Dipartimento di
Economia Marco Biagi

DEMB Working Paper Series

N. 177

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September 2020

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ISSN: 2281-440X online

Coronavirus pandemic, remote learning and emerging education inequalities

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Revised version November 2020

Abstract. Recent studies predict that the school closures and distance learning of the 2020 pandemic will lead to lower average education levels, but they may also result into greater and new education inequalities. Using PISA 2018 data from France, Germany, Italy, Spain and the United Kingdom, we find that, even before the pandemic, students lacking the resources needed to learn remotely – ICT resources at home, at school or a quiet place to study – experience strong and significant cognitive gaps with respect to their peers that, in mathematics, range from 70 percent of a school year in the United Kingdom, Germany and France to 25 percent in Spain. Gaps in reading are similar. With school closures and remote learning, these cognitive losses are predicted to increase. We find similar results by considering days of absence from school. In the longer run, students in Spain, Germany and Italy who cannot learn remotely are more likely to repeat grades and end their education early. Overall, cognitive gaps and school dropouts driven by a lack of ICT resources vary with countries' educational systems and digital divides. Policies should aim to enhance the use of digital resources in education, and must be designed according to countries' characteristics.

Keywords: Covid-19, education inequalities, educational systems, digital divides, PISA
JEL Codes: I21, I24, H52

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1. Introduction

The coronavirus pandemic of 2020 forced countries to close schools and shift to distance learning almost overnight, without the time needed to prepare or evaluate its consequences on education. Several recent studies based on previous research on school interruptions predict that school closures will be followed by generalized declines in education levels (Burgess and Sievertsen, 2020; Haeck and Lefebvre, 2020; Kuhfeld et al., 2020; Psacharopoulos et al., 2020, Van Lancker and Parolin, 2020), but generalized distance schooling is a new phenomenon that can also exacerbate existing education inequalities and generate new ones. Differently from face-to-face schooling, it crucially depends on students being concretely able to attend virtual classes, and on schools and teachers effectively providing them. In this study we research these unprecedented events to gauge the relationships between students' actual possibilities of attending virtual classes and their cognitive outcomes. Subsequently, we test the relationships between these possibilities and students' plans on future education.

Distance schooling poses a problem regarding the adequacy of resources and skills that is particularly dramatic in developing countries but concerns also developed economies, where most distance teaching takes place through the internet. In them, the availability of ICT resources is more widespread, but digital inequalities still exist; some students lack the basic resources needed to learn remotely and some schools or teachers did not provide online classes (Norris, 2001).[1] This study focuses on five European countries – France, Germany, Italy, Spain and United Kingdom – that were hit by the pandemic between the end of February and beginning of March 2020, and adopted similar measures concerning school closures and remote learning[2].

To gauge the relationships between students' possibilities of learning online and education outcomes, we use the 2018 wave of the Program for International Student Assessment (PISA), an

[1] We use the term 'distance schooling' when one or more technologies are used to deliver classes to students who are separated from the teacher and – with electronic technologies – support mutual interaction; 'remote learning', when ICT resources are used for education outside the physical school only temporarily; 'e-learning' when electronic resources permanently substitute education at the physical school.

[2] Some measures differed across the five countries. For example, school closures have been complete in Italy, while in the United Kingdom schools remained partially open for children with parents with specific jobs or from low-income households.

international assessment implemented by the Organization for Economic Cooperation and Development (OECD) that measures 15-year-old students' reading, mathematics, and science literacy every three years and comprises data on ICT resources at home and at school. Specifically, we test the relationships between students’ scores in mathematics and reading and their possessions of a computer for schoolwork, an internet connection, a quiet place to study and their school’s ICT resources. In our data, a proportion of fifteen-year-old students that ranges from more than one third in France to more than 60 percent in Germany lacked at least one of the above digital factors needed to learn remotely.

Considering the longer run, we analyse whether the possibility of learning remotely is also associated with students’ expectations on their future education. In particular, students unable to attend the virtual classes and lagging behind their peers may find the cognitive gap hard to close once back at school and, consequently, revise downwards their plans on future education. These negative choices may be exacerbated in countries where grades repetition is frequent and lagging behind increases the probability of repeating a grade once back at school. Hence, we test whether variations in the conditions for learning remotely are correlated with students’ planned investments in education, the probability of repeating a grade, and the joint probabilities of these two events. To our knowledge, this is the first investigation on education inequalities arising from school closures, remote learning and digital disparities that is based on a large cross-country database. It contributes to the research on education and offers a novel perspective on the essential role of home and school ICT resources and related skills in the formation of human capital.

Our main findings are that the lack of ICT resources at home, particularly a computer for schoolwork, are strongly correlated with students’ negative score gaps in mathematics and reading in all five countries, but cognitive losses emerge also when digital resources at school are scarce. These cognitive losses have long run implications; students unable to learn remotely are more likely to revise downwards their plans on future education, especially where lagging behind increases the probability of repeating grades. We also find that negative gaps and long run implications are associated with countries’ educational systems, school locations and families’ socio-economic conditions. Our results are robust to the use of different specifications and covariates. The rest of this paper is structured as follows, Section 2 discusses the related literature, Section 3 presents the data and some descriptive statistics, Section 4 shows the adopted methodology, results are provided in Section 5 and Section 6 concludes.

2. Main facts and literature.

2.1. Facts

Between March 5 and March 20 2020, schools in Italy, Spain, France, Germany and the United Kingdom closed and adopted distance teaching. During the second part of March, all European countries took similar measures (Viner et al., 2020). In our five countries, teaching was provided mostly online, but in France TV and radio transmissions were also utilized (UNESCO, 2020; Center for Global Development, 2020). After several weeks, when eventually the number of people infected by the coronavirus fell at sufficiently low levels, schools reopened in Germany, France and the United Kingdom, while in Italy and Spain they were kept closed until the autumn.

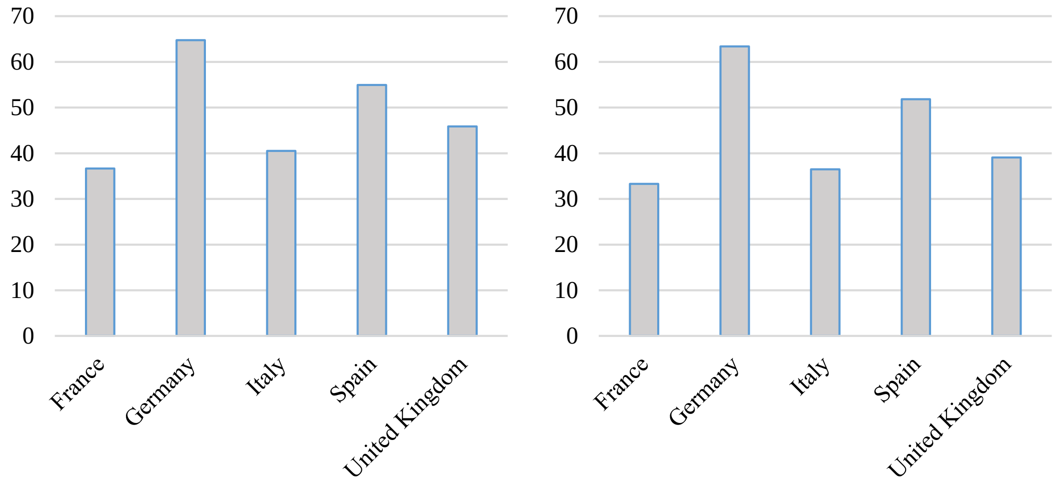
The still scant and fragmentary evidence available while we research on this topic suggests that the percentage of students who could not learn remotely, or could only partially learn, may be higher than expected when the advanced level of digital development of the five countries is considered. The OECD (2020) data on home computer possessions and internet connections in our countries show that between 85 and 90 percent households have access to the internet and between 72 percent and 93 percent have a computer at home, but these data concern pre-pandemic times, when most learning and working activities take place outside home; they focus on households rather than individuals, and do not provide information on the level of efficiency of the ICT devices. During school closures and the lockdown of most economic activities, almost all people in the household are very likely to need to use the ICT resources more than usual and simultaneously. All this suggests that when considered at individual – rather than household – level and during closures of schools and economic activities, the above figures should be substantially revised downwards.[3] At the same time, for remote learning to take place, ICT resources must be available and efficiently used also at school, and teachers must possess the skills needed to teach online. The preliminary and partial evidence available suggests that because of deficiencies in households' possessions and school shortages of ICT devices, digital platforms and skilled teachers, remote learning in our five countries was lower than expected. This especially applies to Germany; Conrads et al. (2017), European commission (2019), Kerres (2020) and UNESCO (2020) show German schools are on average less digitalized than in other developed countries.

Surveys conducted in some of the countries considered provide preliminary and partial evidence on remote learning during school closures. In England, between 10 percent and 12 percent of students had no devices at all (Andrew et al., 2020). A survey on distance learning in Italy evidences that only 40 percent of students could fully participate in remote learning; 10 percent could not participate at all and 20 percent could attend only occasionally (Autorità Garante per le Comunicazioni, 2020). In Germany, a survey of students in their graduation and pre-graduation years, shows that less than 50 percent of respondents received digital learning opportunities or material through online platform, email or video conferencing, and only about 15 percent of them had videoconferencing (such as Skype) interactions with teachers (Anger et al., 2020). There are no data on the proportion of German students that were entirely disconnected from remote learning, but consistently with the available evidence on schools, they are likely to be, also in this case, not less than 10 to 15 percent of all students. If this preliminary evidence from the United Kingdom, Italy and Germany applies also to the other two countries, then, overall, only between 30 percent to 50 percent of students could attend school online. The PISA 2018 dataset we use for this study reveal even higher figures in the five countries considered: a proportion of fifteen-year-old students ranging from more than 30 percent in France to more than 60 percent in Germany lacked at least one of

[3] Data from the Italian Institute of Statistics show that, during the schools and economy lockdown of 2020, households without people able to use ICT resources were about 24.2 percent of the total, with higher than average percentage for households with lower income levels, higher median age, the country's South and small towns (ISTAT, 2020).

the necessary conditions needed to learn remotely: an internet connection, a computer for school work or a school with sufficient digital resources (Figure 1-b).

Figure 1 - Percentage of fifteen-year-old students unable to learn remotely



(a) (b)

Note: In Figure (a) students lacking a computer, an internet connection, a quiet place to study at home or attending a school with few ICT. In Figure (b), a quiet place to study is not included.

2.2. Literature

Several very recent researches trying to gauge the effects of the pandemic on education are based on the very scant data collected during and after the periods of school closures or on previous findings on school vacations or interruptions due to unexpected events.[4] Kuhfeld et al. (2020) predict that students in the United States "are likely to return in fall 2020 with approximately 63-68 percent of the learning gains in reading relative to a typical school year and with 37-50 percent of the learning gains in math" (pg. 1). Moreover, they estimate that losing ground will not be generalized, but the top third of students may make gains in reading. Several studies find that summer vacations are followed by sizable and significant cognitive losses, which often concern mathematics more than reading, and are higher for students from

[4] Hanushek and Woessmann (2020) and Azevedo et al. (2020) consider potential economic losses at individual and country levels. They are expected to be stronger for disadvantaged students and to have long-lasting effects.

lower socio-economic conditions (Downey et al., 2004; Quinn et al., 2017; Atteberry and McEachin 2020; Carvalho et al., 2020). Van Lancker and Parolin (2020) find that summer vacation cognitive losses in the United States are significant for children of low-income families, but not for others. However, in other studies' results, cognitive losses due to school vacations are mostly temporary or negligible (Von Hippel and Hamrock, 2019).

Absenteeism has also been found to negatively influence cognitive outcomes. Students skipping school experience significant and negative cognitive gaps relatively to their peers, which increase with the days of absence (Chang and Romero, 2008; Gottfried, and Kirksey, 2017; Liu et al., 2020). Gottfried (2009 and 2011) and Aucejo and Romano (2016) find that losses associated with absenteeism tend to be higher in mathematics than in reading.

School interruptions due to abnormal events, such as teachers' strikes (Belot and Webbink, 2010; Johnson, 2011), natural disasters or pandemics, are also found to affect education levels. Skidmore and Toya (2002), McDermott (2012), Noy and duPont (2016), Meyers and Thomasson (2017) Cerqua and Di Pietro (2017), Di Pietro (2018), find that natural disasters have important consequences on students' decisions to leave education early (Imberman et al., 2012). In Pane et al (2008) Redlener et al. (2010), after Hurricanes Katrina and Rita in 2005, one over three students in the United States repeated grades, and a significant number of them never returned to school. Dorn et al. (2020) estimate the potential impact of school closures of year 2020 in the United States; they predict increased drop-out rates and long run negative effects on education.

A parallel debate concerns the impact of using ICT resources in teaching and studying. Governments' and experts' opinions on e-learning vary widely, and empirical studies on the effects of providing students with ICT resources remain inconclusive (Banerjee et al., 2004; Fairlie, 2005; Machin et al., 2007; Yanguas, 2020). The evidence suggests that not just computers and the internet, but the software and how ICT devices are used play an important role in the cognitive process (a very complete review is in Escueta et al., 2020). The choices countries made in the past on the use of digital resources for education proved to be crucial in 2020, when schools were suddenly forced to adopt distance teaching.

The survey of the European Commission (2019) and the above mentioned data from PISA 2018 show that even European countries differed substantially in their readiness for teaching remotely.

3. Data and descriptive statistics

We use the data from the 2018 wave of PISA assessment concerning students' test scores in mathematics and reading (except for Spain, from which data are only available on mathematics). To save space, we present most results on reading in Appendix A. We omit our results on science, the third field of PISA surveys, because they are very similar to those in mathematics and reading, but they are available from the authors upon request. Overall, we consider 73,305 students enrolled in over 2,577 schools in the five countries. The PISA dataset is the result of a two-stage stratified design, where, first, individual schools are sampled, and secondly, students are randomly sampled within schools. Given that each participating student in PISA survey answers a limited amount of questions taken from the total test item pool, OECD provides ten test scores (known as plausible values), which can be interpreted as multiple imputed values of students' performance based on students' answers to the test and their background questionnaires. The difficulty of each item represents a weight, used to compute the weighted averages of correct responses. This approach allows having a measure of an individual's proficiency for each student in each subject area, regardless of the questions actually answered. We employ the recommended OECD strategy for estimation of coefficients and their variances, making use of all ten plausible values all throughout the main analysis (OECD, 2018, provides detailed technical information). In each country, the sample represents about 95 percent of the population of 15-year-old students.

Regarding the availability of ICT resources at home and at school and of a quiet place to study, we select from the PISA Student's Questionnaire the answers to the following questions: *Which of the following are in your home*: *A computer you can use for school work, A quiet place to study, A link to the internet*, responses can be 'yes' or no', and from the School's Questionnaire: *To what extent do you agree with the following statements about your school's capacity to enhance learning and teaching using digital devices? The number of digital devices connected to the internet is sufficient*; answers vary from 'Strongly disagree' to 'Strongly agree'. Concerning the planned length of students' education, the question we consider is: *Which of the following do you expect to complete?* answers range from lower secondary to advanced tertiary and research education programs. We build a dummy variable with values equal to one if the student expects to complete at most the lower secondary or the upper secondary studies that do not lead to tertiary education (ISCED levels 2, 3A or 3B) and 0 if the student plans to complete higher levels. Our control variables are gender, age (year and months), higher level of education of parents (HISCED), immigration status (which includes first and second generation immigrant students), age of arrival into the country, whether the student has repeated one or more school years and the school location in a rural or urban area.

Descriptive statistics are summarised in Table A1. Overall, the proportions of students lacking at least one of the four essential factors needed to learn at home – a computer, an internet connection, a quiet place to study at home, a school providing online classes – are about 36 percent of all students in France, 46 percent in the United Kingdom, 41 percent in Italy, 55 percent in Spain and 65 percent in Germany. If only the ICT devices for remote learning are considered (*No quiet place to study* is excluded), these percentages decrease only slightly (Figure 1-a, 1-b).

Grade repetition is unusual in the United Kingdom and frequent in the other four countries, especially Spain and Germany, where it concerns respectively 29 and 20 percent of students. Educational systems also differ in the degree of tracking between schools: the age at which students are tracked for the first time is 10 in Germany, 14 in Italy, 15 in France and 16 in Spain and the United Kingdom (Woessmann, 2009). The proportion of students planning to leave education early varies from about 30 percent in Germany (where vocational school can be attended while working part-time) to six percent in Italy, but secondary studies can be completed at different ages in each of the five countries.[5]

[5] Secondary studies are typically completed after 10 years of schooling in Spain, 11 in the United Kingdom, 12 in Italy and Spain, and 13 in Germany. Children start compulsory education when they are five years old in the United Kingdom and six years in the other four countries. Therefore, the age at which secondary education is completed also depends on the age of starting compulsory education.

4. Empirical strategy

To gauge the links between remote learning and education outcomes, we test, separately for each country, the relationships between the students' scores in mathematics or reading and the lack of the resources needed to learn remotely with the following specification:

$$\text{Test scores}_{ij} = \alpha_1 + \beta_1 \text{No computer}_{ij} + \beta_2 \text{No internet}_{ij} + \beta_3 \text{No quiet place}_{ij} + \beta_4 \text{Few school ICT}_j + X_{ij}\Pi + \lambda_j + v_j + \varepsilon_{ij} \quad (1)$$

where *Test score* is the weighted test score in mathematics or reading of student *i* in school *j*, *No computer*, *No internet*, *No quiet place*, *Few school ICT* are the variables of interest. X_{ij} is the set of covariates, which comprise gender (a dichotomous variable, with value one if female and zero otherwise), age, the highest level of education of parents (HISCED in PISA), the student's status of immigration (a dichotomous variable), age of arrival at the country, and whether the student has repeated one or more school years, λ_j are school fixed effects and v_j and ε_{ij} are error terms at school and student levels.

In a further set of tests, we use Probit specifications to test the correlations between the probability of leaving education early and our four variables of interest regarding the resources needed to learn remotely. The dependent variable, concerning the students' plans on the length of their future education, is a binary variable with value one when students expect to complete at most the lower secondary or upper secondary studies not leading to tertiary education, and zero otherwise. We also test the correlation between the probability of repeating a school year and our variables of interest in all countries except the United Kingdom, where grades repetition is not frequent. Afterwards, we use a Bivariate Probit specification to test the joint probabilities of leaving school early and repeating a school year. The Probit and Bivariate Probit specifications on leaving school early and repeating a school year are:

$$\text{Leaving education early}^{*}_{ij} = \alpha_1 + \beta_1 \text{No computer}_{ij} + \beta_2 \text{No internet}_{ij} + \beta_3 \text{No quiet place}_{ij} +$$

$$\beta_4 \text{Few school ICT}_j + W_{ij}\Pi + v_j + \varepsilon_{1ij} \tag{2}$$

$$\text{Repeated grade}^*_{ij} = \alpha_1 + \beta_1 \text{No computer}_{ij} + \beta_2 \text{No internet}_{ij} + \beta_3 \text{No quiet place}_{ij} + \beta_4 \text{Few school ICT}_j + W_{ij}\Pi + v_j + \varepsilon_{2ij} \tag{3}$$

With Leaving education early:

$$\begin{cases} \text{Leaving education early}_{ij} = 1 \text{ if Leaving education early}^*_{ij} > 0 \\ \text{Leaving education early}_{ij} = 0 \text{ if Leaving education early}^*_{ij} \leq 0 \end{cases}$$

And Repeated grade:

$$\begin{cases} \text{Repeated grade}_{ij} = 1 \text{ if Repeated grade}^*_{ij} > 0 \\ \text{Repeated grade}_{ij} = 0 \text{ if Repeated grade}^*_{ij} \leq 0 \end{cases}$$

The error terms ε_{1ij} and ε_{2ij} are assumed to be independently and identically distributed as bivariate normal. The vector W_{it} comprises the above covariates, except for *Repeated grade*, which is now one of the two dependent variables.

5. Results.

5.1. ICT resources at home and at school and a quiet place to study.

The results of estimating equation (1) in the field of mathematics are in Figure 2; negative values are the differences between the scores of students unable to learn remotely and those of their peers. They are the coefficients on our variables of interest, which derive first base regressions that include only the four variables *No computer*, *No internet*, *No quiet place to study* and *Few school ICT*, and, second, from regressions comprising all covariates and school fixed effects (except, to avoid collinearities, for Figure 2-d, regarding *Few school ICT*, where the full regression controls for all covariates, including school types). Coefficient values are easier to interpret by considering that, in the average of OECD countries, 40 score points (on a mean of about 500) correspond to the cognitive content of about one school year (OECD; 2019). Table A2 in Appendix A reports all coefficients in mathematics while Figure A1 and Table A4 in Appendix A reports coefficients on reading.

In the base regressions of Figure 2, all coefficients on the four variables of interest are strongly negative and significant. Specifically, *not having a computer at home* is correlated with a negative gap of about 1.7 of a school year in Germany, 1.5 year in France, and more than one year in Italy, Spain and the United Kingdom; significance is at the one percent level in all cases. Moreover, coefficients are robust to the inclusion of all control variables. Interestingly, some coefficients shrink when covariates are included into the regressions, but these changes, when they are statistically significant, take place in relation to different covariates in each country. In particular, more than 50 percent of the negative gap in France is explained by the types of schools attended by students (lyceums, technical or vocational, and private or public); in Italy, one third of the gap is explained by the tracking between schools; in Spain, two thirds is explained by grades repetition; in Germany, by school types, grades repetition and social conditions at home; in the United Kingdom, social conditions explain about 23 percent of the gap (Table A2).[6] We find very similar results when analysing the scores in reading (Table A4 in Appendix A).

Hence, in France, Italy and Germany, the type of school students attend explains part of the gap associated with the unavailability of a computer at home, which suggests that these students are more concentrated in technical and vocational schools, where average scores are lower than in lyceums and general schools. In France, the distinction between private and public schools also matters; private schools are more frequent among lyceums and provide higher education standards. As said above, however, part

[6] Measures of statistically significant interactions between the coefficients of variables of interest and cofactors are available from the authors upon request.

of the negative gaps is explained by other factors, but they remain strong and significant even after these factors have been taken into account. In the full regressions, the cognitive losses in mathematics associated with not having a computer at home are more than half of a school year in France, Germany and the United Kingdom, and more than a fourth of a year in Italy and Spain (Figure 2).

Negative gaps in mathematics associated with *unavailability of an internet connection at home* in the base model are negative in all countries and, except for France, also significant (Figure 2). In Italy, the coefficient loses significance when school fixed effects are included into the regression, evidencing that students without internet at home are unevenly distributed across schools, while in Spain the gap is explained by family socioeconomic conditions and grade repetition. Negative gaps in Germany and the United Kingdom are robust to all specifications and, in the full regressions, equal two thirds of a school year in Germany and almost two years in the United Kingdom (column 35, Table A2). It is interesting to note that, among the five countries, the United Kingdom is characterized by both the lowest percentage of families without internet (Table A1) and, everything else given, the largest negative score gaps of students in this households. Hence, the share of these students is smaller than in the other four countries but they appear to be more marginalized. This may be due to digital network effects. Where the use of internet is more widespread, schools and students have more incentives to use it for teaching and learning, and the disadvantages of non-users increase.

Not having a quiet place to study at home matters especially in France and the United Kingdom. In France, about half of the negative gap is explained by the type of school attended by the students. With everything else given, it equals about a fourth of a school year. In the full model concerning the United Kingdom, where the cognitive losses correspond to about a third of a school year (Figure 2 and Table A2). Coefficients are smaller but also negative and significant in Italy and Spain. In Italy they are explained by the social conditions at home and the school type attended, in Spain by the social conditions and grade repetition. [7]

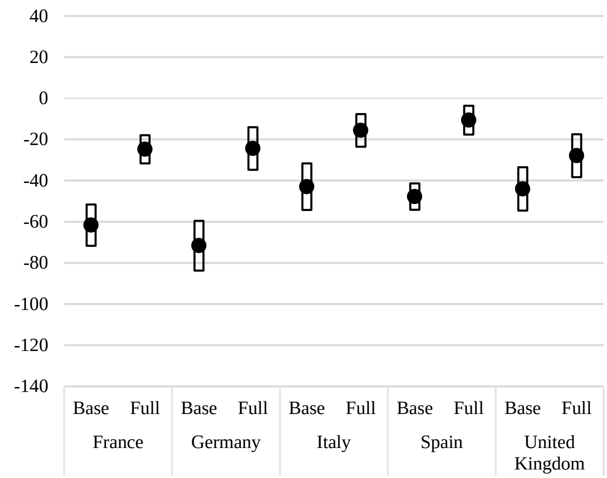
[7] We use the variable on parents' education as a proxy of the family social conditions, but results do not change significantly if, instead of education, we use the level of parents' employment.

A *scarce availability of ICT devices at school* is correlated with negative score gaps in mathematics in the base regressions in all countries, but significance is above 5 percent only in Italy and Spain (Figure 2 and Table A2). Results are similar with reading as the dependent variable, in Table A4. They shrink when school types are controlled for in Italy and private schools in Spain. Hence, a higher availability of ICT resources in lyceums in Italy and in private schools in Spain explain part of the negative gaps. However, among the four variables of interest, this appears to be the less correlated with students' scores.[8] Given its crucial role for remote learning to actually take place, this is an unexpected result. Since the variable has several missing observations (about 3 percent in Spain and Italy, but 18 percent in the United Kingdom, Table A1), we checked whether results were robust to the imputation of missing values. Regressions on the sample with imputed values showed that coefficients do not change significantly (results are in Tables C1, C2, C3 and C4 in Appendix C). The distribution of cognitive losses across the five countries, and their correlations with other explanatory variables are similar when reading is taken as the dependent variable (Figure A1 and Table A4 in Appendix A).

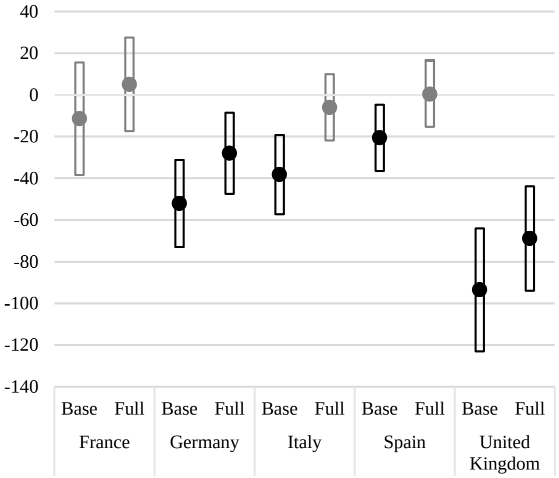
The low explanatory value of this variable might also be driven by heterogeneity in coefficients at a more disaggregated level. In particular, as cities are generally better endowed with internet and broadband infrastructures than rural areas, it can be reasonably expected that schools in urban areas make more use of digital resources than those in rural locations. If this is so, the negative score gaps of students in cities and towns attending schools with scarce ICT resources should be larger than those of students in rural areas also attending schools with few ICT resources. In the first case the digital network effects, and the corresponding losses of outsiders, should be stronger. To test this hypothesis, we use the answers to the question in the School Questionnaire: *Which of the following definitions best describes the community in which your school is located?* to build a categorical variable, denominated *Location*, where rural areas (with fewer than 3,000 people) take value zero, towns (between 3,000 and 100,000 people) value one, and cities (with more than 100,000 people) value two. Then, we interact *Location* with *Few school ICT*.

[8] We obtained similar results with other variables in the School Questionnaire concerning the availability at school of computers, digital platforms and other ICT resources.

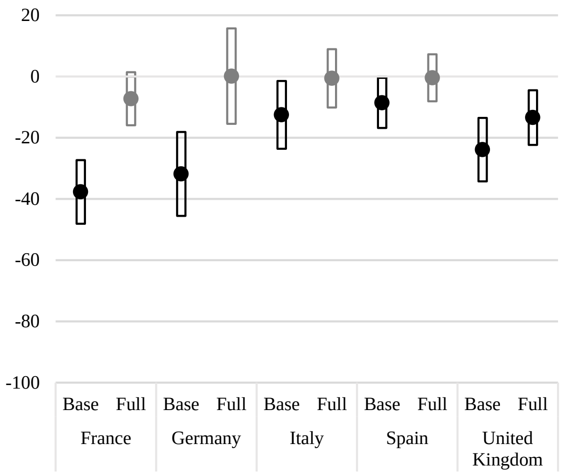
Figure 2 - Gaps in mathematics. ICT resources and a quiet place to study



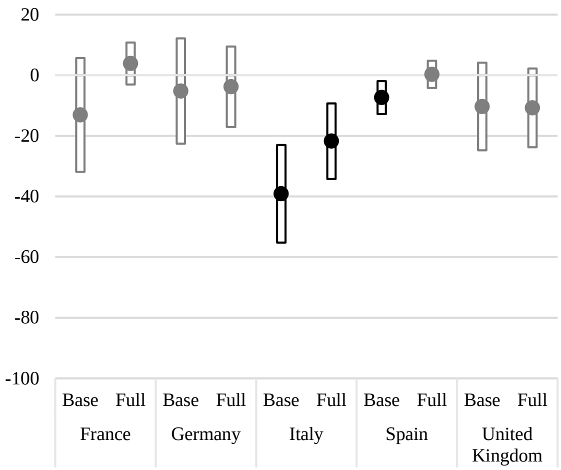
(a) No computer



(b) No internet



(c) No quiet place to study



(d) Few school ICT

Note: Dependent variable: mathematics score. Values in the y-axes are the differences in scores between students without and with the resources for learning remotely at home or at school. The base regression includes only the four variables of interest; the full regression includes all the covariates of equation (1), except for Figure (d), where school fixed effects are not included to avoid collinearities. Grey denotes significance below five percent.

Results in Table 1 show that the coefficients on the interactions of the two variables regarding cities and towns (rural areas are in the intercept) are negative and significant in France, Germany and Italy. More specifically, in France gaps lose significance when the variable *School types* is added to the regression (not shown to save space), which suggests that students in cities and towns attending technical and vocational schools, and public schools, with few ICT resources experience the higher cognitive losses.

In Italy, the type of school attended explain part of the negative gaps (also in this country, lyceums are more concentrated in urban areas and make more use of digital devices), but they remain robust to all specifications. In Germany, the negative gaps of students attending urban schools with scarce digital resources are very strong and robust to all controls. This supports our expectation that, everything else given, students attending schools that make a scarce use of ICT resources for teaching in locations where the use of digital devices is more widespread experience larger cognitive losses. On the other hand, in Spain and the United Kingdom locations appear to be non-significant; the correlations between the use of digital devices by schools and students' scores are unaffected by schools' locations. In Spain, as said above, the cognitive losses of attending a school with scarce digital devices is explained by the distinction between private versus public schools. We find very similar results regarding reading scores, which are not shown to save space.

Table 1 – Few school ICT resources and school locations. Dependent variable: students' scores in mathematics.

	France		Germany		Italy		Spain		United Kingdom	
	Base model	Full model	Base model	Full model	Base model	Full model	Base model	Full model	Base model	Full model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
No computer	-60.810***	-25.892***	-69.941***	-39.661***	-42.936***	-24.399***	-47.680***	-12.740***	-43.709***	-33.247***
No internet	-13.469	-7.315	-51.866***	-28.715***	-35.868***	-20.398**	-19.753**	-0.187	-92.735***	-74.714***
No quiet place	-39.348***	-9.389**	-32.446***	-9.997	-12.852**	1.068	-8.804**	-1.823	-23.563***	-18.855***
(Few school ICT)*(Town)	-38.436**	-9.92	-113.500***	-136.197***	-92.164*	-49.496**	-1.671	-5.421	5.859	3.978
(Few school ICT)*(City)	-32.704	-6.15	-138.865***	-134.872***	-118.420**	-65.532***	-8.244	-11.02	28.873	20.881
Few school ICT	23.791**	12.425	114.612***	131.151***	59.663	31.626	-2.379	7.899	-24.789*	-20.874*
Town	70.414***	-7.998	55.179***	103.942***	40.03	17.711	1.508	-3.175	0.77	6.631
City	78.945***	-4.109	67.509***	87.696***	60.158	27.203	16.225**	7.039	-11.395	-0.594
Constant	440.230***	483.027***	459.915***	-64.002	460.021***	354.371***	483.440***	318.870***	520.361***	166.434
Covariates	no	yes	no	yes	no	yes	no	yes	no	yes
Observations	5,381	5,247	4,024	3,728	11,029	10,779	34,072	32,915	10,689	9,680
R^2	0.075	0.449	0.076	0.302	0.084	0.280	0.035	0.300	0.050	0.109

Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of the variable *Location* is "Rural area". Covariates are: gender, age, repeated grade, immigrant status, age of arrival, highest parents' level of education, school types (general, technical, vocational), public school (versus private).

5.3 Leaving education early and repeating grades.

Not being able to learn remotely may have longer run consequences than the score gaps seen above, which, in principle, could be at least partly reversed once back at school.[9] Students not learning remotely for weeks and months and foreseeing their scores will fall considerably below those of their peers may choose to shorten the length of their planned future education. They may drop out of school altogether, or stop studying when completing their compulsory schooling cycle or secondary school. As already seen, we use the question *Which of the following do you expect to complete*? And, as said above, set equal to one the answers indicating lower and upper secondary education to not leading to tertiary studies, and zero for expected higher levels. Moreover, if falling behind may reduce students' planned investments in education, the concrete possibility of repeating grades may reinforce this decision. Hence, we expect students unable to attend remote learning to cut their planned investments in education and to reduce them even more if they are also likely to repeat grades.

We test whether our four variables indicating the lack of ICT resources at home or at school and of a quiet place to study are correlated with the probabilities of leaving school early and of repeating grades (the latter, except for the United Kingdom). Then, we test whether these two probabilities are significantly correlated. As in equations (2) and (3) above, we use Probit specifications for the first two tests and Bivariate probit regressions for the latter. In the Probit specification, the coefficients of the marginal probabilities on each variable of interest are in columns 1 to 4 of Table 2. The base regressions include only our four variables of interest, while the full regressions control for all covariates of equations (2) and (3). The results on the Bivariate probit regressions are in columns 5 and 6. The *Rho* coefficients report the correlation between the residuals of the regressions having *Leaving education early* and *Repeated grade* as dependent variables. Other than for the United Kingdom, Bivariate probit coefficients are not reported for France because both the raw correlation coefficient between y_1 and y_2 (Table A3 in Appendix A) and the *Rho* coefficient for this country are non-significant.

[9] von Hippel and Hamrock (2019), find that cognitive losses deriving from summer vacations are reversed after variable lengths of time once back at school.

Results from the Probit regressions show that, in all countries, the lack of ICT resources, especially of a computer at home, significantly increase the two probabilities of leaving education early and, except for the United Kingdom, of repeating grades. In the full regressions of column (2) of Table 2, not having a computer at home increases the probability of leaving education early by 15 percent in Germany (the average frequency of leaving education early is the predicted mean of y_1: 19 percent in Germany), 11 percent in the United Kingdom, 10 percent in Spain, and three percent in Italy. Not having an internet connection at home rises the probability of leaving education early by two percent in Spain (column 2). Everything else given, not having a computer is also correlated with a higher probability of repeating a grade of 24 percent in Spain, six percent in Germany, four percent in Italy and two percent in France (column 4).

The Bivariate Probit regressions add interesting insights on the joint probabilities of the two events. The *Rho* coefficients are strong and highly significant for Spain, Germany and Italy, indicating that the use of the biprobit specifications on these countries' data is appropriate. Their positive signs show that the two outcomes, repeating grades and leaving education early, reinforce each other. For example, as seen in the Probit specifications, not having a computer at home in Spain increases the probability of leaving education early by 10 percent and the probability of repeating grades by 24, while in the Bivariate probit regressions, not having a computer at home increases the joint probability of leaving education early and repeating a grade by 13 percent (column 6). In Spain, similar results apply to the other three variables of interest: not having an internet connection at home, not having a quiet place to study and attending a school with scarce ICT resources. The joint probabilities of repeating grades and leaving school early are all significantly correlated with the lack of the factors needed to learn remotely. In Section 5.1 above was seen that, in Spain, the negative score gaps associated with schools having few ICT resources were explained by the distinction between private and public schools, and the lower digitalization of the latter. Here, we see that even controlling for all cofactors, attending a school with few ICT resources significantly increases the joint probabilities of repeating a grade and leaving education early.

Analogous outcomes derive from the lack of computer at home in Germany and Italy. In the Bivariate Probit regressions, it significantly increases the joint probabilities of repeating grades and leaving education early by 14 percent in Germany and by three percent in Italy (column 5). Controlling for all covariates, coefficients shrink but remain significant at the one and five percent levels, respectively (column 6). Not having a quiet place to study in Germany, and a scarcity of ICT resources at school in Italy also increase the joint probabilities of repeating grades and leaving education early (column 5). In Italy, most of the correlation between the joint probabilities and *Few school ICT* resources is explained by the school types attended (Column 4, Table A6).

These results, as all findings in this study, are correlations between variables, not causal relationships. The lack of a time dimension in our data and of potentially valid instruments do not allow us to test for causality or to exclude endogeneity and omitted variables. However, the size and significance of the coefficients on our variables of interest and their robustness to various specifications give our findings the very clear meaning that students unable to learn remotely suffer significant cognitive losses with respect to their peers and tend to leave education earlier. Moreover, to control for the sensitivity of our results, we used an alternative indicator for the lack of schooling experienced by only a subset of students: the absence from school. We tested the correlations between scores in mathematics and reading and the days of absence from school. To save space, they are in Appendix B. As expected, these negative gaps are bigger than those related to the lack of each of the four factors needed to learn remotely considered above, but follow the same general patterns within and across countries, and results are robust to different covariates and specifications. Further robustness controls, based on the imputation of missing observations are in Appendix C.

Table 2 - Marginal probabilities: Leaving education early and repeating grades

		Probit				Bivariate probit	
	Dependent variable:	Leaving education early (y_1) = 1		Repeated grade (y_2) = 1		$y_1 = 1$ & $y_2 = 1$	
		Base	**Full**	**Base**	**Full**	**Base**	**Full**
		(1)	(2)	(3)	(4)	(5)	(6)
France	No computer	0.05**	0.02	0.17***	0.02***		
	No internet	0.01	0.00	0.02	0.03		
	No quiet place to study	0.02	0.00	0.12***	0.01		
	Few school ICT	0.03**	0.02	0.08*	0.01		
	Observations	5,168	5,067	5,370	5,247		
	Predicted mean y_1, y_2	0.13	0.16	0.12	0.07		
Germany	No computer	0.24***	0.15***	0.13***	0.06*	0.14***	0.06***
	No internet	0.17**	0.10	0.07	0.05	0.08	0.04
	No quiet place to study	0.08**	0.04	0.09***	0.06**	0.06***	0.03
	Few school ICT	0.00	0.02	0.01	0.13	0.00	0.00
	Observations	3,778	3,554	4,017	3,752	3,770	3,549
	Rho					*0.42****	*0.26****
	Predicted mean y_1, y_2	0.31	0.19	0.18	0.12	0.10	0.05
Italy	No computer	0.06***	0.03**	0.08***	0.04**	0.03***	0.01**
	No internet	0.01	0.00	0.03	0.00	0.03***	0.00
	No quiet place to study	0.02*	0.01	0.07***	0.03*	0.01	0.00
	Few school ICT	0.02**	0.01	0.05***	0.03**	0.01**	0.00
	Observations	10,482	10,287	11,010	10,779	10,473	10,278
	Rho					*0.50****	*0.40****
	Predicted mean y_1, y_2	0.07	0.13	0.04	0.09	0.03	0.01
Spain	No computer	0.15***	0.10***	0.31***	0.24***	0.15***	0.13***
	No internet	0.04***	0.02**	0.15***	0.10***	0.05***	0.04***
	No quiet place to study	0.03***	0.02*	0.04***	0.02	0.02***	0.02***
	Few school ICT	0.02***	0.00	0.06***	0.02**	0.02***	0.01**
	Observations	33,178	32,074	34,144	32,970	33,166	32,066
	Rho					*0.90****	*0.82****
	Predicted mean y_1, y_2	0.08	0.25	0.09	0.28	0.07	0.08
United Kingdom	No computer	0.14***	0.11***				
	No internet	0.13*	0.13				
	No quiet place to study	0.07***	0.06***				
	Few school ICT	0.01	0.01				
	Observations	10,260	9,400				
	Predicted mean y_1, y_2	0.15	0.03				

Notes: Standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All plausible values employed. All results are weighted and replication weights are taken into account. *Leaving education early* and *Repeated grade* are dichotomous variables taking, respectively, value one when the student plans to leave education early and zero otherwise, and value one when grades are repeated and zero otherwise. Full regressions of columns 2, 4 and 6 include all covariates of equations (2) and (3). Margins are computed at mean values of covariates.

6. Discussion and conclusions

Several recent empirical investigations on school closures due to the coronavirus pandemic predict negative effects on overall education levels, but they can also exacerbate education inequalities. In this study, we used PISA 2018 data to test the extra cognitive loses of students lacking the factors needed to make remote learning actually possible: a computer for schoolwork, an internet connection, a quiet place to study, or a school with enough ICT resources. In the five European countries we consider, the proportion of fifteen-year-old students lacking at least one of them ranges from more than 30 percent in France to more than 60 percent in Germany.

We found that the scores in mathematics and reading of these students are strongly and significantly lower than those of their peers; and most of these cognitive gaps remain strong and significant after controlling for individual and family characteristics, school types and school fixed effects. In particular, everything else equal, the lack of a computer at home is correlated with negative gaps in mathematics that range from a fourth of a school year in Spain to 70 percent of a school year in the United Kingdom, Germany and France. Differently from several empirical studies on school interruptions, we find very similar results in mathematics and reading and, in some cases, even higher cognitive losses in reading (Gottfried, 2009 and 2011; Quinn and Polikoff, 2017; Aucejo and Romano, 2016).

Moreover, in the longer run, students unable to learn remotely are more likely to drop out from school or end their education earlier. This relationship is stronger in countries such as Spain, Germany and Italy, were students falling behind their peers are also more likely to repeat grades. In these countries, and especially in Spain, the two probabilities, of repeating grades when going back at school and of dropping out are significantly and strongly correlated.

More generally, we found that the cognitive inequalities arising from the lack of the resources needed to learn remotely are less explained by students' and families' characteristics than by countries' educational systems. Negative gaps in mathematics and reading associated with the lack of remote learning follow each country's type of differentiation between types of schools. Where tracking starts earlier, such as in Germany and Italy, students unable to learn remotely are more concentrated in technical and vocational schools and are also more likely to drop out early. When tracking interacts with schools being private or public, such as in France, students unable to learn remotely are more concentrated in vocational and technical schools that are also public (Le Donné, 2014). Where the distinction between private and public schools matters more, such as in Spain and the United Kingdom, these negative cognitive gaps are more concentrated in public schools. A further line of demarcation, which involves both types of models, is grades repetition: in countries where it is more frequent, such as Spain, Germany and Italy, digital negative gaps and an early termination of studies is more frequent among repeaters.

In turn, the segmentation between types of schools – with tracking or the private-public distinction – and the existence of digital network externalities can reinforce each other. Students attending schools with scarce ICT resources that are located in urban areas – where the use of digital resources is more widespread – tend to experience the biggest cognitive losses. These schools are typically vocational or technical in French, Italian and German cities and towns; and, in France, they are mostly public rather than private. Similarly, students not having an internet connection at home or a computer for schoolwork experience the highest losses in countries, such as the United Kingdom, where the use of digital resources is more widespread. Hence, our results show that digital divides in countries and their educational systems are interrelated phenomena. This is a crucial issue in the field of education. When countries are forced to close schools and adopt distance learning, existing education inequalities are exacerbated and digital ones emerge. Policymakers should develop targeted policies addressing the needs of disadvantaged students and schools, tailored in accordance with countries' educational systems and digital divides.

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Appendix A. Figures and Tables.

Table A1 – Descriptive statistics

	France				Germany				Italy				Spain				United Kingdom			
	Obs.	Mean	Std. Dev.	Missing	Obs.	Mean	Std. Dev.	Missing	Obs.	Mean	Std. Dev.	Missing	Obs.	Mean	Std. Dev.	Missing	Obs.	Mean	Std. Dev.	Missing
Math score	6,308	495.41	92.57	0.0	5,451	500.04	95.39	0.0	11,785	486.59	93.78	0.0	35,943	481.39	88.40	0.0	13,818	501.77	93.02	0.0
Reading score	6,308	492.61	101.18	0.0	5,451	498.28	105.75	0.0	11,785	476.28	96.87	0.0		-			13,818	503.93	100.21	0.0
Leave educ. early (%)	5,930	11.98	0.32	6.0	4,408	31.02	0.46	19.1	10,943	5.57	0.23	7.1	34,406	8.85	0.28	4.3	12,750	12.85	0.33	7.7
Repeated grade (%)	6,215	16.56	0.37	1.5	4,674	19.63	0.40	14.3	11,495	13.21	0.34	2.5	35,449	28.71	0.45	1.4	13,306	2.52	0.16	3.7
No computer (%)	6,193	9.22	0.29	1.8	4,711	7.98	0.27	13.6	11,485	9.96	0.30	2.5	35,391	8.58	0.28	1.5	13,250	8.06	0.27	4.1
No internet (%)	6,203	1.54	0.12	1.7	4,721	2.03	0.14	13.4	11,491	2.84	0.17	2.5	35,371	2.12	0.14	1.6	13,262	0.82	0.09	4.0
No quiet place to study (%)	6,186	6.31	0.24	1.9	4,723	4.85	0.21	13.4	11,491	8.73	0.28	2.5	35,372	7.34	0.26	1.6	13,204	10.97	0.31	4.4
Few school ICT (%)	5,498	25.69	0.44	12.8	4,718	55.87	0.50	13.4	11,347	28.64	0.45	3.7	34,880	46.70	0.50	3.0	11,324	30.93	0.46	18.0
Days of absence	4,947			21.6	2,523			47.6	9,183			22.1	27,865			22.5	12,620			8.7
Days of absence: 0 (%)	4,947	83	0.38		2,523	87	0.34		9,183	45	0.50		27,865	72	0.45		12,620	78	0.42	
Days of absence: 1-2 (%)	4,947	10	0.31		2,523	9	0.28		9,183	39	0.49		27,865	22	0.41		12,620	17	0.38	
Days of absence 3-4 (%)	4,947	3	0.16		2,523	2	0.14		9,183	7	0.26		27,865	3	0.18		12,620	3	0.16	
Days of absence 5 + (%)	4,947	4	0.18		2,523	2	0.15		9,183	9	0.28		27,865	3	0.16		12,620	2	0.14	
Female (%)	6,308	49.33	0.50	0.0	5,451	46.22	0.50	0.0	11,785	48.26	0.50	0.0	35,943	49.37	0.50	0.0	13,818	51.45	0.50	0.0
Age	6,308	15.86	0.29	0.0	5,451	15.83	0.29	0.0	11,785	15.77	0.29	0.0	35,943	15.84	0.29	0.0	13,818	15.76	0.28	0.0
Parents' education	6,133	4.95	1.30	2.8	4,481	4.41	1.66	17.8	11,439	4.42	1.45	2.9	34,925	4.68	1.65	2.8	12,391	4.89	1.29	10.3
Immigrant status (%)	6,167	14.29	0.35	2.2	4,727	22.17	0.42	13.3	11,354	10.03	0.30	3.7	34,844	12.19	0.33	3.1	12,979	19.76	0.40	6.1
Age of arrival	6,177	0.51	2.29	2.1	4,798	0.71	2.81	12.0	11,479	0.43	1.95	2.6	35,419	0.66	2.48	1.5	13,293	0.84	2.86	3.8
School type	6,308			0.0	5,451			0.0	11,785			0.0	35,943			0.0	13,818			0.0
General school (%)	6,308	63.82	0.48		5,451	54.76	0.50		11,785	48.10	0.50		35,943	99.04	0.10		13,818	100.00	-	
Technical school (%)	6,308	30.22	0.46		5,451	38.10	0.49		11,785	31.46	0.46		35,943	-	0.01		13,818	-	-	
Vocational school (%)	6,308	5.96	0.24		5,451	7.14	0.26		11,785	20.43	0.40		35,943	0.95	0.10		13,818	-	-	
Public school (%)	5,602	80.03	0.40	11.19	4,690	96.09	0.19	13.96	11,575	96.38	0.19	1.78	34,911	67.68	0.47	2.87	11,888	34.01	0.47	13.97
Location of school	5,602			11.19	4,663			14.46	11,575			1.78	34,884			2.95	11,859			14.18
Location: Rural area (%)	5,602	2.50	0.16		4,663	1.14	0.11		11,575	3.75	0.19		34,884	4.44	0.21		11,859	7.09	0.26	
Location: Town (%)	5,602	75.17	0.43		4,663	71.80	0.45		11,575	71.79	0.45		34,884	59.22	0.49		11,859	61.51	0.49	
Location: City (%)	5,602	22.33	0.42		4,663	27.06	0.44		11,575	24.46	0.42		34,884	36.34	0.48		11,859	31.40	0.48	

Notes: All plausible values employed. All results are weighted and replication weights are taken into account.

Table A2 - Remote learning resources. Dependent variable: students' scores in mathematics.

	France							Germany						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
No computer	-61.665***	-62.454***	-54.039***	-28.222***	-41.431***	-25.841***	-24.816***	-71.654***	-72.331***	-51.245***	-57.527***	-59.858***	-42.608***	-24.381***
No internet	-11.409	-11.859	-2.028	-13.101	5.066	-7.114	5.066	-52.083***	-51.585***	-40.398***	-39.117***	-47.646***	-29.673***	-27.994***
No quiet place to study	-37.730***	-37.646***	-25.310***	-16.487***	-23.646***	-9.322**	-7.290*	-31.865***	-31.582***	-20.928**	-22.577***	-22.950***	-9.777	0.092
Few school ICT	-13.096	-13.484	-13.175	5.276	-3.594	3.879		-5.194	-4.805	-2.406	-6.866	-6.039	-3.816	
Female		-11.299***				-23.550***	-20.487***		-10.119***				-19.123***	-23.125***
Age		16.522***				3.966	4.151		23.042***				28.940***	31.463***
Parents' education			15.275***			6.151***	4.509***			12.828***			8.827***	2.575***
Immigrant status			-29.262***			-26.182***	-20.038***			-27.793***			-24.400***	-16.022***
Age of arrival			-2.450***			0.283	-0.293			-4.161***			-3.085***	-1.848***
Technical school				-106.168***		-90.068***					-57.263***		-41.867***	
Vocational school				-159.776***		-138.798***					-113.49***		-76.218***	
Public school				-27.021***		-21.324***					-14.135		-3.283	
Repeated grade					-112.327***	-32.927***	-47.036***					-65.722***	-47.832***	-38.773***
Constant	511.156***	254.832***	440.410***	560.092***	522.622***	476.964***	435.469***	517.389***	157.183	468.540***	558.381***	531.514***	67.782	27.422
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	5,381	5,381	5,251	5,381	5,370	5,247	5,247	4,077	4,077	3,819	4,049	4,017	3,752	3,779
R^2	0.063	0.069	0.135	0.407	0.242	0.448	0.510	0.067	0.075	0.158	0.202	0.138	0.284	0.507

Notes: Standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All plausible values employed. All results are weighted and replication weights are taken into account. The base level for coefficients on *School Type* is “General school”.

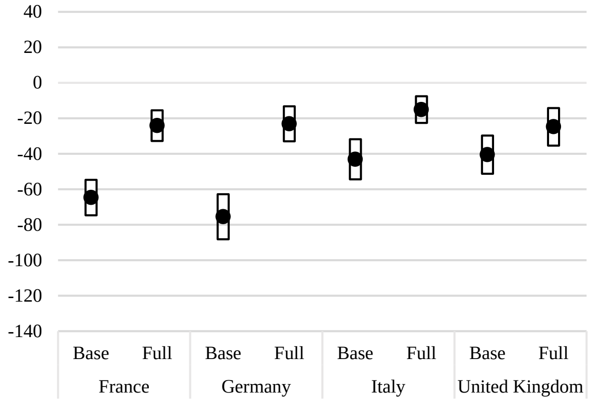
Table A2. - Remote learning resources. Dependent variable: students' scores in mathematics. Continued from previous page.

	Italy							Spain						
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
No computer	-42.997***	-42.869***	-36.175***	-29.858***	-36.798***	-24.348***	-15.621***	-47.796***	-48.504***	-35.001***	-44.512***	-16.909***	-12.792***	-10.671***
No internet	-38.255***	-37.975***	-28.375***	-26.188***	-35.493***	-21.079**	-5.986	-20.609**	-19.945**	-11.933	-17.474**	-5.965	-0.19	0.369
No quiet place to study	-12.559**	-12.935**	-7.766	-3.549	-7.386	1.225	-0.609	-8.648**	-8.521**	-3.775	-8.029*	-4.462	-1.79	-0.437
Few school ICT	-39.119***	-38.502***	-36.914***	-24.642***	-35.405***	-21.774***		-7.378***	-7.457***	-4.190*	-2.982	-2.05	0.274	
Female		-14.222***				-28.059***	-22.622***		-8.505***				-16.401***	-16.824***
Age		16.532***				10.288**	10.240***		19.486***				11.528***	10.970***
Parents' education			9.486***			3.638***	-0.808			10.695***			5.554***	3.606***
Immigrant status			-21.264***			-2.477	-13.657***			-17.487***			-6.401*	-5.831*
Age of arrival			-2.752***			-1.704*	-1.582*			-3.091***			-2.244***	-2.145***
Technical school				-38.475***		-38.404***								
Vocational school				-99.599***		-88.190***					-75.540***		-24.675**	
Public school				-14.011		-6.298					-23.167***		-6.372**	
Repeated grade					-72.036***	-50.653***	-42.139***					-98.301***	-90.676***	-89.502***
Constant	505.411***	251.503***	465.833***	543.225***	512.830***	375.655***	351.802***	490.590***	186.275***	443.601***	504.608***	513.130***	317.048***	330.016***
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	11,029	11,029	10,790	11,029	11,010	10,779	10,779	34,174	34,174	33,056	34,099	34,144	32,970	33,044
R^2	0.073	0.082	0.103	0.226	0.140	0.278	0.525	0.031	0.037	0.089	0.055	0.273	0.298	0.376

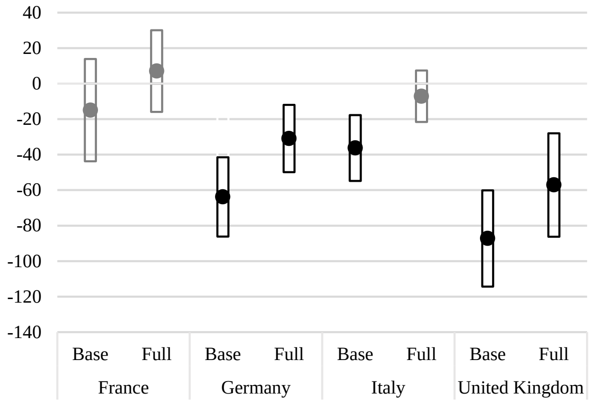
	United Kingdom						
	(29)	(30)	(31)	(32)	(33)	(34)	(35)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
No computer	-44.061***	-44.231***	-34.099***	-42.996***	-43.967***	-33.605***	-27.918***
No internet	-93.525***	-95.301***	-82.958***	-93.147***	-84.543***	-74.200***	-68.881***
No quiet place to study	-23.916***	-23.307***	-19.925***	-24.021***	-22.759***	-19.055***	-13.452***
Few school ICT	-10.327	-10.472	-10.835	-9.807	-10.854	-10.76	
Female		-18.752***				-17.736***	-17.021***
Age		22.596***				20.185***	14.873**
Parents' education			13.221***			12.042***	4.389***
Immigrant status			-13.329**			-12.177**	-5.119
Age of arrival			0.478			0.785	0.556
Public school				-25.117***		-23.675***	
Repeated grade					-58.984***	-53.333***	-40.031***
Constant	516.184***	169.773	456.497***	524.617***	517.962***	162.418	269.686***
School FE	no	no	no	no	no	no	yes
Observations	10,718	10,718	9,724	10,689	10,670	9,680	9,704
R^2	0.046	0.061	0.072	0.063	0.055	0.107	0.280

Notes: Standard errors are clustered at the school level. *** $p < 0.01$, ** p < Notes: Standard errors are clustered at 0.05, * $p < 0.1$. All plausible values employed. All results are weighted and replication weights are taken into account. The base level for coefficients on *School Type* is “General school”.

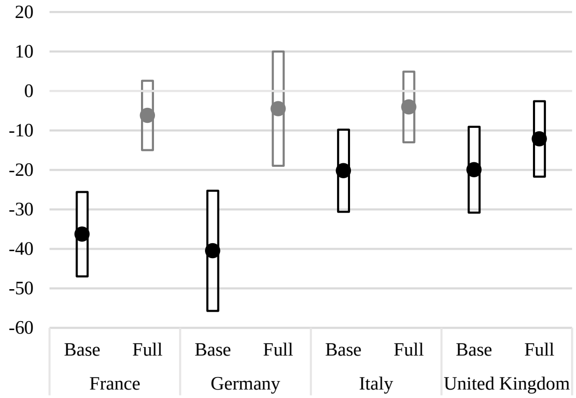
Figure A1. - Gaps in reading. ICT resources and a quiet place to study



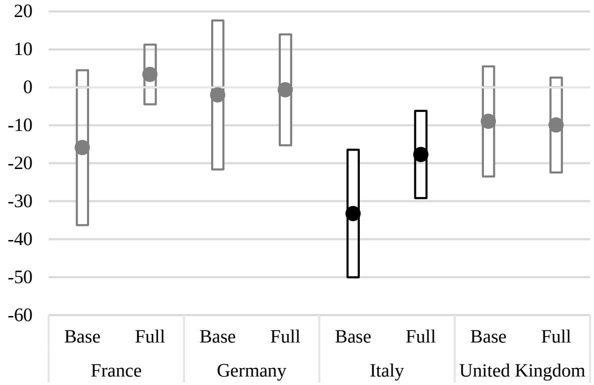
(a) No computer



(b) No internet



(c) No quiet place to study



(d) Few ICT at school

Note: Dependent variable: reading scores. Values in the y-axes are the differences in scores between students without and with the resources for learning remotely at home or at school. The base regressions include only the four variables of interest; the full regressions include all the covariates of equation (1): gender, age, repeated grade, immigrant status, age of arrival, highest parents' level of education, school types (general, technical, vocational), public school (versus private) and school fixed effects, except for Figure (d), where fixed effects are not included to avoid collinearities. Grey denotes significance below five percent.

Table A3 – Main correlation coefficients

Variable 1	Variable 2	France	Germany	Italy	Spain	United Kingdom
Reading score	Math score	0.83 ***	0.82 ***	0.77 ***		0.77 ***
Reading score	Leave educ. Early	-0.18 ***	-0.46 ***	-0.23 ***		-0.30 ***
Reading score	Repeated grade	-0.43 ***	-0.26 ***	-0.29 ***		-0.11 ***
Reading score	No computer	-0.20 ***	-0.17 ***	-0.15 ***		-0.12 ***
Reading score	No internet	-0.04 *	-0.09 ***	-0.09 ***		-0.09 ***
Reading score	No quiet place to study	-0.11 ***	-0.09 ***	-0.07 ***		-0.08 ***
Reading score	Few school ICT	-0.07	0.01	-0.16 ***		-0.05
Reading score	Days of absence: 0	0.26 ***	0.21 ***	0.14 ***		0.15 ***
Reading score	Days of absence: 1-2	-0.16 ***	-0.15 ***	0.01		-0.10 ***
Reading score	Days of absence 3-4	-0.15 ***	-0.09 ***	-0.09 ***		-0.06 ***
Reading score	Days of absence 5 +	-0.14 ***	-0.12 ***	-0.17 ***		-0.11 ***
Math score	Leaving education early	-0.19 ***	-0.45 ***	-0.20 ***	-0.30 ***	-0.32 ***
Math score	Repeated grade	-0.45 ***	-0.27 ***	-0.27 ***	-0.51 ***	-0.10 ***
Math score	No computer	-0.21 ***	-0.18 ***	-0.14 ***	-0.15 ***	-0.14 ***
Math score	No internet	-0.04 *	-0.07 ***	-0.09 ***	-0.07 ***	-0.10 ***
Math score	No quiet place to study	-0.13 ***	-0.09 ***	-0.06 ***	-0.04 ***	-0.10 ***
Math score	Few school ICT	-0.06	-0.01	-0.19 ***	-0.04 **	-0.06
Math score	Days of absence: 0	0.22 ***	0.21 ***	0.16 ***	0.17 ***	0.19 ***
Math score	Days of absence: 1-2	-0.13 ***	-0.15 ***	-0.03	-0.09 ***	-0.13 ***
Math score	Days of absence 3-4	-0.11 ***	-0.09 ***	-0.09 ***	-0.10 ***	-0.10 ***
Math score	Days of absence 5 +	-0.14 ***	-0.10 ***	-0.15 ***	-0.11 ***	-0.11 ***
Leaving education early	Repeated grade	0.01	0.21 ***	0.23 ***	0.39 ***	0.09 ***
Leaving education early	No computer	0.06 ***	0.12 ***	0.10 ***	0.16 ***	0.14 ***
Leaving education early	No internet	0.01	0.05	0.03	0.06 ***	0.07 ***
Leaving education early	No quiet place to study	0.03	0.06 **	0.05 ***	0.04 ***	0.09 ***
Leaving education early	Few school ICT	0.05 **	-0.01	0.05 **	0.04 ***	0.02
Leaving education early	Days of absence: 0	-0.09 ***	-0.12 ***	-0.03 *	-0.11 ***	-0.12 ***
Leaving education early	Days of absence: 1-2	0.06 ***	0.08 ***	-0.02	0.06 ***	0.09 ***
Leaving education early	Days of absence 3-4	0.03	0.07 ***	0.02	0.06 ***	0.06 **
Leaving education early	Days of absence 5 +	0.05 ***	0.05 **	0.08 ***	0.07 ***	0.06 ***
Repeated grade	No computer	0.16 ***	0.07 **	0.08 ***	0.20 ***	0.01
Repeated grade	No internet	0.04 *	0.02	0.03	0.10 ***	0.05
Repeated grade	No quiet place to study	0.10 ***	0.03	0.07 ***	0.05 ***	0.02
Repeated grade	Few school ICT	0.09	0.01	0.06 ***	0.05 ***	-0.03 **
Repeated grade	Days of absence: 0	-0.10 ***	-0.12 ***	-0.08 ***	-0.15 ***	-0.03 *
Repeated grade	Days of absence: 1-2	0.06 ***	0.08 ***	0.02	0.09 ***	0.01
Repeated grade	Days of absence 3-4	0.06 ***	0.04	0.02	0.08 ***	0.00
Repeated grade	Days of absence 5 +	0.06 ***	0.08 **	0.10 ***	0.09 ***	0.08 ***
No computer	No internet	0.14 ***	0.13 ***	0.20 ***	0.27 ***	0.18 ***
No computer	No quiet place to study	0.18 ***	0.26 ***	0.20 ***	0.11 ***	0.14 ***
No computer	Days of absence: 0	-0.08 ***	-0.10 ***	-0.06 ***	-0.04 ***	-0.11 ***
No computer	Days of absence: 1-2	0.03 **	0.09 ***	-0.01	0.02	0.09 ***
No computer	Days of absence 3-4	0.02	0.04	0.04 **	0.04 ***	0.03
No computer	Days of absence 5 +	0.09 ***	0.02	0.08 ***	0.03 ***	0.05 ***
No internet	No quiet place to study	0.07 ***	-0.01	0.07 ***	0.06 ***	0.09 ***
No internet	Few school ICT	0.02	-0.04 *	0.05 **	0.02 **	0.04 **
No internet	Days of absence: 0	-0.07 ***	-0.03	-0.02	-0.03 **	-0.04 *
No internet	Days of absence: 1-2	0.03	0.02	0.00	0.02 *	0.02
No internet	Days of absence 3-4	0.03	-0.02 ***	0.00	0.01	0.00
No internet	Days of absence 5 +	0.07 ***	0.05	0.03	0.02	0.07 *
No quiet place to study	Few school ICT	0.02	0.03	0.07 ***	0.01	0.04 *
No computer	Few school ICT	0.03	-0.01	0.06 ***	0.02 *	0.01
No quiet place to study	Days of absence: 0	-0.09 ***	-0.05 *	-0.04 **	-0.04 ***	-0.08 ***
No quiet place to study	Days of absence: 1-2	0.02	0.02	0.01	0.03 ***	0.07 ***
No quiet place to study	Days of absence 3-4	0.04 ***	0.04	0.00	0.00	0.02
No quiet place to study	Days of absence 5 +	0.11 ***	0.05	0.04 *	0.05 ***	0.03 **
Few school ICT	Days of absence: 0	-0.01	-0.02	-0.05 **	-0.01	-0.01
Few school ICT	Days of absence: 1-2	0.00	0.03	0.00	0.01	0.00
Few school ICT	Days of absence 3-4	0.03	-0.01	0.05 ***	0.02 *	0.01
Few school ICT	Days of absence 5 +	0.00	-0.01	0.04 **	-0.02	-0.01

Notes. All plausible values employed. All results are weighted and replication weights are taken into account.

Table A4 – Remote learning resources. Dependent variable: student scores in reading

	France							Germany						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
No computer	-64.732***	-62.744***	-57.614***	-28.896***	-43.504***	-25.674***	-24.151***	-75.504***	-74.150***	-52.564***	-59.597***	-63.610***	-41.884***	-23.130***
No internet	-14.939	-13.557	-4.413	-16.666	-6.675	-7.593	7.061	-63.841***	-62.881***	-48.034***	-49.197***	-59.217***	-34.707***	-30.961***
No quiet place to study	-36.272***	-36.189***	-22.735***	-13.913***	-21.478***	-6.803	-6.181	-40.495***	-38.693***	-26.004***	-29.941***	-31.686***	-14.032*	-4.470
Few school ICT	-15.905	-14.671	-15.507	3.424	-5.938	3.394		-2.002	-2.284	0.818	-3.643	-2.745	-0.652	
Female		20.993***				4.185***	2.536***		24.854***				9.192***	2.077**
Age		18.803***				-23.177***	-18.301***		16.639**				-22.054***	-13.193***
Parents' education			13.785***			-0.896	-1.647***			13.555***			-5.586***	-4.282***
Immigrant status			-26.300***			8.257***	10.174***			-25.602***			16.467***	9.765***
Age of arrival			-3.763***			6.286*	6.592*			-6.756***			23.334***	28.147***
Technical school				-117.524***		-99.393***					-67.932***		-49.598***	
Vocational school				-165.869***		-142.118***					-129.148***		-90.586***	
Public school				-23.196***		-17.309***					-4.881		7.754	
Repeated grade					-117.434***	-29.387***	-52.264***					-69.709***	-44.503***	-33.991***
Constant	509.784***	200.572**	446.737***	558.486***	521.783***	431.056***	390.221***	515.164***	240.138**	464.591***	551.784***	529.956***	129.132	66.100
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	5,381	5,381	5,251	5,381	5,370	5,247	5,247	4,077	4,077	3,819	4,049	4,017	3,752	3,779
R^2	0.058	0.072	0.113	0.394	0.223	0.408	0.473	0.067	0.083	0.167	0.213	0.131	0.292	0.519

Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients of coefficients on *School type* is "General school".

Table A4. – Remote learning resources. Dependent variable: student scores in reading. Continued from previous page

	Italy							United Kingdom						
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
No computer	-43.131***	-41.625***	-36.336***	-27.733***	-36.227***	-22.098***	-15.123***	-40.546***	-40.269***	-30.262***	-39.594***	-40.836***	-29.535***	-24.823***
No internet	-36.301***	-37.648***	-28.302***	-23.740***	-33.301***	-22.346***	-7.153	-87.267***	-84.213***	-79.169***	-86.935***	-76.362***	-65.126***	-57.124***
No quiet place to study	-20.204***	-19.360***	-13.952***	-9.740*	-14.450***	-3.524	-4.041	-19.950***	-20.164***	-16.480***	-19.949***	-18.757***	-16.205***	-12.137**
Few school ICT	-33.251***	-34.476***	-31.418***	-18.047***	-29.118***	-17.693***		-8.964	-9.096	-9.395	-8.384	-9.472	-9.935	
Female		25.493***				1.760*	-2.151**		14.529***				11.223***	4.013***
Age		17.625***				-7.268	-17.242***		21.997***				-13.341**	-6.750
Parents' education			7.887***			-2.039***	-2.373***			11.819***			-1.001	-1.403**
Immigrant status			-26.734***			8.524***	12.327***			-12.041*			16.528***	16.156***
Age of arrival			-3.267***			11.193**	12.543***			-1.530*			20.472***	13.796***
Technical school				-62.270***		-50.866***								
Vocational school				-112.726***		-95.923***								
Public school				-5.627		-4.011					-21.563***		-20.273***	
Repeated grade					-80.197***	-49.844***	-42.351***					-68.166***	-63.984***	-50.910***
Constant	494.614***	204.328**	463.197***	533.470***	502.932***	344.849***	295.794***	517.697***	163.604*	466.834***	524.790***	519.778***	146.740*	275.850***
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	11,029	11,029	10,790	11,029	11,010	10,779	10,779	34,174	34,174	33,056	34,099	34,144	32,970	33,044
R^2	0.062	0.082	0.090	0.263	0.140	0.294	0.496	0.033	0.042	0.054	0.044	0.044	0.082	0.234

Notes. Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients on *School type* is "General school".

Table A5 -Dependent variable: Marginal probabilities of leaving education early and repeating grades. Probit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variable: Leaving education early					Dependent variable: Grade repetition			
	France	Germany	Italy	Spain	United Kingdom	France	Germany	Italy	Spain
No computer	0.05**	0.24***	0.06***	0.15***	0.14***	0.17***	0.13***	0.08***	0.31***
No internet	0.01	0.17**	0.01	0.04***	0.13*	0.02	0.07	0.03	0.15***
No quiet place	0.02	0.08**	0.02*	0.03***	0.07***	0.12***	0.09***	0.07***	0.04***
Few school computers	0.03**	0.00	0.02**	0.02***	0.01	0.08*	0.01	0.05***	0.06***
No computer	0.05**	0.24***	0.05***	0.14***	0.14***	0.17***	0.13***	0.08***	0.31***
No internet	0.01	0.16**	0.02	0.05***	0.12*	0.02	0.07	0.04	0.16***
No quiet place	0.02	0.08**	0.02*	0.03***	0.07***	0.12***	0.09***	0.06***	0.04***
Few school computers	0.03**	0.00	0.02**	0.02***	0.01	0.08*	0.01	0.05***	0.06***
Covariates: Female, age									
No computer	0.04*	0.171***	0.05***	0.11***	0.11***	0.15***	0.08**	0.06***	0.26***
No internet	-0.01	0.12	0.00	0.02*	0.14*	0.01	0.06	0.01	0.11***
No quiet place	0.01	0.07	0.02	0.02*	0.06***	0.08***	0.07**	0.05***	0.02
Few school ICT	0.03**	0.00	0.02*	0.01**	0.00	0.08*	0.01	0.05***	0.04***
Covariates: Parents' education, immigrant status, age of arrival									
No computer	0.02	0.2***	0.03**	0.13***	0.14***	0.02***	0.09***	0.05**	0.30***
No internet	0.01	0.12	0.00	0.03**	0.13*	0.03	0.05	0.01	0.13***
No quiet place	0.00	0.05	0.01	0.03***	0.07***	0.02*	0.07**	0.04**	0.04***
Few school ICT	0.02	0.01	0.01	0.01*	0.01	0.01	0.01	0.02*	0.03**
Covariates: Type of school, and private/public									
No computer	0.04*	0.17***	0.05***	0.10***	0.11***	0.15***	0.07**	0.06***	0.25***
No internet	0.00	0.12	0.00	0.03**	0.13*	0.01	0.06	0.01	0.11***
No quiet place	0.01	0.06	0.02	0.02**	0.06***	0.08***	0.07**	0.05**	0.02
Few school ICT	0.03**	0.00	0.02**	0.01**	0.01	0.08*	0.01	0.05***	0.04***
Covariates: Female, age, parents' education, immigrant status, age of arrival									
No computer	0.02	0.15***	0.03**	0.1***	0.11***	0.02***	0.06*	0.04**	0.24***
No internet	0.00	0.10	0.00	0.02**	0.13	0.03	0.05	0.00	0.10***
No quiet place	0.00	0.04	0.01	0.02*	0.06***	0.01	0.06**	0.03*	0.02
Few school ICT	0.02	0.02	0.01	0.00	0.01	0.01	0.13	0.03**	0.02**
Covariates: Female, age, parents' education, immigrant status, age of arrival, school types									

Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account.

Table A6 - Marginal probabilities of Leaving education early and Grade repetition. Bivariate Probit

	(1)	(2)	(3)	(4)	(5)	(6)
	Early & not repeating	Early & repeating	Early & not repeating	Early & repeating	Early & not repeating	Early & repeating
	Germany		Italy		Spain	
No computer	0.12***	0.14***	0.03**	0.03***	0.00	0.15***
No internet	0.09	0.08	0.01	0.03***	0.00	0.05***
No quiet place	0.02	0.06***	0.01	0.01	0.01*	0.02***
Few school ICT	0.00	0.00	0.01	0.01**	0.00	0.02***
	Rho =0.42; p value = 0.00		*Rho =0.50; p value = 0.00*		*Rho =0.90; p value = 0.00*	
No computer	0.12***	0.13***	0.03**	0.03***	0.00	0.14***
No internet	0.09	0.07	0.01	0.01	0.00	0.05***
No quiet place	0.02	0.06***	0.01	0.01**	0.01*	0.02***
Few school ICT	0.00	0.00	0.01*	0.01***	0.00	0.02***
	Rho =0.41; p value = 0.00		*Rho =0.48; p value = 0.00*		*Rho =0.89; p value = 0.00*	
Covariates: Female, age						
No computer	0.09***	0.08***	0.025**	0.02***	0.01*	0.11***
No internet	0.06	0.06	0.01	0.00	0.00	0.02***
No quiet place	0.02	0.04*	0.01	0.01*	0.00	0.01**
Few school ICT	0.00	0.00	0.01	0.01***	0.00	0.01**
	Rho =0.38; p value = 0.00		*Rho =0.48; p value = 0.00*		*Rho =0.86; p value = 0.00*	
Covariates: Parents' education, immigrant status, age of arrival						
No computer	0.11***	0.10***	0.02**	0.01**	0.00	0.13***
No internet	0.07	5.00	0.01	0.00	0.00	0.04***
No quiet place	0.01	0.04**	0.01	0.01	0.01*	0.02***
Few school ICT	0.01	0.00	0.01	0.00	0.00	0.01**
	Rho =0.29 p value = 0.00		*Rho =0.41; p value = 0.00*		*Rho =0.87; p value = 0.00*	
Covariates: School type, private/public						
No computer	0.09***	0.06***	0.01**	0.01**	0.01*	0.09***
No internet	0.06	0.04	0.00	0.00	0.00	0.02**
No quiet place	0.01	0.03	0.00	0.00	0.01*	0.01**
Few school ICT	0.01	0.00	0.00	0.00	0.00	0.01
	Rho =0.26; p value = 0.00		*Rho =0.40; p value = 0.00*		*Rho =0.82; p value = 0.00*	
Covariates: Female, age, parents' education, immigrant status, age of arrival, school types, private/public						

Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account.

Appendix B. Absence from school.

To predict the potential relationships between not attending school, either physical or virtual, and scores, we use a variable concerning the days of absence from school, which is an ordinal variable built from answers to the question, in the Students' Questionnaire: *In the last two full weeks of school, how often did [you] skip a whole school day*; answers vary from 'never' to 'more than five days'. Control variables are as in equation (1).[10]

$$\text{Test scores}_{ij} = \alpha_1 + \beta_1 \text{Days of absence}_{ij} + X_{ij}\Pi + \lambda_j + v_j + \varepsilon_{ij} \qquad \text{(SA1)}$$

More specifically, the variable *Days of absence* takes four values, each corresponding to the days of absence: 'zero days' is 'absorbed' into the intercept, and the other values correspond to, respectively, one or two days, three or four days, and five or more days. Figure B1 below depict the results of these tests. The main findings are that not attending school is correlated with strong, negative and significant score gaps in both mathematics and reading, which substantially grow with the days of school missed. Moreover, losses in reading tend to be slightly bigger than those in mathematics. As in Section 5.1, this result differs from previous findings of the empirical literature on vacations and school interruptions. (Cooper et al, 1996; Gottfried, 2009 and 2011; Quinn and Polikoff, 2017). Additionally, all coefficients are robust to the inclusion of covariates and school fixed effects, showing that students who miss school days lose ground with respect to their peers even when all other factors are equal.

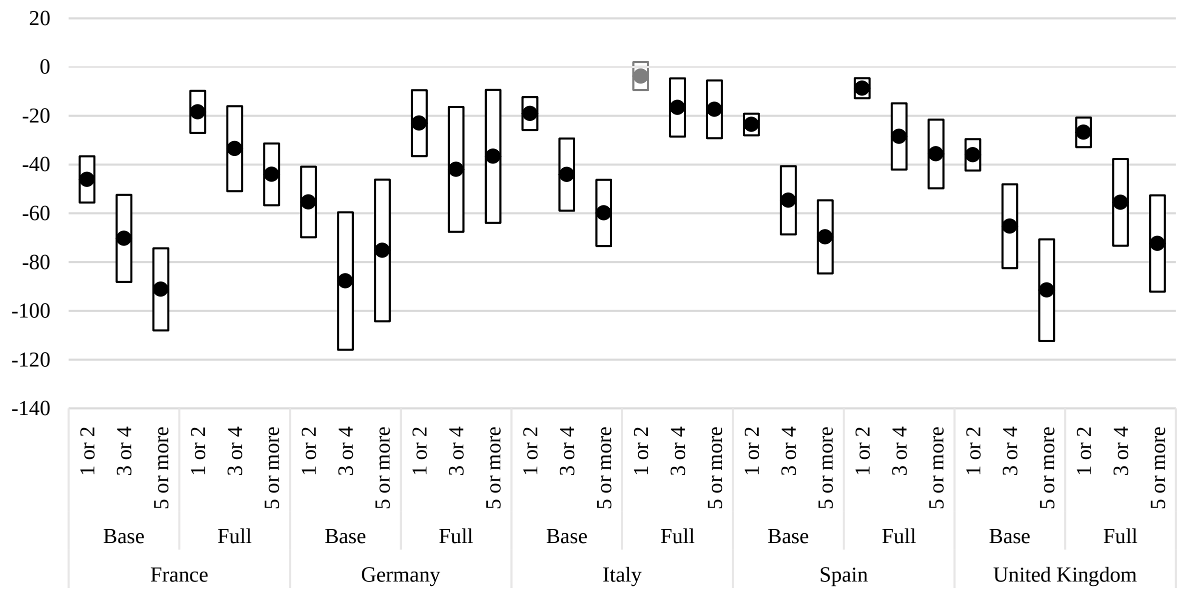
[10] A student can skip remote schooling because of a lack of ICT resources at home or at school or a quiet place to study. Since they can be alternative explanations of the same phenomenon, equation (1) does not control for absence from school, and equation (SA1) does not control for the lack of ICT resources or a quiet place to study. The question concerns the last two full weeks of school, but can be interpreted as a proxy for the student's general behavior during the school year. Moreover, this variable is more appropriate for our analysis than an indicator of summer or winter vacations when all students are out of school. Some studies find that part of the concepts learnt at school are forgotten during summer, especially concerning mathematics (Cooper et al, 1996; Quinn and Polikoff, 2017).

Because of the ordinal character of the variable *Days of absence*, with unequally spaced intervals between values and not upper bound (five or more days), we cannot compute and predict the potential cognitive losses of students who did not attend remote learning during the school closures of year 2020. However, because of the long duration of school closures during year 2020, we can reasonably hypothesise that they are as large as or larger than those of skipping five or more days of the physical school in two weeks. In the first case, the interruption in learning is continuous and lasts for weeks and months, while in the second it can be sporadic and distributed along the school year. Hence, regarding the scores in mathematics, the coefficients on 'skipping five or more days' that in the full models range from almost one school year in Italy to almost two years in the United Kingdom (Figure B1, Table B1), should be read as the smallest predicted negative gaps of students unable to learn remotely.

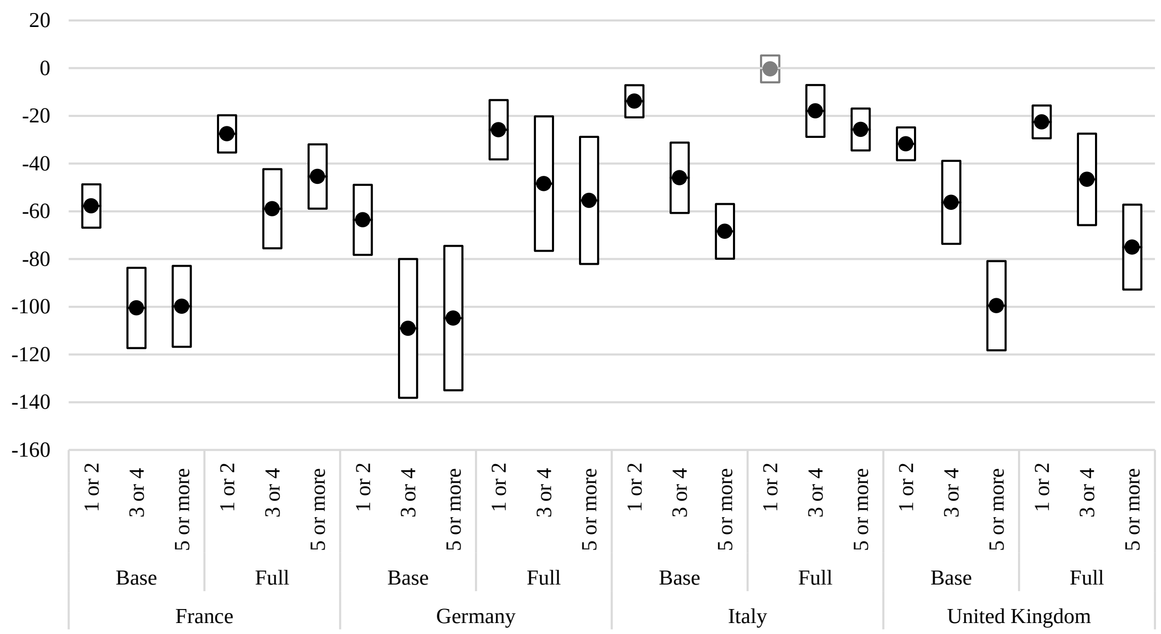
It may be noted that these negative gaps are larger than those of Section 5.1. This could be expected, given that *Days of absence* registers an interruption in learning due to any reason or group of reasons, while each of the four variables of interest in Section 5.1 were specific, and its correlation with scores was always tested controlling for the other three. Moreover, some motives for being absent from school can be correlated. For example, regarding remote schooling, it may be noted that the variables *No internet* and *No computer* at home are positively and significantly correlated in all five countries (Table SA1).

As in Section 5.1, most coefficients on our variables of interest are robust to the introduction of the control variables but can vary significantly with some of them. In France, coefficients shrink significantly when the types of schools attended are controlled for (columns 1 and 4 in Table SA1); in Italy, they vary when controlling for the types of schools and grades repetition; in Spain, they vary with grades repetition. These results, as those of Section 5.1, provide support to the findings of the literature on the relationships between inequalities in students' cognitive outcomes and countries' school systems (Checchi et al. 1999; Hanushek and Woessmann 2006; Brunello and Checchi, 2007; Ammermueller, 2013; Murat and Frederic, 2014; Woessmann, 2016).

Figure B1. - Absence from school. Student scores in mathematics and reading



(a) Days of absence - Math score



(b) Days of absence - Reading score

Note: Dependent variable: (a) mathematics score; (b) reading score. Coefficients on days of absence in the y-axis (base: no days of absence). The base regression includes only the four variables of interest; the full regression includes all the covariates of equation (SA1) gender, age, repeated grade, immigrant status, age of arrival, highest parents' level of education, school types (general, technical, vocational), public school (versus private) and school fixed effects. Grey denotes significance below five percent.

Table B1. - Absence from school. Dependent variable: Students' scores in mathematics.

	France							Germany						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
Days of absence: 1-2	-46.098***	-47.203***	-38.982***	-19.423***	-38.617***	-20.122***	-18.392***	-55.351***	-55.581***	-49.426***	-48.971***	-48.897***	-40.497***	-23.009***
Days of absence: 3-4	-70.258***	-71.619***	-63.651***	-31.616***	-52.233***	-35.290***	-33.471***	-87.753***	-87.846***	-78.399***	-79.600***	-77.065***	-66.699***	-41.986***
Days of absence: 5 +	-91.166***	-94.313***	-81.159***	-46.620***	-72.238***	-49.214***	-44.005***	-75.230***	-77.126***	-66.694***	-59.951***	-60.375***	-52.007***	-36.627***
Female		-13.594***				-25.272***	-21.764***		-8.922**				-14.857***	-25.516***
Age		18.536***				4.524	2.725		21.318**				28.872***	28.798***
Parents' education			16.695***			7.352***	5.427***			13.680***			10.338***	3.597***
Immigrant status			-30.724***			-27.363***	-25.014***			-29.130***			-20.915***	-16.396***
Age of arrival			-1.917**			0.496	-0.008			-4.733***			-3.753***	-1.455
Technical school				-105.227***		-85.643***					-61.434***		-46.629***	
Vocational school				-159.500***		-131.944***					-94.507***		-78.911***	
Public school				-26.924***		-20.766***					-9.089		0.058	
Repeated grade					-114.059***	-38.465***	-46.929***					-68.965***	-44.519***	-36.117***
Constant	509.438***	222.381***	431.249***	561.208***	524.477***	464.059***	456.225***	521.411***	187.983	469.254***	554.346***	532.968***	57.296	69.424
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	4,947	4,947	4,834	4,455	4,940	4,368	4,831	2,523	2,523	2,374	2,202	2,489	2,065	2,370
R^2	0.063	0.072	0.142	0.403	0.255	0.455	0.522	0.054	0.060	0.147	0.172	0.128	0.269	0.538

	Italy							Spain						
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
Days of absence: 1-2	-19.082***	-19.088***	-18.183***	-16.429***	-16.306***	-15.133***	-3.697	-23.560***	-23.710***	-20.499***	-22.295***	-12.221***	-11.466***	-8.698***
Days of absence: 3-4	-44.113***	-43.943***	-44.325***	-27.999***	-40.667***	-28.993***	-16.576***	-54.656***	-55.167***	-50.992***	-52.086***	-33.654***	-33.709***	-28.440***
Days of absence: 5 +	-59.820***	-60.944***	-57.499***	-40.407***	-49.802***	-37.420***	-17.359***	-69.657***	-70.642***	-63.674***	-64.672***	-40.633***	-40.512***	-35.631***
Female		-16.606***				-28.421***	-22.461***		-7.455***				-15.538***	-16.872***
Age		23.701***				14.358***	13.220***		20.339***				11.651***	11.348***
Parents' education			10.375***			4.009***	-0.354			11.108***			5.503***	3.432***
Immigrant status			-20.991***			-1.490	-12.646**			-20.530***			-7.242**	-6.387*
Age of arrival			-2.687**			-1.750*	-1.580			-3.214***			-2.209***	-2.259***
Technical school				-40.444***		-40.815***								
Vocational school				-103.905***		-92.031***					-82.226***		-27.909**	
Public school				-17.415		-9.092					-22.820***		-5.327*	
Repeated grade					-69.921***	-47.619***	-41.165***					-98.603***	-89.857***	-89.220***
Constant	505.496***	139.885*	463.173***	551.219***	512.242***	317.725***	305.641***	494.372***	176.048***	447.042***	509.645***	516.965***	318.689***	329.055***
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	9,183	9,183	8,993	9,019	9,176	8,826	8,988	27,865	27,865	27,014	27,105	27,845	26,262	27,004
R^2	0.040	0.054	0.080	0.208	0.103	0.264	0.523	0.037	0.043	0.103	0.061	0.276	0.300	0.388

Appendix C. Robustness check: missing observations.

Table A1, on descriptive statistics, shows that observations are missing for some of the variables used in this study. While the problem is minor at the single variable level, it can become more serious in the full regressions, comprising several variables. Dropping all student observations that have a missing value on at least one variable could mean a substantial reduction in sample size that, in itself, could lead to biased results. Therefore, to control for the robustness of our results, we impute the missing values by using the 'mean imputation method' described in Little and Rubin (1987) and adapted to the PISA data by Woessmann et al. (2007) and Puma et al. (2009).

This method predicts the conditional mean for each missing observation on the explanatory variables using non-missing values of the specific variables and a set of explanatory variables observed for all students. It addresses the problem of missing values consistently with the multilevel analysis of estimation with PISA data (Puma et al., 2009).

More specifically, for each student *i* with missing data on a specific variable *M*, a set of 'fundamental' explanatory variables *E* with data available for all students is used to impute the missing data in the following way. Let *S* denote the set of students *z* with available data for *M*. Using the students in S, the variable *M* is regressed on *E*. Following Woessmann et al. (2007), the set of fundamental variables, *E*, includes gender, age, five grade dummies and five dummies for the number of books at home.[11]

$$M_{z\in S} = E_{z\in S}\theta + \varepsilon_{z\in S}$$

[11] We substituted the very few missing observations regarding the number of books at home with the median imputation of the lowest available value of the variable in either school or country.

Then, the coefficients from these regressions and the data on E_i are used to impute the value of *Mi* for the students with missing data.

$$\widetilde{\mathrm{M}}_{\mathrm{i}\notin\mathrm{S}} = \mathrm{E}_{\mathrm{i}\notin\mathrm{S}}\theta$$

Furthermore, to account for the possibility of non-randomly missing observations, and to avoid results being driven by imputed data, we include a vector of imputation dummy variables as controls in the estimation. This vector contains one dummy for each variable of the model that takes the value of one for observations with missing and thus imputed data and zero for observations with original data. The vector allows the observations with missing data on each variable to have their own intercepts. Also, we include interaction terms between each variable and the corresponding imputation dummy, which allows observations with missing data to also have their own slopes for the respective variable. These imputation controls make the results robust against possible bias arising from imputation errors in the variables (Woessmann et al., 2007).

We run OLS regressions with continuous or ordinal dependent variables and Probit or Bivariate Probit regressions with binary dependent variables. In the first case, missing observations are substituted by predicted values, in the second, by the values with the highest predicted probability.

We find that almost all coefficients from the regressions run with the sample comprising the imputed missing data are not significantly different from those obtained with the original sample. Results on data from Germany evidence a minor variation in the coefficient on *No computer* at home in the full biprobit regression; it loses significance (Table B1, in the Appendix). Results on the United Kingdom show the coefficient that the coefficient on *Few school ICT* is now significant in the full regression. Other coefficients do not differ significantly from those obtained with the regressions on the original data, which supports the robustness of this study's results.

Table C1. – Remote learning resources. Imputed values. Dependent variable: student scores in mathematics.

	France			Germany			Italy			Spain			United Kingdom		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE
No computer	-59.628***	-22.588***	-21.200***	-75.415***	-42.305***	-26.493***	-43.112***	-24.741***	-16.018***	-47.712***	-12.976***	-10.931***	-45.418***	-36.917***	-29.689***
No internet	-25.275**	-18.757*	-3.565	-47.625***	-26.727***	-24.359***	-36.248***	-19.703**	-6.486	-21.078***	-0.884	0.066	-90.690***	-80.475***	-69.929***
No quiet place to study	-34.927***	-8.891**	-5.635	-33.515***	-11.444*	-0.632	-12.775**	0.217	-0.193	-8.269**	-1.527	-0.358	-24.743***	-20.531***	-13.627***
Few school ICT	-13.234	3.820		-3.966	-3.369		-39.999***	-21.725***		-7.218***	0.183		-10.667	-11.377*	
Female		-22.721***	-19.554***		-14.782***	-19.961***		-28.804***	-23.227***		-15.845***	-16.395***		-13.251***	-14.578***
Age		2.653	3.397		32.172***	33.567***		10.293**	9.607***		11.729***	11.158***		18.521***	14.842***
Parents' education		5.722***	4.041***		8.816***	3.165***		3.307***	-0.940		5.509***	3.532***		11.313***	4.917***
Immigrant status		-25.372***	-20.585***		-24.026***	-16.294***		-1.299	-12.462***		-6.106*	-4.934		-10.698**	-3.991
Age of arrival		0.006	-0.278		-2.984***	-1.985***		-1.612*	-1.632*		-2.375***	-2.342***		0.800	0.716
Technical school		-90.421***			-41.056***			-41.364***			127.433				
Vocational school		-142.423***			-80.405***			-92.156***			-27.502***				
Public school		-22.165***			1.877			-5.524			-6.548***			-25.244***	
Repeated grade		-31.466***	-45.061***		-49.002***	-37.180***		-50.626***	-43.253***		-90.535***	-89.726***		-56.686***	-46.333***
Constant	510.594***	499.580***	444.879***	516.701***	8.185	-5.817	505.478***	377.900***	369.105***	490.384***	313.813***	329.524***	516.010***	189.506**	265.303***
Vector of imputation dummy and interaction	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
School FE	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Observations	6,308	6,308	6,308	5,451	5,451	5,451	11,785	11,785	11,785	35,943	35,943	35,943	13,818	13,818	13,818
R^2	0.075	0.469	0.530	0.098	0.350	0.541	0.076	0.299	0.533	0.042	0.317	0.392	0.049	0.129	0.284

Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients on *School type* is “general school”. Regressions on sample with imputed values.

Table C2. – Remote learning resources. Imputed values. Dependent variable: student scores in reading

	France			Germany			Italy			United Kingdom		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE
No computer	-62.433***	-22.008***	-20.572***	-80.717***	-43.102***	-26.919***	-42.202***	-21.840***	-14.683***	-43.323***	-34.158***	-27.708***
No internet	-28.441**	-21.092**	-5.942	-58.807***	-33.578***	-28.778***	-35.007***	-20.099***	-6.974	-82.179***	-66.431***	-56.234***
No quiet place to study	-34.369***	-8.332**	-5.851	-40.708***	-14.123*	-2.160	-20.551***	-5.620	-5.160	-21.011***	-17.478***	-11.501**
Few school ICT	-15.825	3.094		-1.445	-0.502		-34.390***	-17.565***		-9.660	-11.024*	
Female		7.787***	9.744***		17.982***	10.583***		8.173***	11.874***		19.119***	16.684***
Age		5.385	6.246*		25.706***	28.329***		9.551**	10.197***		17.271***	13.423***
Parents' education		3.815***	2.150**		8.941***	2.426***		1.432	-2.411***		10.897***	4.874***
Immigrant status		-22.720***	-19.748***		-22.283***	-14.705***		-6.872	-16.459***		-11.777**	-5.384
Age of arrival		-0.986*	-1.483***		-5.715***	-4.656***		-1.931***	-2.333***		-0.878	-1.059*
Technical school		-99.295***			-46.062***			-53.751***				
Vocational school		-145.384***			-89.696***			-99.824***				
Public school		-18.477***			10.130			-4.276			-21.126***	
Repeated grade		-29.183***	-51.874***		-46.756***	-33.344***		-49.084***	-42.968***		-59.941***	-49.086***
Constant	509.180***	447.886***	393.965***	515.041***	87.767	66.936	494.699***	373.638***	340.275***	517.736***	196.797***	276.992***
Vector of imputation dummy and interaction	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
School FE	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Observations	6,308	6,308	6,308	5,451	5,451	5,451	11,785	11,785	11,785	13,818	13,818	13,818
R^2	0.075	0.438	0.502	0.097	0.351	0.548	0.066	0.313	0.507	0.041	0.116	0.255

Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients on *School type* is “general school”. Regressions on sample with imputed values.

Table C3. - Absence from school. Imputed values. Dependent variable: student scores in mathematics

	France			Germany			Italy			Spain			United Kingdom		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE
Days of absence: 1-2	-46.098***	-19.309***	-17.847***	-55.351***	-41.961***	-23.997***	-19.082***	-14.224***	-2.606	-23.560***	-11.012***	-8.601***	-36.014***	-30.865***	-25.238***
Days of absence: 3-4	-70.258***	-32.629***	-31.828***	-87.753***	-65.461***	-45.455***	-44.113***	-27.555***	-14.462**	-54.656***	-32.600***	-27.274***	-65.262***	-62.114***	-53.037***
Days of absence: 5 +	-91.166***	-49.286***	-44.647***	-75.230***	-55.612***	-42.126***	-59.820***	-36.800***	-14.965**	-69.657***	-40.422***	-36.775***	-91.505***	-80.210***	-68.337***
Female		-23.777***	-20.343***		-15.747***	-20.520***		-30.039***	-23.280***		-15.853***	-16.443***		-13.538***	-14.638***
Age		2.954	3.776		32.436***	33.517***		10.356**	10.119***		12.108***	11.420***		18.090***	14.943***
Parents' education		6.217***	4.321***		9.772***	3.753***		3.519***	-0.921		5.709***	3.695***		11.984***	5.333***
Immigrant status		-26.054***	-21.060***		-24.545***	-15.854***		-0.021	-12.424***		-6.935**	-5.511*		-10.006**	-4.618
Age of arrival		-0.011	-0.253		-3.509***	-2.349***		-1.751**	-1.678*		-2.323***	-2.311***		0.684	0.650
Technical school		-87.818***			-42.300***			-41.286***			84.376**				
Vocational school		-139.841***			-81.041***			-95.177***			-27.969***				
Public school		-20.555***			3.246			-9.356			-6.085**			-23.164***	
Repeated grade		-34.697***	-45.705***		-51.031***	-38.403***		-49.103***	-42.268***		-89.926***	-89.014***		-57.192***	-48.218***
Constant	509.438***	493.673***	439.148***	521.411***	1.392	-17.758	505.496***	384.318***	353.856***	494.372***	311.017***	324.366***	513.717***	192.163**	261.105***
Vector of imputation dummy and interaction	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
School FE	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Observations	6,308	6,308	6,308	5,451	5,451	5,451	11,785	11,785	11,785	35,943	35,943	35,943	13,818	13,818	13,818
R^2	0.059	0.472	.0.534	0.040	0.344	0.538	0.064	0.297	0.534	0.030	0.323	0.396	0.052	0.138	0.292

Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients on *School type* is "general school". The base level of the days of absence is no days. Regressions on sample with imputed values.

Table C4. - Absence from school. Imputed values. Dependent variable: student scores in reading.

	France			Germany			Italy			United Kingdom		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE
Days of absence: 1-2	-57.775***	-28.822***	-26.908***	-63.560***	-47.933***	-27.068***	-13.878***	-9.281***	0.853	-31.715***	-27.296***	-21.774***
Days of absence: 3-4	-100.495***	-56.730***	-56.465***	-109.104***	-78.958***	-54.718***	-45.943***	-28.197***	-16.911***	-56.252***	-54.678***	-46.469***
Days of absence: 5 +	-99.803***	-50.915***	-46.404***	-104.759***	-79.614***	-63.764***	-68.396***	-42.493***	-22.916***	-99.557***	-83.372***	-70.724***
Female		6.389***	8.624***		16.932***	9.970***		7.093**	11.734***		18.569***	16.405***
Age		5.802*	6.762*		25.828***	28.307***		9.650**	10.556***		16.604***	13.350***
Parents' education		4.172***	2.384***		9.935***	3.057***		1.729*	-2.250***		11.519***	5.291***
Immigrant status		-23.110***	-20.183***		-22.391***	-14.210***		-5.717	-16.593***		-10.863**	-5.786
Age of arrival		-0.838	-1.291**		-6.253***	-5.024***		-2.130***	-2.451***		-0.991	-1.129**
Technical school		-94.986***			-47.292***			-53.992***				
Vocational school		-140.306***			-90.081***			-101.823***				
Public school		-15.868***			11.429			-7.315			-18.855***	
Repeated grade		-32.147***	-51.168***		-48.517***	-34.364***		-47.309***	-41.991***		-59.958***	-50.812***
Constant	511.736***	443.192***	389.969***	522.872***	85.553	54.102	494.983***	378.395***	326.514***	516.464***	203.720***	275.230***
Vector of imputation dummy and interaction	yes	yes	yes	yes	yes	Yes	yes	yes	yes	yes	yes	yes
School FE	no	no	yes	no	no	Yes	no	no	yes	no	no	yes
Observations	6,308	6,308	6,308	5,451	5,451	5,451	11,785	11,785	11,785	13,818	13,818	13,818
R^2	0.084	0.449	0.511	0.045	0.350	0.548	0.069	0.318	.0509	0.053	0.130	0.265

Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients on *School type* is “general school”. The base level of the days of absence is no days. Regressions on sample with imputed values.