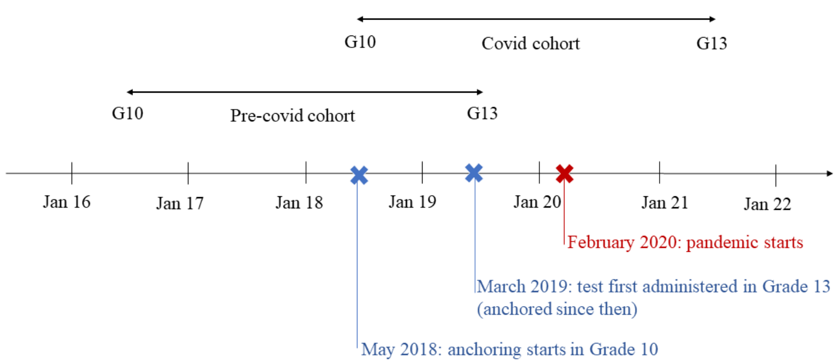
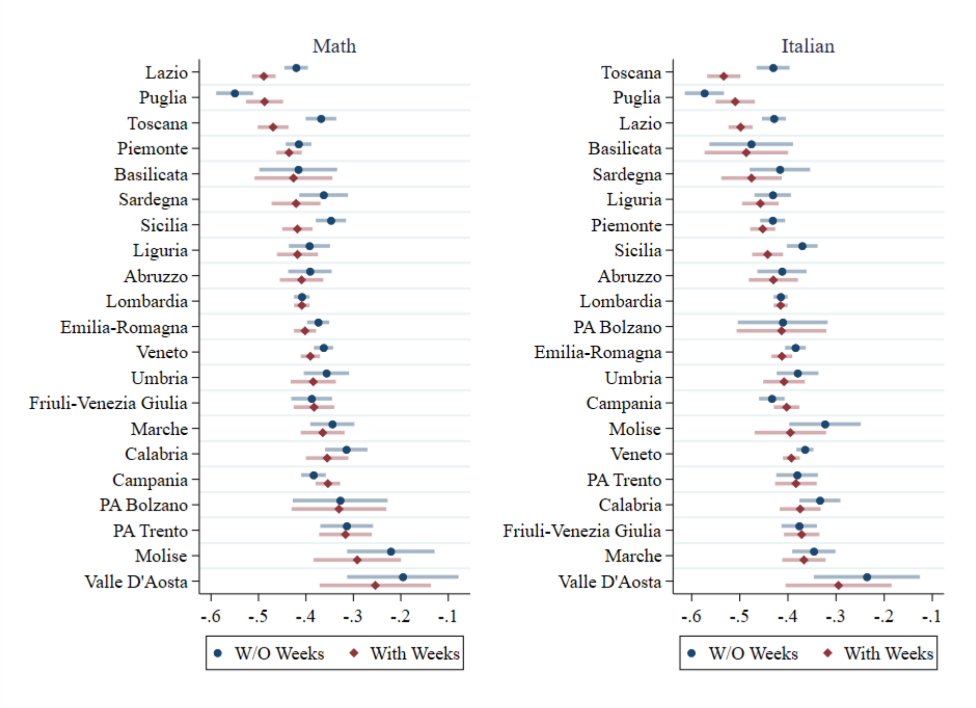
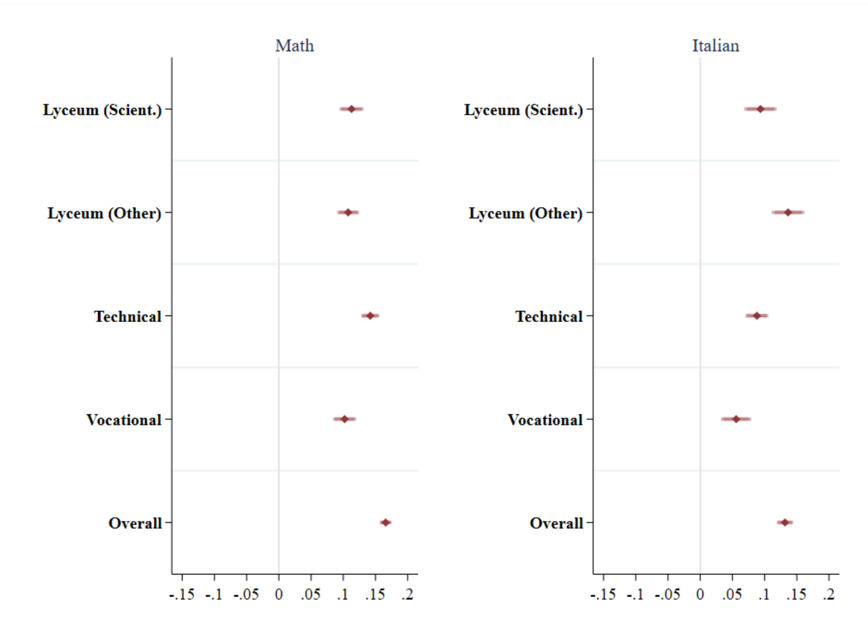


Figure 3: Regional differences in the impact of COVID-19 on maths and Italian test scores, Grade 13, with and without weeks of school closure



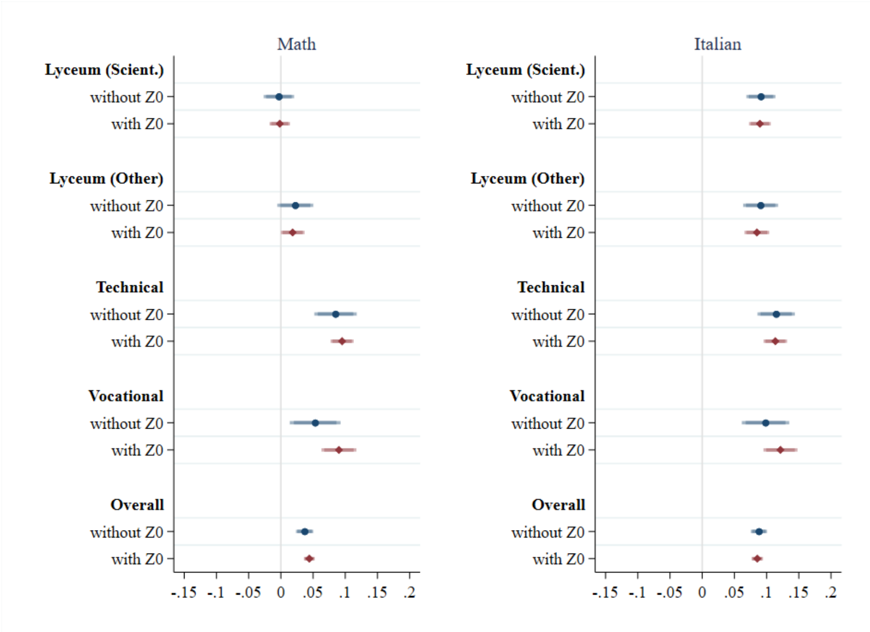
Note: The estimation models include control for initial abilities (maths and Italian INVALSI test scores, teacher-assigned marks in the subject related to the assessment test in Grade 10), socio-demographic characteristics (gender, first and second generation migrant status, age, parental occupations, and high-educated parents - at least one parent has a tertiary degree). Confidence intervals at 95% level.

Figure 4: Changes in achievement gaps by prior skills due to COVID-19, Grade 13



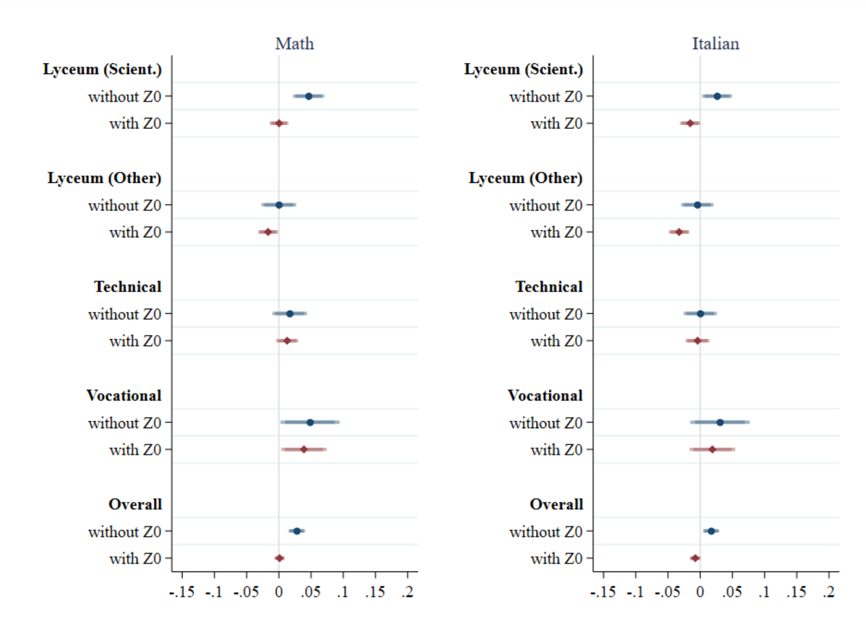
Note: We control for socio-demographic characteristics gender, first/second generation migrant status, age, and high-educated parents (at least one parent has a tertiary degree), school fixed effects. Confidence intervals at 95% and 90% level.

Figure 5: Changes in gender differences due to COVID-19 (girls vs boys), Grade 13



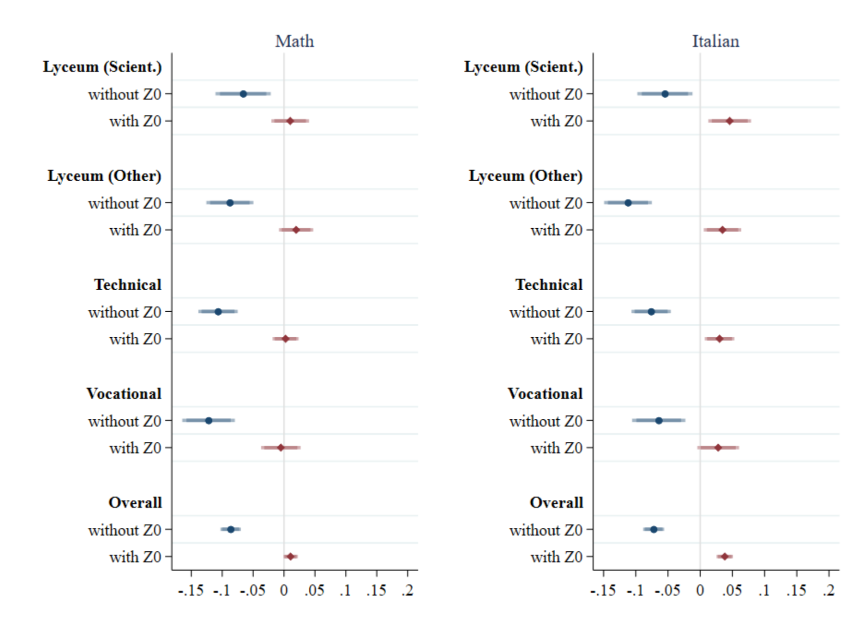
Note: Z_0 is the student's prior ability in Grade 10 in maths (left-hand side) and in Italian (right-hand side), measured with INVALSI test scores in Grade 10 for maths and Italian standardised at the cohort level. In both models (with and without Z_0) we control for socio-demographic characteristics (gender, first/second generation migrant status, age, and high-educated parents - at least one parent has a tertiary degree). In the model with Z_0, we also include school fixed effect; in the model without Z_0, when we consider Grade 13 overall, we include a school track variable. Confidence intervals at 95% and 90% level.

Figure 6: Changes in parental education inequalities due to COVID-19 (high vs low), Grade 13



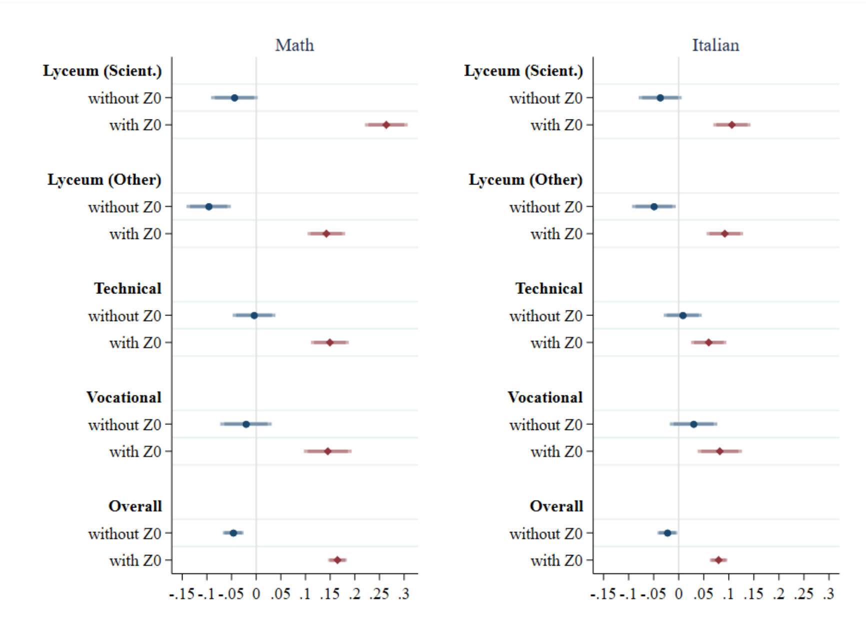
Note: Z_0 is the student's prior ability in Grade 10 in maths (left-hand side) and in Italian (right-hand side), measured with INVALSI test scores in Grade 10 for maths and Italian standardised at the cohort level. In both models (with and without Z_0) we control for socio-demographic characteristics (gender, first/second generation migrant status, age, and high-educated parents - at least one parent has a tertiary degree). In the model with Z_0, we also include school fixed effect; in the model without Z_0, when we consider Grade 13 overall, we include a school track variable. Confidence intervals at 95% and 90% level.

Figure 7: Changes in migrant vs native inequalities due to COVID-19, Grade 13



Note: With the term migrant we refer to students born either in Italy or outside Italy from non-Italian parents (first and second generation migrants). Z_0 is the student's prior ability in Grade 10 in maths (left-hand side) and in Italian (right-hand side), measured with INVALSI test scores in Grade 10 for maths and Italian standardised at the cohort level. In both models (with and without Z_0) we control for socio-demographic characteristics (gender, first/second generation migrant status, age, and high-educated parents - at least one parent has a tertiary degree). In the model with Z_0, we also include school fixed effect; in the model without Z_0, when we consider Grade 13 overall, we include a school track variable. Confidence intervals at 95% and 90% level.

Figure 8: Changes in geographical inequalities due to COVID-19 (South vs North), Grade 13



Note: Z_0 is the student's prior ability in Grade 10 in maths (left-hand side) and in Italian (right-hand side), measured with INVALSI test scores in Grade 10 for maths and Italian standardised at the cohort level. In both models (with and without Z_0) we control for socio-demographic characteristics (gender, first/second generation migrant status, age, and high-educated parents - at least one parent has a tertiary degree). In the model without Z_0, when we consider Grade 13 overall, we include a school track variable. Confidence intervals at 95% and 90% level.

Tables

Table 1: Descriptive statistics, overall and by cohort

	Overall		Pre-Covid cohort		Covid cohort	
Variables	mean	sd	mean	sd	mean	sd
Covid cohort	0.536					
Italian Invalsi test score G10	0.095	1.030	0.079	1.125	0.109	0.940
Maths Invalsi test score G10	0.092	1.048	0.056	1.098	0.123	1.001
Italian Invalsi test score G13	-0.082	1.032	0.130	1.013	-0.266	1.012
Maths Invalsi test score G13	0.009	1.007	0.211	0.999	-0.165	0.981
Italian teachers' mark first term G10	6.257	1.631	6.282	1.545	6.236	1.702
Maths teachers' mark first term G10	5.953	1.898	5.990	1.836	5.921	1.950
Age	18.446	0.621	18.449	0.625	18.443	0.617
Female	0.519		0.524		0.514	
Native	0.863		0.896		0.834	
Migrant first generation	0.037		0.033		0.040	
Migrant second generation	0.047		0.044		0.050	
At lest one parent with university degree	0.277		0.266		0.286	
School track						
Lyceum Scientific	0.268		0.271		0.264	
Lyceum Other	0.300		0.293		0.305	
Technical	0.292		0.296		0.289	
Vocational	0.141		0.140		0.142	
Observations	618,226		289,197		329,029	

Note: G10 stands for Grade 10; G13 stands for Grade 13. Source: own elaboration on INVALSI data.

Table 2: Impact of Covid-19 on maths and Italian test scores, in Grade 13 overall and by school track

	Grade 13 (1)	Lyceum Scientific (2)	Lyceum Other (3)	Technical (4)	Vocational (5)
			Maths		
Covid	-0.389^{***} (0.004)	-0.415^{***} (0.007)	-0.359^{***} (0.006)	-0.400^{***} (0.006)	-0.299^{***} (0.007)
Bounds	$[-0.338^{***};$ $-0.439^{***}]$	$[-0.376^{***};$ $-0.455^{***}]$	$[-0.312^{***};$ $-0.405^{***}]$	$[-0.355^{***};$ $-0.445^{***}]$	$[-0.255^{***};$ $-0.344^{***}]$
			Italian		
Covid	-0.410^{***} (0.004)	-0.415^{***} (0.007)	-0.399^{***} (0.007)	-0.446^{***} (0.006)	-0.327^{***} (0.007)
Bounds	$[-0.358^{***};$ $-0.462^{***}]$	$[-0.369^{***};$ $-0.460^{***}]$	$[-0.350^{***};$ $-0.449^{***}]$	$[-0.394^{***};$ $-0.499^{***}]$	$[-0.276^{***};$ $-0.378^{***}]$
Obs.	618,226	166,859	185,426	180,543	85,398
Initial Abilities	Yes	Yes	Yes	Yes	Yes
Socio-Demogr.	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes

Note: Initial abilities include maths and Italian INVALSI test scores, and teacher-assigned marks in the subject related to the assessment test (either maths or Italian) in Grade 10. Socio-demographic controls include gender, first and second generations migrant status, age, parental occupations, and high-educated parents (at least one parent has a tertiary degree). Standard errors in parentheses are clustered at the class level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Impact of COVID-19 on maths and Italian test scores by weeks of school closure, Grade 13

	Final Sample (1)	Covid cohort Sample (2)
	Maths	
Weeks school closure	-0.013***	-0.009***
	(0.000)	(0.001)
	Italian	
Weeks school closure	-0.013***	-0.012***
	(0.000)	(0.001)
Obs.	618,226	329,029
Initial Abilities	Yes	Yes
Socio-Demogr.	Yes	Yes
School FE	Yes	Yes
Pre-Covid cohort	Yes	No

Note: The final sample (1) consists of all students in pre-Covid and Covid cohorts who performed both Italian and Math INVALSI assessment tests in G13 and were successfully matched with the observations with INVALSI sample in Grade 10. The Covid cohort sample (2) includes only students from the Covid cohort who performed both Italian and Math INVALSI assessment tests in G13 and were successfully matched with the observations with INVALSI sample in Grade 10. Initial abilities include maths and Italian INVALSI test scores, and teacher-assigned marks in the subject related to the assessment test (either maths or Italian) in Grade 10. Socio-demographic controls include gender, first and second generations migrant status, age, parental occupations, and high-educated parents (at least one parent has a tertiary degree). Standard errors in parentheses are clustered at the class level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: The impact of COVID-19 on maths and Italian test scores in Grade 13, not controlling for prior achievements in Grade 10 - final and initial sample

	Final sample (1)	Initial sample (2)
	Maths	
Covid cohort	-0.329^{***}	-0.334^{***}
	(0.004)	(0.003)
	Italian	
Covid cohort	-0.358^{***}	-0.369^{***}
	(0.004)	(0.004)
Obs.	618,226	852,862
Initial Abilities	No	No
Socio-Demogr.	Yes	Yes
School FE	Yes	Yes

Note: The final sample (1) consists of all students in pre-Covid and Covid cohorts who performed both Italian and Math INVALSI assessment tests in G13 and were successfully matched with the observations with INVALSI sample in Grade 10. The initial sample (2) includes all the students in pre-Covid and Covid cohort who performed both Italian and Math INVALSI assessment tests in G13. Since the variables for parental occupation and high-educated parents (at least one parent has a tertiary degree) are not available for the initial sample, in columns (1) and (2) we control for student ESCS. Socio-demographic controls include gender, first and second generations migrant status, age, and student ESCS. Standard errors in parentheses are clustered at the class level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: The impact of COVID-19 on maths and Italian test scores, in Grade 13 accounting for grade retention and outlier regions

	Main results (1)	Accounting for grade retention[1] (2)	Without Puglia (3)	Without Campania (4)	Without Calabria (5)
			Maths		
Covid cohort	-0.389^{***}	-0.386^{***}	-0.382^{***}	-0.391^{***}	-0.391^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
			Italian		
Covid cohort	-0.410^{***}	-0.404^{***}	-0.403^{***}	-0.408^{***}	-0.412^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Obs.	618,226	601,117	583,892	554,457	599,157
Initial Abilities	Yes	Yes	Yes	Yes	Yes
Socio-Demogr.	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes

Note: [1]Grade retention was suspended in the school year 2019-20. We drop a share of low performing students in the Covid cohort according to Grade 12 retention in the school year 2018/2019 (3.33% Lyceum Scientific, 2.95% Lyceum Other, 7.15% Technical and 10% Vocational). Initial abilities include maths and Italian INVALSI test scores, and teacher-assigned marks in the subject related to the assessment test (either maths or Italian) in Grade 10. Socio-demographic controls include gender, first and second generation migrant status, age, parental occupations, and high-educated parents (at least one parent has a tertiary degree). Standard errors in parentheses are clustered at the class level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendices

Appendix A. Additional tables

Table A1: Sample selection, by cohort

	Overall	Pre-Covid cohort	Covid cohort
Initial sample in Grade 13	879,786	465,774	414,012
Excluding absents from one of the tests in Grade 13	852,862	456,878	395,984
Excluding not-matched observations with sample in Grade 10	618,226	289,197	329,029
Final Sample	618,226	289,197	329,029

Data source INVALSI.

Table A2: Additional descriptive statistics, by cohort

Variables	Overall mean	Pre-Covid cohort mean	Covid cohort mean
Paternal occupation			
Unemployed	0.027	0.028	0.025
Househusband	0.005	0.006	0.004
Manger/univ. professor/personnel	0.044	0.047	0.043
Entrepreneur	0.068	0.068	0.069
Freelance professional	0.176	0.176	0.176
Self-employed	0.191	0.192	0.191
Employee/teacher	0.120	0.131	0.111
Other occupation	0.238	0.240	0.236
Retired	0.020	0.020	0.020
Maternal occupation			
Unemployed	0.030	0.032	0.028
Housewife	0.278	0.285	0.272
Manger/univ. professor/personnel	0.023	0.025	0.022
Entrepreneur	0.021	0.024	0.018
Freelance professional	0.108	0.108	0.109
Self-employed	0.083	0.085	0.081
Employee/teacher	0.196	0.202	0.191
Other occupation	0.170	0.165	0.174
Retired	0.003	0.003	0.003
Geographic area			
North	0.470	0.484	0.457
Centre	0.202	0.191	0.211
South	0.328	0.325	0.332
Observations	618,226	289,197	329,029

Source: own elaboration on INVALSI data.

Table A3: Variable definition

Variable	Definition
Maths Invalsi test score G10	Score in maths INVALSI test, Grade 10 (standardised at the national level)
Maths Invalsi test score G13	Score in maths INVALSI test, Grade 13 (standardised at the national level and horizontally anchored)
Italian Invalsi test score G10	Score in Italian INVALSI test, Grade 10 (standardised at the national level)
Italian Invalsi test score G13	Score in Italian INVALSI test, Grade 13 (standardised at the national level and horizontally anchored)
Maths teachers' mark first term G10	Teachers' mark in maths, first term Grade 10 (mark that teachers assign to students at the end of the first semester, based on their overall performance during the term; it can range between 0 and 10, and 6 is the pass grade)
Italian teachers' mark first term G10	Teachers' mark in Italian, first term Grade 10 (mark that teachers assign to students at the end of the first semester, based on their overall performance during the term; it can range between 0 and 10, and 6 is the pass grade)
Covid cohort	1 if Covid cohort, 0 if pre-Covid cohort
Female	1 if female, 0 if male
Age	Age of the student
Native	1 if the student is born in Italy with at least one parent born in Italy, 0 otherwise
Migrant first generation	1 if the student is born outside Italy from non-Italian parents, 0 otherwise
Migrant second generation	1 if the student is born in Italy from non-Italian parents, 0 otherwise
Low-educated parents	1 if no parent has a tertiary degree, 0 otherwise
High-educated parents	1 if at least one parent has a tertiary degree, 0 otherwise
Mother/father's occupation	
Unemployed	1 if the parent is unemployed, 0 otherwise
Housewife/Househusband	1 if the parent manages the home and often raises children instead of earning money from a job, 0 otherwise
Manger/univ. professor/personnel	1 if the parent is a manager, a university professor or a university staff member, 0 otherwise
Entrepreneur	1 if the parent is an entrepreneur, 0 otherwise
Freelance professional	1 if the parent is a freelance professional, 0 otherwise
Self-employed	1 if the parent is self-employed, 0 otherwise
Employee/teacher	1 if the parent is an employee or a teacher, 0 otherwise

Table A3: Variable definition

Other occupation	1 if the parent works in none of the mentioned occupational categories, 0 otherwise
Retired	1 if the parent is retired, 0 otherwise
Geographic area	
North	1 if the student lives in the North of Italy, 0 otherwise
Centre	1 if the student lives in the Center of Italy, 0 otherwise
South	1 if the student lives in the South of Italy or in an Italian island, 0 otherwise
School track	
Lyceum Scientific	1 if the student is in a scientific lyceum, 0 otherwise
Lyceum Other	1 if the student is in a classical, linguistic or other lyceums, 0 otherwise
Technical	1 if the student is in a technical school, 0 otherwise
Vocational	1 if the student is in a vocational school, 0 otherwise

Note: G10 stands for Grade 10; G13 stands for Grade 13.

Table A4: Differential attrition from G10 to G13 by cohort

Region	Covid cohort	Pre-Covid cohort	Region	Covid cohort	Pre-Covid cohort
Abruzzo	0.21	0.18	Piemonte	0.28	0.21
Basilicata	0.24	0.18	PA Bolzano	0.25	0.25
Calabria	0.36	0.17	PA Trento	0.16	0.21
Campania	0.36	0.14	Puglia	0.59	0.18
Emilia-Romagna	0.24	0.22	Sardegna	0.34	0.30
Friuli-Venezia Giulia	0.24	0.21	Sicilia	0.22	0.21
Lazio	0.22	0.19	Toscana	0.24	0.23
Liguria	0.24	0.24	Umbria	0.17	0.17
Lombardia	0.24	0.22	Valle D'Aosta	0.26	0.33
Marche	0.20	0.19	Veneto	0.18	0.19
Molise	0.21	0.18			
Italia[1]	0.28	0.21			

Note: Proportion of students who participated in Grade 10 assessments and not in Grade 13 ones, separately for the Covid and the pre-Covid cohort, across Italian Regions. [1]Average at the national level.

Table A5: Probability of participating in Grade 13 assessments given Grade 10 participation

	Pre-Covid cohort (1)	Covid cohort (2)	Pre-Covid cohort (3)	Covid cohort (4)
Italian Invalsi test score G10	0.057***	0.069***	0.039***	0.051***
	(0.001)	(0.001)	(0.001)	(0.001)
Maths Invalsi test score G10	0.037***	0.052***	0.045***	0.060***
	(0.001)	(0.001)	(0.001)	(0.001)
Female			0.085***	0.074***
			(0.001)	(0.001)
High-educated parents			0.029***	0.029***
			(0.001)	(0.001)
Migrant first generation			−0.206***	−0.119***
			(0.003)	(0.003)
Migrant second generation			−0.113***	−0.074***
			(0.003)	(0.003)
Constant	0.819***	0.743***	0.786***	0.708***
	(0.001)	(0.001)	(0.001)	(0.001)
Obs.	363,025	458,506	363,025	458,506

Note: Estimation of the probability of participating in Grade 13 INVALSI assessment tests in maths and in Italian, given participation in Grade 10, using a linear probability model. The sample is composed of the population of students who undertook the national assessment in maths and Italian in Grade 10, and the dependent variable is a dummy variable equal to 1 if the student has participated in the assessment in grade 13, 0 otherwise. High-educated parents: at least one parent has a tertiary degree. Standard errors in parentheses are clustered at the class level. G10 stands for Grade 10. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix B

B.1. The extended difference-in-differences

In the following, we show that equation (2) in the main text can be seen as an extended or generalised version of a difference-in-differences model, when γ is not necessary equal to 1. Let us start from the classical difference-in-differences model:

$$Y_{Gikj} = b + \theta C_k + \alpha_0 G + \alpha_1 C_k * G + \lambda_G X_{ikj} + \delta_{Gj} + e_{Gikj} \tag{7}$$

where G takes value 1 if test scores are measured in Grade 13 and value 0 if they are measured in Grade 10 (it corresponds to "Post" in the usual DID formulation); as above C takes value 1 if the child is in the Covid cohort and 0 otherwise (it corresponds to "Treated" in the usual DID formulation). In a common difference-in-differences, the causal parameter of interest is α_1.

We can derive equation (7) for Grade 13 ($G = 1$) and Grade 10 ($G = 0$). For $G = 1$:

$$Y_{1ikj} = (\alpha_0 + b) + (\alpha_1 + \theta)C_k + \lambda_1 X_{ikj} + \delta_{1j} + e_{1ikj} \tag{8}$$

For $G = 0$:

$$Y_{0ikj} = b + \theta C_k + \lambda_0 X_{ikj} + \delta_{0j} + e_{0ikj} \tag{9}$$

And the difference between the two test scores is:

$$Y_{1ikj} - Y_{0ikj} = \alpha_0 + \alpha_1 C_k + \lambda X_{ikj} + \delta_j + e_{ikj} \tag{10}$$

where $\lambda = \lambda_1 - \lambda_0$, $\delta_j = \delta_{1j} - \delta_{0j}$, and $e_{ikj} = e_{1ikj} - e_{0ikj}$.

Equation (10) is a special case of equation (2) (in the main text) with $\gamma = 1$. As discussed above, given that Y_1 (test scores in Grade 13) and Y_0 (test scores in Grade 10) are not vertically equated, equation (2) is more appropriate because it does not make untestable assumptions on the relation between Y_1 and $Y : 0$.

B.2. Conditional and unconditional changes in inequalities

In the following, we discuss in details the possible sources of changing inequalities due to Covid-19 and how to assess changes in both a conditional (net) and unconditional (gross) perspective.

Consider one single cohort. The average distance between achievements across social groups (assuming only one binary explanatory variable for simplicity) can be decomposed into three components:

$$\begin{aligned} &E(Z_{1ij}|X=1) - E(Z_{1ij}|X=0) = \\ &= \lambda' + \gamma'[E(Z_{0ij}|X=1) - E(Z_{0ij}|X=0)] + [E(\delta'_j|X=1) - E(\delta'_j|X=0)] \end{aligned} \tag{11}$$

The first component captures 'new' social inequalities that developed between time 0 and time 1 between children with the same prior abilities and in similar schools (λ');

the second captures carryover effects of prior achievement gaps ($\gamma'[E(Z_{0ij}|X=1) - E(Z_{0ij}|X=0)]$); the third is related to possible differences in the average quality of schools attended by children in different social groups ($[E(\delta'_j|X=1) - E(\delta'_j|X=0)]$).

Hence, the coefficients of the interaction terms in equation (6) capture the gross gain (or loss) of different social groups relative to each other that occurred in the pandemic years, which could be attributed to one of the following mechanisms: differences in 'new' gaps developed between Grades 10 and 13 given prior abilities and school features; differences in carryover effects of prior ability; and differences in the value-added of the schools attended. Instead, the coefficients of the interaction terms in equation (5) capture the net gain (or loss) of different social groups relative to each other, which occurred in the pandemic years, imputable only to differences in new gaps, conditional on prior abilities and school characteristics.