Coronavirus pandemic, remote learning and education inequalities

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Abstract. School closures during the coronavirus pandemic of 2020 forced countries to swiftly adopt distance learning, with uncertain effects on education inequalities. Using PISA 2018 data from France, Germany, Italy, Spain and the United Kingdom, we find that students unable to learn remotely, because of a lack of the necessary ICT resources at home or at school or of a quiet place to study, experience significant cognitive losses that, everything else equal, range from 70 percent of a school year in the United Kingdom to 50 percent in Italy. Similar results are found by considering days of absence from school. In both approaches, the distribution of cognitive losses is associated with countries' educational systems. In the longer run, students who cannot learn remotely are more likely to end their education early and repeat grades. The two outcomes strongly reinforce each other in Spain, Germany and Italy. Results – robust to different specifications and the imputation of missing data – imply that countries must enhance e-learning and support disadvantaged students, but tune these measures to the characteristics of their educational systems.

Keywords: Coronavirus pandemic, education, inequality, PISA.
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1. Introduction

The coronavirus pandemic of 2020 forced countries to close schools and swift to distance learning almost overnight, without having the possibility to implement it properly or even consider its potential effects on education. However, recent studies find that distance learning can only partially substitute for physical school attendance and predict a generalized decline in education levels as an effect of school closures (Burgess and Sievertsen, 2020; Haeck and Lefebvre, 2020; Kuhfeld et al., 2020; Psacharopoulos et al., 2020, Van Lancker and Parolin, 2020). Moreover, and possibly with longer-lasting consequences, distance learning may exacerbate existing education inequalities. Differently from face-to-face schooling, its effectiveness crucially depends on students' concrete possibilities to attend virtual classes, and on schools and teachers effectively providing them. The problem of inadequate resources and skills is particularly dramatic in low-income economies, but concerns also middle-income and developed countries. In the latter, where most distance schooling takes place through the internet, students must possess, at least, a computer for their schoolwork and an internet connection at home, and schools must provide online teaching.[1] The available evidence shows that, even in rich countries, these basic conditions are often not met. This paper focuses on the education inequalities arising from school closures during the pandemic; it measures the cognitive losses of students unable to learn remotely, and the consequences of these losses on their planned lifetime investments in education.

Since during our investigation reliable data on students' school performance during the 2020 pandemic are not available, we gauge the links between students learning remotely and their education performances by using data from the 2018 wave of the Program for International Student Assessment (PISA), an 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. We focus on five developed countries – France, Germany, Italy, Spain and United Kingdom – which share geographic, cultural, economic and institutional characteristics but differ in some aspects of their school systems. They were all reached by the COVID-19 pandemics between the end of February and beginning of March 2020, and adopted similar measures concerning school closures and remote learning.[2] They are all rich and technologically advanced, but the still preliminary available data evidences that about 10 to 20 percent

[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 – to 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] However, measures differ in some degree 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.

of students in them were not able to learn remotely (Andrew et al., 2020; Autorità garante per le comunicazioni, 2020; Anger et al. 2020;).

To test the potential relationships between students' cognitive outcomes and remote learning, we follow two main routes. The first is based on students' concrete possibilities of learning remotely and focuses on whether they possess a computer for their schoolwork, an internet connection and a quiet place to study at home, and on whether schools can provide classes remotely. The second, more directly measures the correlations between scores and not attending remote schooling, and relies on data of days of absence from school.[3] The first approach measures the importance of home and school possessions and environment for remote learning to succeed, the second tests the consequences of the absence of remote learning.

Subsequently, we analyze whether learning remotely is also associated with students' expectations on their future education. In particular, students who fall behind their peers during school closures may find hard to reach them once back at school and, consequently, revise downwards their plans of investing in future education. These negative choices can be exacerbated in countries where repeating grades is more frequent, and students unable to learn online are likely of repeating a grade once back at school. We test these hypotheses by measuring whether variations in the conditions for learning remotely are correlated with students' planned investments in education, with the probability of repeating a grade, and with the joint probabilities of these two events. This study contributes to the research on education by providing measures of potential increases in short and long-run inequalities linked with remote learning during school closures. It also offers a novel perspective on the essential role of home and school ICT resources and skills in the formation of human capital.

Our main findings are that the lack of ICT resources, especially a computer at home for schoolwork, are strongly correlated with cognitive losses in all five countries. Results are similar when we test the correlations between scores and absence from school. Moreover, we find that these losses have long run implications. Students not able to learn remotely are more likely to revise downwards their plans on future education, especially when falling behind with respect to their peers increases their probability of repeating grades. We also find that cognitive losses are distributed across schools and family social conditions in relation to countries' educational systems. Our results are robust to the use of different specifications, covariates and to the imputation of missing data. The rest of this paper is structured as follows, Section 2 discusses the related literature, Section 3 presents the

[3] This variable is more appropriate for our analysis than that 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)

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

In March 5, 2020, schools closed in Italy, with the aim of reopening after ten days, but, six days later they closed also in Spain, eleven days later in France and most of Germany, and by March 20, also in the United Kingdom. During the second half of March, schools closed in almost all of Europe (Viner et al., 2020). Our five countries, as most countries in the world, opted for distance learning. They provided it mostly online, but TV and, in France, also radio transmissions were utilized (D'Addio, 2020; UNESCO, 2020; Center for Global Development, 2020). After several weeks, when eventually the number of people infected by the coronavirus fell at levels considered safe enough, schools started to reopen, first in Germany, in May 4, then in France, in May 16, and in the United Kingdom, in June 15. Italy and Spain kept them closed, with the aim of reopening them after the summer vacation. During the weeks of school closure, students in low-income households received some form of government support for learning online. The United Kingdom provided laptops and routers, while Italy supplied schools with funds to be used to furnish teachers or students with computers.

Although the five countries provided distance learning, the still scant and fragmentary evidence available while we research on this topic, suggests that the percentage of students who could not attend or attended only partially the virtual schooling may be higher than expected, especially if the advanced level of technological development of our five countries is considered. OECD data (OECD, 2020) on home computer possessions and internet connections show that, in them, about 90 percent households have access to the internet– except for Italy, where the figure is 85 percent - and between 72 percent and 93 percent households have a computer at home. The countries with the highest percentages of households with internet and computers are the United Kingdom and Germany.

Although they provide very basic information, these data are not truly useful for understanding the real possibilities of students to learn remotely because they regard normal times, when most of the learning and working take place outside home, and because they concern households, not individuals. During school closures and the lookdown of most economic and social activities, household members are likely to find that they need to use the available ICT resources much more than usual, but, in that situation, they also must share them. At the same time, they may also find that devices don't fill the standards needed to work efficiently; for example, computer softwares may be not updated, or internet access may be not powerful enough to handle multiple connections. 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.[4]

Moreover, for remote learning to work, ICT resources must be available and fully working also at school, and teachers must be skilled in teaching remotely. Some preliminary and partial evidence suggests that remote learning has been well below what could have been expected from our five rich and developed countries, not just because of households' deficiencies, but also because of school shortages of ICT devices, digital platforms and skilled teachers. Unexpectedly, this applies even to Germany; a country that has not extended its technological prominence to schools. Conrads et al. (2017), European commission (2019), Kerres (2020), UNESCO (2020) show German schools are on average less digitalized than those of other developed countries.

These shortages and disparities are evidenced also by PISA 2018 data on ICT resources in the schools of fifteen-year-old students (mostly upper secondary). Figure 1 shows the percentages of positive answers to the question *Does your school have a programme to use digital devices for teaching and learning in specific subjects?* of the schools' PISA Questionnaire [SC156Q03HA]. In the United Kingdom and France, positive answers are about 70 percent, in the other three countries, they are between 30 percent and 40 percent.

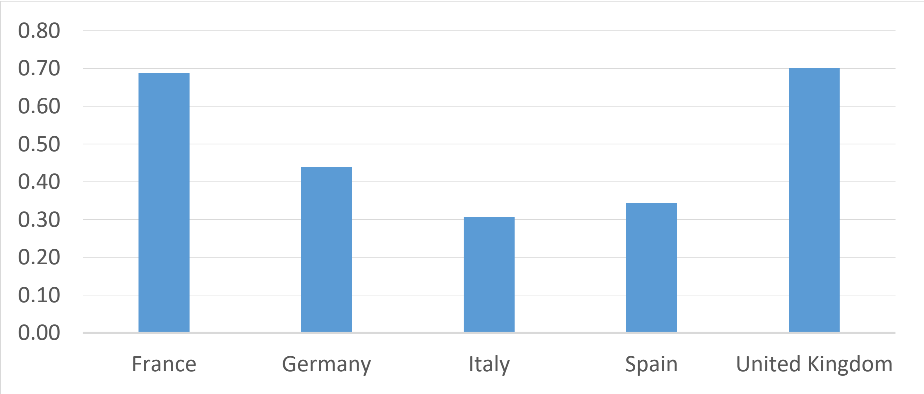


Figure 1. - Percentage of schools providing a digital devices programme for teaching and learning in specific subjects.
Note. Percentages of "yes" in each country to the related question (SC156Q03HA) in PISA 2018 School questionnaire.

[4] 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 8,175,000, representing about 24.2 percent of the total. Percentages increase to about 30 percent at lower income levels, higher median age, the country's South and small towns (ISTAT, 2020)

The answers to a related question, regarding whether *An effective online learning support is available at school*? are in Figure 2, where percentages concern 'agree' and 'strongly agree'. [SC155Q09HA]. Also in this case, about 70 percent schools respond positively in the United Kingdom, followed by about 50 percent in France and by lower percentages in the other three countries.[5] The descriptive statistics of Table A1 show similar results for a question regarding the availability of only few ICT resources at school; in 56 percent of schools in Germany computers are not enough; these percentages are lower in France (26 percent), Italy (29 percent) and the United Kingdom (31 percent).

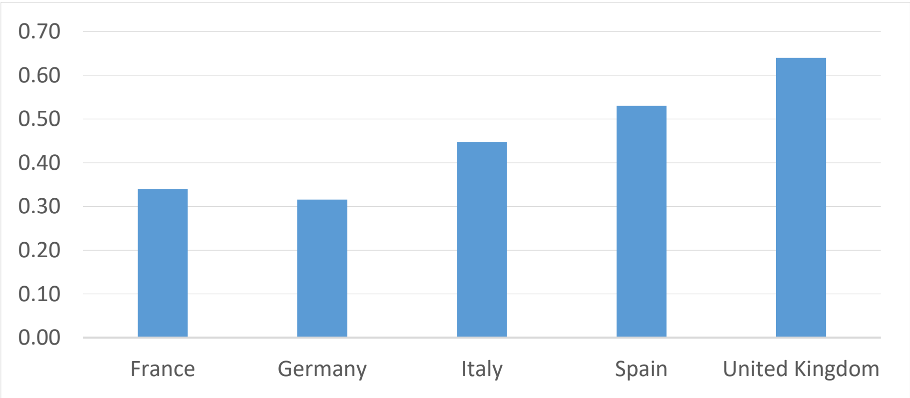


Figure 2. Percentage of schools providing an effective online learning support.
Note: Percentage of "agree" and "strongly agree" in each country to the related question (SC155Q09HA) in PISA 2018 School questionnaire

The preliminary and partial evidence on remote learning during school closures is provided by surveys conducted in some of the countries considered. In England (not the whole of the United Kingdom), a survey of 3,091 children in primary and 1,554 students in secondary school, shows that only about 25 percent children in primary school and 62 percent of students in secondary school had exclusive access to a computer for school work. Only about 40 percent of children in primary and 58 percent in secondary school attended online classes, and the percentages regarding online video chats were 16 percent and 26 percent respectively. At both levels, primary and secondary, between 10 percent and 12 percent of students had no devices at all (Andrew et al., 2020). A survey on distance learning in Italy shows that only 40 percent of students could fully participate in remote learning; 10 percent could not participate at all; 20 percent said that they could attend only occasionally (Autorità Garante per le Comunicazioni, 2020). A survey in Germany considering only 1,027 students in their

[5] A related indicator, concerning the lack of computers at school, is in the descriptive statistics of Table A1. A study by the European Commission on the use of ICT in education, at the ISCED 1, 2 and 3 levels, provides evidence that is similar to that of Table A1 and Figures 1 and 2 (European Commission, 2019).

graduation and pre-graduation years, in 195 high schools in eight German federal states, evidences that less than 50 percent of respondents received digital learning opportunities or material through online platform, email or video conferencing. However, only about 15 percent of them had videoconferencing (such as Skype) interactions with teachers. There are no data on the proportion of students that were entirely disconnected from the 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 is thought to apply also to the other two countries, then, overall, only between 30 percent to 50 percent of students could attend school online, and from 10 to 20 percent had no remote learning at all. The latter percentages are most likely to increase in primary education and in poorer households and schools.

2.2. Literature

The potential educational, economic, social and health effects of the unprecedented long school closure due to the coronavirus pandemic are analyzed by many researchers from different disciplines. Empirical studies are based on the very scant data collected in a few countries during and after the periods of school closures and, mostly, on previous findings on school interruptions during vacations or unexpected events. Several studies find that summer vacations are followed by sizable and significant cognitive losses, which often concern mathematics more than reading, and tend to be higher for students from lower socio economic status (Downey et al., 2004; Quinn et al., 2017; Atteberry, and McEachin 2020; Carvalho et al., 2020).

Trying to predict the effects of the coronavirus pandemic, Kuhfeld et al. (2020) review the existing evidence on missing school during normal times, due to vacations or absenteeism. They 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. Van Lancker and Parolin (2020) find that summer vacation 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). Another factor likely to negatively influence cognitive outcomes is absenteeism. Students missing school days are found 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 deeper 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. In Pane et al (2008) and 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 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, while several empirical studies on the effects of providing students with ICT resources remain inconclusive (Yanguas, 2020; Fairlie, 2005). 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 concrete choices made by countries on this issue have proven crucial in 2020, when schools suddenly had to go online because of the pandemic. As seen above, and as clearly evidenced by the survey of the European Commission (2019) on the use of ICT resources at school, even among our five European countries there are important disparities.

3. Data and descriptive statistics

3.1. Data

To test our hypotheses, we use the 2018 wave of PISA assessment, focusing on data from France, Germany, Italy, Spain and the United Kingdom and using information from both the Student and the School Questionnaires. We focus on students' test scores in mathematics and reading, except, for the latter, Spain, from which these data are not available in PISA 2018. To save space, we do not include results on science, the third field of PISA surveys, but we checked that results based on these data mostly replicate those in mathematics and reading. They are available from the authors upon request. Overall, we consider 73,305 students enrolled in over 2,577 schools in the five countries. [6] 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. All throughout the paper we make use of the final student weights, which allow us to scale the sample up to the size of the countries' populations and take into account the oversampling of specific regions and provinces. In

[6] Surveyed schools are 1,089 in Spain, 471 in United Kingdom, 542 in Italy, 252 in France, 223 in Germany. Students are 35,943 in Spain, 13,818 in United Kingdom, 11,785 in Italy, 6,308 in France, 5,451 in Germany.

each country, the sample represents about 95 percent of the population of 15-year-old students. 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 (PISA, 2018, provides detailed technical information).

3.2. Descriptive statistics

Our variables of interest are the ICT resources at home and at school, the availability of a quiet place to study, absenteeism and the plans made by students on the length of their future education. To build these variables, we use data from some questions in the PISA questionnaires. Regarding the availability of ICT resources at home and at school and of a quiet place to study, we use the data from the following questions: (in the Student's Questionnaire) *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 (in 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'. To derive a measure of absenteeism, we focus on 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'. Regarding the planned length of students' education, the question is: *Which of the following do you expect to complete?* answers range from lower secondary to advanced tertiary and research education programs. Our control variables are gender, age, higher level of education of parents (HISCED), immigration status (which includes first and second generation immigrant students), age of arrival into the country, and whether the student has repeated one or more school years.

Descriptive statistics and correlations are in Table A1 and Table A2 in the Appendix. There, the percentage of students without a computer at home range between 8 percent in Germany to 10 percent in Italy, while an internet connection is absent in the homes of 1 percent of students in the United Kingdom and 3 percent in Italy. The lack of a quiet place to study varies from 5 percent in Germany to 11 percent in the United Kingdom. Students are absent from school more frequently in

Italy and in Spain than in other countries. Consistently with the evidence considered above, ICT resources at school are undersupplied in more than 50 percent of schools in Germany and about 26 percent in Spain.

Grade repetition is unusual in the United Kingdom and frequent in the other four countries, especially Spain and Germany, where it reaches, respectively 29 and 20 percent of students. Schools 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). Leaving school early, at most when completing upper secondary studies, ranges from 30 percent in Germany (where, however, vocational school may be attended while working part-time) to seven percent in Italy.

4. Empirical strategy

To gauge the links between remote learning and education outcomes, we follow different routes. First, we test the correlations between the students' scores in mathematics or reading and the lack of ICT resources at home or at school and of a quiet place to study. Second, we test the correlation between students' scores and days of absence from school. Third, we test the correlations between the probabilities of leaving education early and repeating a grade, both regressed on our variables of interest and control variables. In all cases, regressions are run separately for each country. To test the first of our hypotheses, we use the 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, 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 our second specification, where we measure the correlation between scores in mathematics or reading and days of absence from school, we use an ordinal variable, with values going from no days of absence to five or more days of absence in the two full school weeks before the test. Control variables are as in equation (1).

$$\text{Test scores}_{ij} = \alpha_1 + \beta_1 \text{Days of absence}_{ij} + X_{ij}\Pi + \lambda_j + v_j + \varepsilon_{ij} \qquad (2)$$

In our third set of tests, we use Probit specifications to test the correlations between the probability of leaving education early and our variables of interest: lack of computer at home or at school, a quiet place to study, or an internet connection. To build the dependent variable, concerning the students' plans on the length of their future education, we consider the question *Which of the following do you expect to complete*? from the PISA Questionnaire, and give value 1 to students expecting to complete only lower or upper secondary studies (ISCED levels 2, 3B or 3C), and zero to students expecting to complete higher education levels.[7] 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 repeating a school year is unusual. Afterwards, by using a Bivariate Probit specification, we test the joint probabilities, by checking whether the residuals of the two regressions are significantly correlated. The Probit and Bivariate Probit specifications on leaving school early and repeating a school year are:

$$\text{Leaving education early}^*_{ij} = \alpha_1 + \beta_1 \text{No computer}_{ij} + \beta_2 \text{No internet}_{ij} + \beta_3 \text{No quiet place}_{ij} + \beta_4 \text{Few school ICT}_j + W_{ij}\Pi + v_j + \varepsilon_{1ij} \qquad (3)$$

$$\text{Repeated grade}^*_{ij} = \alpha_1 + \beta_1 \text{No computer}_{ij} + \beta_2 \text{No internet}_{ij} + \beta_3 \text{No quiet place}_{ij} + \beta_4 \text{Few school ICT}_j + W_{ij}\Pi + v_j + \varepsilon_{2ij} \qquad (4)$$

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:

[7] ISCED 3 B or C are typically completed after 10 years of schooling in Spain, 11 in the United Kingdom, 12 in Italy and Spain, and 13 in Germany. Therefore, the age at which secondary education is completed depends on the starting age of compulsory education and the design of lower and upper secondary school in each country (children start compulsory education when they are five years old in the United Kingdom and six years in the other four countries).

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

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 and a quiet place to study.

In this Section we present the results of estimating equation (1) using the data from our countries (all regarding mathematics and all except Spain concerning reading). Figure 3depicts the negative gaps in mathematics. They are the coefficients on our variables of interest, first from a base regression – including only the variables of interest *No computer*, *No internet*, *No quiet place to study*, *Few school ICT* –, and, second, from the full regressions comprising all covariates and school fixed effects (except, to avoid collinearities, for the coefficient on *Few school ICT*, which corresponds to the full regression without school fixed effects) Tables A3 and A4 in the Appendix report complete coefficients, regarding the scores in mathematics and reading. Coefficients are easier to interpret by considering that, as specified in OECD (2019), in the average of OECD countries, 40 score points (over a mean of about 500) equals the cognitive content of about one school year.

In Figure 3, all coefficients on the four variables of interest resulting from the base regressions are strongly negative. With the exception of *No internet* at home in France and *Few school ICT* at school in France, Germany and the United Kingdom, they are also all significant at least at the 5 percent level. Specifically, in the base specifications, *not having a computer at home* is correlated with a negative gap of about one and 70 percent of a school year in Germany, one and a half year in France, more than one year in Italy, Spain and the United Kingdom; significance is at the one percent level in all cases. Moreover, as shown in Table A3, these coefficients are robust to the inclusion of gender and age in the regressions. Coefficient sizes, but not their significance, decrease slightly when controlling for the level of parents’ education, immigrant status and age of arrival into the country. Their size shrinks more when school types are included in the regressions on data from France, Germany and Italy. With grade repetition, they shrink especially in the countries where the phenomenon is more frequent, Spain, Germany, France and Italy (descriptive statistics in Table A1).

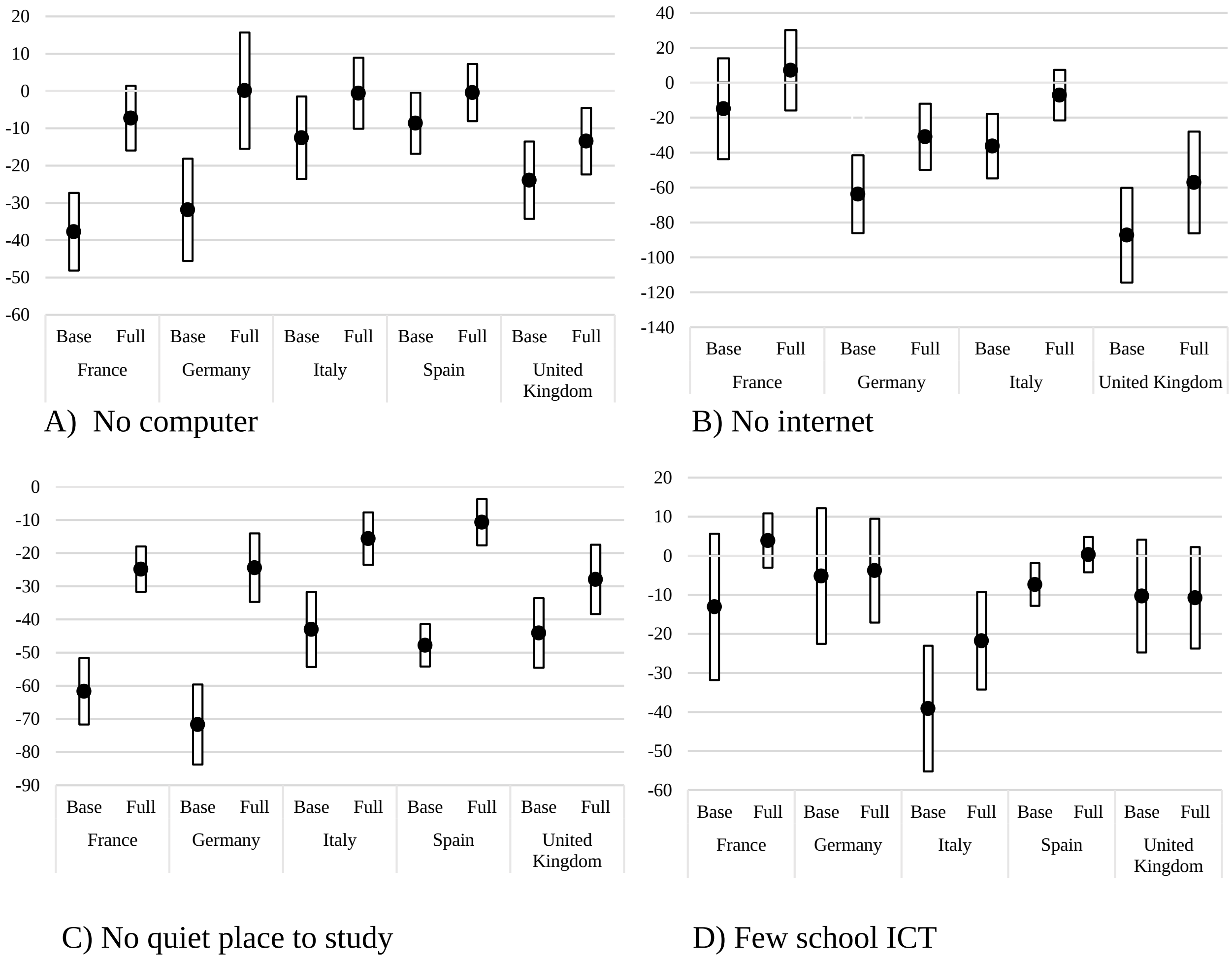


Figure 3. - Gaps in mathematics, ICT resources and a quiet place to study.
Note. Coefficients on each variable in the y-axes. Dependent variable: math score

When all cofactors are controlled for, and school fixed effects are included into the regressions, the cognitive losses of students not having a computer at home remain significant at the one percent level in the five countries, with their size decreasing by about 60 percent in Germany, Spain, France and Italy, and by less than 50 percent in the United Kingdom (Figure 3a). In France and Italy, coefficients vary with the types schools attended more than with other cofactors; in Germany and the United Kingdom, they interact with social conditions at home, and in Spain with grade repetition (Table A3).

Coefficients on the *unavailability of an internet connection at home* in the base model are negative in all countries and are also significant, except, as said above, France (Figure 3; Tables A3-4). Not having an internet connection is correlated with a cognitive losses corresponding to two school years in the United Kingdom, more than one year in Germany, and less than one school year in Spain and Italy. In Italy, the coefficient loses significance when school fixed effects are included into the regression, evidencing that students without internet at home are not evenly distribute across schools, while in Spain it loses significance when family social conditions are controlled for (parents' levels of education, immigrant status, age of arrival). Coefficients in Germany and the United Kingdom are robust to all specifications and, when all cofactors and school fixed effects are controlled for, losses equal two thirds of a year in Germany and almost two years in the United Kingdom (column 34 in Table A3 and 28 in Table A4). It is interesting to note that, among the five countries, the United Kingdom exhibits both the highest losses and the lowest percentage of families without internet access (Table A1), which suggests that proportionately fewer students in the United Kingdom live in households without internet, but they are more marginalized than in the other four countries.

Not having a quiet place to study at home is correlated with negative gaps of about one school year in France and Germany and more than half year in the United Kingdom. Coefficients are smaller but also negative and significant in Italy and Spain; there, they lose significance once social conditions are controlled for. In Germany the coefficient size shrinks and loses significance when school fixed effects are controlled for. In France and the United Kingdom, negative gaps remain significant even when all other variables are controlled for (Figure 3; and Tables A3-4).

The *scarce availability of ICT devices at school* is negatively correlated with scores in all regressions, but significance is above 10 percent only in Italy and Spain. In the base regressions, they equal one school year in Italy and about a fourth of a year in Spain. In both countries, gaps shrink when school types are controlled for and, when all cofactors are included, remain significant only in Italy. Among the four variables of interest, this appears to be the less correlated with students' scores. However, this result may depend on the still scarce development of e-learning in schools. More generally, most coefficients on our variables of interest are robust to all controls. This especially applies to a lack of a computer at home, followed by not having an internet connection, or a quiet place to study. Moreover, the cognitive losses deriving from the lack of the resources needed to learn online are similar in mathematics and reading; they are not smaller in reading (Figure A1 and Table A4). This differs from results of empirical studies on school interruptions that find the losses in mathematics to be wider than those in reading Gottfried, 2009 and 2011; Quinn and Polikoff, 2017).

5.2. Absence from school

We now follow the alternative approach to gauge the correlations between not learning and school outcomes that focuses on students' days of absence from school (equation 2, above).[8] As

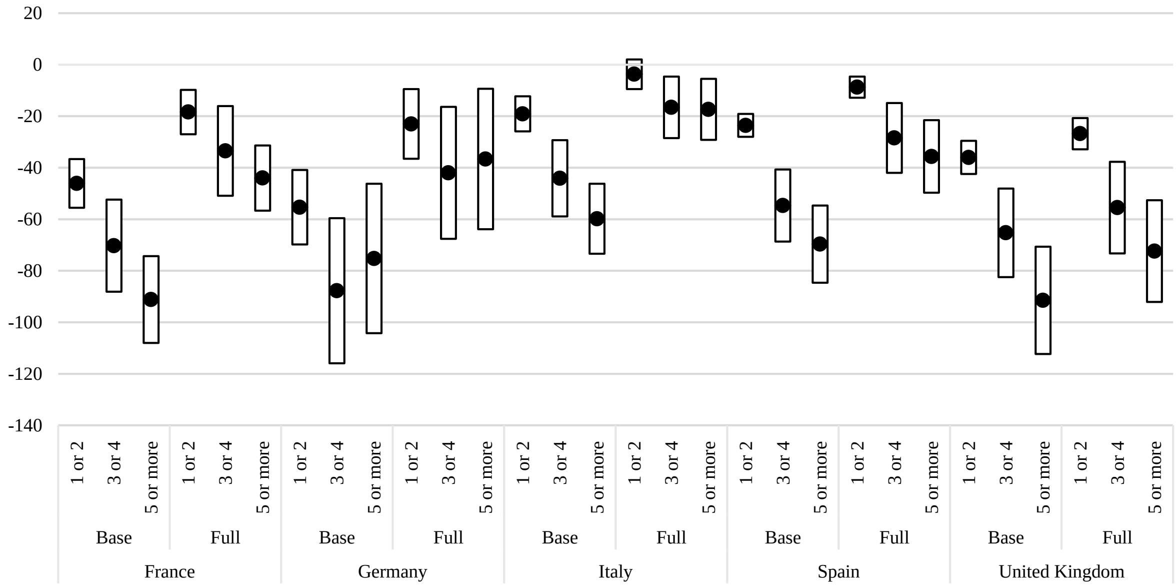
[8] A student can skip remote schooling because of a lack of ICT resources at home or at school or a quiet place to study. Since they are meant to be alternative explanations of the same phenomenon, equation (1) did not control for absence from school, and equation (2) does not control for the lack of ICT resources or a quiet place to study.

already seen, the question on absence from school in the PISA survey regards the number of school days the student missed in the last full two weeks; answers can range from zero to more than five days.[9] In the regression, the variable *Days of absence* from school takes four values, each corresponding to the days of absence: ‘zero days’ is ‘absorbed’ into the intercept, and values one, two and three correspond to absences of, respectively, one or two days, three or four days, and five or more days.

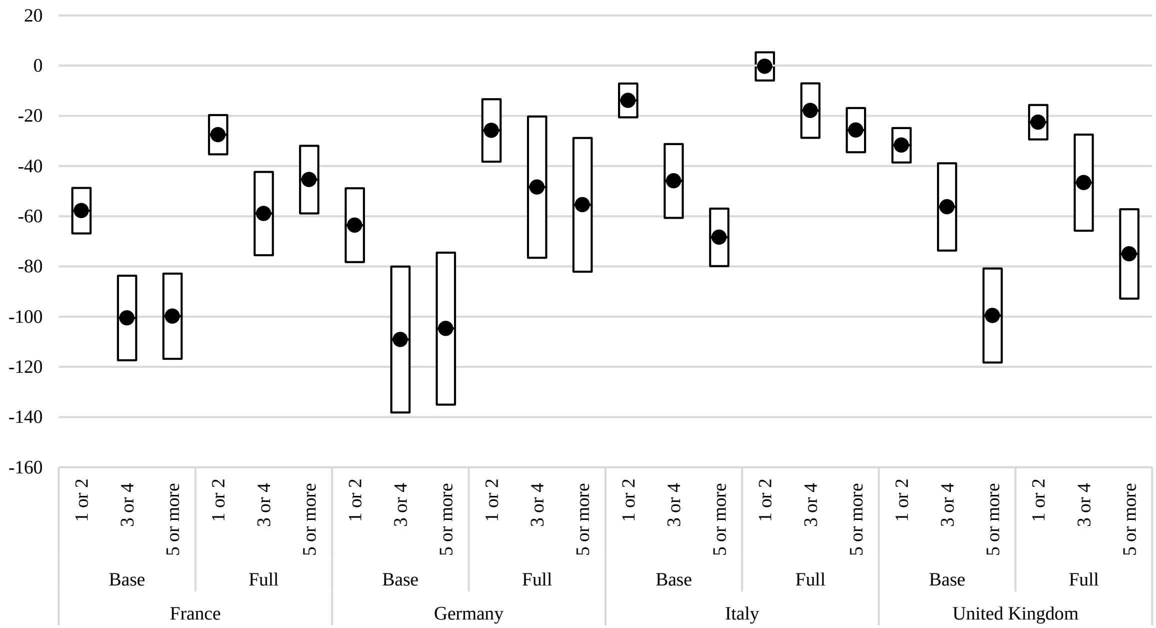
Figures 4 a-b and Tables A5-A6 report the results of these tests. The main findings are that, first, not attending school is correlated with strong, negative and significant gaps in scores in both mathematics and reading, which substantially grow with the days of school missed. Second, losses in reading tend to be slightly wider than those in mathematics; also in this case, this 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). Third, 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.

Specifically, in Figure 4 and the base regressions of Tables A5-A6, being absent from school *one or two days* in two weeks is correlated with cognitive losses in mathematics and reading corresponding to more than a school year in France and Germany, almost a school year in the United Kingdom, and about two thirds of a school year in Italy and Spain (columns 1, 8, 15, 22 and 29 in Table A5, and 1, 8, 15 and 22 in Table A6). Being absent for *five or more days* leads to substantially higher losses, of more than two and half years in Germany in reading and slightly less in mathematics, of almost two and a half years in France and the United Kingdom in both fields, and of about one and a half year in Italy and Spain in both mathematics and reading (columns 7, 14, 21, 28 and 35 in Table A5, and 7, 14, 21 and 28 in Table A6). As expected, coefficients shrink in all countries when cofactors are included into the regressions. In particular, they shrink with the inclusion of school types in Germany, Italy and France, which suggests that these countries’ systems of tracking between schools, which are associated with significantly different education levels between tracks, interact with the ‘costs’ of skipping school days; cognitive losses are bigger in lyceums and lower in vocational schools. Moreover, losses are also wider where school absences are less frequent and where mean scores in mathematics and reading are higher, in both cases these countries are Germany, France and the United Kingdom (Table A1).

[9] 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. The alternative question ‘How many days do you skip school or expect to skip school during the school year’ would have been more problematic, because the test is not taken at the end of the school year and students may only vaguely know or predict their average behavior regarding skipping school days.



A) Days of absence - Math score



B) Days of absence - Reading score

Figure 4. - Absence from school and students' scores in mathematics and reading.
Note. Coefficients on days of absence in the y-axes (base: no days of absence). Dependent variable: math score.

We cannot precisely compute the cognitive losses of students who did not attend remote learning during the school closures of 2020 pandemic because of the ordinal character of the variable *Days of absence*, where intervals between values are not equally spaced and the highest value (five or more days) has no upper bound. We can, however, reasonably predict that these losses are at least as big as those of skipping five or more days of the physical school in two weeks and, most likely, they are significantly bigger. A continuous interruption in learning that lasts for weeks and months can prove to have much worse effects than the occasional absence from school during a normal school year. Hence, the coefficients on 'skipping five or more days', which, everything else equal, range from almost one school year in Italy, to almost two years in the United Kingdom (full models with school fixed effects in Tables A4 and A5), should be read as the lower bounds of the negative gaps associated with the school closures of year 2020. More generally, this Section's findings, of bigger cognitive losses in the United Kingdom, Germany and France and smaller in Italy and Spain, are consistent with those of Section 5.1. where knowledge losses are associated to the lack of resources needed to learn remotely. The magnitude and significance of coefficients are also similar in the two approaches.

The two approaches evidence also some interesting links between remote learning, inequality and the educational and social characteristics of the countries considered. It has already seen that most results on our variables of interest are robust to the introduction of control variables, but it can also be seen that these same coefficients may change substantially as certain covariates are included into the regressions (Tables A3 to A6). Moreover, the covariates they change with are not always the same across countries. Hence, we computed whether the coefficients on the variables of interest differed significantly (at the five percent level) across regressions. We found that, in France, coefficients on *No computer* at home and *No quiet place* to study shrink significantly relatively to the base model when the types of schools are controlled for, both in the regressions concerning the scores in mathematics and in reading. Similarly, the cognitive losses related to the absences from school shrink significantly when school types are controlled for (columns 1 and 4 in Tables A3, A4, A5 and A6). These results are linked to an uneven distribution of students unable to learn remotely across school types: disadvantaged students are more concentrated in technical and vocational schools. For example, the percentage of students without a computer at home is about five percent in lyceums, about 18 percent in technical and 25 percent in vocational schools. In Italy, even more than in France, the distribution of students across school types affects results: coefficients on *No computer*, *No internet*, *No quiet place*, *No school ICT* and on *Days of absence* are significantly smaller when school types are controlled for. Also in this country, students lacking the needed resources or skipping more school days are more concentrated in vocational or technical schools (columns and 18 in Tables A3-

6). In Spain, coefficients on the variables of interest shrink significantly when the cofactor *Repeated grade* is added among regressors. In the country, students lacking the resources needed for remote learning or skipping more school days tend to repeat grades more than other students (columns 25 in Tables A3, and A56). In Germany, coefficients on *No computer*, *No internet*, *No quiet place* shrink significantly when students' social conditions are controlled for (parents' levels of education or immigrant status), but also when types of school and grades repetition are included among regressors (columns 8 and 10, or 11, or 12). In the United Kingdom, *No computer* at home and social conditions appear to interact, in both the regressions concerning the scores in mathematics and reading.[10]

Overall, these findings show that countries' educational systems and social conditions can affect the relationships between cognitive outcomes and remote learning. In countries with a marked segregation of students across school types, scores are strongly associated with school types. Hence, the cognitive losses related to the lack of ICT resources at home or at school or to skipping school days are smaller within than across school types. When the lack of resources or of absences from school interact with grades repetition, segregation takes places within schools. In countries where social conditions are significantly linked to the coefficients on the variables of interest, not having the needed ICT resources or skipping school days will be associated with higher cognitive losses for students in families with lower social conditions. These findings clearly imply that policy measures should be tuned to countries' specific characteristics. In countries, such as Italy, France and Spain, where segregation between school types and grade repetition especially matter, measures must especially focus on students attending vocational and technical schools and in schools where grades repetition is more frequent. On the other hand, where social conditions come first, the attention must be turned to the students in the most disadvantaged families, across schools.

These results, as all findings in this study, concern correlations among 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 or omitted variables. However, the size and significance of the coefficients on our variables of interest, and their robustness to various specifications, give our findings a very clear meaning, which is that students not allowed to learn remotely suffer significant cognitive losses. In what follows, we test whether these losses may become permanent.

5.3 Leaving education early and repeating grades.

[10] In this study, we use the level of parents' education as a proxy of the family socio-economic condition. Results do not change significantly if, instead of education, we use the level of parents' employment.

Not being able to learn remotely may have longer run consequences than those of losses in cognitive content that, in principle, could be temporary and at least partly reversed once back at school.[11] Students not connected to distance schooling for weeks and months, and foreseeing they will fall considerably behind their peers, may choose to shorten their plans on future education; some may choose to drop out of school altogether, or stop studying as they complete compulsory schooling or secondary school. We group these three possibilities by setting equal to one answers indicating ISCED levels 2, 3B or C (which, as seen above, comprise lower and upper secondary education) to the question *Which of the following do you expect to complete*? and zero otherwise. Moreover, if falling behind may reduce students' planned investments in education, the concrete possibility of repeating grades may be a further incentive to cut them down. 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.

To this end, we test, first, whether the probability of leaving school early is correlated with our variables of interest; second, whether the probability of grade repetition is also linked with these variables (except for the United Kingdom, where grade repetition is uncommon; Table A1); and, third, whether these two probabilities are significantly correlated. As in equations (3) and (4) above, we use Probit specifications for the first two tests and Bivariate probit regressions for the third. The raw frequencies (means) of the two dependent variables, *Leaving education early*, y_1, and *Grade repetition*, y_2, are in Table A1 in the Appendix, while the predicted probabilities of y_1 and y_2 in the Probit regressions, and the joint probabilities of both abandoning education early and repeating grades, $y_1 = 1$ and $y_2 = 1$ in the biprobit regressions are in Table 1. The coefficients of the marginal probabilities of the Probit specification compared against the base group on each variable of interest are in columns 1 to 4 of Table 1, and those of the Bivariate probit regressions are in columns 5 and 6. The base regressions include our four variables of interest, while the full regressions include all covariates of equations 3 and 4. The *Rho* coefficient reports the correlation between the residuals of the two regressions in the biprobit specifications (columns 5 and 6). Other than for the United Kingdom, biprobit coefficients are not reported for France because both the country's raw correlation coefficient (table A2) and *Rho* are non-significant. These results are available from the authors upon request.

The main findings in Table 1 are that in all countries the lack of ICT resources, especially of a computer at home, significantly increase the probability of leaving education early and, except for the United Kingdom, of repeating grades. In the base Probit regressions of all countries, students not

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

having a quiet place to study are more likely to shorten their planned length of studies and-or of repeating grades. Not having internet at home matters especially in Italy, Spain and the United Kingdom. The scarcity of ICT resources at school affect expectations and grade repetitions especially in Spain, Italy and France. More specifically, in the base regressions of column 1, not having a computer at home increases the probability of leaving education early by 24 percent in Germany, 15 percent in Spain, 14 percent in the United Kingdom, six percent in Italy and five percent in France. It rises the probability of repeating grades by 31 percent in Spain, 17 percent in France, 13 in Germany and eight percent in Italy (column 3). When controls are included into the regressions, coefficients tend to shrink, but in the regression concerning leaving education early, y_1, they remain significant in all countries except France (column 2), while in that concerning grade repetition, y_2, they remain strong and significant in the four countries (column 4). Not having an internet connection at home rises the probability leaving education early by 17 percent in Germany, 13 percent in the United Kingdom and four percent in Spain (column 1). Also in this case, coefficients shrink or lose significance when other variables are controlled for (column 4).

Table 1.- 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 y1, y2	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 y1, y2	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 y1, y2	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 y1, y2	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 y1, y2	0.15	0.03				

Note. Robust standard errors, clustered at the school level, in parentheses. *** 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 Grade repetition are dichotomous variables taking 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 (3) and (4). Margins are computed at mean values of covariates.

The Bivariate probit regressions regarding Spain, Germany and Italy add interesting findings. In the three cases, the *Rho* coefficients are strong and highly significant, indicating that the use of the biprobit specifications is appropriate. Their positive signs also show that the two outcomes, of repeating grades and leaving education early, strengthen each other. For example, in the Probit specifications, everything else given, not having a computer at home in Spain, increases the probability of leaving education early by 10 percent (on an average probability of 25 percent; column 2) and the probability of repeating grades by 24 percent (on a mean of 28 percent; column 4), while in the Bivariate probit regressions (*Rho* equal to 0.82, significance at one percent) not having a computer at home increases the joint probability of repeating a grade and leaving education early by 13 percent (on $y_1 = 1$ and $y_2 =1$ equal to eight percent; column 6). In the same country, 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. They are all significantly correlated with the two dependent variables, and the outcomes are mutually interdependent: the lack of ICT resources and of a quiet place to study jointly increase the probabilities if repeating grades and leaving school early (column 6).

Not having a computer at home leads to similar results 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 the other 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 in each of the two countries (column 5). It is interesting to compare these results to the biprobit specification applied to the joint probabilities of leaving education early but *not* repeating a grade ($y_1 = 1$ and $y_2 = 0$); Table A7 (column 7) shows that in that case coefficients are smaller and less significant to those related to leaving education early and repeating a grade, $y_1 = 1$ and $y_2 = 1$ (column 8). In this case, the condition of falling behind by not attending remote schooling and also repeating a grade because of the same reason, leads to losses that students are likely to consider too deep to reverse once back at school and, hence, opt for quitting education early or dropping out of school altogether.

5.4. Robustness checks: missing observations.

Table A1 shows that there are missing data 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 variable. However, we choose not to drop all student observations that have a missing value on at least one variable, because that could mean a substantial reduction in sample size that, in itself, could lead to biased results. Therefore, to control for the robustness of our previous results, we impute the missing values by using the mean imputation method. Clearly described in Woessmann et al (2007) and Puma et al. (2009), it is frequently used with education and multilevel data. However, a detailed explanation of the methodology adopted in this study is in Section II of the Appendix. This Section also includes the results obtained by re-running the above regressions with the sample comprising the imputed observations.

In the descriptive statistics of Table A1, the variable of interest with the highest proportion of missing values is *Days of absence* from school: it is more than 47 percent in Germany, but lower in other countries, such as the United Kingdom. In Germany, the missing data regarding *Leaving education early* are 19 percent, and *Repeated grade* are 14 percent.

Supporting the robustness of our main results, almost all coefficients from the regressions run on the sample comprising the imputed missing data are quite similar to those obtained with the original sample. One minor exception concerns the coefficient on *Days of absence* +5 in the full model with fixed effects concerning Germany, which loses significance (column 5, Table A5-I) relatively to the previous result (Table A5). Another exception, again concerning data from Germany, is the coefficient on *No computer* at home in the biprobit regression with all covariates, regarding the joint probability of repeating a grade and leaving education early, which also loses significance (Table 1-I, in the Appendix). Other coefficients do not differ significantly from those obtained with the regressions on the original data.

6. Concluding remarks

Until the coronavirus pandemic of 2020, the diffusion of e-learning varied widely among countries. Even among developed ones, it was partly related to the governments' and educational institutions' beliefs on its effects on education, which went from very positive, for example in Estonia, to very cautious, for example in Germany. With the advent of the pandemic, in very few days, distance learning ceased to be option and became the only viable form of education. Suddenly, countries found that their previous choices on the matter strictly delimited their real options during the pandemic. An education digital divide emerged not just between developed and developing nations, but also between countries at the same, even high, levels of development. Children and students not able to connect to the virtual school found themselves to be out of the education system. Preliminary evidence from the main Western European countries shows that between 10 to 20 percent of students were entirely disconnected from remote learning, and about 30 to 40 percent could only attend occasionally.

Using data from the PISA 2018 survey on fifteen-year-old students, we measured the links between students' scores in mathematics and reading and their possibilities of attending remote learning in France, Germany, Italy, Spain and the United Kingdom (scores on reading were not available for Spain). We then tested the links between students without distance schooling and their plans on the length of their future education. Our main results show that the lack of ICT resources and a quiet place to study are negatively correlated with cognitive outcomes in all countries.

After controlling for all covariates and school fixed effects, the lack of a computer is linked with a negative gap in mathematics that ranges from 70 percent of a school year in the United Kingdom to about 30 percent in Spain. Losses in reading range from 64 percent in the United Kingdom to 50 percent in Italy. The lack of an internet connection matters especially in the United Kingdom and Germany. Not having a quiet place to study at home is correlated with significant cognitive losses in the United Kingdom and France. A scarcity of ICT resources at school in Italy is associated with a negative gap of more than half of a school year, both in mathematics and reading, while in Spain, the negative association ceases to be significant when school types are controlled for, indicating a significant polarization of ICT resources among schools. Among the countries considered, the United Kingdom has the lowest percentage of households without internet connections, and the higher cognitive losses linked to its absence; this may capture the outcomes of students in very marginalized situations. Differently from previous findings in the literature on vacations and school interruptions, we find that losses in reading are similar to those in mathematics. (Gottfried, 2009 and 2011; Quinn and Polikoff, 2017)

Using the days of absence from school to measure the consequences of not learning remotely during school closures, we find highly negative and significant coefficients in the five countries. These results are similar to those obtained by using the lack of ICT resources and a quiet place to study to measure the same phenomena. In both approaches, losses are proportionately bigger in the United Kingdom, Germany and France, and smaller in Italy and Spain. Moreover, while in principle, cognitive losses can be reversed when students go back to school, we find that not being able to attend remote learning significantly increases the probability of dropping out school or ending education early. These negative choices are exacerbated in countries where repeating grades is a common feature of education systems.

We found that the distribution of cognitive losses of students unable to learn remotely are strongly associated with countries educational systems. In countries with tracking between schools, such as Italy, France and Germany, more students falling behind are concentrated in vocational and technical schools, and less in lyceums and gymnasiums; in countries with comprehensive schools, such as the United Kingdom, family social conditions, and the distinction between private and public schools, matter more. In Spain, grades repetition can be a form of segregation within schools, and in Italy and Germany as a way to select students across schools.

More generally, countries' policies to overcome the pandemic without losses of human capital must be tuned to the characteristics of their educational systems. While some countries should prioritize disadvantaged students in vocational and technical schools, and schools with lower ICT resources, others should firstly focus on socially marginalized families across schools. Every country should guarantee that all students have a computer and internet connection at home and are taught the skills needed to use them for school work. When not available at home, a quiet place to study could be provided by schools. Extra learning support should also be provided to students falling behind during school closures. In turn, less endowed schools must be provided with ICT resources, and teachers must learn the skills needed for teaching online. More generally, these measures would prove to be extremely useful also for normal times. Recent research finds that modern ways of knowledge transmission may be more effective when physical interaction is complemented with online communication (Anderson, 2003). Finally, because of their strong negative effects on individuals' investments in education, learning inequalities reduce countries' overall levels of human capital, but human capital is exactly the resource countries most need to reverse the socially and economically devastating effects of the coronavirus pandemic.

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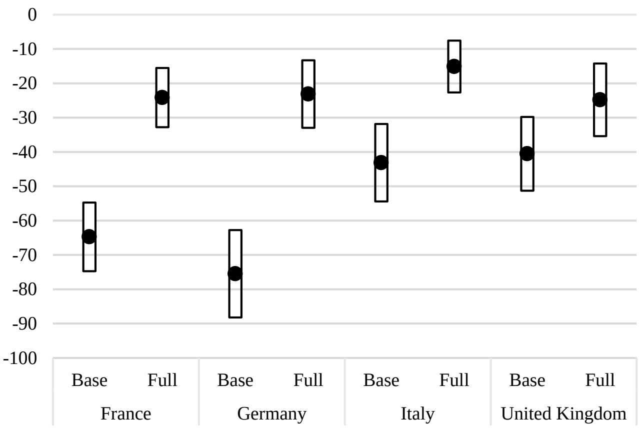
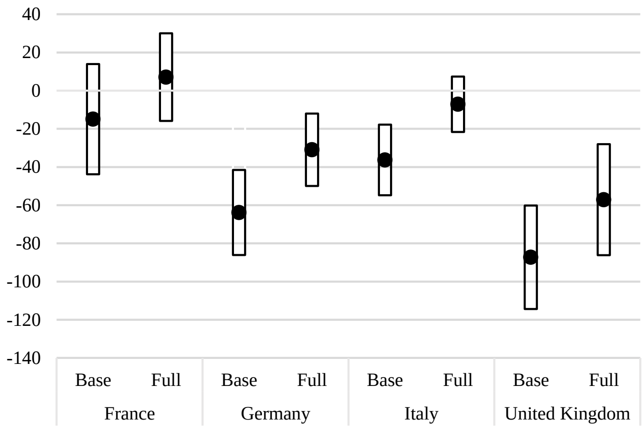
APPENDIX

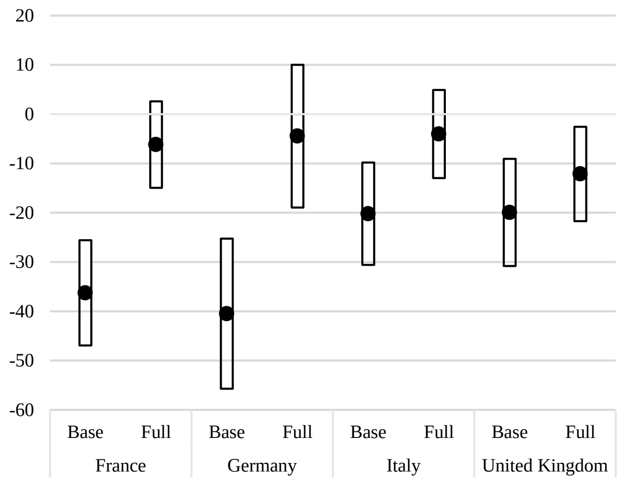
I. Figures and Tables



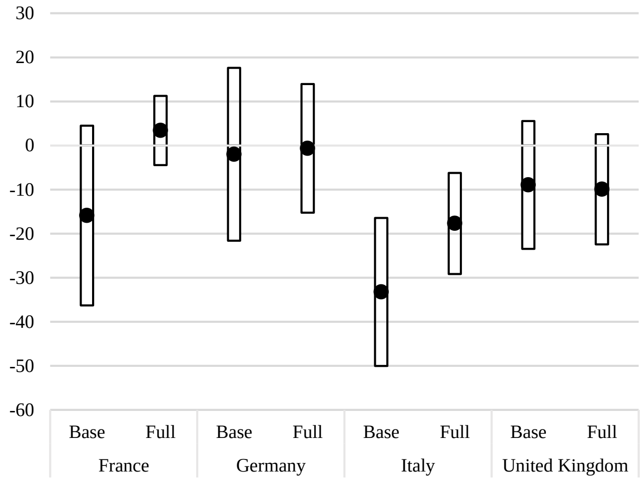
A) No computer



B) No internet



C) No quiet place to study



D) Few school ICT

Figure A1. - Gaps in reading, ICT resources and a quiet place to study.
Note. Coefficients on respective variables in the y-axis. Dependent variable: reading scores

Table A.1 – 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 (%)	6,308	11.43	0.32	6.0	5,451	30.08	0.45	19.1	11,785	5.30	0.22	7.1	35,943	8.66	0.28	4.3	13,818	11.80	0.32	7.7
Repeated grade (%)	6,308	16.58	0.37	1.5	5,451	19.75	0.40	14.3	11,785	13.23	0.34	2.5	35,943	29.05	0.45	1.4	13,818	2.42	0.15	3.7
No computer (%)	6,308	9.09	0.29	1.8	5,451	6.87	0.25	13.6	11,785	9.74	0.30	2.5	35,943	8.45	0.28	1.5	13,818	7.74	0.27	4.1
No internet (%)	6,308	1.52	0.12	1.7	5,451	1.76	0.13	13.4	11,785	2.78	0.16	2.5	35,943	2.09	0.14	1.6	13,818	0.79	0.09	4.0
No quiet place to study (%)	6,308	6.21	0.24	1.9	5,451	4.17	0.20	13.4	11,785	8.54	0.28	2.5	35,943	7.22	0.26	1.6	13,818	10.47	0.31	4.4
Few school ICT (%)	6,308	22.93	0.42	12.8	5,451	60.81	0.49	13.4	11,785	27.11	0.44	3.7	35,943	46.05	0.50	3.0	13,818	24.04	0.43	18.0
Days of absence	6,308			21.6	5,451			47.6	11,785			22.1	35,943			22.5	13,818			8.7
Days of absence: 0 (%)	6,308	86.64	0.34		5,451	94.00	0.24		11,785	49.18	0.50		35,943	78.37	0.41		13,818	79.48	0.40	
Days of absence: 1-2 (%)	6,308	8.47	0.28		5,451	4.09	0.20		11,785	38.12	0.49		35,943	16.97	0.38		13,818	16.22	0.37	
Days of absence 3-4 (%)	6,308	2.14	0.14		5,451	0.90	0.09		11,785	5.80	0.23		35,943	2.70	0.16		13,818	2.49	0.16	
Days of absence 5 + (%)	6,308	2.76	0.16		5,451	1.01	0.10		11,785	6.90	0.25		35,943	1.96	0.14		13,818	1.82	0.13	
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	6,308	4.94	1.28	2.8	5,451	4.35	1.52	17.8	11,785	4.42	1.43	2.9	35,943	4.67	1.63	2.8	13,818	4.87	1.22	10.3
Immigrant status (%)	6,308	14.11	0.35	2.2	5,451	19.37	0.40	13.3	11,785	9.70	0.30	3.7	35,943	11.77	0.32	3.1	13,818	18.51	0.39	6.1
Age of arrival	6,308	0.52	2.28	2.1	5,451	0.72	2.65	12.0	11,785	0.43	1.93	2.6	35,943	0.66	2.46	1.5	13,818	0.83	2.80	3.8
School type	6,308			11.2	5,451			14.0	11,785			1.8	35,943			2.9	13,818			14.0
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			
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 (%)	6,308	81.80	0.39		5,451	96.73	0.18		11,785	96.47	0.18		35,943	68.45	0.46		13,818	29.41	0.46	

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

Table A2. – Main correlation coefficients.

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

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

Table A3. - ICT 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	-3.975	-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

Notes: Robust standard errors, clustered at the school level, in parentheses. *** 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 "vocational school" and "technical school" is "general school".

Table A3. - ICT resources. Dependent variable: students' scores in mathematics. Continued from previous page.

	Italy						
	(15)	(16)	(17)	(18)	(19)	(20)	(21)
	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***
No internet	-38.255***	-37.975***	-28.375***	-26.188***	-35.493***	-21.079**	-5.986
No quiet place to study	-12.559**	-12.935**	-7.766	-3.549	-7.386	1.225	-0.609
Few school ICT	-39.119***	-38.502***	-36.914***	-24.642***	-35.405***	-21.774***	
Female		-14.222***				-28.059***	-22.622***
Age		16.532***				10.288**	10.240***
Parents' education			9.486***			3.638***	-0.808
Immigrant status			-21.264***			-2.477	-13.657***
Age of arrival			-2.752***			-1.704*	-1.582*
Technical school				-38.475***		-38.404***	
Vocational school				-99.599***		-88.190***	
Public school				-14.011		-6.298	
Repeated grade					-72.036***	-50.653***	-42.139***
Constant	505.411***	251.503***	465.833***	543.225***	512.830***	375.655***	351.802***
School FE	no	no	no	no	no	no	yes
Observations	11,029	11,029	10,790	11,029	11,010	10,779	10,779

	Spain						
	(22)	(23)	(24)	(25)	(26)	(27)	(28)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
No computer	-47.796***	-48.504***	-35.001***	-44.512***	-16.909***	-12.792***	-10.671***
No internet	-20.609**	-19.945**	-11.933	-17.474**	-5.965	-0.19	0.369
No quiet place to study	-8.648**	-8.521**	-3.775	-8.029*	-4.462	-1.79	-0.437
Few school ICT	-7.378***	-7.457***	-4.190*	-2.982	-2.05	0.274	
Female		-8.505***				-16.401***	-16.824***
Age		19.486***				11.528***	10.970***
Parents' education			10.695***			5.554***	3.606***
Immigrant status			-17.487***			-6.401*	-5.831*
Age of arrival			-3.091***			-2.244***	-2.145***
Technical school							
Vocational school				-75.540***		-24.675**	
Public school				-23.167***		-6.372**	
Repeated grade					-98.301***	-90.676***	-89.502***
Constant	490.590***	186.275***	443.601***	504.608***	513.130***	317.048***	330.016***
School FE	no	no	no	no	no	no	yes
Observations	34,174	34,174	33,056	34,099	34,144	32,970	33,044

	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

Notes: Robust standard errors, clustered at the school level, in parentheses. *** 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 “vocational school” and “technical school” is “general school”.

TABLE A4. - ICT resources. Dependent variable: students' 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

Notes. Robust standard errors, clustered at the school level, in parentheses. *** 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 “vocational school” and “technical school” is “general school”.

TABLE A4. - ICT resources. Dependent variable: students' 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

Notes. Robust standard errors, clustered at the school level, in parentheses. *** 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 “vocational school” and “technical school” is “general school”.

TABLE A5 - 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

Notes: Robust standard errors, clustered at the school level, in parentheses. *** 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 “vocational school” and “technical school” is “general school”. The base level of the days of absence is no days.

TABLE A5 - Absence from school. 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
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

	United Kingdom						
	(29)	(30)	(31)	(32)	(33)	(34)	(35)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
Days of absence: 1-2	-36.014***	-35.789***	-33.773***	-36.287***	-35.466***	-33.400***	-26.789***
Days of absence: 3-4	-65.262***	-64.516***	-65.667***	-66.833***	-64.852***	-64.258***	-55.487***
Days of absence: 5 +	-91.505***	-93.232***	-91.693***	-91.309***	-84.163***	-89.895***	-72.380***
Female		-14.519***				-15.759***	-16.605***
Age		19.713***				19.400***	14.999***
Parents' education			13.037***			12.261***	5.140***
Immigrant status			-12.120**			-12.785**	-7.708
Age of arrival			0.422			0.696	0.911
Public school				-24.729***		-22.528***	
Repeated grade					-59.604***	-50.184***	-43.495***
Constant	513.717***	210.473**	456.106***	524.560***	515.437***	173.177	265.697***
School FE	no	no	no	no	no	no	yes
Observations	12,620	12,620	11,432	10,863	12,560	9,848	11,406

Notes: Robust standard errors, clustered at the school level, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of the days of absence is no days. The coefficients of "technical school" and "vocational school" are to consider on the base level "general school". The base level of coefficients "vocational school" and "technical school" is "general school".

TABLE A6 - Absence from school. Dependent variable: Students' 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
Days of absence: 1-2	-57.775***	-56.957***	-50.895***	-30.684***	-50.136***	-29.985***	-27.528***	-63.560***	-62.005***	-56.527***	-57.635***	-55.867***	-47.411***	-25.834***
Days of absence: 3-4	-100.495***	-96.935***	-93.767***	-60.038***	-81.586***	-59.290***	-58.919***	-109.104***	-102.207***	-97.838***	-91.492***	-97.828***	-69.865***	-48.403***
Days of absence: 5 +	-99.803***	-96.202***	-88.797***	-54.432***	-79.762***	-51.023***	-45.418***	-104.759***	-102.102***	-92.790***	-82.152***	-88.686***	-69.203***	-55.437***
Female		17.070***				5.926**	7.338***		30.053***				24.088***	8.295**
Age		22.645***				7.557*	7.178*		13.328				22.408***	24.062***
Parents' education			14.801***			5.301***	3.242***			14.381***			10.815***	3.209**
Immigrant status			-27.700***			-24.361***	-24.285***			-28.201***			-19.130***	-15.949***
Age of arrival			-3.022***			-0.520	-1.188*			-6.695***			-5.655***	-3.994***
Technical school				-114.345***		-93.754***					-73.220***		-56.027***	
Vocational school				-162.700***		-133.716***					-114.940***		-96.175***	
Public school				-20.863***		-14.951**					4.847		14.744	
Repeated grade					-117.467***	-34.117***	-50.824***					-72.827***	-39.307***	-30.991***
Constant	511.736***	143.668*	443.238***	560.957***	527.233***	409.307***	384.777***	522.872***	297.484**	468.545***	546.766***	535.087***	129.821	131.463
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

	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
Days of absence: 1-2	-13.878***	-14.038***	-13.195***	-10.970***	-10.789***	-10.153***	-0.309	-31.715***	-31.824***	-29.282***	-31.800***	-31.067***	-28.285***	-22.555***
Days of absence: 3-4	-45.943***	-44.926***	-45.278***	-28.630***	-42.135***	-28.272***	-17.928***	-56.252***	-56.565***	-55.569***	-53.110***	-55.944***	-49.830***	-46.618***
Days of absence: 5 +	-68.396***	-67.506***	-66.118***	-46.531***	-56.895***	-43.199***	-25.698***	-99.557***	-95.624***	-99.859***	-101.063***	-90.310***	-93.669***	-75.012***
Female		24.687***				9.833***	13.849***		18.497***				18.767***	15.658***
Age		24.128***				14.637***	14.591***		18.350***				19.109***	13.282***
Parents' education			8.787***			2.227**	-1.621*			12.375***			11.817***	5.458***
Immigrant status			-28.523***			-7.917	-16.319***			-11.417**			-14.031***	-9.165*
Age of arrival			-2.578***			-1.637**	-1.844**			-1.385*			-0.873	-0.755
Technical school				-63.907***		-52.337***								
Vocational school				-115.858***		-99.542***								
Public school				-10.620		-9.383					-20.757***		-18.204***	
Repeated grade					-78.151***	-48.088***	-42.347***					-66.110***	-59.665***	-49.966***
Constant	494.983***	102.332	460.648***	543.583***	502.566***	297.991***	262.931***	516.464***	217.525***	463.985***	525.532***	518.444***	164.378**	279.041***
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

Notes: Robust standard errors, clustered at the school level, in parentheses. *** 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 days of absence is no days. The base level of coefficients “vocational school” and “technical school” is “general school”.

Table A7. - Marginal probabilities of Leaving education early and of grade repetition (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, 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: Robust standard errors, clustered at the school level, in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account.

Tab A8. - Dependent variable: Marginal probabilities of leaving education early and repeating grades (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 computers	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 computers	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 computers	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 computers	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 computers	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						

Note. Robust standard errors, clustered at the school level, in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account.

II. Robustness check: missing observations.

To impute the values of missing observations, we use the 'mean imputation method' (Little and Rubin, 1987), which predicts the conditional mean for each missing observation on the explanatory variables using nonmissing 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 (2007), the set of fundamental variables, *E*, includes gender, age, five grade dummies and five dummies for the number of books at home.[12]

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

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.

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

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).

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

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.

Table A3-I. ICT resources. Dependent variable: students' 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

Notes: Robust standard errors, clustered at the school level, in parentheses. *** 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 “vocational school” and “technical school” is “general school”. Regressions on sample with imputed values.

Table A4-I. ICT resources. Dependent variable: students' 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

Notes: Robust standard errors, clustered at the school level, in parentheses. *** 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 “vocational school” and “technical school” is “general school”. Regressions on sample with imputed values.

Table A5-I. Absence from school. Dependent variable: students' 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	-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***
Days of absence: 3-4	-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***
Days of absence: 5 +	-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***
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

Notes: Robust standard errors, clustered at the school level, in parentheses. *** 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 “vocational school” and “technical school” is “general school”. The base level of the days of absence is no days. Regressions on sample with imputed values.

Table A6-I. Absence from school. Dependent variable: students' 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	-46.648***	-24.090***	-23.497***	-42.330***	-43.094***	-26.094***	-23.681***	-10.205***	-1.743	-24.792***	-22.921***	-18.291***
Days of absence: 3-4	-89.368***	-51.608***	-52.320***	-87.874***	-73.910***	-53.583***	-44.488***	-23.983***	-16.927***	-49.329***	-50.145***	-43.274***
Days of absence: 5 +	-88.676***	-45.733***	-42.374***	-83.529***	-74.571***	-62.620***	-69.365***	-38.495***	-22.272***	-92.634***	-77.757***	-65.618***
Female		6.634***	8.774***		16.864***	9.959***		7.517***	11.921***		18.987***	16.722***
Age		5.716*	6.646*		26.362***	28.375***		10.112**	10.545***		17.578***	13.996***
Parents' education		4.375***	2.468***		10.062***	3.071***		1.851*	-2.153**		11.622***	5.345***
Immigrant status		-23.490***	-20.238***		-22.283***	-14.220***		-6.796	-17.341***		-11.386**	-5.711
Age of arrival		-0.987*	-1.410***		-6.406***	-5.057***		-2.225***	-2.532***		-1.010	-1.177**
Technical school		-96.343***			-47.357***			-53.084***				
Vocational school		-142.806***			-91.217***			-102.881***				
Public school		-16.664***			10.127			-8.037			-19.762***	
Repeated grade		-32.857***	-52.424***		-49.099***	-34.440***		-48.500***	-42.552***		-59.575***	-50.230***
Constant	500.610***	440.621***	388.296***	501.642***	73.463	51.949	493.529***	367.257***	326.416***	509.541***	184.432***	261.547***
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

Notes: Robust standard errors, clustered at the school level, in parentheses. *** 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 “vocational school” and “technical school” is “general school”. The base level of the days of absence is no days. Regressions on sample with imputed values.

Table 1-I. 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	0.19***	0.03***		
	No internet	0.01**	0.00	0.04	0.02		
	No quiet place to study	0.01	0.00	0.11***	0.01		
	Few school ICT	0.03*	0.02	0.09	0.01		
	Observations	6,308	6,308	6,380	6,308		
	Predicted mean y1, y2	0.12	0.11	0.12	0.07		
Germany	No computer	0.25***	0.16***	0.16***	0.10*	0.01***	0.00
	No internet	0.16***	0.11	0.07	0.04	0.00	0.00
	No quiet place to study	0.08**	0.02	0.07***	0.03	0.01***	0.00
	Few school ICT	0.01	0.02	0.03	0.27	0.00	0.00
	Observations	5,451	5,451	5,451	5,451	5,451	5,451
	Rho					*0.40****	*0.26****
	Predicted mean y1, y2	0.31	0.17	0.18	0.12	0.09	0.04
Italy	No computer	0.05***	0.03**	0.09***	0.04**	0.02***	0.01**
	No internet	0.01	0.00	0.03	0.00	0.00	0.00
	No quiet place to study	0.03*	0.01	0.07***	0.03*	0.01**	0.00
	Few school ICT	0.03**	0.01	0.05***	0.03**	0.01**	0.01*
	Observations	11,785	11,785	11,785	11,785	11,785	11,785
	Rho					*0.50****	*0.41****
	Predicted mean y1, y2	0.07	0.04	0.04	0.09	0.02	0.01
Spain	No computer	0.15***	0.10***	0.32***	0.25***	0.10***	0.04***
	No internet	0.05***	0.03**	0.16***	0.10***	0.03***	0.01**
	No quiet place to study	0.03***	0.02*	0.05***	0.03**	0.02***	0.01***
	Few school ICT	0.02***	0.01*	0.07***	0.04***	0.01***	0.01**
	Observations	35,943	35,943	35,943	35,943	35,943	35,943
	Rho					*0.90****	*0.81****
	Predicted mean y1, y2	0.08	0.09	0.09	0.28	0.01	0.06
United Kingdom	No computer	0.13***	0.10***				
	No internet	0.14**	0.13				
	No quiet place to study	0.07***	0.06***				
	Few school ICT	0.01	0.00				
	Observations	13,818	13,818				
	Predicted mean y1, y2	0.15	0.15				

Note: Robust standard errors, clustered at the school level, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All plausible values employed. All results are weighted and replication weights are taken into account. Leaving education early, y1, and Grade repetition, y2, are dichotomous variables taking 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 (3) and (4). Margins are computed at mean values of covariates. Regressions on sample with imputed values.