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Coronavirus pandemic, remote learning and education inequalities

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Abstract.

By using PISA 2018 data, we investigate the associations between digital divides and educational inequalities in France, Germany, Italy, Spain and the United Kingdom. We find strong and significant cognitive losses of students lacking the resources needed to learn remotely; everything else given, they range from 25 to 70 percent of a school year. In Germany, Italy and France, where tracking between schools starts earlier, digital gaps are strongly associated with school types. They are also wider in urban areas, where the use of ICT resources is more widespread. Grades repetition in Spain is associated with the digital divide, while family characteristics matter in the United Kingdom. In the longer run, students who cannot learn remotely are more likely to repeat grades and end their education early, especially where grades repetition is more common: Spain, Germany, and Italy. Education policies should be designed accordingly.

Keywords: Digital divide, education inequalities, educational systems, remote learning, PISA.

JEL Codes: I21, I24, H52

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1. Introduction

The coronavirus pandemic that suddenly spread in 2020, forced countries to close schools and shift to distance learning almost overnight, without the time needed for preparing and evaluating the consequences on education. Several recent studies based on previous research on school breaks predict that physical school closures will be followed by generalized declines in education levels (Burgess and Sievertsen 2020; Haeck and Lefebvre 2020; Kuhfeld et al. 2020; Psacharopoulos et al. 2020; Van Lancker and Parolin 2020; Bacher-Hicks 2021). However, differently from school interruptions and vacations, distant learning affects some students substantially more than others. In particular, it affects more the students who lack the devices needed to learn remotely.¹ Their cognitive losses go beyond those deriving from distant learning in itself, or the lack of physical interactions with teachers and peers; they are dictated by both physical and virtual disconnections, and may have longer-run consequences. In this study, we try to gauge the extent and significance of these extra-losses. Because of the shortcomings of the very recent empirical evidence on distance learning, we use pre-pandemic standardized cross-country data. This implies that our results derive from normal times, but their usefulness relies on being a benchmark for the similar but potentially much larger schooling disparities that arise when virtual classes substitute the physical school. Hence, our study fits in the general research on inequalities in education. More precisely, it focuses on inequalities that are related to digital disparities and factors associated to them.

Distance schooling poses a problem regarding the adequacy of resources and skills that is particularly dramatic in developing countries but concerns also rich economies, where most of the distance teaching takes place through the internet. In them, the availability of ICT resources is more widespread, but digital inequalities still exist (Fairlie 2004); some students lack the basic resources needed to learn remotely and some schools or teachers do not provide online classes (Norris 2001).² This study analyses

¹ Normal-times school closures have been found to affect students differently in relation, especially, on their characteristics and those of their families (Carvalho et al. 2020). However, these results cannot be generalized: other factors may be associated to inequalities in the case of distant learning.

² We use the term ‘distance schooling’ when one or more technologies are used to deliver classes to students who are separated from the teacher and – with electronic technologies – support mutual interaction; ‘remote learning’, when ICT resources are used for education outside the physical school only temporarily; ‘e-learning’ when electronic resources permanently substitute education at the physical school.

five European countries – France, Germany, Italy, Spain and United Kingdom - that were hit by the pandemic between the end of February and beginning of March 2020 and initially adopted similar measures concerning school closures and remote learning.³

To gauge the relationships between students' possibilities of learning online and education outcomes, we use the 2018 wave of the Program for International Student Assessment (PISA), an international assessment implemented by the Organization for Economic Cooperation and Development (OECD) that measures 15-year-old students' reading, mathematics, and science literacy every three years, and comprises data on ICT resources at home and at school. In these data, a proportion of fifteen-year-old students that ranges from more than one third in France to more than 60 percent in Germany lacked at least one of the above digital factors needed to learn remotely.

Specifically, we test the relationships between students' scores in mathematics and reading and their possessions of a computer for schoolwork, an internet connection, a quiet place to study and their school's ICT resources, while controlling with a wide set of covariates and school fixed-effects.⁴ In this setting, we explore the contribution of each set of covariates on the students' cognitive gaps.

Considering the longer run, we analyse whether non being able to learn remotely is also associated with students' plans on their future education. In particular, students unable to attend virtual classes and lagging behind their peers may find their cognitive gap too hard to close and, consequently, revise downwards their plans on future education. These pessimistic expectations may be exacerbated in countries where grades repetition is frequent and lagging behind increases the probability of repeating a grade. Hence, we test 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. To our knowledge, this is the first investigation on education inequalities related to digital disparities that is based on a large and standardized cross-country database. The

³ Some measures differed across the five countries. For example, school closures have been complete in Italy, while in the United Kingdom schools remained partially open for children with parents with specific jobs or from low-income households.

homogeneity of data allows us to compare similarities and differences in the sizes of the digital gaps and in the confounding factors in the countries considered.

Our main findings are that the lack of ICT resources at home and a scarcity of ICT resources at school are strongly correlated with students' negative scores in mathematics and reading, although with differences across countries. Specifically, we find that gaps are associated with school systems, in particular with early tracking, school locations, grades repetition and, in a lesser degree, with family characteristics. These cognitive losses have long run implications: students unable to learn remotely are more likely to revise downwards their plans on future education, especially where the probability of grades repetition is high.

Although our estimates are not causal relationships, results are robust to rich sets of covariates, fixed effects, different specifications, and tests. Policy implications are clear and become more urgent when distant education substitutes the physical school, such as during years 2020 and 2021: every student and school should possess the necessary ICT resources and the knowledge needed to use them for learning from home.⁵ Only this can mitigate important educational disparities that, as our study shows, were present in normal times and are likely to have been significantly exacerbated with the Covid pandemic. The real extent of these gaps during and after the pandemic will be estimated when homogenous and standardized data will be made available by PISA 2021 or other sources. The rest of this paper is structured as follows, Section 2 discusses the related literature, Section 3 presents the data and some descriptive statistics, Section 4 shows the adopted methodology, results are provided in Section 5 and Section 6 concludes.

⁵ Miniaci and Parisi (2006) point out that just possessing a computer and having an internet connection increases digital skills, suggesting that making these resources available is a policy priority.

2. Main facts and literature

2.1. Facts

The OECD (2020) data on home computer possessions and internet connections in our five countries show that between 85 and 90 percent households have access to the internet and between 72 percent and 93 percent have a computer at home, but these figures concern pre-pandemic times, when most learning and working activities took place outside home. Moreover, they focus on households rather than individuals, and do not provide information on the level of efficiency of the ICT devices. During school closures and the lockdown of most economic activities, almost all household members are likely to use the ICT resources more than usual. Hence, when considered at individual – rather than household – level and during closures of schools and economic activities, the above figures should be substantially revised downwards.⁶ At the same time, for remote learning to take place, ICT resources must be available and efficiently used also at school, and teachers must possess the skills needed to teach online. The partial evidence available suggests that because of deficiencies in households' possessions and school shortages of ICT devices, digital platforms and skilled teachers, remote learning in our five countries was lower than expected.⁷

Survey data collected during the first wave of the pandemic, in the first half of 2020, provide some evidence on the extent of the effective remote learning. In England, between 10 percent and 12 percent of students had no devices at all (Andrew et al. 2020). Only 40 percent of students in Italy could fully participate in remote learning; 10 percent could not participate at all, and 20 percent could attend only occasionally (Autorità Garante per le Comunicazioni 2020). In Germany, less than 50 percent of students in their graduation and pre-graduation years received digital learning opportunities or material through an online platform, email or videoconferencing, and only about 15 percent of them had

⁶ Data from the Italian Institute of Statistics show that, during the schools and economy lockdown of 2020, households without people able to use ICT resources were about 24.2 percent of the total, with higher than average percentage for households with lower income levels, higher median age, the country's South and small towns (ISTAT 2020).

⁷ This especially applies to Germany; Conrads et al. (2017), European commission (2019), Kerres (2020) and UNESCO (2020) show German schools are on average less digitalized than in other developed countries.

videoconferencing (such as Skype) interactions with teachers (Dietrich et al. 2021). No data were available on the proportion of German students that were entirely disconnected from remote learning, but consistently with the evidence on schools, they are likely to be, also in this case, not less than 10 to 15 percent of all students. If this preliminary evidence from the United Kingdom, Italy and Germany applies also to the other two countries, then, overall, only between 30 percent to 50 percent of students could attend school online. In Section 2.3 below, the data from PISA 2018 depicts more negative figures.

2.2. Literature

Several very recent researches trying to gauge the effects of the pandemic on education are based on the scarce data collected during and after the periods of school closures or on previous findings on school vacations or on interruptions due to unexpected events.⁸ Kuhfeld et al. (2020) predict that students in the United States are likely to return in fall 2020 with approximately 63-68 percent of the learning gains in reading relative to a typical school year and with 37-50 percent of the learning gains in math (pg. 1). Moreover, they estimate that losing ground will not be generalized, but the top third of students may make gains in reading. Several studies find that summer vacations are followed by sizable and significant cognitive losses, which often concern mathematics more than reading, and are higher for students from lower socio-economic conditions (Downey et al. 2004; Quinn and Polikoff 2017; Atteberry and McEachin 2020; Carvalho et al. 2020). Van Lancker and Parolin (2020) find that summer vacation cognitive losses in the United States are significant for children of low-income families, but not for others. However, in other studies' results, cognitive losses due to school vacations are mostly temporary or negligible (Von Hippel and Hamrock 2019).

Absenteeism has also been found to negatively influence cognitive outcomes. Students skipping school experience significant and negative cognitive gaps relatively to their peers, which increase with the days of absence (Chang and Romero 2008; Gottfried and Kirksey 2017; Liu et al. 2020). Gottfried

⁸ Hanushek and Woessmann (2020) and Azevedo et al. (2020) consider potential economic losses at individual and country levels, which are expected to be stronger for disadvantaged students and to have long-lasting effects.

(2009 and 2011) and Aucejo and Romano (2016) find that losses associated with absenteeism tend to be higher in mathematics than in reading.

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

A parallel debate concerns the impact of using ICT resources in teaching and learning. Governments' and experts' opinions on e-learning vary widely, and empirical studies on the effects of providing students with ICT resources remain inconclusive (Fairlie 2005; Banerjee et al. 2007; Machin et al. 2007; Yanguas 2020). The evidence suggests that not just computers and the internet, but the software and how ICT devices are used play an important role in the cognitive process (a very complete review is in Escueta et al. 2020). The choices countries made in the past on the use of digital resources for education proved to be crucial in 2020, when schools were suddenly forced to teach remotely. A survey by the European Commission (2019) and the data from PISA 2018 show that even our European countries were very different prepared.

3. Data and descriptive statistics

The data from the 2018 wave of PISA assessment concerns students' test scores in mathematics and reading, except for Spain, from which data are only available on mathematics. To save space, we present most results on reading in the separate Online Appendix A. We also omit results on science, the third field of PISA surveys, which are very similar to those in mathematics and reading. They are available

upon request. Overall, we consider 73,305 students enrolled in over 2,577 schools in the five countries. The PISA dataset is the result of a two-stage stratified design, where, first, individual schools are sampled, and secondly, students are randomly sampled within schools. Given that each participating student in PISA survey answers a limited amount of questions taken from the total test item pool, OECD provides ten test scores (known as plausible values), which can be interpreted as multiple imputed values of students' performance based on students' answers to the test and their background questionnaires. The difficulty of each item represents a weight, used to compute the weighted averages of correct responses. This approach allows having a measure of an individual's proficiency for each student in each subject area, regardless of the questions actually answered. We employ the recommended OECD strategy for estimation of coefficients and their variances, making use of all ten plausible values (OECD 2018, provides detailed technical information).

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

concerning parents' jobs, number of books and other home possessions, and language spoken at home (whether that of the country of residence or another language).

Descriptive statistics are summarised in Table A1. Overall, students lacking at least one of the four essential factors needed to learn at home – a computer, an internet connection, a quiet place to study at home, a school providing online classes – are about 36 percent of all students in France, 46 percent in the United Kingdom, 41 percent in Italy, 55 percent in Spain and 65 percent in Germany. If only the ICT devices for remote learning are considered (*No quiet place to study* is excluded), these percentages decrease only slightly (Figure SA1-a, SA1-b).

Grade repetition is unusual in the United Kingdom and common in the other four countries, especially Spain and Germany, where respectively 29 and 20 percent of students repeat grades. Educational systems also differ in the degree of tracking between schools: the age at which students are tracked for the first time is 10 years in Germany, 14 in Italy, 15 in France and 16 in Spain and the United Kingdom (Woessmann 2009). The proportion of students planning to leave education early varies from about 30 percent in Germany (where vocational school can be attended while working part-time) to six percent in Italy, but secondary studies can be completed at different ages in each of the five countries (Stratton et al., 2018, clearly expose this heterogeneity in OECD countries).⁹

4. Empirical strategy

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

⁹ Secondary studies are typically completed after 10 years of schooling in Spain, 11 in the United Kingdom, 12 in Italy and Spain, and 13 in Germany. Children start compulsory education when they are five years old in the United Kingdom and six years in the other four countries. Therefore, the age at which secondary education is completed also depends on the age at which compulsory education start.

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

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 comprises gender (a dichotomous variable, taking value one if female and zero otherwise), age (years and months), the highest level of education of parents (HISCED in PISA), the student's status of immigration (a dichotomous variable), age of arrival at the country, and whether the student has repeated one or more school years, λ_j are school fixed effects and v_j and ε_{ij} are error terms at school and student levels.

In a further set of regressions, we use separate Probit specifications to gauge the correlations between the probabilities of leaving education early or of repeating a grade with our four variables of interest. An exception is the United Kingdom, where grades repetition is uncommon. The variable on the students' planned length of the investment in education takes value one when it is lower secondary studies or upper secondary not leading to tertiary education, and zero otherwise. Subsequently, we use a Bivariate Probit specification to test the joint probabilities of leaving school early and repeating a school year when these probabilities are correlated with difficulties in learning online. The Probit and Bivariate Probit specifications on leaving school early and repeating a school year are:

$$\text{Leaving education early}_{ij}^* = \alpha_1 + \beta_1 \text{No computer}_{ij} + \beta_2 \text{No internet}_{ij} + \beta_3 \text{No quiet place}_{ij} + \beta_4 \text{Few school ICT}_j + W_{ij}\Pi + v_j + \varepsilon_{1ij} \quad (2)$$

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

With Leaving education early:

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

And Repeated grade:

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

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

5. Results

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

The results of estimating equation (1) in the field of mathematics are in Table 1; negative coefficients are the gaps between the scores of students unable to learn remotely and those of their peers. In this and the following tables, standard errors or t-values are not reported to save space, but are available from the authors upon request. The base regressions include only our four variables of interest, *No computer*, *No internet*, *No quiet place to study* and *Few school ICT*, and full regressions (the last two columns for each country in Table 1) comprise first all covariates and then all covariates and school fixed effects. Coefficient values are easy to interpret by considering that, in the average of OECD countries, 40 score points (on a mean of about 500) correspond to the cognitive content of about one school year (OECD; 2019). Table SA2 in the Online Appendix reports results in reading.

In the base regressions of Table 1, all coefficients on the four variables of interest are strongly negative and significant. Specifically, not having a computer at home (*No computer*) is correlated with a

negative gap of about 1.7 of a school year in Germany, 1.5 year in France, and more than one year in Italy, Spain and the United Kingdom; significance is at the one percent level in all cases. In the subsequent specifications, coefficients remain robust to the inclusion of all control variables. They remain significant while their sizes shrink. Interestingly, significant changes in the sizes of these coefficients take place in relation with some covariates, which are not the same in all countries. Similar patterns emerge when reading is the dependent variable, as shown in Table SA2 in the Online Appendix. In Section 5.1.2, below, we measure the relationships of covariates with our variables of interest. In the full regressions with school FE, the cognitive losses in mathematics associated with *not having a computer at home* remain strong and significant: they are more than half of a school year in France, Germany and the United Kingdom, and more than a fourth of a year in Italy and Spain. The evidence that, everything else given and within schools, the lack of a computer at home for schoolwork is associated with significant cognitive gaps.

Coefficients on the unavailability of an internet connection at home (*No internet*) are negative in the base model of all countries and, except for France, also significant. In Germany and the United Kingdom, they are robust to all specifications and, in the full regressions, equal two thirds of a school year in Germany and almost two years in the United Kingdom. It is interesting to note that, among the five countries, the United Kingdom has both the lowest percentage of families without internet (Table A1) and, everything else given, the largest negative score gaps of students in these families. Hence, while the share of these students is smaller than in the other four countries, they appear to be more marginalized. This may be due to digital network effects: where the use of internet is more widespread, schools and students have more incentives to use it for education related activities, and the disparities with non-users increase.

Not having a quiet place to study (*No quiet place*) at home matters especially in the United Kingdom, where, everything else equal, cognitive losses correspond to about a third of a school year. Coefficients are negative and significant in the base model of all the other countries, but loose statistical significance when controlling for covariates.

A scarce availability of ICT devices at school (*No school ICT*) is correlated with negative scores gaps in mathematics in the base regressions in all countries, but is significant only in Italy and Spain and remains significant, and equal to half of a school year, in the full model only in Italy. Since this variable has several missing observations (about 3 percent in Spain and Italy, but 18 percent in the United Kingdom, Table A1), we checked whether results are robust to the imputation of missing values. Re-running all regressions in the balanced database, we found that coefficients do not change significantly. The explanation of the imputation method and all results are in Section C of the Online Appendix, Tables SC1 and SC2. Overall, the distribution of cognitive losses across the five countries, and their correlations with other explanatory variables are similar when reading is used as the dependent variable (Table SA2 in the Online Appendix).

5.1.1. School locations

The low explanatory value of the variable *No school ICT* might be driven by heterogeneity in coefficients at a geographical level. In particular, as cities are generally better endowed than rural areas with internet and broadband infrastructures, it can be reasonably expected that urban schools make more use of digital resources than rural ones. If this is so, at given levels of school ICT resources, the negative score gaps of students in cities and towns should be larger than those of students in rural areas. In cities, digital network effects, and the corresponding losses of ‘outsiders’, should be stronger. To test this hypothesis, we use the question in the School Questionnaire: *Which of the following definitions best describes the community in which your school is located?* to build a categorical variable, where rural areas (with fewer than 3,000 people) take value zero, towns (between 3,000 and 100,000 people) value one, and cities (with more than 100,000 people) value two. Then, we interact this variable with *Few school ICT*.

Results in Table 2 show that the coefficients on the interactions of the two variables with cities and towns indicators (rural areas are in the intercept) are negative and significant in France, Germany and Italy. However, in France gaps lose significance when the variable *School types* is added to the regression (not shown to save space), which suggests that students in cities and towns attending technical and vocational, and public, schools with few ICT resources experience bigger cognitive losses than those in

rural areas. In Italy, and Germany negative gaps are robust to all specifications. This supports our expectation that, everything else given, students attending schools located where the use of digital devices is more widespread experience larger cognitive losses. In Spain and the United Kingdom locations appear to matter less, which suggests that schools' locations and school types, when differentiated by tracking, may be correlated; i.e. in countries with early tracking, lyceums are located in urban areas and students attending vocational and technical schools register the larger cognitive losses.

5.1.2 Gelbach decomposition

All results above show that some covariates significantly interact with the coefficients of our variables of interest, but these covariates are not the same across countries. To explore systematically these relationships, in this Section we use the Gelbach (2016) decomposition method. It allows us to see how much of the changes of our coefficients of interest from the base to the full regressions are due to each group of cofactors.¹⁰ Specifically, for each country we decompose the variation of the coefficients into three components, which concern individual, family and school covariates. A positive feature of this method is that results are independent from the order in which variables are included into the regression. A more detailed decomposition, considering each covariate, is in Table SA3 in the Online Appendix.

Results are in Table 3. In France, 78 percent of the difference between the coefficients on *Not having a computer at home* in the base and the full model is due to school characteristics. Similarly, 65 and the 90 percent of the variations of the coefficients on *No quiet place* and *Few school ICT* are explained by them. These results support the above findings and evidence a strong differentiation and segregation between schools.¹¹ In Italy (as pointed out by Di Giacomo and Pennisi 2015), almost as in France, between 63 to 70 percent of the variations of the coefficients on the four variables of interest are explained by school variables. However, in this country, more than in France, individual students' features also matter: their contributions to the total variations range from 19 to 24 percent. Germany, both sets of family and

¹⁰ To take into account the variable of interest *Few school ICT*, we consider coefficient variations between the base model and the full model without school FE.

¹¹ Results are fully consistent with the above findings despite this second set of regressions also includes urban or rural schools' locations. This is related to lyceums being mostly located in urban areas.

school covariates contribute to explain coefficients' variations (except for *No school ICT*, which is not significant). The contribution of family characteristics ranges from 41 to 48 percent, while that of schools ranges from 32 to 41 percent. Hence, in France, Italy and Germany, where tracking starts earlier, school variables explain an important part of the gap associated with the unavailability of ICT resources at home and at school, which suggests that these students are more concentrated in technical and vocational schools. Table SA3 in the Online appendix, shows that the covariates significantly correlated with the variations in the coefficients on our variable of interest are school types, rather than the distinction between private and public schools. Moreover, in Italy and Germany, grades repetition also matters.

In Spain individual characteristics matter more than in other countries, followed by family factors. Table SA3 in the Online Appendix shows that these 'individual characteristics' mostly are 'grades repetition'. This is because in Spain, students unable to study at home because of a lack of ICT resources, are also frequently grade repeaters. These results are consistent with the country's comprehensive school system mixed with a high frequency of grades repetition. Finally, in the United Kingdom, only the variations from the base to the full model on the coefficients on *No computer* and *No quiet place* are significant, although small. In both cases, they are mainly due to family factors, which contribute by, respectively, 87 and 78 percent. In turn, this is consistent with late tracking and low grades repetition. In sum, cognitive gaps due to a lack of ICT resources or a quiet place to study are mainly associated with school types in France, Italy, and Germany. In the latter, family characteristics also matter. In Spain, they are correlated with grades repetition and family features, and in the United Kingdom, with the latter. Interestingly, among individual factors, being an immigrant student is correlated with the coefficient on the lack of a computer at home and of quiet place to study, but, except for the United Kingdom, not with the lack of internet access.

We tested the robustness of our findings by rerunning our regressions with wider sets of covariates, comprising home possessions, language spoken at home, parents' employment levels, different ICT resources available at school, and teachers' digital training. We found no significant changes in our main results. These results are available upon request. Furthermore, to control for the sensitivity of our findings,

we used the absence from school as an alternative proxy for the digital divide among students, and tested its association with scores. Not being able to study remotely is not comparable to a full school absence during normal times, but the similarity between the two situations increases when distant learning substitutes physical school classes, as occurred during the school closures of 2020 and 2021. Results are in Section B of the Online Appendix. As expected, these negative gaps are larger than those related to the lack of each of the four factors needed to learn remotely, but follow the same general patterns within and across countries. Also in this case, results are robust to different covariates and specifications. Further robustness controls, based on the imputation of missing observations are in Section C of the Online Appendix.

5.2 Leaving education early and repeating grades.

Not being able to learn remotely may have longer run consequences than the score gaps seen above, which, in principle, could be at least partly reversed once back at school.¹² Students not learning remotely for weeks and months and foreseeing their scores will fall considerably below those of their peers may choose to shorten the length of their planned future education. They may drop out of school altogether, or stop studying when completing their compulsory schooling cycle or secondary school. As already seen, we use the question *Which of the following do you expect to complete?* And, as said above, set equal to one the answers indicating lower and upper secondary education to not leading to tertiary studies, and zero for expected higher levels. Moreover, if falling behind may reduce students' planned investments in education, the concrete possibility of repeating grades may reinforce this decision. Hence, we expect students unable to attend remote learning to cut their planned investments in education and to reduce them even more if they are also likely to repeat grades.

We test whether our four variables indicating the lack of ICT resources at home or at school and of a quiet place to study are correlated with the probabilities of leaving school early and of repeating

¹² von Hippel and Hamrock (2019), find that cognitive losses deriving from summer vacations are reversed after variable lengths of time once back at school.

grades (the latter, except for the United Kingdom). Then, we test whether these two probabilities are significantly correlated. As in equations (2) and (3) above, we use Probit specifications for the first two tests and Bivariate probit regressions for the latter. In the Probit specification, the coefficients of the marginal probabilities on each variable of interest are in columns 1 to 4 of Table 4. The base regressions include only our four variables of interest, while the full regressions control for all covariates of equations (2) and (3). The results on the Bivariate probit regressions are in columns 5 and 6. The *Rho* coefficients report the correlation between the residuals of the regressions having *Leaving education early* and *Repeated grade* as dependent variables. Other than for the United Kingdom, Bivariate probit coefficients are not reported for France because both the raw correlation coefficient between y_1 and y_2 (Online Appendix Table SA1) and the *Rho* coefficient for this country are non-significant.

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

The Bivariate Probit regressions add interesting insights on the joint probabilities of the two events. The *Rho* coefficients are strong and highly significant for Spain, Germany and Italy, indicating that the use of the Biprobit specifications on these countries' data is appropriate. Their positive signs show that the two outcomes, repeating grades and leaving education early, reinforce each other. For example, as seen in the Probit specifications, not having a computer at home in Spain increases the probability of leaving education early by 10 percent and the probability of repeating grades by 24, while in the Bivariate

probit regressions, not having a computer at home increases the joint probability of leaving education early and repeating a grade by 13 percent (column 6). In Spain, similar results apply to the other three variables of interest: not having an internet connection at home, not having a quiet place to study and attending a school with scarce ICT resources. The joint probabilities of repeating grades and leaving school early are all significantly correlated with the lack of the factors needed to learn remotely. In Section 5.1 above was seen that, in Spain, the negative score gaps associated with schools having few ICT resources were explained by the distinction between private and public schools, and the lower digitalization of the latter. Here, we see that even controlling for all cofactors, attending a school with few ICT resources significantly increases the joint probabilities of repeating a grade and leaving education early.

Analogous outcomes derive from the lack of computer at home in Germany and Italy. In the Bivariate Probit regressions, it significantly increases the joint probabilities of repeating grades and leaving education early by 14 percent in Germany and by three percent in Italy (column 5). Controlling for all covariates, coefficients shrink but remain significant at the one and five percent levels, respectively (column 6). Not having a quiet place to study in Germany, and a scarcity of ICT resources at school in Italy also increase the joint probabilities of repeating grades and leaving education early (column 5). In Italy, most of the correlation between the joint probabilities and *Few school ICT* resources is explained by the school types attended (Column 4, Table SA4).

6. Conclusions

In this study, we used PISA 2018 data from five important European countries to test the educational outcomes of students who lack the necessary ICT devices to learn remotely or do not have a quiet place to study. Our findings show that they experience strong and significant cognitive gaps relatively to their peers, and that these gaps tend to remain significant even after all controls have been taken into consideration. At the same time, we find significant relationships between these cognitive losses and other covariates, which help to evidence some main similarities and differences across

countries. Among these are tracking between schools, grades repetition, urban or rural schools' locations and, to a lesser extent, family characteristics.

Tracking between schools starts earlier in Germany, Italy and France. In these countries, students unable to learn remotely who attend vocational and technical schools register the larger cognitive losses. These gaps are wider when schools are located in urban areas, where the human capital endowment is higher (Ballatore and Mariani 2019) and the use of ICT resources is more widespread. Grades repetition is common in these three countries, but is substantially higher in Spain, where it constitutes the main covariate related to the digital scores gaps. In the United Kingdom, family characteristics contribute to explain negative scores related to the lack of a computer at home or a quiet place to study, but, in general, covariates play a smaller role than in other countries. Results have also long run implications: where grades repetition is more common, students lacking the resources needed to learn at home are more likely to both repeat grades and leave education earlier

Our findings derive from normal-times data, when online study complemented rather than substitute classes at the physical school, but are nonetheless useful in providing a benchmark – or lower bound – for the education inequalities likely to emerge from the school closures of 2020 and 2021, when distant schooling entirely substituted the physical school, and for the appropriate policy actions. Among these, the obvious and most urgent one is guaranteeing to all students and schools the resources needed to learn remotely. This is even more important considering that part of the learning process could remain permanently online when back to normality. The necessity of this direct measure is evidenced by the strong and significant gaps associated with the lack of the ICT resources that we find every country we consider after controlling for everything else and within schools. The possession of these resources and the ability to efficiently use them would substantially mitigate these gaps.

However, in parallel with these direct measures, other policy actions are also needed. Among them, the improvement of digital infrastructures is crucial especially in countries, such as Italy and Germany, where the disparities in cognitive outcomes between schools located in urban and rural areas are strong and significant. Other actions are more related to structural characteristics of schooling systems,

which have been discussed at length in the education's literature (Ammermueller, 2013), and which, we show, contribute to enlarge the education inequalities related to digital divides: among these, early tracking and grades repetition. Particularly the latter, considering its long run implications on expected education levels, should be mitigated, especially in relation to students unable to learn at home because of a lack of ICT resources or a quiet place to study.

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Table 1. - Remote learning resources. Dependent variable: students' scores in mathematics.

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

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

Table 1. - Remote learning resources. Dependent variable: students' scores in mathematics. Continues from previous page

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

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

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

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

Table 2 - Few school ICT resources and school locations.
Dependent variable: students' scores in mathematics

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

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

Table 3 – Gelbach decomposition by country

		Individual	(%)	Family	(%)	School	(%)	Total explained
France	No computer	-4.33***	11%	-4.14***	11%	-30.73***	78%	-39.20***
	No internet	0.35	-	-2.44	-	2.70	-	0.61
	No quiet place to study	-4.57***	15%	-6.10***	20%	-19.66***	65%	-30.34***
	Few school ICT	-1.85	10%	0.02	0%	-16.53**	90%	-18.36**
Germany	No computer	-4.11**	14%	-13.94***	48%	-10.90***	38%	-28.95***
	No internet	-5.57	19%	-12.00**	41%	-12.01***	41%	-29.57***
	No quiet place to study	-5.96**	24%	-10.85***	44%	-7.83**	32%	-24.64***
	Few school ICT	-0.92	-	-1.27	-	0.97	-	-1.23
Italy	No computer	-4.27***	24%	-1.80***	10%	-12.02***	66%	-18.09***
	No internet	-3.21	19%	-2.97***	18%	-10.68**	63%	-16.86***
	No quiet place to study	-3.38**	24%	-1.46**	10%	-9.10***	65%	-13.94***
	Few school ICT	-4.62***	24%	-0.99**	5%	-13.37**	70%	-18.98***
Spain	No computer	-29.36***	79%	-6.62***	18%	-1.15**	3%	-37.12***
	No internet	-17.12***	72%	-5.55***	23%	-1.10**	5%	-23.77***
	No quiet place to study	-3.99**	63%	-2.18***	34%	-0.20	3%	-6.36***
	Few school ICT	-5.15***	58%	-1.67***	19%	-2.07***	23%	-8.89***
United Kingdom	No computer	0.04	-1%	-6.24***	87%	-0.97	14%	-7.16***
	No internet	-3.28	-	-2.88	-	-0.92	-	-7.09
	No quiet place to study	-1.28	27%	-3.71***	78%	0.24	-5%	-4.76***
	Few school ICT	0.47	-	-0.08	-	-0.20	-	0.19

Notes: Standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the average of the ten plausible values in mathematics. All results are weighted. Individual includes: gender, age (years and months), repeated grade. Family includes: immigrant status, age of arrival, highest parents' level of education. School includes: types (general, technical, vocational), public or private, location (city, town or urban).

Table 4 - Marginal probabilities: Leaving education early and repeating grades

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

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

APPENDIX

Table A1. – Descriptive statistics

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

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