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HIDDEN DROP-OUTS: SECONDARY EDUCATION (UNSEEN) FAILURE IN PANDEMIC TIMES

by Lorenzo Alderighi*, Rosario Maria Ballatore** and Marco Tonello♦

Abstract

In this paper, we estimate the effects of the COVID-19 pandemic on hidden drop-outs, a new indicator of failure to acquire the minimum skills deemed necessary to obtain a high school diploma. We use the exogenous variation induced by the pandemic by comparing two cohorts of students from the same school, one affected and the other not affected by the pandemic. We find that the indicator increased by 8.6 percentage points. The effect is stronger for students with lower levels of prior achievement, those from lower-income households, but also for those who showed emotional distress during the standardized tests and those who report lower educational aspirations.

JEL Classification: I21, I24, I18.
Keywords: hidden drop-outs, secondary education, school failure, COVID-19.
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Contents

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1 Introduction[1]

The pandemic outbreak in 2020 resulted in a significant worsening of many aspects of daily life. Young people, especially students, were among the most affected. From one day to the next, many governments decided to close schools and went from in-person to online remote teaching (Svaleryd & Vlachos, 2022). Often this occurred in places where schools, families, or both were not prepared to handle the new learning environment (OECD, 2019). Indeed, many schools and households were not equipped with adequate technology (IT solutions), and often teachers did not have sufficient digital skills to provide effective education, making learning very difficult.

These disruptions raised serious concern about the negative consequences for children, and resulted in a large number of studies mostly analyzing the effect on achievement of the pandemic-induced school disruption. These studies make use of standardized test scores and focus especially on young children at the beginning of their educational path. Large consensus has been found on the substantial negative impact of the pandemic, with the effects on achievement being strongly heterogeneous across the students' and families' characteristics (Betthäuser et al., 2023).[2] That said, the question whether these learning losses translated into a failure to achieve the minimum level of skills required for a given grade remains unanswered, as this educational failure cannot be seen in standardized test scores alone and is often masked by the formal academic success in passing from one grade to the next. Investigating this aspect is even more important for high school students, as they may have no time to recover.

This paper aims to unveil this "unseen" failure by analyzing an innovative aspect on which the literature has not yet focused: the *hidden drop-out* of students at the end of secondary school. Different from the usual notion of "high-school drop-out" (i.e. students who are no longer enrolled in secondary school and have not received a secondary school diploma or recognized equivalent), hidden drop-out refers to students who formally completed secondary school and received a diploma, but who nonetheless did not acquire the skills or competences required for the grade reached.[3]

[1]We want to thank INVALSI for their constant support and help in using their data archives (in particular: Valeria Tortora, Patrizia Falzetti, and President Roberto Ricci), and Andrea Ichino, Ylenia Brilli, Giulia Bovini, Raffaello Bronzini, Silvia Del Prete, Elena Gennari, and Andrea Cintolesi for useful comments and discussions. The views expressed in this paper are those of the authors and do not necessarily reflect those of the institutions to which they belong. The usual disclaimers apply.

[2]The most affected appeared to be pupils of low socio-economic status (Engzell et al., 2021; Jack et al., 2023; Goldhaber et al., 2023; Agostinelli et al., 2022),those with lower prior achievement (Grewenig et al., 2021), minorities (Jack et al., 2023), students with a worse learning environment at home (Di Pietro et al., 2020), and those experiencing longer periods of school closures (Engzell et al., 2021).

[3]The notion of hidden drop-out was first proposed by Ricci (2019), who pointed out that official statistics on school drop-out underestimate the number of students who do not achieve the minimum standard of education. The hidden drop-out measure is also in line with the notion of learning poverty, recently introduced by the World Bank to describe primary school students who are unable to read and understand simple texts by age 10. See:https://www.worldbank.org/en/topic/education/brief/what-is-learning-poverty.

To this end, for our study we evaluate Italian students in Grade 13 during the pandemic. This last year of high school is an important time when students often decide whether to pursue tertiary education or look for a job in the labor market. While some recent evidence on primary school students points to a rapid recovery of learning losses once the usual learning environment has been re-established (Singh et al., 2022), secondary school students, who have already left the educational system, accumulate losses that, in the absence of specific recovery policies, no schooling or labor market institution can remediate.[4] This means that any unfilled educational loss at the end of high school may plausibly affect success permanently in tertiary education or in the labor market, or both.

The evidence on the impact of the pandemic on learning loss for high school students is still very scarce compared to primary and middle school students (Betthäuser et al., 2023). A notable exception is by Riudavets and Uusitalo, 2023 who, focusing on the matriculation exam taken by Finnish students at the end of secondary school, find no impact of the pandemic on achievement. To the best of our knowledge, we innovate the literature by providing new information by looking at this new measure of hidden drop-out and focusing on the last grade of secondary school, which has been largely overlooked, despite being crucial from a policy perspective.

We use the administrative data provided by the National Institute for the Evaluation of the Education and Training System (INVALSI), covering the universe of students attending school in Italy, which we linked to rich survey questionnaires. We focus on students in grade 13, the last year of high school in Italy, and exploit the exogenous variation induced by the pandemic comparing two cohorts of students: the last group of students to complete grade 13 before the outset of COVID-19; and the next group whose high school experience was disrupted for about one-and-a-half-years owing to the pandemic. The effect on hidden drop-out is observed by comparing students in the two cohorts within the same school, taking into account several pre-determined student characteristics, including prior level of achievement.

Italy is an important country when studying the impact of the pandemic because it is considered one of the worst-case scenarios among developed economies in terms of the effects of the pandemic on the school system. Italy was one of the first countries to deal with the virus, had one of the highest mortality rates, and experienced some of the longest educational disruptions due to lockdown restrictions and school closures, which lasted longer than in most European countries (Ritchie et al., 2020).[5] Moreover, Italian

[4]Singh et al., 2022 estimate that after 18 months of school closures, students aged between 5 and 7 accumulated a learning loss in test scores between 0.7 and 0.34 standard deviations (equivalent to a loss of 1 to 2 years of schooling). Most importantly, the authors observed a rapid catch-up within six months of schools' reopening: about two-thirds of the learning loss was made up by May 2022.

[5]For a comparison of mortality rates, see HOPKINS, 2022. For reports on pandemic-related education disruption, see UNICEF et al., 2021.

schools and teachers' ICT skills were among the worst in Europe from a technological perspective (Wastiau et al., 2013); their preparedness for technology-enhanced remote teaching was far below the European average (OECD, 2019).

We found that hidden drop-out increased by 8.6 percentage points following the pandemic. The pandemic has severely affected students with previously existing learning disabilities, those coming from poorer socio-economic backgrounds, those with high test anxiety, and those who had previously expressed lower educational aspirations for their future. We also found that the probability of becoming a hidden drop-out increased more for students in regions that had longer school closures, which suggests that the substitution of in-person schooling with hybrid and remote teaching was the main factor that negatively affected students' learning during the pandemic.

The paper proceeds as follows. Section 2 describes the institutional setting; Section 3 presents the data used; Section 4 illustrates the identification strategy; Section 5 describes the baseline results, the robustness and specification tests, and the heterogeneity analysis. Section 6 concludes and provides policy implications.

2 Background

2.1 The Italian schooling system

The Italian school system consists of three levels of education before university: primary school (grades 1-5; ISCED level 1), junior high school (grades 6-8; ISCED level 2), and high school (grades 9-13; ISCED level 3) with three main tracks (academic, technical, and vocational). Our work makes use of two cohorts of grade 13 students from all three tracks.

The academic track is generally for students who plan to attend university. The technical track allows students to acquire both theoretical and practical skills. The vocational track focuses on providing students with essential vocational skills for finding jobs after graduating. Compulsory education in Italy ends at age 16 (generally, grade 11). At this point, students may drop out of school, though they are obliged to attend courses or apprenticeship programs until they turn 18. Students who desire to continue their formal education after grade 13 must pass a national final examination, required to receive a high school diploma and mandatory to attend university.

The school year lasts from mid-September to mid-June. During the school year, students have access to training programs and on-site learning at certain firms and institutions; however, these were not available during the first wave of the pandemic in spring 2020 and were provided mainly online during the 2020-2021 school year. Grade retention is possible and it depends on teachers' evaluations and the student's grades in different subjects. The retention rate is usually very low in primary and junior high school, and

increases in high school.[6]

2.2 The spread of COVID-19 and school closures

Italy was one of the first western countries severely impacted by the spread of COVID-19. During the first wave of the pandemic, one of the main restrictions put in place resulted in school closures. Schools closed February 24, 2020, and did not open again for 15 consecutive weeks, an in-person loss of education equal to about one semester. In this first stage of the pandemic, there were no distinctions in terms of grades, as school closures affected all Italian students equally.

Students' lives changed drastically not only because of school closures but also because of social distancing measures implemented to limit the spread of the virus. People were not allowed to go further than 200 meters away from their homes and could visit shops only to buy "essential products" (e.g., food, drugs). Cultural and social activities were prohibited, and sports centers remained closed. These limitations substantially affected the daily life of students, who lost opportunities to participate in activities fundamental in developing cognitive, social, and emotional skills complementary to more formal academic education. The lockdown contributed to reducing the daily time devoted to learning, in favor of other leisure activities, such as TV watching or playing video games (Grewenig et al., 2021).

At the beginning of the 2020-2021 school year, Italy implemented different measures in order to prevent additional comprehensive school closures. Depending on the contamination level of the area in which a school was located, diverse sets of restrictions were put in place. Based on the diffusion and severity of the COVID-19 infections, areas were given statuses of white (lowest concern), yellow, orange, or red (highest concern).[7] Each color also corresponded to limits on how many school days would be taught in school and at home, which were further differentiated by grade.

Although the restrictions connected with a specific color changed frequently during the pandemic period, the underlying principle that guided the restrictions always remained the same: preserve as much as possible in-person teaching, giving priority to younger students. As shown in Figure 1, high school students experienced the largest disruption in terms of loss of in-person schooling during the 2020-2021 school year. Indeed, while primary and junior high school students attended 90.5% and 83.2% of in-person school days, respectively, high school students attended only 16%.

[6]For instance, in the 2018-2019 school year, the retention rate in junior high school was close to 2%, while in high schools it was 6.8% (MIUR, 2019).

[7]See Ministero della Salute (2021) for a general overview about the measures implemented by Italy to contain the infection in the autumn and winter of 2021. Official parameters that determined the "color status2 of the region were continuously updated during the pandemic using Decree-Laws established by the Ministry of Health.

3 Data

3.1 The INVALSI National Evaluation Program in grade 13

INVALSI implemented the National Evaluation Program of Students' Achievement (NEPSA) in the 2009-2010 school year with the aim of attaining yearly census data by testing core skills in language (Italian) and mathematics in students in primary (grades 2 and 5), junior high (grade 6), and high school (grade 10). Since the 2018-2019 school year, grade 13 students also take the tests. The NEPSA exams are low-stakes tests; each school's results are returned to the school staff, parents and students presented in aggregate (averages). Furthermore, the tests offer no incentives for schools, teachers, or students.

The NEPSA in grade 13 consists of computer delivered, standardized Italian language and math tests that students complete toward the end of the second semester (i.e., between April and May) during school time.

Importantly for our identification strategy, thanks to an anonymous individual-level identifier, we merged the NEPSA tests of grade 13 students with the grade 10 NEPSA results of the same students. This allows us to collect data about the same student across years and tests.[8] In grade 10, the NEPSA test comes with a *Student Questionnaire*, which collects additional information on students (e.g., parents' job and education, IT equipment at home or place of study, personal feelings about the tests, and educational aspirations) that we use mainly in our heterogeneity analysis (see Section 5.3).

3.2 Hidden drop-out measure and descriptive statistics

Using the NEPSA archives, we gather two cohorts of grade 13 students: those who took the tests during the 2018-2019 school year (hereafter, the pre-COVID cohort) and those who took the tests during the 2020-2021 school year (after almost one year since the beginning of the emergency; hereafter, the COVID cohort).[9]

Together with the standard test scores results and basic demographic characteristics, for students in grade 13 INVALSI also provides a new variable which, for each subject, classifies students into five increasing levels of ability (Desimoni, 2018). This variable is the result of an accurate psychometric analysis that identifies the true student's capacity. In contrast to simple tests, which assign all answers the same relative importance, to obtain the attainment levels the psychometric analysis weights each item used for evaluation according to the skills required to answer it. Level 3 corresponds to the minimum threshold of knowledge and skills that the student should have by the end of high school. Based on

[8] We matched about 83% of students observed in grade 13. As a matter of fact, the match is only possible for those students who had a regular progression across grades 10 to 13. See Appendix A for further details on the sample construction.

[9] The NEPSA exams were not taken in the 2019-2020 school year because of the lockdown procedure during the first wave of the pandemic.

this variable, we create our measure of hidden drop-out, which is a dummy that identifies students who fail to reach level 3 both in math and Italian language assessments. Note that all students defined here as hidden dropped-out formally completed high school. In other words, they received their diplomas without possessing the minimum knowledge and skills sufficient to earn them.[10]

Table 1 reports the summary statistics of the sample that we use for our analysis. Panel A describes our measure of hidden drop-out. In the pre-COVID cohort, the average probability that a student would become a hidden drop-out was 17.4%, while in the COVID cohort, this figure almost doubles (30.0%). This raw gap between the two groups is a first evidence of the impact of the pandemic on hidden drop-out. Panels C and D in Table 1 report the summary statistics of the variables used as controls in our baseline regression specification and those employed in the study of heterogeneity, respectively.

4 Identification strategy

To estimate the effects of the COVID-19 pandemic on hidden drop-out, we compare students of the pre-COVID cohort (control group) with those of the COVID cohort (treatment group, identified by the dummy C_k). While the pre-COVID cohort comprises individuals who completed their secondary education without being affected by the pandemic, the COVID cohort had to deal with the effects of the pandemic on school activities for almost half of grade 12 (February 2020 to June 2020) and for the entirety of grade 13 (September 2020 to June 2021).

In our setup, the outbreak of the pandemic offers a natural experiment in which one group is exogenously treated. The baseline regression takes the following form:

$$HD^{t}_{i,k,j} = \beta_0 + \beta_1 C_{i,k} + \beta_2 X^{t}_{i,k,j} + \beta_3 \widetilde{X}^{t-1}_{i,k,j} + \beta_4 A^{t-1}_{i,k,j} + \eta_j + \epsilon_{i,k,j} \tag{1}$$

where: $HD^{t}_{i,k,j}$ is a dummy that identifies student (i) of cohort (k) and school (j) that did not reach the minimum level of Italian language and math competences in grade 13 (i.e., hidden drop-out) and $C_{i,k}$ is a dummy indicating whether the student belongs to the COVID cohort. We also control for a vector of students' and class characteristics ($X^{t}_{i,k,j}$), including dummies for female, foreign (i.e., non-Italian citizen), grade retained (before grade 10), class size (measured by the number of students in the class, both in linear and quadratic terms), and for school fixed effects (η_j). Crucially for our identification strategy, we exploit the longitudinal dimension of the data by adding to the specification a measure of student's achievement at the previous assessment in grade 10 ($A^{t-1}_{i,k,j}$),[11] as in

[10] Table B.1 of the Appendix shows that more than 99% of grade 13 students obtained the diploma.

[11] In our baseline estimates, we use the average score between Italian language and math tests in grade

a value-added specification (Todd & Wolpin, 2003), and the family socio-economic status index measured in grade 10 ($\widetilde{X}_{i,k,j}^{t-1}$).

The main coefficient of interest is β_1, which identifies the change in the probability of being a hidden drop-out student, across the two cohorts of students, and within the same school.[12] The coefficient captures an Intention-To-Treat (ITT) effect as it embeds all direct and indirect effects of the pandemic on hidden drop-out. Nevertheless, among the possible channels driving our results (Asadullah et al., 2023; De Paola et al., 2023), we will show that that the effect is sensitive to the differences in length of school closures experienced in different areas of the country, pointing to the substitution of in-person with online schooling as a prevailing channel.

The main assumption for attaching a causal interpretation to β_1 is that - conditionally on predetermined controls - the treatment is independent of potential outcomes of both treated and control cohorts. While we can safely assume that the pandemic affected the COVID cohort in an exogenous way, our estimates also root on the assumption that the two cohorts of students are similar in all observable and unobservable aspects that could affect the human capital accumulation process. Given that the two cohorts of students are really close to each other, we believe that this assumption is basically free of all the concerns regarding cohort-specific demographic composition and trends. As a matter of fact, Table 1 shows that the many observable predetermined characteristics we have in our data do not differ substantially across cohorts.

5 Results

5.1 Main results

Baseline estimates of the effects of the pandemic on hidden drop-out are reported in Table 2. We perform OLS regressions with robust standard error clustered at the school level, starting from a conservative specification with only school fixed effects and progressively adding all the control variables.

In our preferred specification (Column 4), we estimate that the pandemic induced a 8.6 percentage points increase in the probability of hidden drop-out, corresponding to a 49.4% increase with respect to the average probability of hidden drop-out in the pre-COVID cohort.

10.

[12] A specification like the one we estimate is sometimes referred to as a Difference-In-Differences (DID) strategy, as we do observe one treated and one control group, a pre-treatment period (i.e., achievement in grade 10), and a post-treatment period (i.e., achievement in grade 13). However, we detach from a classical DID strategy because: (*i*) the hidden drop-out is available only for grade 13; and (*ii*) INVALSI test scores cannot be consistently linked across grades (so that - for example - an increase of in a student's test score from grade 10 to grade 13 would not necessarily imply an increase in underlying ability).

Our estimate corresponds to an annual learning loss of 0.23 units of standard deviations (SD), with respect to the pre-COVID period. Our results lie below the median negative impact of 0.08 SD units found by Hammerstein et al. (2021) or the average loss of about 0.14 SD units that Storey and Zhang (2021) and Betthäuser et al. (2023) reported in literature review and meta-analysis of studies related to learning loss due to the pandemic. However, two main caveats are in order. First, our study considers the effects of the pandemic on learning in the wider time horizon of the first and second waves (February 2020-May 2021). Second, usual yearly progress in math and language are declining over time (Bloom et al., 2008), such that the comparison above could be misleading in understanding the learning loss suffered by older students. Indeed, as already noted, the literature has concentrated especially on students below grade 10, to the exclusion of older ones. For these reasons, we believe more appropriate to compare our results with the average natural yearly progress in high schools, which is estimated around 0.20 SD units (Bloom et al., 2008). With respect to this estimate, the pandemic completely destroyed one year of learning progress in high school students.[13]

5.2 Robustness checks

In Table 3, we test the robustness of our findings under many perspectives. First, given the importance of controlling for a previous level of students' skill in models accounting for human capital accumulation (Todd & Wolpin, 2003), we test for different specifications of the variable expressing students' attainment in grade 10 ($A^{t-1}_{i,k,j}$ in Equation 1). In our baseline specification, we control for the adjusted average Italian language and math tests in grade 10; the adjustment makes it possible to include in the estimation sample students who took only one of the two tests. We observe no substantial changes in estimating our model, dropping students (about 440) who missed one of the two tests (Column 1). In Column 2, we use a non-parametric specification of previous achievement using dummies, identifying the quintile in which the student is located relatively to the average math and Italian scores in grade 10. In Column 3, we add to the baseline regression the square of ($A^{t-1}_{i,k,j}$), and Column 4 includes its cube. In the three specifications, we do not observe substantial changes in the estimates of our treatment effect.

In the baseline model, we use standard error clustered at the school level. The results in Columns 5 and 6 show that our inference is not compromised if we apply a different type of clusterization (i.e., at the class or province level).[14]

For three Italian regions (Puglia, Campania, and Calabria, see Appendix A), we have

[13]Many works on learning loss caused by the pandemic also compare their estimates with the World Bank's projection of yearly progress of 0.40 SD units (Azevedo et al., 2021). However, this yearly progress refers especially to primary school students, who are not comparable to students in their last year of high school. See Bloom et al. (2008) for a detailed description of the natural yearly progress trajectory from grades 1-12.

[14]Provinces (NUTS 3) in Italy approximately correspond to school districts.

fewer observations in the COVID cohort than in the pre-COVID cohort, plausibly because of longer restriction periods in the 2021 spring semester, which hampered the INVALSI assessments.[15] The results obtained by excluding these three regions (Column 7) are not statistically different from our baseline.

5.3 Heterogeneity

In this section we analyze the impact of the pandemic on hidden drop-out along different dimensions of possible heterogeneity, such as student's traits, families' socio-economic characteristics, the length of school closures, and the subjects of assessment. This section helps to identify the categories of students most affected by the pandemic, towards which public policies should be concentrated. Panel D of Table 1 summarizes the variables on which we perform our heterogeneity analysis. All the variables are both time invariant or pre-determined at grade 10, with the only exception of the number of days of schools closures. The results are reported in Figure 2 (and in Appendix Table B.2).

Students' traits. We start by considering individual traits, such as students' prior achievement, citizenship, gender, emotional distress felt during assessments, and aspirations about their educational career. Figure 2 shows that the most relevant dimension of heterogeneity is the one related to the prior level of achievement. Among low achieving students in grade 10, the probability of becoming a hidden drop-out increased by 15.7 percentage points due to the pandemic, a figure almost doubled with respect to the average effect reported in Table 2. The point estimate for the high achievers is definitely smaller (1.8 percentage points) but still statistically significant. As pointed out by the educational literature on students disparities, low achievers are less able to acquire competences on their own (Todd & Wolpin, 2003), tend to procrastinate more on their homework (De Paola et al., 2023), and spend less time devoted to learning, substituting it with other leisure activities (Grewenig et al., 2021). By replacing time in the classroom with more independent time at home, the pandemic has magnified the existing differences in educational outcomes. This finding is in line with those highlighted in the emerging literature about the differential effects of the pandemic, even if the gap that we found between the two groups is quite large.

We also found a sizeable difference between native and foreign students, with the latter experiencing a higher increase in the likelihood of hidden drop-out, in line with what was found by Jack et al. (2023) for the U.S. on the impact of the pandemic in minorities attending grades 3-8.

We do not find strong heterogeneous effects along the gender dimension. We also

[15]The INVALSI tests in the 2020-2021 school year could have been performed on different days if the school had closed because of COVID-related reasons. However, in the case of these three regions, the last part of the school year was particularly problematic from an infection point of view, making performing the tests difficult.

checked if there was a statistical difference between males and females when we use subject-specific hidden drop-out measures (see Appendix Figure B.1), given the well-known differences in test performances across gender and subjects (Delaney & Devereux, 2021). We did not find any heterogeneity for math, although males resulted more disrupted by the pandemic than females in the Italian language.

The pandemic outbreak may have had stronger effects on students who were more emotionally unstable during assessments, or on those who showed lower educational aspirations (La Ferrara, 2019). We shed lights on these two aspects by relying on answers provided by students in a very detailed questionnaire taken in grade 10. As far as emotional aspects are concerned, we looked at anxiety during assessments. We implement a principal component analysis and extract the first factor from the eight questions about anxiety in the assessments of Italian language and math available in the grade 10 NEPSA questionnaire. We then repeated our baseline regression by splitting the sample between those who resulted above and below the median of our indicator of anxiety. We found that students who experimented a higher level of anxiety during tests suffered the most from the pandemic compared to those more emotionally balanced. Figure 2 shows that the effect of the pandemic on the likelihood of becoming a hidden drop-out is even stronger for students who experienced extreme levels of anxiety during assessments.[16] These evidence are extremely relevant, since, as depicted by Sandner et al. (2023), a worse emotional status, together with learning loss, could create a dramatic mix of factors that could have a direct impact on long-run choices and future performances (e.g. the decision to attend tertiary education).

Recent literature on students' aspirations has found that they are strong predictors of future choices, and that low aspirations fire back in lower effort, and, consequently, in a reduction of achievement, as in a poverty trap (Dalton et al., 2016; Genicot & Ray, 2017). When we looked at aspirations regarding students' own educational careers, we found that the probability of becoming a hidden drop-out increased more for students who already displayed lower educational aspirations (before the pandemic outbreak). In other words, the increase in the hidden drop-out indicator at the end of secondary education was more pronounced for those who did not aspire to enroll at university. Given that statements of educational aspirations were made in grade 10, identifying students with lower aspirations would contribute in targeting specific correctional policies, to prevent both educational and aspirational failures.

Family's socio-economic characteristics. Family background could play a very important role in magnifying or attenuating the disruption of the pandemic on educational outcomes. The substitution between time at school and time spent at home implies that the domestic learning environment has become more important in the production function

[16] We classified students with severe anxiety as those who resulted above the 75^{th} percentile of the distribution of our anxiety indicator.

of human capital. Students coming from more disadvantaged families have benefited less from their parents' investment in education and cultural activities, as evidence stemming from the pandemic's first outbreak has shown (Andrew et al., 2020).

Figure 2 shows that socio-economic background plays a role when it comes to evaluating the effect of the pandemic on educational outcomes. The larger impact of the COVID-19 outbreak on the hidden drop-out probability in students coming from families with lower socio-economic statuses is a topic that has already been highlighted in the literature, mainly for younger students (Engzell et al., 2021; Jack et al., 2023; Di Pietro et al., 2020; Contini et al., 2022). However, a brand new piece of evidence is that students at the end of their school path who should be more independent in the learning process with respect to younger students also show this dimension of heterogeneity. Availability of an internet connection at home is another source of heterogeneity that we found,[17] although point estimates are not very precise.

Length of school closures. To evaluate the role of school closures, we split our sample between regions that experienced a number of school closures above and below the national median. The estimates reported in Figure 2 show that students who experienced more days of school closures also had a higher increase in the hidden drop-out indicator. This evidence mirrors that of an emerging stream of literature that tries to disentangle the effect of the pandemic's severity from the effects from school closures and teaching modalities (De Paola et al., 2023; Jack et al., 2023).[18]

6 Concluding remarks

This paper contributes to the growing literature on the effect of pandemic disruptions on educational outcomes. We study their effect on the probability of becoming a hidden drop-out by the end of secondary school in Italy, which is a new indicator of educational failure that identifies students who have formally completed secondary school (i.e., they received a diploma), but did not acquire a sufficient level of skills with respect to the level of education attained. Identification is achieved by comparing two cohorts of students attending grade 13 in close but different academic years. Conditionally on prior achievement, these two groups differ only because of the pandemic outbreak that affected students attending grade 13 in the 2020-2021 school year.

Our results indicate a substantial increase in the hidden drop-out probability in the cohort of students exposed to the pandemic outbreak. The effect is even larger when we look at low achievers, students coming from less affluent families, immigrants, those with

[17] This is in line with the results illustrated by the technical report of the European Commission (Di Pietro et al., 2020).

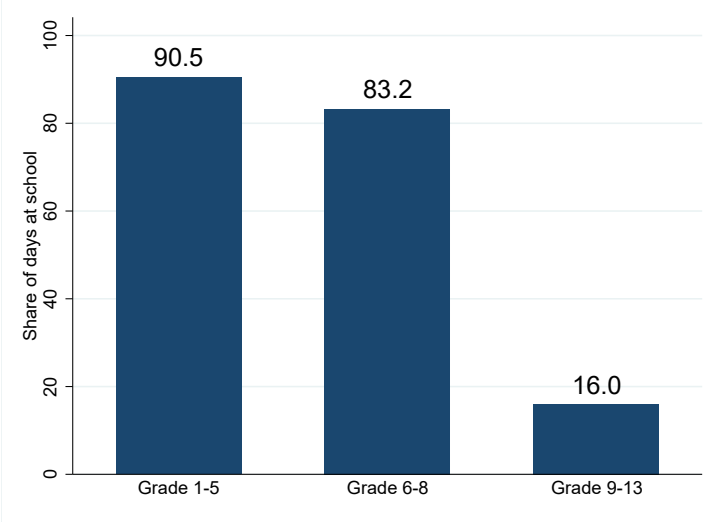
[18] Of course, in our ITT estimation framework, the impact of virtual and hybrid teaching modes *per se* cannot be distinguished by other contextual changes induced by the pandemic (e.g. the reduction of peer interactions).

greater anxiety during examinations, and those with lower aspirations. These students are typically the marginal individuals to look to for the design of policy interventions, as these students probably would have achieved the level of skills adequate for the grade they completed had it not been for the pandemic.

The importance of our results stems from two main facts. First, by looking at hidden drop-out, we highlight a brand new piece of information that was overlooked by previous literature on disruption due to the pandemic. This claim is grounded by the fact that the pandemic-related increase in hidden drop-out involves an educational failure that cannot be seen by looking at test scores only. Second, by focusing on students at the end of secondary school, we shed light on the educational effect of the pandemic outbreak for those who are in a crucial stage in their lives (Sandner et al., 2023). Indeed, these students might not have the possibility to recover the educational losses, as they would not be remediated by other schooling. This educational failure could easily pour into the labour market or affect success in the academic career. In the long run, if these educational losses are not recovered, they could translate into worse outcomes later in life, such as lower income, and also increase already existing inequalities (Doty et al., 2022).

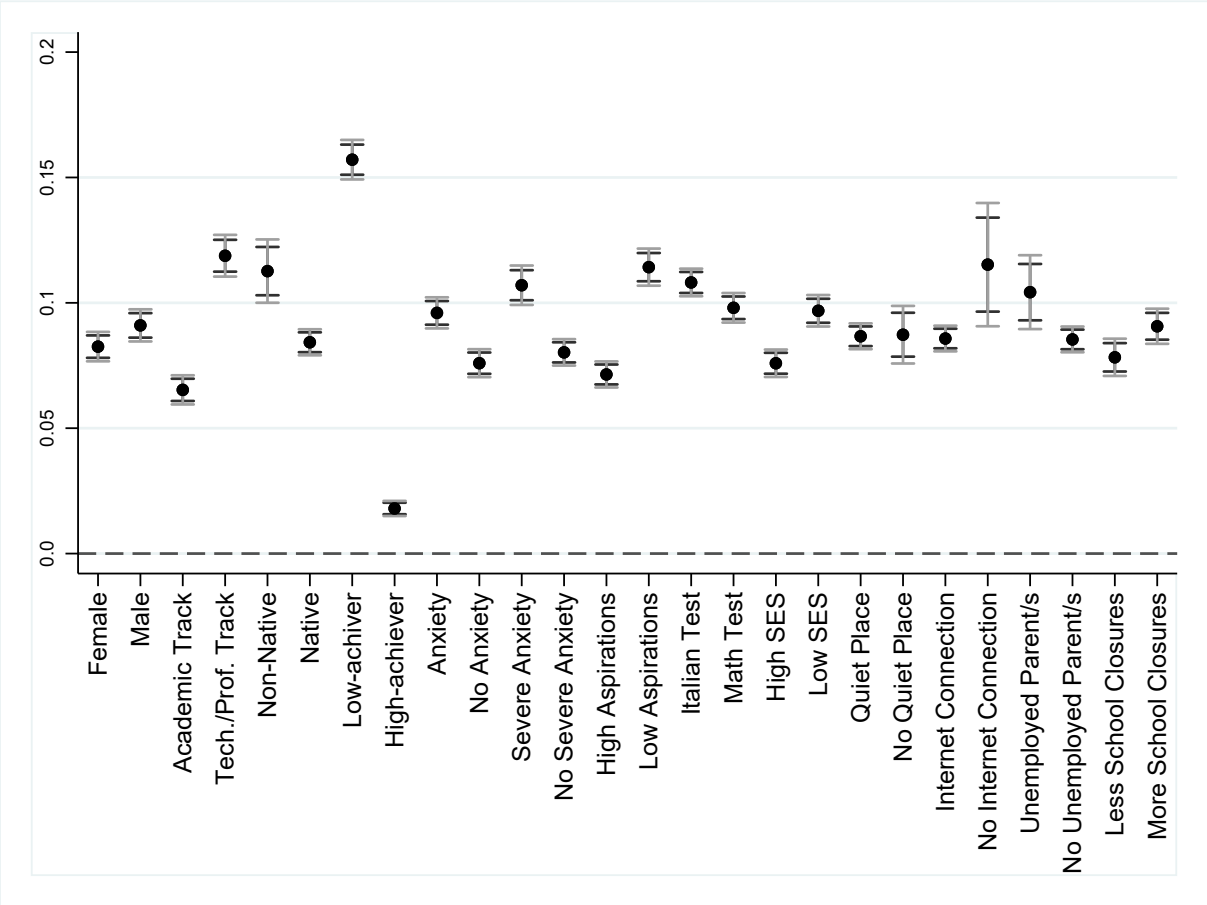
Figures

Figure 1
Share of days at school during the 2020-2021 school year.



Notes: the figure shows the share of days at school during the 2020-2021 school year. Each bar shows the average of the share of days spent at school as obtained from the regulations in the Italian regions. The three bars correspond to elementary school (grades from 1 to 5); junior high school (grades from 6 to 8); high school (grades from 9 to 13). **Source**: authors' elaborations on data from *The Economy of Italian Regions*, Bank of Italy, 2022.

Figure 2
Heterogeneous effects.



Notes: the figure shows the regression coefficients (black dots) and their 95% (and 99%) confidence intervals grey (black) ticks of our baseline regression performed on various sub samples. The regression coefficients are estimated according to students' gender, type of school, native and non-native status, low achievement in G10, socio-economic status (SES) above and below the median, math and Italian language tests, whether the student declares having a *Quiet Place for Studying (in G10)*, *Internet Connection (in G10)*, *Anxiety (in G10)*, *Severe Anxiety (in G10)*, *High Aspiration (in G10): Degree* and *Parent/s Unemployed (in G10)*; schools in regions above or below the median number of days of school closures (see Table 1 for the definition of each variable). **Source**: based on data from INVALSI.

Tables

Table 1
Descriptive statistics.

	All Sample		Pre-COVID cohort		COVID cohort	
	Mean	Sd	Mean	Sd	Mean	Sd
A. Dependent Variable						
Hidden drop-out	0.245	0.430	0.174	0.379	0.300	0.458
B. Treatment Variable						
COVID cohort	0.566	0.496	0.000	0.000	1.000	0.000
C. Control Variables						
Female	0.529	0.499	0.532	0.499	0.528	0.499
Foreign	0.077	0.266	0.069	0.254	0.082	0.275
Grade Retained	0.103	0.304	0.102	0.302	0.104	0.305
Class Size	19.876	4.955	20.131	4.898	19.681	4.990
Socio-Economic Status G10	0.129	0.959	0.129	0.954	0.130	0.963
Previous Achievement G10	210.067	34.291	213.307	33.973	207.580	34326
D. Other variables						
Academic Track	0.583	0.493	0.573	0.495	0.591	0.492
Low Achiever G10	0.500	0.500	0.457	0.498	0.533	0.499
Anxiety G10	0.506	0.500	0.558	0.497	0.466	0.499
Severe Anxiety G10	0.250	0.433	0.298	0.457	0.214	0.410
Internet Connection G10	0.974	0.158	0.974	0.159	0.975	0.157
Computer for Studying G10	0.916	0.158	0.933	0.250	0.904	0.295
Quiet Place for Studying G10	0.298	0.457	0.931	0.253	0.914	0.280
High Aspiration G10: Degree	0.617	0.486	0.613	0.487	0.620	0.485
Parent/s Degree G10	0.298	0.457	0.279	0.449	0.312	0.463
Parent/s Unemployed G10	0.055	0.229	0.058	0.235	0.053	0.224
N: Observations	523,216		227,162		296,054	

Notes: the table shows the descriptive statistics of two cohort of students in grade 13 who took the NEPSA in the 2018-2019 (Pre-COVID cohort) and 2020-2021 (COVID cohort) school years, respectively; *G*10, when specified, indicates that the variable is obtained by linking the student who took the test in G13 with the information of the same student as reported in NEPSA taken in grade 10. *Hidden Drop-out* is a dummy equal 1 for students who obtained less than 3 in the NEPSA 5-levels score both in math and Italian language test; *COVID cohort* identifies students who took the test in grade 13 during the pandemic (school year 2020-2021); *Female*, *Foreign*, and *Grade retained* are dummies equal to 1 for, respectively, females, students with non-Italian citizenship, students who repeted a grade before grade 10; *Class Size* is the number of students in the class; *Socio-Economic Status (SES)* is a synthetic index built by INVALSI that represents the socio-economic status of the family. *Previous Achievement G10* is the average of the test scores in math and Italian language when the student was in grade 10 (if the student took only the Italian or Math test, we pick the result of that test); *Academic Track* is a dummy equal to 1 for students enrolled in an academic high school track; *Low Achiever G10* is a dummy equal 1 for students who obtained a score in the INVALSI test of grade 10 below the national median; *Anxiety G10* and *Severe Anxiety G10* are dummies equal to 1 for students who have an anxiety index in grade 10 above the national median or the 75^{th} percentile. The anxiety index was generated by applying a principal component analysis (PCA), and extracting the first principal factor, to a total of six questions contained in the NEPSA G10 Questionnaire. *Internet Connection G10*, *Computer for Studying G10*, *Quiet Place for Studying G10*, *High Aspiration G10: Degree* are dummies equal to 1 for students that in grade 10 answered in the NEPSA Questionnaire that they had not, respectively, an internet connection at home, a PC for studying at home, a quiet place at home for studying, and had the aspiration of obtaining a college degree; *Parent/s with a Degree G10*, and *Parent/s Unemployed G10* are dummies equal to 1 for students who have at least one parent with a degree, and at least one parent unemployed. **Source**: based on data from INVALSI, grade 13 (2018-2019 school year for the pre-COVID cohort and 2020-2021 school year for the COVID cohort); grade 10 (2015-2016 school year for the pre-COVID cohort and 2017-2018 school year for the COVID cohort).

Table 2
Baseline results.

	(1)	(2)	(3)	(4)
	Hidden drop-out			
COVID cohort	0.110***	0.107***	0.107***	0.086***
	(0.002)	(0.002)	(0.002)	(0.002)
Adj.R2	0.26	0.27	0.27	0.39
N.Clusters	4321	4321	4321	4321
N.Observations	523216	523216	523216	523216
School Fixed Effect	✓	✓	✓	✓
Individual Characteristics and Class Size		✓	✓	✓
Socio-Economic Status G10			✓	✓
Previous Achievement G10				✓

Notes: the table shows the coefficients (and standard errors) of OLS regression with robust standard error clustered at school level; see Table 1 for the definition of the variables included in the regressions; individual characteristics include *Female*, *Foreign*, and *Grade Retained* dummies. **Source**: based on data from INVALSI.

Table 3
Robustness and sensitivity checks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Hidden drop-out						
COVID cohort	0.086***	0.099***	0.086***	0.084***	0.086***	0.086***	0.083***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Adj.R2	0.39	0.41	0.42	0.43	0.39	0.39	0.37
N.Clusters	4321	4321	4321	4321	28745	107	3272
N.Observations	522776	523216	523216	523216	523216	523216	428960
All Controls and Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Specification:							
(i) Attainment in G10 not Adjusted	✓						
(ii) Attainment in G10 Specified in Quintiles		✓					
(iii) Attainment in G10 Quadratic Specification			✓				
(iv) Attainment in G10 Cubic Specification				✓			
(v) Clusterization at Class level					✓		
(vi) Clusterization at Province level						✓	
(vii) Excluding Campania, Calabria and Puglia							✓

Notes: the table shows the coefficients (and standard errors) of OLS regression with variations from the baseline estimates of col. (4) of Table 2. In Specification (i) we exclude from the sample students for whom either math or Italian test in G10 is missing in the original data (440 individuals); in Specification (ii) attainment in G10 is discretized in five quintiles based on the achievements distribution of the school year when he/she took the test in grade 10; Specification (iii) adds to the baseline regression a the squared value of the variable *Previous Achievement G10*, while Specification (iv) also adds the cubic of *Previous Achievement G10*; in Specification (v) the regression model is estimated with robust standard error clustered at the class level, while in Specification (vi) it is estimated with robust standard error clustered at the province (NUTS 3) level; Specification (vii) excludes from the regression the three regions (Campania, Calabria and Puglia) that have less observations in the COVID cohort respect to the pre-COVID cohort in grade 13. **Source**: based on data from INVALSI.

A Appendix: Sample Selection Procedure

Our estimates are performed on a sample of 523,216 students in grade 13, belonging to two different cohorts, the *Pre-COVID* (227,162 individuals) and *COVID cohort* (296,054 individuals). The sample employed in our analysis takes into considerations only students observed both in grade 13 and grade 10.

The control group resulted to be larger than the group of students that experimented COVID in the original data. We identified as the main source of this imbalance between the two groups a significant lack of observations in the South of Italy (especially in Calabria, Campania and Puglia regions) in the 2020-2021 school year. Regions in South of Italy experimented more days in distance learning as compared to regions in North (see Appendix Figure B.2). Moreover, given that NEPSA evaluation were conducted in May, it is likely that many schools in the South remained closed from the official day of the tests until the end of the school year (in June), making impossible to perform the assessments not only in the official day, but also in the following weeks.

Notice that the longitudinal linkage is possible only for students who had a regular progression along grades 10 to 13, as those who were grade retained cannot be traced back. Net of this mechanical factor due to grade retention, the share of unmatched observations is about 17%.

We further excluded from our sample students with some missing in the variables that we use both for our baseline analysis or for the study of heterogeneity (about 15% of the original number of observations).

B Appendix: Additional Tables and Figures

Table B.1
Grade retention over school years.

COVID cohort			
Grade and School Year	Grade Retention	Suspended	Diploma
G9 (2016-17)	11,9	21,7	
G10 (2017-18)	6,4	23,4	
G11 (2018-19)	6	22,0	
G12 (2019-20)	1,3	No suspended	
G13 (2020-21)	1,4	-	99,9
Pre-COVID cohort			
Grade and School Year	Grade Retention	Suspended	Diploma
G9 (2014-15)	14	24,7	
G10 (2015-16)	6,8	24,4	
G11 (2016-17)	6,2	21,6	
G12 (2017-18)	4	20,0	
G13 (2018-19)	3,9	-	99,7

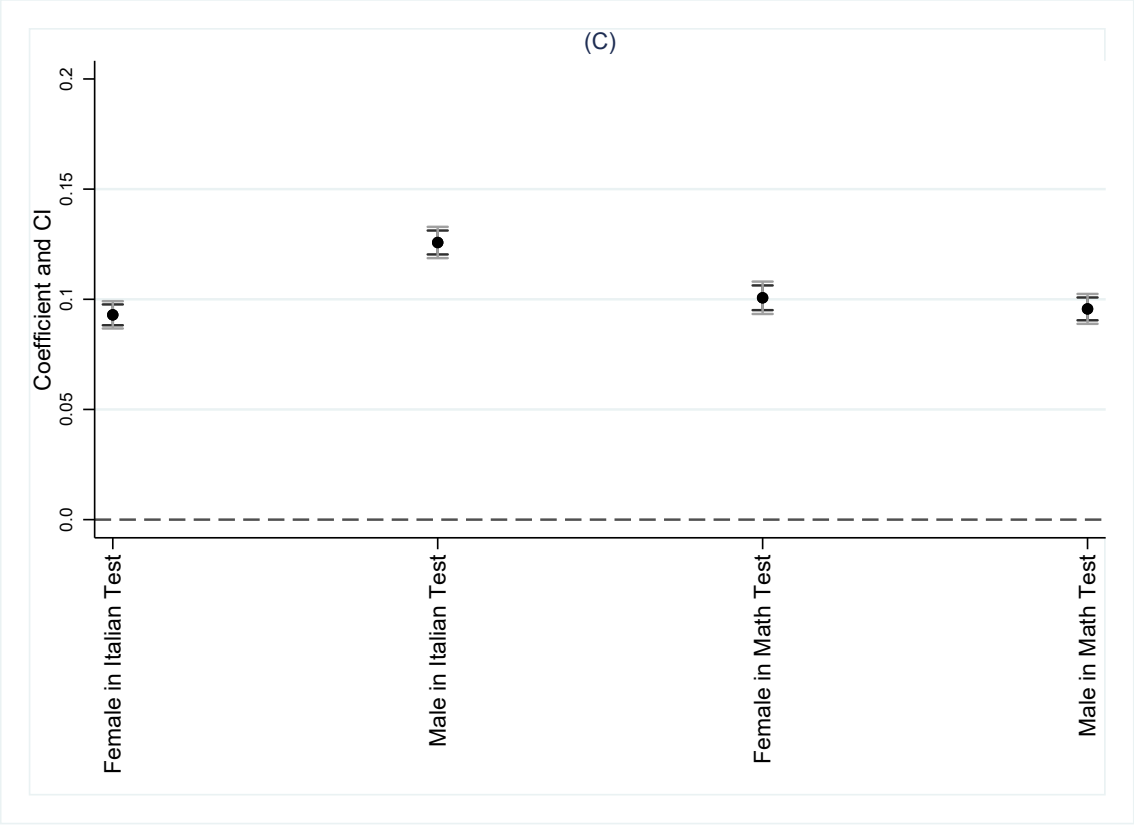
Notes: the table shows the percent rate of grade retention and suspended assessment over the entire period of high-school (from grade 9 to 13) for the two cohorts under study. Suspended assessment at the end of the school year: the students' promotion to the upper grade is conditioned to the succeeding of a specific test on one or more subjects failed at the end of school year. Usually the vast majority of students pass this exam, while only few students have to repeat the year (approximately 1% of the students that ended the corresponding school year). In the school year 2019-20, the one characterized by Covid outbreak, the suspension of the assessment was not permitted. The (-) sign: the phenomenon does not exists for that particular grade (that is, grade 13 students can not be suspended: they are admitted at the final high school exam or they are directly grade retained). **Source**: Official Bulletins of the Italian Ministry of Education, which at the end of every school year are published on the official website of the Italian Ministry of Education (see https://www.miur.gov.it/-/scuola-i-dati-degli-scrutini-alla-secondaria-di-ii-grado-, accessed on February 2023).

Table B.2
Regression results of the heterogeneous effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Individual Characteristics of the Student	Gender		School Tack		Nationality		Previous Achievements	
	Female	Male	Academic	Professional/Technical	Foreign	Italian	Low	High
Covid Cohort	0.083***	0.091***	0.065***	0.119***	0.113***	0.084***	0.157***	0.018***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.002)	(0.003)	(0.001)
Adj.R2	0.38	0.41	0.29	0.41	0.41	0.39	0.30	0.13
N.Clusters	4042	4233	2647	2423	3289	4315	4247	3951
N.Observations	277008	246208	305035	218181	40086	483130	261549	261667
Panel B. Family Characteristics	Socio-economic Status		Unemployed parent/s		Quiet place at Home for Study		Internet Connection at Home	
	High	Low	Yes	No	Yes	No	Yes	No
Covid Cohort	0.076***	0.097***	0.104***	0.085***	0.087***	0.087***	0.086***	0.115***
	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)	(0.004)	(0.002)	(0.010)
Adj.R2	0.35	0.40	0.42	0.39	0.39	0.39	0.39	0.41
N.Clusters	4211	4114	3308	4316	4310	3540	4318	3010
N.Observations	263812	259404	28998	494218	482122	41094	509832	13384
Panel C. Soft skills and School Closures	Anxiety		Severe Anxiety		High Aspiration: Degree		Region with School closures above the Median	
	Yes	No	Yes	No	Yes	No	Yes	No
Covid Cohort	0.096***	0.076***	0.107***	0.080***	0.071***	0.114***	0.091***	0.078***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Adj.R2	0.40	0.37	0.41	0.38	0.31	0.40	0.40	0.35
N.Clusters	4228	4193	4084	4273	4140	4157	2706	1615
N.Observations	264556	258660	131012	392204	322645	200571	318052	205164
Specification:								
All Controls and Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓

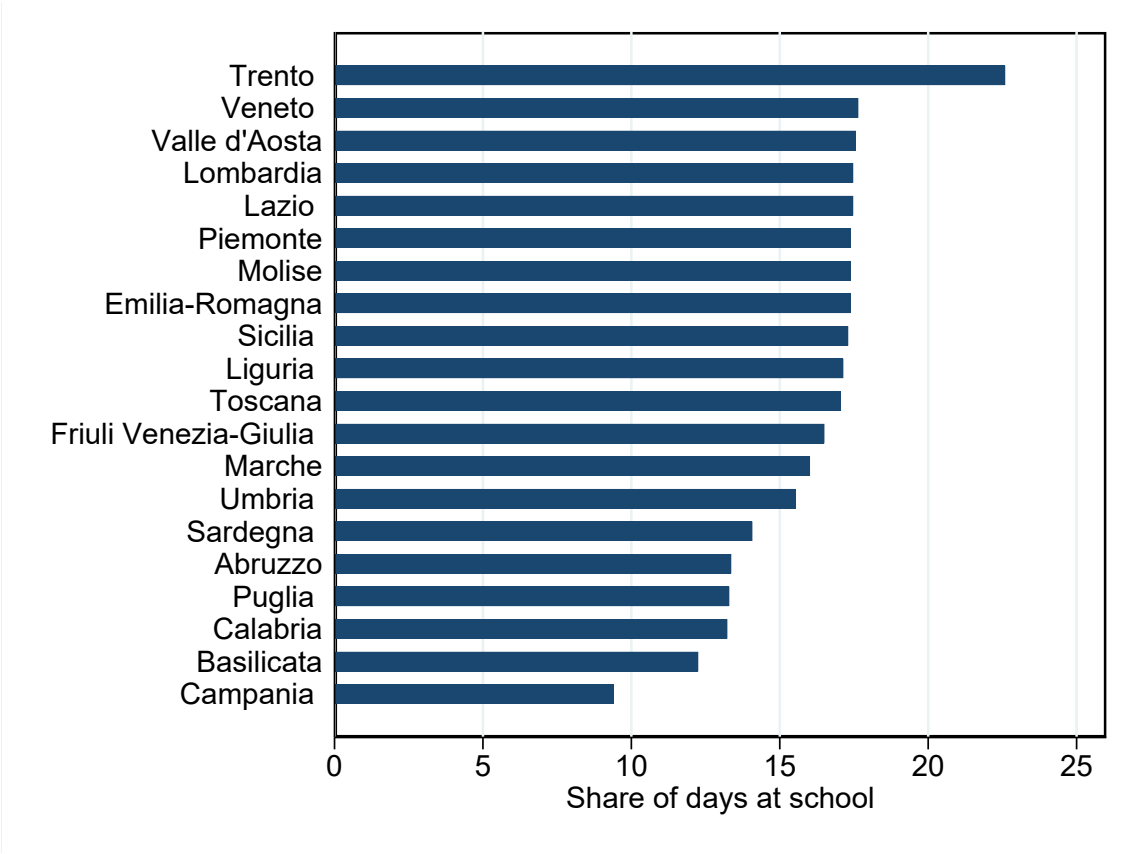
Notes: the table shows the coefficients (and standard errors) of OLS regression with robust standard error clustered at school level; see Table 1 for the definition of the variables included in the regressions; columns (7) and (8) employed the dummy variable *Region with School Closures above the Median* which indicates regions that during the 2020-2021 school year had a total number of remote lessons above the median national value. **Source**: based on data from INVALSI.

Figure B.1
Heterogeneity and Interaction between gender and subject



Notes: the figure shows the regression coefficients and their related confidence intervals of our baseline regression, black confidence intervals are 95% confidence levels of the COVID regression coefficient, while grey lines correspond to 99% confidence level. The figure shows the results related to the interaction of students' gender and the different results in Italian language and math. *Female in Italian Test* and *Male in Italian Test* compares the impact of the pandemic according to the gender of the student, only in Italian language test; *Female in math test* and *Male in math test*, captures the same type of heterogeneity, but focusing only on math tests. **Source**: based on data from INVALSI.

Figure B.2
Share of days at school in high schools during the 2020-2021 school year across Italian regions.



Notes: the figure shows the share of days at school (over the total number of days in the school years) during the 2020-2021 school year in Italian high schools across regions. Regional differences are due to the Italian color mechanism to contain the pandemic (see Section 2.2).
Source: authors' elaborations based on *The Economy of Italian regions*, Bank of Italy, 2022.

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