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# Will the last be the first? School closures and educational outcomes[☆]

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ABSTRACT

Governments have implemented school closures and online learning as one of the main tools to reduce the spread of Covid-19. Despite the potential benefits in terms of containment of virus diffusion, the educational costs of these policies may be dramatic. This work identifies these costs, expressed as decrease in test scores, for the whole universe of Italian students attending the 5th, 8th and 13th grade of the school cycle during the 2021/22 school year. The analysis is based on a difference-in-difference model in relative time, where the control group is the closest generation before the Covid-19 pandemic. Results suggest a national average loss between 1.8–4.0% in Mathematics and Italian test scores. After collecting the precise number of school closure days for the universe of students in Sicily, this work also estimates that the average days of closure decrease the test score by 2.4%. In this context, parents appear to have a partial compensatory effect, but only when holding higher levels of education and when their children are attending low and middle schools. This is likely explained by the lower relevance of parental inputs and higher reliance on other inputs, such as peers, for the higher grades. Finally, the effects are also heterogeneous across class size, parents' country of birth and job conditions, pointing towards potential growing inequalities driven by the lack of frontal teaching.

## 1. Introduction

After public schooling became the norm for western societies, scholars started referring to schools as great equalizers or as social elevators, mainly because of their potential to reduce disparities and provide similar learning opportunities to children from different socio-economic environments (Cremin, 1951; Agostinelli et al., 2022). A wide strand of literature has criticized this concept and suggested how students with initial advantages often attend schools with higher resources, more compelling programs and highly interactive teachers (Condron and Roscigno, 2003; Downey et al., 2004; Roscigno et al., 2006). Disadvantaged students, such as the ones coming from inner cities or rural areas of the United States, are often associated to lower educational achievements and higher likelihood of dropping out during high-schools (Roscigno et al., 2006). Whether or not schools are functional in reducing inequalities across different geographical areas, students within the same school and attending the same classes receive similar inputs, as they are exposed to the same teachers and curricula. In contexts such as the Italian educational system, students attend the same class with the same group of peers for several years, which makes even more relevant the equalizer argument. Students learn from their peers and from the environment in which they are embedded (Angrist, 2014), and develop their human capital also depending on their set of unobserved skills.

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As a consequence of the Covid-19 pandemic, governments have implemented school closures and online learning to reduce the spread of cases in areas with higher contagion rates, especially when vaccinations were not available and largely up-taken. While these policies may have brought some benefits depending on a set of factors, such as the timing of adoption (Amodio et al., 2022b; Vlachos et al., 2021; Hsiang et al., 2020), these also came with a potentially high cost for the generation of students attending school (Stantcheva, 2022). A growing number of works studies the short and long run effects on a series of outcomes linked to educational losses. Some authors, such as Psacharopoulos et al. (2021), report that the long run human capital losses could translate in a decrease of about 8% in future earnings of the generation exposed to educational losses, with negative indirect consequences for the high-, middle-, and low-income countries' GDP. Others, such as Fuchs-Schündeln et al. (2022), use a structural-life cycle model and highlight that educational losses will induce a decrease in the college attainment rate of about 4%, a reduction of lifetime earning of 2.1% and a drop in permanent consumption of 1.2%.

The present study contributes to the existing literature by identifying the educational costs of school closures, expressed as decrease in test scores, for the whole universe of approximately 1,4 million Italian students attending the 5th, 8th and 13th grade of the school cycle during the 2021/22 school year.[1] The identification relies on a difference-in-difference model in relative time, where the control group is the closest generation before the Covid-19 pandemic.

Our estimates at national level suggest a loss between 1.8%–4% in Mathematics and Italian test scores. These results contribute to a small but growing number of studies investigating the educational losses by the mean of test scores. In general, these studies find a sizable reduction in learning, equal to about 4%–5% for the cases of Netherlands (Engzell et al., 2021) and Belgium (Maldonado and De Witte, 2022). These works identify the direct effect of school closures by comparing the human capital dynamics of the affected generation with those of the previous generations, and define the treatment as an aggregated shock. Departing from these studies, our work finds that the impact of school closures is unequal across three dimensions: the school grade the students' are attending, the family background and the geographical area.

With respect to the existing literature[2] we offer new evidence on the heterogeneous impact of school closures across the geographical territory and estimate the effect of an additional school closure days on the students' test score. The analysis gathers original data on the precise number of school closures days by grade at municipality level for the case study of Sicily. These are merged with census socio-economic variables and granular information on Covid-19 cases. The empirical results suggest that average days of closures imply a loss of educational score equal to about 2.4%. This result hides a high level of heterogeneity across school level and parental background, with a peak for students attending high schools and with a less advantaged parental background. The latter is defined on the parents' education and employment status, as these may proxy their ability to recover the gap generated by the lack of front-learning. Taken together, the results from our work inform on the unequal costs of school closures and online teaching in Italy. Finally, a dose–response function suggests that school closures may have a non linear impact on test scores, with students loosing more days of front-teaching observing a sharper decline on their test scores after a first threshold, while the loss stabilize after a second threshold.

The remainder of the article is organized as follows. The first part of Section 2 provides a background on school closures during the pandemic. Section 3 introduces the data sources and the identification strategy. Section 4 presents the empirical strategy. The first part of Section 5 discusses the core results at national level, while results on the impact of additional school days of closure are presented in the Section 5.2. Section 6 reports the results from additional heterogeneity and robustness tests, while Section 7 presents our conclusive considerations.

## 2. Background

The educational outcomes of the Italian system are highly comparable with the ones of other developed countries. From a qualitative perspective, the assessment scores during the last twenty years suggest that the Italian students hold a level of knowledge which is very similar to the OECD average, with a score about 6%–8% lower than the frontier, embodied by the South Korea. EUROSTAT highlights that the share of low achieving 15 years old students in Italy is also aligned to the EU average, equal to 23.8% and 22.9%, respectively (Eurostat, 2022a). The Timms scores describe a similar pattern with, for instance, 8th grade Italian students assessing on an average score of 494 in mathematics, a result that is only 6 points below to the OECD countries average (Fishbein et al., 2021).

As for the general socio-economic development, Italy was highly diversified in terms of education already at the time of unification. Illiteracy rates of Southern regions were 4 times higher than those of North-West and three times higher than the country average (Bertola and Sestito, 2011), but this gap narrowed down due to the increasing mandatory education. At the present day, some differences persist between the North and the South of the country. Data from the national agency for school results evaluation (INVALSI) show that, at the end of high school, students from the south of Italy obtain scores about 20% lower in Mathematics and Italian with respect to North-West counterparts. Also, in Southern regions the scores have wider variance, about 2–3 times larger than Northern regions, which highlights the wider levels of inequality within the Southern territories. Eurostat data for 2019 show that early school leavers in Sicily are equal to 22.2% of the total students, about 9 percentage points higher than Italian average, and 12 percentage points higher than the European average (Eurostat, 2022b).

[1] In Italy, schools were fully closed and lessons suspended only in the first week of the pandemic (March 2020). After that, school closures implied online learning for all the students. Therefore, this article refers to school closure as the event of moving teaching to online modality.

[2] See the works surveyed in Storey and Zhang (2021) and Donnelly and Patrinos (2021).

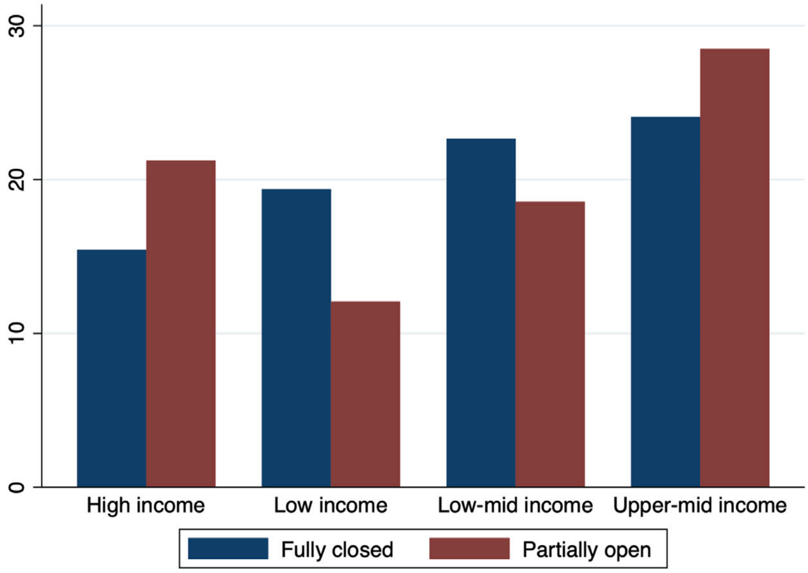


**Fig. 1.** Average number of weeks of school closures from 2020 by country groups. Source: UNESCU (2022).

From March 2020, Covid-19 pandemic has strongly hit the world, with the number of cases steadily raising on a daily basis in all the western countries. As first response, governments have limited the possibility of contagion by enforcing social restrictions (for a complete survey see Hsiang et al. (2020)). School physical closures has embodied one of the major actions to prevent the diffusion of Covid-19 cases. Schools, indeed, could have represented an occasion of contagion and could have allowed the spread of the virus between students, and from these to their household members (Amodio et al., 2022b).

During the so called first wave of pandemic (March–July 2020), the majority of the developed countries have opted for school closures and substituted frontal teaching with the distance learning. However, from the second wave of the pandemic onward, the set of policy answers implemented by the governments has depended on the economic and political contexts.[3] As Fig. 1 shows, the number of weeks without frontal teaching ranges between 30 and 45. Also, the internal composition of fully closed and partially opened schools was very heterogeneous, ranging from high income countries that closed schools for 50% or more of the weeks during the period of reference, to low income where the percentage of fully closed weeks has been only one third with respect to the high income group.

Italy is among the OECD countries with the highest number of weeks of school closures and distance learning, followed by Greece, Denmark and Finland. This response, however, appears to be driven by internal policy considerations and not by common socio-economic traits. Indeed, even with similar income group countries, it is still possible to observe a substantial divergence in the adopted policies, such as for Switzerland and US that used completely different approaches despite having comparable GDP levels.

## 3. Data

The analysis develops on a unique dataset obtained by merging two data sources. The data on test scores derive from the Italian National Institute for the Evaluation of the Educational System (INVALSI). The institute is responsible for evaluating, every year, the learning levels of Italian students across all the cycles of the Italian educational system. The institute conducts yearly basis tests for the universe of the Italian students attending the second, fifth, eighth, tenth, and thirteenth grade of the school (that means intervals of 2–3 years for the students along their educational patterns). To make the results comparable, the test consists of identical questions for students in the same school grade but varying across grades.

During the school year 2020/21, about 6,6 millions of Italian students attended primary, middle and secondary schools (ISTAT, 2022). According to the official statistics, the data on test scores for the 2020/2021 school years cover 93.7% of the students in the targeted grades. These data allow, therefore, to estimate the impact on the whole population of students attending the targeted classes, and to conduct a set of heterogeneity analyses for different geographical and socio-economic extraction of individuals in this population. The results from the tests are harmonized through the Rasch model, which consists in simultaneously weighting and modeling the level of difficulty of the question and the skills of the respondents. The Rasch model attaches more weight, and thus higher scores, to a difficult question (correctly answered) than to an easy one. This approach serves the purpose of reconstructing

[3] A decisive factor, among the others has been the presence of vaccination that reduced the virus spread due to school openings, as for instance found in Amodio et al. (2022a).

**Table 1**
Treated and control cohorts by grade and year.

| School level | Grade at t = 0 (school year) | Grade at t = 1 (school year) | Treatment status |
|---|---|---|---|
| High School | 8th (2015/16) | 13th (2020/21) | Treated group |
| | 8th (2013/14) | 13th (2018/2019) | Control group |
| Middle School | 5th (2017/18) | 8th (2020/21) | Treated group |
| | 5th (2015/16) | 8th (2018/2019) | Control group |
| Low School | 2nd (2017/18) | 5th (2020/21) | Treated group |
| | 2nd (2015/16) | 5th (2018/2019) | Control group |

the level of learning heterogeneity across students, especially when compared to alternative approaches, such as a count indicator on the number of correct answers. The tests focus on three subjects of study: Italian, Mathematics and English (listening, reading, speaking). The current analysis is based only on the results from Mathematics and Italian that are administered to all the grades, while the students are tested on their English knowledge only from the 8th grade.[4] The INVALSI tests have been conducted every year since 2009/10. The only notable exception is the school year 2019/20, as the unexpected events following the pandemic prevented their implementation. The results from the anonymized tests are provided at individual level, and include school, municipality and province identifiers. More importantly, each student is associated to a unique panel identifier which can be used to link together his/her test scores during the school cycle.

### *3.1. Building a counterfactual*

Covid-19 related school closures have affected an entire generation of students. In the second part of the 2019/2020 school year, for the first time in the Italian history, schools were closed and teaching was suspended for about one week. After that, schools closed at different times and with diverse intensities, and teaching was always moved online until the number of Covid-19 cases allowed to re-open the schools. Therefore, this article refers to school closure as the event of moving teaching to online modality. Studying the impact of school closures on test scores of students is not an easy task due to the absence of a true counterfactual. To tackle this challenge, we compare two cohorts as close as possible in time, differing only on the experience of school closures and on-line learning. The cohort of treated is the one experiencing the Covid-19-related closures, i.e. the one observed during the school year 2020/2021. The second cohort is the one taking the test in 2018/2019, the year before the pandemic occurred. For both these cohorts, we build a panel of two waves in relative time, adding backwards the same individuals test score results from the closest year available. This is equivalent to take a relative time, where $t = 0$ is the time before treatment and $t = 1$ the time of the treatment. The final sample, therefore, is a panel containing the entire universe of Italian students that at time$t = 1$ was attending the 5th, 8th, and 13th grade, and their closest observation in time for $t = 0$.[5] This means, for instance, that in our panel, all the cohort of students attending the 13th grade in 2020/2021 will also be observed during the 8th grade in 2015/2016. Similarly, the dataset will contain individuals attending the 13th grade in 2018/19 ($t = 1$) and the 8th grade during the school year 2013/14 ($t = 0$). Table 1 sums up the panel data collected for each grade of school by treatment status and reports the school-level at the time of the treatment:

Using these data, we generate a treatment dummy taking value one for individuals in the treatment groups when the relative time is $t = 1$. This dummy takes value zero for the individuals belonging to the control group and for those in the treatment group at time $t = 0$. Beside the student's score on the test, the INVALSI data provide information on the educational background/title of the parents, their place of birth, being that Italy, European Union, or extra-EU, the parents' employment status and typology. In principle, these dimensions are time-invariant and get absorbed by the presence of individual level fixed-effects in the empirical specification. However, these are used to build interaction terms with the treatment dummy in the study of the heterogeneous impact of Covid-19 on human capital accumulation. The dependent variables are standardized with respect to the control generation distribution at $t = 0$, following an approach similar to Abdulkadiroğlu et al. (2014) and Angrist et al. (2016). Fig. 2 displays the Mathematic scores' distribution before and after the treatment, by treatment status and for all the grades in the dataset. As the figure suggests, the treated and control generations are characterized by highly comparable distributions in test scores before treatment ($t = 0$). This changes substantially after the treatment occurs ($t = 1$), as the distribution of treated generation is characterized by lower mean and it is more right-skewed, compared to the controls' distribution.

### *3.2. Other data sources for the case study in Sicily*

The variables presented above are sufficient to study the average impact of the Covid-19-related school closures on students' learning. However, the average effect may overlook the variation of this impact, as schools were closed for different time spans across the Italian territory. While during the first Covid-19 wave the schools were all kept closed (March-June 2019/2020) due to central government decision, from the second wave onward the schools closures occurred through two mechanisms. As first mechanism, the

[4] Unfortunately, English scores are not available for the period preceding the pandemic for the selected grades, so we are unable to test the impact of school closures on these outcomes using panel data.

[5] We exclude the 10th grade as INVALSI has not administered the test to students of this grade during 2021.

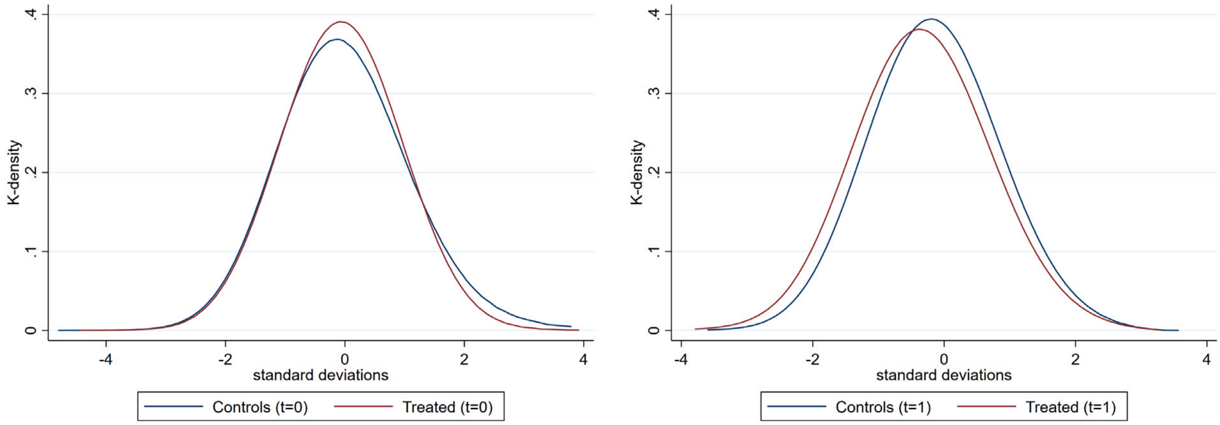


**Fig. 2.** Distribution of standardized Mathematic score before ($t = 0$) and after ($t = 1$) treatment.

**Table 2**
Summary statistics for the national sample by relative time.

| | Relative time = 0 | | | | | Relative time = 1 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Full sample | Treated | Control | T-test | Cohen | Full sample | Treated | Control | T-test | Cohen |
| Score in Italian test | 208.19<br>(37.92) | 205.96<br>(36.88) | 210.30<br>(38.77) | 0.00 | 0.11 | 202.49<br>(37.40) | 200.43<br>(37.70) | 204.43<br>(37.00) | 0.00 | 0.11 |
| Score in Math test | 210.86<br>(38.71) | 209.17<br>(37.06) | 212.44<br>(40.14) | 0.00 | 0.08 | 201.76<br>(38.52) | 198.05<br>(38.43) | 205.25<br>(38.30) | 0.00 | 0.19 |
| Parents' years of education | 13.18<br>(3.48) | 13.31<br>(3.53) | 13.05<br>(3.44) | 0.00 | 0.07 | 13.28<br>(3.27) | 13.40<br>(3.32) | 13.17<br>(3.21) | 0.00 | 0.07 |
| Student repeating the year (1 = yes) | 0.02<br>(.14) | 0.02<br>(.14) | 0.02<br>(.14) | 0.50 | 0.00 | 0.02<br>(0.13) | 0.02<br>(0.13) | 0.02<br>(0.13) | 0.70 | 0.00 |
| 5th grade - Low School (1 = yes) | 0.38<br>(.48) | 0.39<br>(.48) | 0.37<br>(.48) | 0.00 | 0.04 | 0.34<br>(0.47) | 0.33<br>(0.47) | 0.34<br>(0.47) | 0.00 | 0.03 |
| 8th grade - Middle School (1 = yes) | 0.29<br>(0.45) | 0.29<br>(.45) | 0.29<br>(.45) | 0.00 | 0.01 | 0.38<br>(0.48) | 0.39<br>(0.49) | 0.37<br>(0.48) | 0.00 | 0.04 |
| 13th grade - High School (1 = yes) | 0.00<br>(0.00) | 0.00<br>(0.00) | 0.00<br>(0.00) | – | – | 0.29<br>(0.45) | 0.29<br>(0.45) | 0.29<br>(0.45) | 0.00 | 0.01 |

*Notes:* The table reports the mean values of the variables displayed in the first column by relative times. Standard deviations are displayed in parentheses.

school administration could decide to move to distance learning a given class if the Covid-19 cases within the same were above three. Secondly, school closures were implemented through an administrative act from the municipality administration when the number of local cases of Covid-19 were above 150 cases per 100,000 inhabitants. This act was enforced together with other restrictions foreseen from a regulation named *zona rossa* (red-zone). Administrations, thanks to this regulation, were authorized to implement differentiated school closures depending on school grades, for example keeping in-person teaching for low and middle schools, while moving high school classes to online teaching. This suggests that the number of school closures days may substantially vary both across municipalities and across school-levels within the same municipality. This heterogeneity is likely hidden behind the average impact of the treatment dummy and can be unpacked only if the specification accounts for the number of days in which learning was moved online. To the best of our knowledge, a harmonized dataset on school closure days for the universe of Italian schools is not available. We tackle this challenge collecting a unique set of information on school closures by grade and school level for the Sicilian territory. This information is coded using the administrative acts published by the Health Department of the Sicilian Regional Government and available on their website, with precise information on the school grade targeted by the act, duration of closure and municipality proposing the act.[6] For the heterogeneity and robustness analysis, we integrate this information with records on population level obtained from the national census data, conducted by the national statistical office (ISTAT) in 2011. These are used together with Covid-19 data at municipality level, to build two indicators capturing the pattern of the pandemic, which are employed as instrumental variables for a robustness test. These instruments are the Covid-19 cumulative cases (per inhabitant) for a given municipality and the variance of cases across time in a given municipality. As for the other continuous variables, also the indicator on day of school closures is standardized around zero using its mean and standard deviation. Table 2 reports the statistics

[6] The decrees are available at the following website: https://www.regione.sicilia.it/la-regione-informa/covid-19-ordinanze-disposizioni-attuative

**Table 3**
Summary statistics for the Sicily sample by relative time.

| | Relative time = 0 | | | | | Relative time = 1 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Full sample | Treated | Control | T-test | Cohen | Full sample | Treated | Control | T-test | Cohen |
| Score in Math test | 214.03<br>(39.84) | 211.21<br>(36.73) | 217.13<br>(42.78) | 0.00 | 0.15 | 188.71<br>(38.52) | 185.19<br>(40.34) | 192.58<br>(36.01) | 0.00 | 0.19 |
| Score in Italian test | 207.72<br>(39.57) | 204.16<br>(37.39) | 211.63<br>(41.50) | 0.00 | 0.19 | 191.79<br>(38.13) | 190.20<br>(39.05) | 193.55<br>(37.01) | 0.00 | 0.09 |
| School closure days | 0.00<br>(0.00) | 0.00<br>(0.00) | 0.00<br>(0.00) | – | – | 73.96<br>(77.29) | 141.20<br>(43.70) | 0.00<br>(0.00) | 0.00 | 1.83 |
| Parents' years of education | 12.18<br>(3.55) | 12.28<br>(3.57) | 12.07<br>(3.53) | 0.00 | 0.06 | 12.32<br>(3.31) | 12.42<br>(3.34) | 12.20<br>(3.27) | 0.00 | 0.07 |
| Student repeating the year (1 = yes) | 0.02<br>(0.12) | 0.01<br>(0.12) | 0.02<br>(0.13) | 0.00 | 0.02 | 0.02<br>(0.12) | 0.01<br>(0.12) | 0.02<br>(0.13) | 0.00 | 0.02 |
| Parents are unemployed or blue-collars (1 = yes) | 0.21<br>(0.41) | 0.21<br>(0.41) | 0.20<br>(0.40) | 0.00 | 0.02 | 0.21<br>(0.40) | 0.21<br>(0.41) | 0.20<br>(0.40) | 0.00 | 0.02 |
| Foreigner parents | 0.03<br>(0.17) | 0.04<br>(0.19) | 0.02<br>(0.14) | 0.00 | 0.11 | 0.03<br>(0.17) | 0.04<br>(0.19) | 0.02<br>(0.14) | 0.00 | 0.11 |
| Class size | 19.30<br>(2.93) | 19.36<br>(2.91) | 19.23<br>(2.96) | 0.00 | 0.04 | 20.27<br>(2.83) | 20.34<br>(2.82) | 20.18<br>(2.86) | 0.00 | 0.06 |
| Covid-19 cases per inhabitant | 0.00<br>(0.00) | 0.00<br>(0.00) | 0.00<br>(0.00) | – | – | 0.02<br>(0.03) | 0.04<br>(0.03) | 0.00<br>(0.00) | 0.00 | 1.49 |
| Municipality's variance of Covid-19 cases over time | 0.00<br>(0.00) | 0.00<br>(0.00) | 0.00<br>(0.00) | – | – | 20600.75<br>(26032.68) | 39333.17<br>(23603.64) | 0.00<br>(0.00) | 0.00 | 1.51 |
| Municipality's population | 261179.17<br>(415524.74) | 258047.31<br>(411105.19) | 264623.41<br>(420307.14) | 0.00 | 0.02 | 286324.89<br>(426068.03) | 282208.08<br>(421388.71) | 290852.30<br>(431112.75) | 0.00 | 0.02 |
| Number of classes in the school | 13.99<br>(7.38) | 14.15<br>(7.43) | 13.82<br>(7.32) | 0.00 | 0.05 | 21.59<br>(16.17) | 21.72<br>(16.08) | 21.45<br>(16.27) | 0.00 | 0.02 |

*Notes:* The table reports the mean values of the variables displayed in the first column by relative times. Standard deviations are displayed in parentheses.

of the variables for the national sample, while those belonging to the Sicilian sample are displayed on Table 3. Note that the average difference between treated' and controls' test scores is similar for both national and Sicilian data. Also, by design, at the relative time $t = 0$ the sample does not contain any student attending the 13th grade, as all the grades are lagged with respect to time $t = 1$. The second last columns of Tables 2 and 3 display the p-values obtained from a t-test on the between-group difference of the reported variables, while the last columns display the Cohen's $d$ standardized mean difference (Cohen, 2013; Ellis, 2010). The latter is a statistic informing on the degree of similarity between two means when the number of observations is extremely high. Indeed, a large number of observations may artificially lower the p-values of t-tests, pointing to a rejection of the null hypothesis of no-difference in mean between groups, even when the two means are comparable, as in our case. The Cohen's d standardized mean difference, instead, adopts a stricter rule of thumbs and considers the between means differences as negligible if these are associated to a $d$ lower than 0.20 (Funder and Ozer, 2019). Since all reported statistics are lower than this value, it is possible to conclude that the differences in means between treated and control groups are negligible across all the variables displayed in Tables 2 and 3.[7]

For the school year 2020/21, the INVALSI data include information on 1,9 million of students.[8] Excluding the 2nd grade due to the lack of counterfactual reduces our sample to about 1,379,000 students. Among them, we consider students that completed tests in both subjects (Math and Italian), so that the final 2020/21 national sample reduces to about 1,1 million of students, to which is added the control group, for a final number of observations of 2,248,194 students. Finally, note that to safely compare two generations it is necessary to ascertain that Covid-19 related school closures are not pushing a substantially higher number of students, or different typologies of students, not to attend the test. If this occurs, indeed, the coefficient could be biased. For both the samples the attrition is around 20,%[9] with higher attrition for the treated group, as expected. However, when comparing the average scores of stayers versus leavers within treatment group, their difference is quite stable for both treated and controls, with the ratio leavers/stayers ranging between 0.90–0.92 for Mathematics and Italian. Also, for both Italian and Mathematics scores, the differences in Cohen's $d$ between stayers and leavers is about 0.10, well below 0.20, considered as threshold for small effect size.

[7] For an application of Cohen coefficient in economics see Lane (2016).

[8] The entire population of students in the selected grades is about 2,105,000, but only 93.7% of students attended the test.

[9] Attrition rates are respectively 18.2% and 24% for control and treated groups in the Italian sample, while these are extremely similar for the Sicilian sample (21.6% and 22.2%).

**Table 4**
Effect of Covid-19 closures on educational attainment.

| | Mathematics score | | | Italian score | | |
|---|---|---|---|---|---|---|
| | Cross-section (1) | Cross-section (2) | Panel - Diff. in Diff. (3) | Cross-section (4) | Cross-section (5) | Panel - Diff. in Diff. (6) |
| School closures (Treated = 1 X t = 1) | −0.192*** (0.003) | −0.202*** (0.003) | −0.150*** (0.004) | −0.114*** (0.003) | −0.125*** (0.003) | −0.096*** (0.004) |
| Student repeating the year (1 = yes) | −0.419*** (0.005) | −0.367*** (0.005) | | −0.568*** (0.006) | −0.512*** (0.005) | |
| Years of parents' education | | 0.195*** (0.001) | | | 0.206*** (0.001) | |
| Grade dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| School dummies | Yes | Yes | No | Yes | Yes | No |
| Student FEs | No | No | Yes | No | No | Yes |
| Relative-time dummies | No | No | Yes | No | No | Yes |
| Adj. R-squared | 0.183 | 0.214 | 0.541 | 0.167 | 0.201 | 0.562 |
| Observations | 2,248,194 | 2,248,194 | 4,496,388 | 2,248,194 | 2,248,194 | 4,496,388 |
| Number of students | 2,248,194 | 2,248,194 | 2,248,194 | 2,248,194 | 2,248,194 | 2,248,194 |

*Notes:* the table reports the estimates from an OLS cross-sectional model (columns 1–2 and 4–5) and a two-way fixed effect model (columns 3 and 6) on the impact of Covid-19 related closures on the students' educational score. The main explanatory variable is a dummy activated for the treated group observed during the 2021/22 school year. The panel specification includes year dummies. For more details on the treated and control group see Section 3 and Table 1. Standard errors clustered at school level for relative time equal to one and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

## 4. Empirical strategy

We estimate the average impact of school closures on educational outcomes using a panel setting and comparing the cohort of students during the pandemic with the one before, applying a difference-in-difference approach in relative time. Formally, we consider two cohorts $j = \{p, c\}$ observed at $t = 0, 1$. The cohort $p$ corresponds to the population of treated students which were affected by the school closures. For these students, $t = 1$ corresponds to the school year 2020/21, while $t = 0$ depends on the school grade, as reported in Table 1. Similarly, with the cohort $c$ we refer to the population of control students observed during the school year 2018/19 ($t = 1$), and the respective preceding grade available from the INVALSI test (see Table 1). Using the same methodology of Engzell et al. (2021), and considering that parents' education is time-invariant and absorbed by the individual fixed-effects, we formalize the approach as follows:

$$Y_{i,j,g,t} = \beta_0 + \delta T_{i,t} + \Phi_i + \Theta_t + \Gamma_g + \varepsilon_{i,t} \tag{1}$$

Where the dependent is the educational score of student $i$ of the cohort $j$ attending the school grade $g$ at time $t$, $\beta_0$ denotes the intercept, and $T_{i,t}$ is the treatment dummy, taking value equal to 1 for students belonging to the cohort $p$ at time $t = 1$ and zero otherwise. Also, the set of controls include a set of student-level fixed effects $\Phi_i$, two relative time dummies $\Theta_t$ and a set of grade-level dummies $\Gamma_g$, while $\varepsilon_{i,t}$ is the error term, clustered at individual level.

We also investigate the specific impact of additional school closure days on the same scores. To do so, we slightly modify Eq. (1), substituting the treatment dummy with a continuous indicator, as follows:

$$Y_{i,m,j,g,t} = \beta_0 + \eta DaysClosures_{m,g,t} + \Phi_i + \Theta_t + \Gamma_g + \upsilon_{i,t} \tag{2}$$

Where the $DaysClosures_{i,t}$ denotes a variable capturing the school closure days and online learning for a given grade $g$ attended by the student $i$ in municipality $m$, and $\eta$ is the coefficient. As for the other continuous variables, also this indicator is standardized to have zero mean and unitary variance. The other components of the model remain identical and, as before, the specification includes individual fixed effects and time dummies. Finally, to investigate the potential heterogeneity behind the average impact, we extend Eq. (2) by including the interaction terms between the school closure days and proxies of the parents' background or class size. This further specification takes the following form:

$$\begin{aligned} Y_{i,m,j,g,t} = &\beta_0 + \eta DaysClosures_{m,g,t} + \zeta \Pi_i * DaysClosures_{m,g,t} \\ &+ \Phi_i + \Theta_t + \Gamma_g + \upsilon_{i,t} \end{aligned} \tag{3}$$

Where the $\zeta$ is the coefficient of interest linked to the interaction between the school closure days and these additional indicators.

## 5. Effect of school closures on educational scores

### 5.1. Average impact at a national level

Table 4 introduces the results of the Mathematics and Italian score specifications incrementally accounting for cross-sectional and panel differences. Columns 1 and 2 report the results from an OLS specification for the sample observed only at relative time

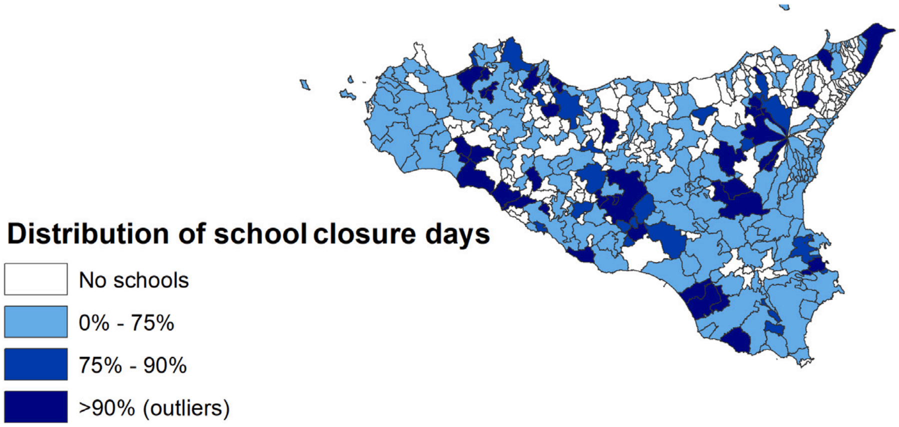


**Fig. 3.** Average school closure days in Sicilian municipalities.

$t = 1$, including grade and school dummies, and differing only on the inclusion of parents' education as control. Columns 3 reports the results from the baseline specification in Eq. (1). The impact of school closures is negative, significant and very similar in all the three specifications, while having higher educated parents is positively correlated with higher scores. Note that controlling for unobserved characteristics and time dummies through the DiD specification confirm the cross-sectional results both in sign and magnitude. Since all variables are standardized, a punctual interpretation of these results needs the original standard deviation and mean of the test scores, equal to about 40.14 and 201.76, respectively, for the Mathematics score in the cross-sectional sample. Taken together, the cross-sectional coefficients on Mathematic scores imply a loss between 3.8 and 4.0%.[10] For the DiD specification, the magnitude of the loss is about 2.9%. A similar result holds for the Italian score, with a negative and significant impact of school closures on educational scores bounded between 1.8 and 2.4%. Taking into account these differences in the specifications, our model suggests that the average impact of school closures at national level is between 1.8 and 4%. These findings are in line with what found in other contexts. For the case of Netherlands, indeed, Engzell et al. (2021) identify an impact of 0.08 standard deviations, corresponding to about 3% of educational loss.

### 5.2. Impact of additional school closure days

While the average national impact aligns with other works, it may still hide a wide heterogeneity across grades, parental background, and institutional setting. To unpack some of these factors, this work takes advantage of a unique dataset on school closures days by grade and municipality in Sicily. As already introduced, schools were closed with different degrees, depending on the local trend of Covid-19 cases, which substantially varied across the regional territory. Depending on the trend in cases and occupancy of intensive care units, the decisions about closures were suggested by the municipalities and approved by the Regional Government. This allows estimating the impact of an additional day of school closures and, therefore, shifting to a continuous treatment setting.

Fig. 3 displays the map of average school closure days by municipalities.[11] White areas denote municipalities without schools, which are usually low populated. These hold an average of 150 inhabitants with a maximum of 482 inhabitants. If we consider the regional population by age, these municipalities should hold on average 21 students and a maximum of 67. Dividing these by the number of grades in the Italian school systems, the municipalities without schools hold maximum 5 individuals in school-age per grade.

Fig. 3 shows that the data distribution is right skewed. Indeed, one fourth of municipalities are associated to a number of school closure days substantially higher than the remaining ones. Also, the percentage difference between the 90th percentile and the mode value of school closures is about 7%–12%,[12] When considering the 95th percentile of school closure days, the difference from the mode is between 14 and 25%, depending on the grade.

Table 5 displays the results from the specification in Eq. (2), where again the identification relies on a between-cohort comparison. Results from the first column suggest that an increase of a standard deviation in schools days is associated with a decrease in the average Mathematics score. Considering that the standard deviation of school closure days and of the Mathematics score are equal to 43.70 and 38.52, respectively, while the average of the same score is 201.4, this finding means that the average school closure days are linked to a decrease in the score of about 2.4%.[13] Results reported in column 2 come from a specification

[10] This is calculated multiplying the coefficient by the standard deviation and dividing the result by the average of the score.

[11] Mapping school closure days for separate grades determine a similar level of spatial heterogeneity.

[12] We obtained this share by dividing the school closure days by a total of 200 days for Italian schools according Baïdak and Sicurella (2019).

[13] This result is obtained calculating the impact of one school closure day on the standardized score and re-scaling the result using the mean and the standard deviation of the score multiplied by the average school closure days.

**Table 5**
School closure days and educational score.

| | Panel | | | | | Cross-section (year = 2021) |
|---|---|---|---|---|---|---|
| Model | OLS with FE | | | Low & Middle school | High school | 2SLS-IV |
| VARIABLES | Math (std.) (1) | Math (std.) (2) | Italian (std.) (3) | Math (std.) (4) | (5) | Math (std.) (6) |
| School closure days | −0.038*** | −0.116*** | −0.146*** | −0.170*** | −0.131*** | −0.113*** |
| | (0.008) | (0.023) | (0.018) | (0.019) | (0.019) | (0.012) |
| School closure days X Years of parents' education | | 0.009*** | 0.007*** | 0.016*** | 0.002* | |
| | | (0.001) | (0.001) | (0.001) | (0.002) | |
| Other controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Student FEs | Yes | Yes | Yes | Yes | Yes | No |
| Relative time dummies | Yes | Yes | Yes | Yes | Yes | No |
| Grade dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 327,324 | 327,324 | 327,324 | 224,898 | 102,426 | 163,662 |
| Adj. R-squared | 0.457 | 0.460 | 0.492 | 0.444 | 0.505 | 0.053 |
| | First stage results and statistics | | | | | |
| Covid-19 cases per person | | | | | | 0.015** |
| | | | | | | (0.008) |
| Variance of Covid-19 cases | | | | | | 0.000*** |
| | | | | | | (0.000) |
| F-test ($P$-value) | | | | | | 659.81 (0.000) |
| Hansen overid. test ($P$-value) | | | | | | 2.235 (0.135) |

*Notes:* the table reports the estimates of a two-way fixed effect on panel data (columns 1–5) on students from Sicily, and from a 2SLS model including the number of Covid-19 cases per persons and its variance as instruments on the 2020/21 cross sectional sample (column 6). Standard errors clustered at school level for relative time equal to one and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

including the interaction term between the school closure days and the years of parents' education. In this case, the coefficient associated to school closure days remains negative and significant but substantially increases in magnitude, while the coefficient of the interaction term is positive and significant. Together, these suggest that highly educated parents appear to compensate the negative impact of school closures that remains at about 3%, when considering mean values of the score and school closure days. A similar result emerges from the specification on the Italian score displayed in the third column.

To further explore this level of heterogeneity, columns 4 and 5 of Table 5 show the results obtained when pooling the sample across the school levels, to study whether school closures have disproportionately impacted students from a specific level. Note that, while the parents' educational background continues to moderate the impact of additional school closure days for low and middle school students, this effect is weakly significant and almost zero for the specification considering high school students.

Finally, column 6 of Table 5 shows results from an additional test aimed at investigating whether the findings are affected by residual endogeneity, such as measurement errors. This may occur as some students may have observed higher turnover of peers/staffs than others, or they may have loss the same amount of days but with different time spells, with some students observing a single long-term closure, and others experiencing smaller windows of closure repeated during the school year. To this scope, we run a 2SLS Instrumental Variable regression on the cross-sectional 2020/2021 sample and we instrument the days of closures with the mean and variance of Covid-19 cases per population. This approach relies upon the exclusion restriction that Covid-19 cases will affect the test scores only through school closures.[14] We expect that both the mean and the variance of Covid-19 cases will be positively correlated with the school closure days, as additional cases, on average, will push municipalities in keeping the school closed and shift schooling to distance learning. As expected, the mean and variance of Covid-19 cases have a positive effect on the school closure days. The mean coefficient is significant at 5% level while the level of significant of the variance coefficient is 1%. Also, note that the F-test is largely above the rule of thumb, and the test on over-identification does not reject the validity of the instruments (see bottom part of Table 5). The second stage coefficient linked to school closure days increases substantially. The magnitude of this result is higher than the baseline, however this one is calculates as local average treatment effect conditional on Covid-19 cases, while the baseline coefficient denotes the average treatment effect.

Lastly, we run a dose response function with a two degrees polynomial, to test whether additional school days may have a non linear impact on the score. This exercise needs the treatment to be distributed between 0–100, so we rescale the school closure days indicator to comply with this criterion. As displayed in Fig. 4, the impact of an additional school day is very similar in magnitude for the lowest part of the distribution, while an additional day of school closure appears to contribute more to educational losses when the students already observed the 40%–50% of school closure days in our sample. This impact, then, stabilizes at a higher level of magnitude when the dose is above 60% of the school closure days.

[14] Even if students may have been infected by Covid-19, loosing some school days, it is reasonable to assume that this is a plausible assumption supported by the limited symptoms of Covid-19 in the young population, and by the fact that the present analysis considers the average cases at municipal level.

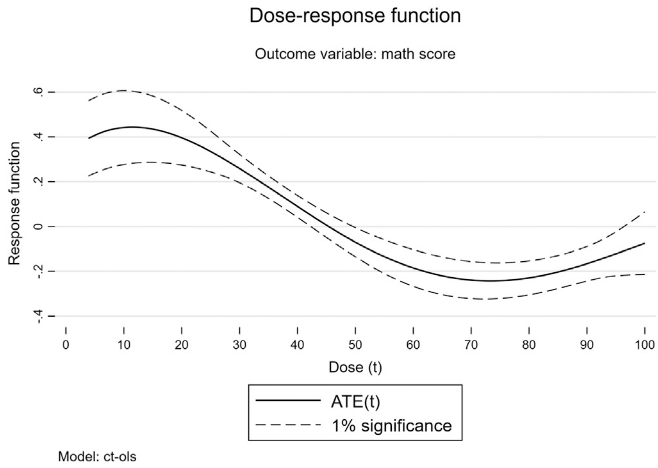


**Fig. 4.** Dose response function of school closures on math score.

## 6. Heterogeneity and robustness

This section presents a set of additional heterogeneity results using the baseline specification for the case study in Sicily. Fig. 5 below shows the coefficients obtained when pooling the sample across the parents' type of employment, parents' origins, and class size. For parents' employment we consider whether the parents' are unemployed or blue collars, or any combination of these, and we compare these with the remaining employment categories. For parents' origin, we consider the case of both parents' having foreign origins and compare this with cases where at least one parent is Italian. Unfortunately, the INVALSI data do not provide the information about the parents' country of origin, so we are unable to identify whether they were born in a developing or developed country.

The top-left panel of Fig. 5 reports the effects of school closure days depending on parents' type of employment suggesting that students experiencing higher losses are the ones with parents being either unemployed or blue collar. This is in line with the literature showing how the current school system is not filling the role of great leveler (Agostinelli et al., 2022) and suggests that school closures may have had a prominent role in increasing inequalities between students, even for those attending the same school and receiving the same inputs. In magnitude terms, the percentage difference of an additional school closure days for these disadvantaged students is about 30% larger than the rest of the sample.

The top-right panel of Fig. 5 reports the coefficients obtained when pooling along the parents' origins. Again, the coefficient is larger for students with less advantaged background, i.e. those with foreigner parents. The bottom panel of Fig. 5 presents the coefficients obtained when pooling the sample around class size, using the regional median as threshold. The result points to the fact that the impact of additional school closure days changes substantially depending on the number of students, with those attending small classes experiencing about 50% higher loss compared to the ones attending larger classes. As suggested by the development or education economics literature such as Case and Deaton (1999), this may derive from the teacher/pupil ratio, which is one of the main determinants of the human capital accumulation during schools, as it ensures higher quality of teaching inputs. For an additional school closure day, students attending smaller size classes may be losing higher quality inputs and experience larger cumulated losses. Also, the socio-economic literature stresses that in smaller groups, the social ties are stronger and individuals are more influenced by their peers. For example, network studies such as McPherson et al. (2006) find that the number of confidants for Americans constantly declined in the last two decades and people reporting not having a person with whom discussing important matter tripled. The small class size results, therefore, could derive by the fact that loosing direct contact with peers in groups where these ties are lower in number but stronger, may imply higher costs in terms of educational score.[15]

Table 6 offers the results from a set of robustness checks, testing if the choices on variables' specification and group comparison may have affected the final outcome. The first three columns use alternative transformations of the dependent and explanatory variables. Column 1 considers the natural log of the continuous dependent and explanatory variables, adding 1 to include the zero valued observations. Column 2 adopts the Inverse Hyperbolic Sine Transformation (IHS) developed by Bellemare and Wichman (2020). Both these exercises show very similar results and the magnitudes of the coefficients, when duly accounting for the difference in functional forms, are similar to the baseline. Column 3 reports the results when using the Rasch score and, again, these remain consistent both in sign and in magnitude. Finally, column 4 considers the inverse probability weight to the specification of column

[15] If we add peers effects, lagged or contemporary, to the benchmark specification, these are strongly significant and, when interacted with treatment, they increase the magnitude of the estimated loss. However we did not report these results due to the fact that peers variable is a bad control in a reduced form, given the potential many channels that may affect the outcomes.

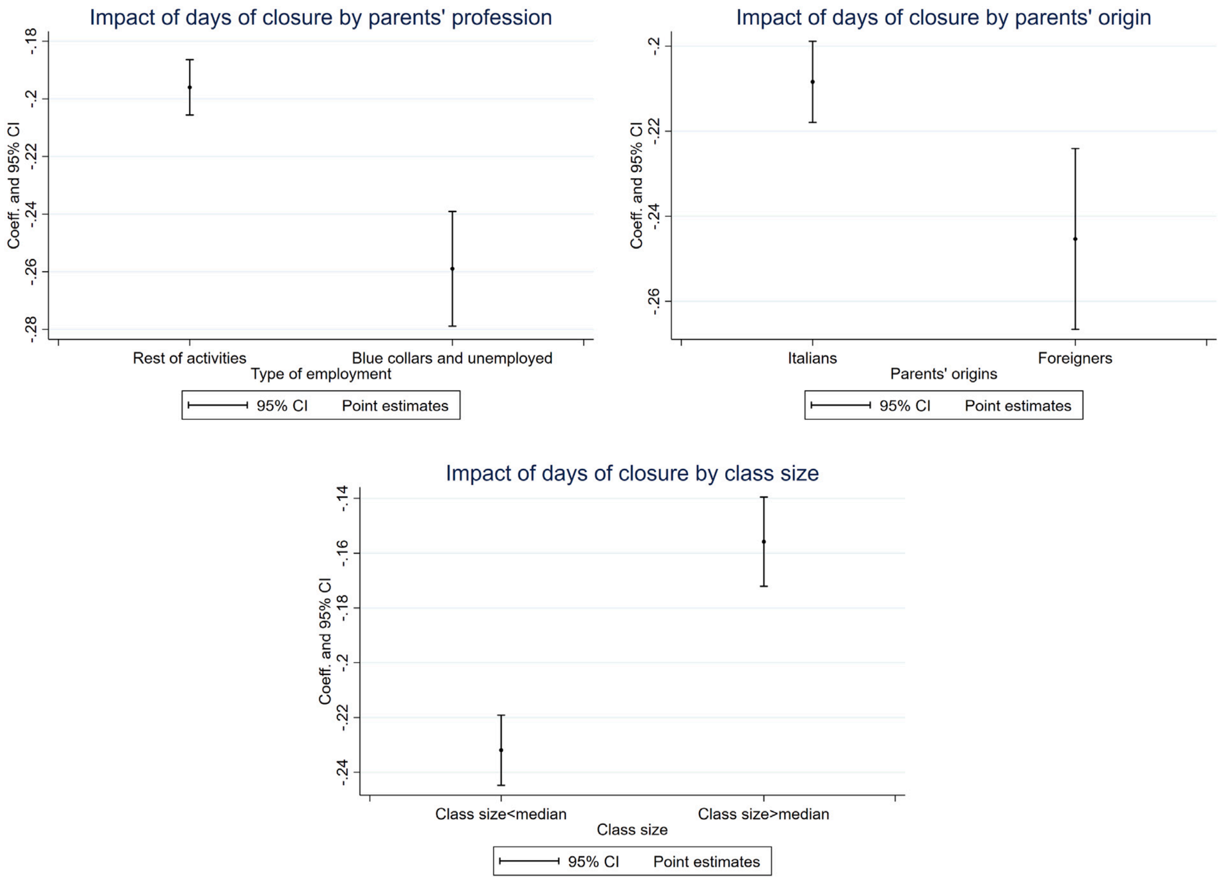


**Fig. 5.** Heterogeneity by parent's professions, origins and class size.

1 in Table 5. These weights derive from scores obtained running a propensity score matching on the probability of being treated and controlling for a large set of covariates, including Mathematic and Italian score at baseline, parents' year of education, average peers' score at baseline, province dummies, parents' employment typology, number of classes and total population. As shown in Table 6, also this additional test confirms the negative impact of experiencing additional school closure days on the test score. Finally, Table 7 in the Appendix reports the results from a similar set of robustness tests for the national level data. In particular, it considers three specifications taking the natural log of the dependent and explanatory variables, the Rasch score, and the inverse probability weighted standardized variables. Again, the results remain consistent with the benchmark.

## 7. Conclusions

In the last two years, the governments adopted school closures to reduce the diffusion of Covid-19, especially during the first wave (Haug et al., 2020; Hsiang et al., 2020; Kucharski et al., 2020). While a growing literature discussed the potential effects in terms of future human capital losses, most of this literature based itself on theoretical assumptions of standard human capital models and a common shock on the present cohort with respect to the previous ones that did not experience these closures.

This work feeds the debate using a newly collected dataset of local school closures, motivated by the fact that few months after a first general lockdown, closures were not equally distributed across the Italian territory, but depended on the local levels of Covid-19 diffusion. Our findings suggest that, at national level, the educational losses are comparable with what the literature found in other settings, such as Netherlands (Engzell et al., 2021) and Belgium (Maldonado and De Witte, 2022). However, the current work is also able to estimate the contribution of each school closure day on students' human capital. These estimates suggest that the average school closure days implied a 2.4% decline of the educational scores in the tests implemented by the general Italian agency of students evaluation. Also, our findings shed light on the compensatory role of well educated parents, as spending more time at home with higher educated parents reduced the loss experienced by the students. This effect holds for low- and middle-school students, while it becomes negligible for high school students, who are likely less dependent on parental inputs for their educational enhancement. The findings also show a more pronounced impact on more disadvantaged students, which likely translated in more unequal educational attainment and human capital formation across the Italian social stratification.

**Table 6**
Robustness specifications on the effect of school closures on test scores in Sicily.

| | Math (ln) (1) | Math (IHS) (2) | Math (Rasch) (3) | Math (std. - PSM) (4) |
|---|---|---|---|---|
| School closure days (ln) | −0.005*** | | | |
| | (0.001) | | | |
| School closure days (IHS) | | −0.004*** | | |
| | | (0.001) | | |
| School closure days (level) | | | −0.014*** | |
| | | | (0.005) | |
| School closure days (std.) | | | | −0.070*** |
| | | | | (0.007) |
| Other controls | Yes | Yes | Yes | Yes |
| Student FEs | Yes | Yes | Yes | Yes |
| Relative time dummies | Yes | Yes | Yes | Yes |
| Grade dummies | Yes | Yes | Yes | Yes |
| Observations | 327,324 | 327,324 | 327,324 | 327,322 |
| Adj. R-squared | 0.436 | 0.436 | 0.457 | 0.454 |
| Number of students | 163,662 | 163,662 | 163,662 | 163,661 |

*Notes:* the table reports the estimates from a two-way fixed effect model on the impact of Covid-19 related closures on test scores. The main explanatory variable is a variable capturing the number of school closure days. The specification corresponds to the one reported on column 2 of Table 5. Columns 1 considers the natural log of the dependent and explanatory continuous variables. Columns 2 reports the results when using the Inverse Hyperbolic Sine Transformation developed by Bellemare and Wichman (2020). Column 3 displays the results with the level variables. Column 4 is similar to the baseline but includes inverse probability weights calculated through a propensity score matching (PSM). PSM includes the treatment as dependent variable and, as controls, the following variables: score in Mathematic and Italian at baseline, year of educations of parents at baseline, average peers' score at baseline, province dummies and parents' employment typology, number of classes and total population. Standard errors clustered at school level for relative time equal to one are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

**Table 7**
Robustness specifications on the effect of school closures on test scores at national level.

| | Math (ln) (1) | Italian (ln) (2) | Math (Rasch) (3) | Italian (Rasch) (4) | Math (std. - PSM) (5) | Italian (std. - PSM) (6) |
|---|---|---|---|---|---|---|
| School closures | −0.035*** | −0.021*** | −6.065*** | −3.760*** | −0.150*** | −0.096*** |
| | (0.001) | (0.001) | (0.155) | (0.139) | (0.004) | (0.004) |
| Other controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Student FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Relative time dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Grade dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,496,388 | 4,496,388 | 4,496,388 | 4,496,388 | 4,496,388 | 4,496,388 |
| Adj. R-squared | 0.518 | 0.519 | 0.540 | 0.563 | 0.540 | 0.563 |
| Number of students | 2,248,194 | 2,248,194 | 2,248,194 | 2,248,194 | 2,248,194 | 2,248,194 |

*Notes:* the table reports the estimates from a Two-way fixed effect model on the impact of Covid-19 related closures on test scores. The main explanatory variable is a dummy activating for the treated group after the Covid-19 pandemic occurred. The specification corresponds to the one reported on column 2 of Table 4. Columns 1–2 consider the natural log of the dependent variables and explanatory continuous variables. Columns 3–4 report the results when using the level variables from the Rasch model reported by INVALSI. Columns 5–6 display the results from the baseline specification with standardized variables but includes inverse probability weights calculated through a propensity score matching (PSM). PSM includes the treatment as dependent variable and, as controls, the following variables: score in Mathematic and Italian at baseline, year of educations of parents at baseline, province dummies. Standard errors clustered at school level for relative time equal to one are reported in parentheses.***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

While the present work has estimated the short-term educational costs of the so-called Covid-19 mitigation policy on school closures, it leaves open a set of questions about how the long-term perspective of the affected students will look like. Whether these short-term costs will translate into long-term lower salaries, as some work predicts, or if any policy actions will impede the expected growing inequality, is left to future work.

## Data availability

Data will be made available on request.

## Appendix

See Table 7.

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