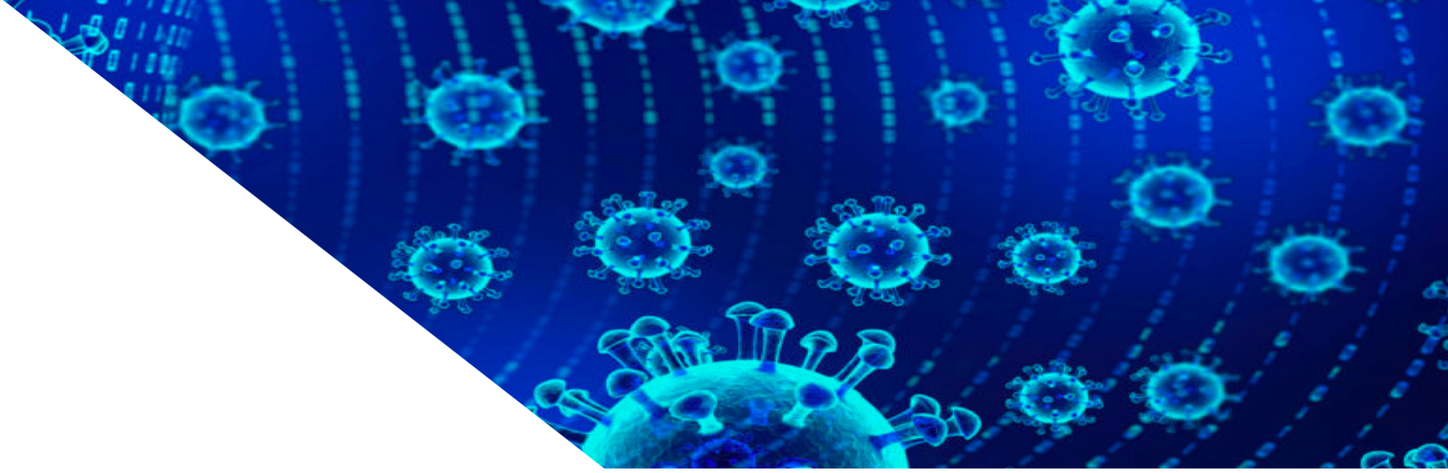


Andalucía se mueve con Europa

COVID 19

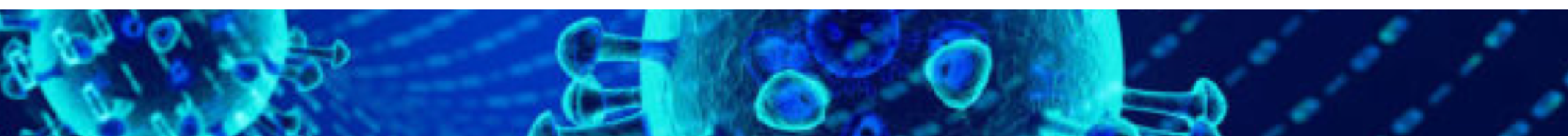
Nuevas dinámicas del mercado laboral tras el confinamiento en Andalucía: el empleo del futuro post-Covid 19 y respuesta a nuevos confinamientos

ACCESO AL USO DE LAS TECNOLOGÍAS

uhu.es

Junta de Andalucía

UNIÓN EUROPEA
Fondo Europeo de Desarrollo Regional



(In)Equality in children's access to technological resources in Spain during the lockdown: Evidence from the Spanish Survey on Equipment and Use of ICT in Households.

Borra, Cristina[1], Quesada, Odra[2], and Rebollo-Sanz, Yolanda[3]

[1]Department of Economics and Economic History, University of Seville, Seville, Spain.
[2]Granted by SARS-COV-2 and COVID-19 Reasearch Project - Junta de Andalucía.
[3]Department of Economics, Quantitative Methods and Economic History, University Pablo de Olavide, Seville, Seville.

Abstract

Almost two years after the outbreak of Corona, the effect of some sort of inequality on children's knowledge process continue being main issue in educational policy. This paper provides empirical evidence for the impact of the outbreak of Corona on the children's access and use of a broad range of technological outcomes in Spain. We compare children who belong to *high educated* and *high income* families with those who do not and we estimate the effects of the lockdown using a causal inference approach in order to evaluate whether the Covid-19 pandemic had an unequal effect among children depending on their socio-economic situation. We find that the household's income level had no effect on the access nor use of ICT devices but education of the adult of reference in the child's home has a positive effect on the children's access to Internet during the lockdown.

1 Introduction

Children's computer and Internet use has followed an upward trend during the last decades. The literature related to education tries to disentangle if the expansion of both, computers and Internet, used by children in schools, has a positive effect on their educational achievement. Before the outbreak of Corona, online learning resources did not have an important role in education, neither at home nor at schools. In addition, as computers were not included in the learning process and households have not the same consumption preferences, income levels were crucial for determining the decision of acquiring a computer or getting an Internet connection at home.

Despite that the world has moved towards a provision and use of technology convergence, large disparities remain among children's Internet access (Malamud et al. 2019). In Spain, as occurred in the majority of OECD countries, schools closed due to the Covid-19 pandemic, causing that children were more than five months out of school, jeopardizing their learning and development, and setting both back (Andrew et al. 2020). Our paper seeks to determine whether or not inequality in technological resources was already in the Spanish society and if Corona took place to narrow or widen it. In addition, if there were already differences in computer and Internet use among households, the main interest would be to assess and quantify the factors that were driving it, related to educational background, gender, household composition, income, among others. Gaps in access and use of digital technologies at a pre-covid period have been documented by previous literature.

Prior work shows that considerable gaps in learning time emerges between primary school children from poorer and better-off families (ibid. and Bacher-Hicks, Goodman, and Mulhern 2021). The authors analyze the effect of lockdown on inequalities in learning time by income. With the data of computers and Internet use available in Spain, we can determine the effects of inequality in resources that will drive long-run disparities in human capital accumulation of those children who did not have access during the lockdown to good learning support at home.

As the closure of schools disrupted during the usual school calendar cycle and this could not be anticipated, families had to adapt their actual digital resources to the new home-learning process. This suspension of face-to-face instruction in schools during the pandemic led to an increase in the importance of parent's devoted hours to children's education and to an unprecedented virtual schooling. Since online education became an imperfect substitute for in-person learning (Agostinelli et al. 2020), parents had to compensate through their abilities, capabilities, and efforts some of the inputs provided by the teachers. Related to this, it is worth mentioning that low-educated parents are not equally able to help their children than those high-educated, and the same case applies when we compare those parents who had to work from home during the lockdown compared to those who did not have to. Thus, apart from the level of effort, parent's socioeconomic characteristics play a role, both in the provision of computers and Internet connection, and the children's performance at school during the pandemic.

We further complemented this evidence by combining Covid-19 lockdown and pre-lockdown data from the Spanish Survey on Equipment and Use of Information and Communication Technologies in Households, which, as far as we know, is the first study that has been carried out using this database for the case of interest. We started by comparing the provision of technological goods, Internet connection, time of use, and online shopping with those levels observed years before the lockdown. This gives us the intuition of how children were performing in time devoted to computer and Internet use, and if the differences between poor and better-off children remain constant compering to those before the outbreak. The fact that online learning is less effective than in-school learning is well-recognized (ibid.) and, thus, unequal access to the Internet and to computers can hinder learning opportunities with a negative effect on the children's educational performance. For this reason, we calculate the gap between those who are considered as more prepared for remote learning, due to their availability of home-learning resources (Engzell, Frey, and Verhagen 2021), and those who are not using a Difference-in-Differences approach. We expect to find that differences in technological equipment at a household level are caused by differences in parent's education, as well as, their household's socioeconomic situation, and this, at the same time, has effects on the provision of support, as they have to struggle with economic uncertainty and/or demands of working from home

(Engzell, Frey, and Verhagen 2021). Our research further highlights how parent's (or children's household head) educational attainment can affect their children's access and use of digital resources as a measure of schooling during the lockdown. Therefore, inequality in technological use among households due to external factors can require extra mechanisms that provide to those children in the most vulnerable families the tools to mitigate the effects of the Covid-19 in their future.

1.1 Case of study: The outbreak of Corona in Spain.

Comentar que los colegios estuvieron todos clausurados desde el día X y que, por tanto, no hubo clases presenciales. No hubo homogeneización en la enseñanza, por lo que se espera que los colegios privados tuviesen más medios para impartir clases de la misma calidad que las presenciales pero de manera remota. La disponibilidad de internet y ordenador fue clave en el seguimiento de las clases y de ahí su importancia.

PAPER DE ENGELL.

The emergence of the coronavirus pandemic brought major disruptions to Spanish society, as well as, worldwide. Health systems were stressed, businesses were shuttered, jobs were lost, and all the schools were closed to mitigate the spread of the coronavirus. As the education system was forced to adapt to the new circumstances, parents' role as educators and online teaching were key factors to, almost, maintain the same children's performance. Although online programs have enabled educational activities to continue while schools have been physically closed, differences in households' availability of ICT resources can be an important factor of future differences in children's academic performance.

Levels of technological resources at home are closely related to the socioeconomic status of the household, leaving families with lower incomes more likely to face obstacles in internet access and use. This aspect of the digital divide, often referred to as the "homework gap" (the gap between school-age children who have access to high-speed internet at home and those who don't), has been exacerbated by the outbreak of the pandemic, as all the school-based instructional time was reduced to zero. As it has been studied in previous literature, the reduction in instructional time has negative effects on education outcomes, whether it is related to time away from school during the summer break (Stewart, Watson, and Campbell 2018) as due to weather issues (Marcotte 2007; Marcotte and Hansen 2010).

2 Empirical strategy

2.1 Data and the sample

The main source of data for our study is the Spanish Survey on Equipment and Use of Information and Communication Technology in Households, which is collected and made publicly yearly available by the Spanish Statistical Bureau (hereafter INE, by its Spanish initials). The statistical operation follows the methodological recommendations of the Statistical Office of the European Union (Eurostat), allowing comparisons between Spain and other countries and satisfying the requirements of international organisations. The objective of the Information and Communication Technology (hereafter ICT) Survey is to obtain data on the development and evolution of the Information Society, which includes ICT household equipment (telephone, computer equipment, Internet access) and the use of the Internet and electronic commerce by residents of these homes. In order to analyze more aspects of the use of new technologies, the questionnaire is dynamic and includes new sections with different periodicity[1].

Furthermore, we complement the ICT survey with information of the Public Registry of Non-university Training Centres, dependant from the Spanish Ministry of Education and High Vocational Training[2] to control if the impact of the lockdown in the kid's access and use of ICT resouces was affected by a different type of schooling, state and private, and, if that was the case, taking this into a account to run the estimations, in order to account for a potential demand effect. As any other control variable, the type of schooling can not be related with the treatment status.

Due to the endogeneity that characterizes including households' income level in the estimation of children's ICT access and use, we decide to define the treatment based on the type of schooling.

While family financial resources are doubtless an important factor determining the attendance to private education, recent studies suggest that there are a number of other important factors that enter into the decision-making process, such as the potential role of parental values and of the geographical availability of state-funded schools that parents may see as 'substitutes' for private schools. Blundell, Dearden, and Sibieta find evidence that parental traditional values and education values are important in predicting attendance at a private school, and that this is the case over and above the role of income instead of what the previous evidence found (Anders et al. 2020).

Thus, the selection of the variable that define the treatment is a proxy for both, household's income level and educational attainment of the reference adult[3]

Por ello, no deberíamos introducir como control *medpriv* cuando el tratamiento sea HIGH EDUCATION????

Our main interest relies on the information about children's access and use of ICT household equipment to determine the availability of adequate support across families depending on their socio-economic status, and to clarify if the lockdown had an impact increasing the existing inequality in technological resources. For this purpose, we construct a panel data structure from a five years window data, waves from 2016 to 2020, where we have contained about 205,000 observations. The possibility of constructing a panel data structure is based on the opportunity of observing a household in one period or more depending on which shift of rotation, from 1 to 4, it is situated. In other words, the rotation shifts are sample sections that are used to gradually incorporate changes in the sample (Scott and Smith 1974). This process of refreshing the sample is applied by the INE to ensure the non-exhaustiveness of the collaborating households, as well as, contributing to the updating of the probabilities of selection of other households.

Although we have a serial number which identifies each household in each wave in the ICT

[1] Further information can be found on the Methodological Notes published by the Spanish National Institute of Statistics on its web page: `https://www.ine.es/dyngs/INEbase/en/operacion.htm?c=estadistica_C&cid=1254736176741&menu=ultiDatos&idp=1254735976608`

[2] More details: `https://www.educacionyfp.gob.es/en/contenidos/centros-docentes/buscar-centro-no-universitario.html`

[3] As the database does not provide any information about family ties, we use the term *reference adult* to each individual who answered the survey on behalf of the household.

database, this is not an unique number among all the waves (years) the household appears. This drawback needs to be solved by processing the data, finding a precise and homogeneous criterion in which based the new identification of the household units to allow the following-through of those among waves. After testing and proving the new household identification number, we have based the criterion on the following time invariant characteristics of the adult of reference: date of birth[4], gender, region of residence, rotation shift number, country birth, code of the degree of urbanization area, and Eurostat code of the degree of urbanization area.

For the aim of the analysis, we restrict the sample based on three different criteria. First, as the survey also gathered detailed information on the children's use of ICT resources by asking one adult per household, our main sample is composed of households with children aged 10 to 15 thus excluding all those households without children in that age range since they are not reporting any information that could contribute to the aim of this study. The second restriction is related with the age of the adult respondents. As the database does not contain any information about family ties among individuals living in the same household, we limit the adult respondents' age between 25 to 60 years old in their first observation, trying to ensure that they are the actual parents. Therefore, we expect that the reported information by the adult of reference about the children's access and use of ICT resources is the closest to the real kid's behavior. Thirdly, we exclude all those observations belonging to August and September, since the questions related to the children's use of ICT resources are formulated with respect to the last three months, which would be indicating a summer vacation period. However, it is worth mentioning that all the results remains almost unchanged in magnitude but we achieve an increment in the statistical significant of the causal effects estimates. Table A1 in the Appendix shows the final sample size by wave and month of interview after applying the restrictions mentioned above. It is composed by 10,726 10- to 15-year-olds children living in a total of 8,641 households.

2.1.1 Outcomes and variables of interest

The ICT survey, combined with the Public Registry of Non-university Training Centres data, provides individual data for the adult respondent and for all the children aged 10-15 in each household. Related with the latter, the reference adults report information about children's ICT access and use which are part of the set of outcomes of interest, in particular, children's computer and internet use and children's mobile phone access. This set of outcomes are supplemented with another three outcome variables, which are cornerstones to analyze jointly the effect of the confinement in the children's access and use of ICT resources among households depending on their sociodemographic and socioeconomic characteristics, such as the combination of children's computer and internet use, mobile phone access and internet use, and children's computer, mobile phone and internet use and access.

Furthermore, we need a set of covariates to ensure a causal interpretation of the estimates. Our database includes sociodemographic characteristics for both children (age, gender, province, number

[4]As interviewed individuals are asked to report either their date of birth or their age, large proportion of them answered with their age. In those cases in which we do not have information about the individual's date of birth, we simply extract her/his age to the interview year, obtaining an approximation of the date of birth.

of siblings, number of people in the household, type of family, type of schooling, among others) and reference adults (age, gender, nationality, and educational level), as well as, socioeconomic status information (such as labor situation, income level, and degree of urbanization area in which the household is situated). To determine the robustness of our results, these covariates are included sequentially in the estimated models to determine if the findings are affected by those changes.

More detailed information about the outcomes and variables of interest can be found in Table A2 in the Appendix.

2.1.2 Treatments

The credibility or interpretation of our results relies on the validity of the methods of analysis and models used. Sensitivity analysis play a crucial role in assessing the robustness of the findings and conclusions (L. Thabane et al. 2013), as we show in Section XXX. Will the results change if we modify the definition of the treatment such as using a different cut-off points? We decide to test the impact of the lockdown under different treatments as the treatment status is defined by achieving a certain threshold of an education and income measure. Therefore, we define two treatments. The first treatment (hereafter T1) is defined by a dummy variable which is equal to 1 if the reference adult is high educated (from undergraduate studies to doctorate), and 0 otherwise. The second treatment is based on the household income level. In this case, the dummy variable takes value equals 1 if the overall household monthly income is located above the first quartile of the income distribution. As we show in Table XX, this means that almost 25% of the households with children aged 10 to 15 in Spain reported an overall net monthly income higher than 2,500 €.

2.2 Estimation strategy

The emergence of the coronavirus pandemic brought major disruptions to Spanish society, as well as, worldwide. Health systems were stressed, businesses were shuttered, jobs were lost, and all the schools were closed to mitigate the spread of the coronavirus. As the education system was forced to adapt to the new circumstances, parents role as educators and online teaching were key factors to, almost, maintain the same children's performance. Although online programs have enabled educational activities to continue while schools have been physically closed, differences in households' availability of ICT resources can be an important factor of future differences in children's academic performance.

Levels of technological resources at home are close related with the socioeconomic status of the household, leaving families with lower incomes more likely to face obstacles in the internet access and use. This aspect of the digital divide, often referred to as the "homework gap" (the gap between school-age children who have access to high-speed internet at home and those who don't), has been exacerbated by the outbreak of the pandemic, as all the school-based instructional time was reduced to zero. As it has been studied in previous literature, the reduction in instructional time has negative effects on education outcomes, whether it is related with time away from school during the summer break (Stewart, Watson, and Campbell 2018) as due to whether issues (Marcotte 2007; Marcotte and Hansen 2010).

Due to the endogeneity that characterizes including households' income level in the estimation of children's ICT access and use, we decide to define the treatment based on the type of schooling.

Our main question is how the type of schooling has an impact on the children's access and use of ICT resources and whether this vary between children before and during the Corona breakout. This hypothesis is motivated by the availability of technological resources in private schools, acce

The existing literature evidences that differences in the levels of educational investments drive differences in educational attainment (Attanasio 2015). Thus, if this assumption is true, we can test whether the lockdown had an impact on a given group of children depending on their socio-economic characteristics (reference adults' education and households' income levels). Worse academic performance of this group could be attributed to differences in ICT endowment levels. To investigate the first hypothesis, we select six outcomes as a measure of access and use of technological resources, as it has been explained in Section 2.1.1.

The empirical framework involves two different comparisons based on two different treatment status. First, we compare the effect of the lockdown between children belonging to the first treatment, meaning that s/he lives with a high educated adult, with those who does not.

To determine if the educational level of the adult of reference has an impact in the access and use of ICT resources in Spain, the easiest strategy is to estimate:

$$\begin{aligned} Y_{it} = \alpha + \beta_t Lockdown_t + \gamma_i HighEducation_i \\ + \delta_{it}(Lockdown_t \cdot HighEducation_i) + \eta_i Covariates_i + \epsilon_{it}, \end{aligned} \tag{1}$$

where the subscript i identifies each child in the sample and the subscript t tells us whether we are looking at data from 2016 to 2019 (before the outbreak of Corona) or 2020 (after). The dependent variable is denoted Y_{it}, for the children's computer, Internet or mobile phone, access and use, reported by the child i[5] on the year t. $Lockdown_t$ is a dummy variable indicating the outbreak of Corona, $HighEducation_i$ is a dummy variable indicating if the reference adults are high educated, and the interaction term $Lockdown_t \cdot HighEducation_i$ indicates high educated reference adults observations from the lockdown period (covering from March to September of 2020). The coefficient δ_{it} captures the effect of the confinement on children's computer, Internet, and mobile phone access and use depending on the educational level of the reference adult, as well as, η_i is a vector of control variables assumed to not to be affected neither by the treatment (high education) nor by the lockdown or outbreak of Corona.

The set of control variables includes sociodemographic characteristics such as child's gender, child's age (in years) dummies, if the child has siblings, if s/he is the oldest sibling, if s/he belongs to a single-parent family, if the child attends to a secondary school, the proportion of private schools per region, if the adult of reference is immigrant, the age of the adult of reference, and if the household is located in a thinly population area.

However, to ensure the causal interpretation of our findings and due to the heterogeneity that characterizes the households behavior, as well as, to exploit the panel structure of our data, we estimate an individual-fixed effect model, with intuitions borrowed from the DiD literature.

[5] In particular, it is reported by the adult respondent in each household.

We based our empirical strategy in recent literature findings which demonstrate that, with a common intervention date, a pooled OLS regression that includes an indicator for eventually being *treated*, a post-treatment time period dummy, and the treatment indicator – three regressors in addition to an overall constant – is numerically the same as the full TWFE estimator (Wooldridge 2021). Furthermore, Wooldridge provides a recent analysis, showing that an entire class of regressions – including pooled OLS – reproduce the FE estimator, even in the unbalanced case, provided one is careful about using only the complete cases in defining the unit-specific time averages.

Another application of the general result is to common timing difference-in-differences (DiD) designs – without or with covariates – and also staggered interventions. In Section 5 I show that,

Nevertheless, the information contained on the ICT database also enables us to estimate multi-regional regression Diff-and-Diff procedure which reflects the fact that there could be regions driving causal comparisons. This multiregions setup controls for the differing children's use of ICT devices in each region and year is the same as introduce *region* and *year effects*[6], as we can observe in the following equation:

$$\begin{aligned} Y_{it} = \alpha + \beta_t Lockdown_t + \gamma_i HighEducation_i + \delta_{it}(Lockdown_t \cdot HighEducation_i) \\ + \eta_i Covariates_i + \sum_{j=1}^{52} \theta_j Region_{ji} + \sum_{k=2016}^{2020} \sigma_k Year_{ki} + \lambda_i + \epsilon_{it} \end{aligned} \tag{2}$$

where λ denotes individual-fixed effects. In addition, we adjust in Equation 2 for the fact that repeated outcomes for the same region tend to be correlated by clustering on regions. In principle, clustering solves any sort of dependence problem in the data (Angrist and Pischke 2014).

Moreover, we compare the effect of the lockdown between children living in a household situated under the median income distribution with those who live in one located above it (what we call $HighIncome_i$)[7]. In this case, we run the models from Equations **??** and **??** with the dummy variable $HighIncome_i$ instead of $HighEducation_i$. In this case, the interaction term $Lockdown_t \cdot HighIncome_i$ indicates children living in *High Income* households during the lockdown period. The coefficient η captures the effect of the outbreak of Corona on the children's use of computers, mobile phones, and Internet depending on the income level of the household.

3 Main results

In this section, we present the results of two alternative approaches for estimating the impact of the lockdown on the children's use and access to Internet and ICT devices. First, we compare the estimated impact of *HighEducation*.

Table 1 shows our findings related with the effect of the Corona crisis on the children's use of Internet, mobile phones, and computers. As we can observe in the first row of the table, the lockdown had a clear positive effect on the children's use of Internet, showing that the high education of the reference adults matters much more on the Internet use of the child during the lockdown than before,

[6] A set of dummies for every region and year in the sample, except for one, which is omitted as a reference group.

[7] We are dealing with income responses that are given by intervals. For this reason, we treat as median value the third category of the five, to be able to construct a treatment dummy from this information.

with an expected mean change of 2.4 percentage points (hereafter p.p.) more access between a child with high educated references at home and a child with an adult of reference with low education. Thus, we find a marginally significant increase in inequality in children's use of Internet depending on the educational level at home.

Table 1: Effect of lockdown on inequalities in children's use of Internet, mobile phones, and computers by education of the refence adults in the household.

VARIABLES	(1) *Child_Internet*	(2) *Child_mobile*	(3) *Child_computer*
$Lockdown_t \cdot HighEducation_i$	0.0240**	0.0139	-0.00110
	(0.0110)	(0.0274)	(0.0163)
Constant	0.991***	0.684***	0.982***
	(0.00263)	(0.00608)	(0.00241)
Observations	12,751	12,796	12,777
R-squared	0.032	0.034	0.050
Regions fixed effects	X	X	X
Year fixed effects	X	X	X

Note: Differences in the sample size are due to N/A responses. Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Determining the role of the access to ICT devices may be specially important due to the rapid transformation from full time school learning to an improvised home learning, whereby teaching was undertaken remotely and on digital platforms. The COVID-19 has resulted in schools shut all across the world. Globally, over 1.2 billion children are out of the classroom[8], so determine whether the adoption of online learning presents any sort of inequality is a key aspect to evaluate a future introduction of e-learning methods on the traditional education.

Thus, we estimate Equation 1 on a new group of treated: low income and high income households. This ensures that the causal effect of the lockdown is not affected by the endogeneity of the income in the level of education, as well as, it estimates itself if the inequality in access depending on the education is affected by income reasons.

As Table 2 presents, children's access to the use of Internet, mobile phones, and computers in Spain during the last five years' time is not conditioned on the household income level, but on the reference adults educational level, as we have seen before. For instance, the estimates in the first line of the table mean that a child from a household situated under the median of the family income distribution has not experimented a lower access to Internet, mobile phone nor computers during the lockdown than a child from a household located above the median of family income distribution.

In other words, Spain presents convergence in the availability of technological resources at home in the last five years. Due to the outbreak of Corona, have access to good learning support at home was crucial since the education was exclusively online. Based on the results obtained in this study, we have proven that there is no inequality in the access of internet depending on level of income of the household which evidences the universality of technological resources among all the types of the families.

[8]https://www.weforum.org/agenda/2020/04/coronavirus-education-global-covid19-online-digital-learning/

Table 2: Effect of lockdown on inequalities in access to ICT resources by income.

VARIABLES	(1) *Child_Internet*	(2) *Child_mobile*	(3) *Child_computer*
$Lockdown_t \cdot Treated_i$	0.00891	0.0419	0.0154
	(0.0147)	(0.0317)	(0.0221)
Constant	0.978***	0.617***	0.955***
	(0.00512)	(0.0103)	(0.00582)
Observations	10,263	10,286	10,274
R-squared	0.040	0.034	0.067
Regions fixed effects	X	X	X
Year fixed effects	X	X	X

Note: Differences in the sample size are due to N/A responses. Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

However, the education of the adults do change children's behaviour in light of ICT resources.

4 Robustness Checks

4.1 Robustness Analysis

As the goal of sensitivity analyses is to assess the consistency of the results under different methods, subgroups, definitions, assumptions, and so on, we decided to test the impact of the lockdown under different treatments as the treatment status is defined by achieving a certain threshold of an education and income measure as we have mention in Section 2.1.2.

Methodologically, we have relied on the assumption that, in the absence of lockdown, the differences in the children's internet use between the treated and comparison groups would have remained constant. But, given the particular context of analysis –Outbreak of Corona-, one could argue that the worsening in mental health between treated and control individuals could be caused by third factors –for instance, COVID incidence levels-. As this assumption is not testable, we carry out some sensitivity analysis which can also be considered a placebo test.

4.2 Pre-lockdown Trends and Placebo Tests

5 Heterogeneity of the results

The main results assume a homogeneous effect of the educational level on children's internet use. To account for potentially heterogeneous effects, we carry on X different analyses.

Aquí, poner que hemos realizado el análisis por gender, grade, and type of schooling.

6 Conclusions and Discussion

Appendix

Table A1: Interviews distribution among waves and months.

	Month of the interview							
	January	February	March	April	May	June	July	Total
2016	143	816	734	497	85	0	0	2,275
2017	74	697	807	555	230	15	0	2,378
2018	113	729	752	631	183	3	0	2,411
2019	0	385	659	592	395	8	0	2,039
2020	0	0	123	40	660	446	352	1,621
Total	330	2,627	3,075	2,315	1,553	472	352	10,724

Table A2: Variables description

Outcomes	
Computer	It takes value 1 if the child had used Internet in the last 3 months, and zero otherwise.
Internet	It takes value 1 if the child had used a computer in the last 3 months, and zero otherwise.
Mobile	It takes value 1 if the child had accessed to a mobile phone in the last 3 months, and zero otherwise.
Computer_Internet	It takes value 1 if the child had used a computer and Internet in the last 3 months, and zero otherwise.
Mobile_Internet	It takes value 1 if the child had accessed to a mobile phone and Internet in the last 3 months, and zero otherwise.
Computer_mobile_Internet	It takes value 1 if the child had used a computer, Internet and had accessed to a mobile phone in the last 3 months, and zero otherwise.
Socio-demographic characteristics	
Girl	It takes value 1 if the child is a girl, and zero otherwise.
Childrens_age10	It takes value 1 if the child is 10 years old, and zero otherwise.
Childrens_age11	It takes value 1 if the child is 10 years old, and zero otherwise.
Childrens_age12	It takes value 1 if the child is 10 years old, and zero otherwise.
Childrens_age13	It takes value 1 if the child is 10 years old, and zero otherwise.
Childrens_age14	It takes value 1 if the child is 10 years old, and zero otherwise.
Childrens_age15	It takes value 1 if the child is 10 years old, and zero otherwise.
Old_child	It takes value 1 if the child is the oldest child in the HH (only taking into account all those children between 10 and 15 years old), and zero otherwise.
N_siblings	Number of siblings (only taking into account all those individuals younger than 18 years old) living in the HH.
N_pers	Number of people in the HH.
Monoparental	It takes value 1 if there is a only breadearner in the HH, and zero otherwise.
Immigrant	It takes value 1 if the adult respondant is immgirant, and zero otherwise.
Int_age	Age (in years) of the adult respondant.
Low_density	It takes value 1 if the HH is located in a thinly populated area (based on the european measure DEG_URBA), and zero otherwise.
Prop_private	Proportion of private schools in each region.
Secondary	It takes value 1 if the child attends to a secondary school, and zero otherwise.
Med_private	It takes value 1 if the region is located above or equal the median of private schools.
Time variables	
2016	It takes value 1 if the interview was conducted in 2016, and zero otherwise.
2017	It takes value 1 if the interview was conducted in 2017, and zero otherwise.
2018	It takes value 1 if the interview was conducted in 2018, and zero otherwise.
2019	It takes value 1 if the interview was conducted in 2019, and zero otherwise.
2020	It takes value 1 if the interview was conducted in 2020, and zero otherwise.

References

Agostinelli, Francesco et al. (2020). *When the great equalizer shuts down: Schools, peers, and parents in pandemic times*. Tech. rep. National Bureau of Economic Research.

Anders, Jake et al. (2020). "Determinants of private school participation: All about the money?" In: *British Educational Research Journal* 46.5, pp. 967–992.

Andrew, Alison et al. (2020). "Inequalities in Children's Experiences of Home Learning during the COVID-19 Lockdown in England". In: *Fiscal Studies* 41.3, pp. 653–683.

Angrist, Joshua D and Jörn-Steffen Pischke (2014). *Mastering'metrics: The path from cause to effect*. Princeton university press.

Attanasio, Orazio P (2015). "The determinants of human capital formation during the early years of life: Theory, measurement, and policies". In: *Journal of the European Economic Association* 13.6, pp. 949–997.

Bacher-Hicks, Andrew, Joshua Goodman, and Christine Mulhern (2021). "Inequality in household adaptation to schooling shocks: Covid-induced online learning engagement in real time". In: *Journal of Public Economics* 193, p. 104345.

Blundell, Richard, Lorraine Dearden, and Luke Sibieta (2010). *The demand for private schooling in England: the impact of price and quality*. Tech. rep. IFS Working Papers.

Engzell, Per, Arun Frey, and Mark D Verhagen (2021). "Learning loss due to school closures during the COVID-19 pandemic". In: *Proceedings of the National Academy of Sciences* 118.17.

Malamud, Ofer et al. (2019). "Do children benefit from internet access? Experimental evidence from Peru". In: *Journal of Development Economics* 138, pp. 41–56.

Marcotte, Dave E (2007). "Schooling and test scores: A mother-natural experiment". In: *Economics of Education Review* 26.5, pp. 629–640.

Marcotte, Dave E and Benjamin Hansen (2010). "Time for School? When the snow falls, test scores also drop". In: *Education Next* 10.1, pp. 52–60.

Scott, AJ and TMF Smith (1974). "Analysis of repeated surveys using time series methods". In: *Journal of the American Statistical Association* 69.347, pp. 674–678.

Stewart, Hilary, Nick Watson, and Mhairi Campbell (2018). "The cost of school holidays for children from low income families". In: *Childhood* 25.4, pp. 516–529.

Thabane, Lehana et al. (2013). "A tutorial on sensitivity analyses in clinical trials: the what, why, when and how". In: *BMC medical research methodology* 13.1, pp. 1–12.

Wooldridge, Jeff (2021). "Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Difference-in-Differences Estimators". In: *Available at SSRN 3906345*.