



Adapting to Crisis: The dynamics of homeschooling during COVID-19 in Colombia

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Adapting to Crisis: The dynamics of homeschooling during COVID-19 in Colombia

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Abstract

This paper investigates the repercussions of the COVID-19 pandemic on homeschooling in Colombia, with a specific focus on the academic outcomes of students from vulnerable households. Utilizing Saber 11 test scores as a metric for academic achievement, the study delves into the influence of internet access and school migration on learning outcomes. The findings indicate that the closure of schools and the transition to homeschooling exacerbated disparities in academic performance, particularly affecting students from low-income backgrounds. Additionally, it is found that inequality also increased due to parental decisions to change pupils from private to public institutions. The study underscores the significance of considering socioeconomic factors and internet accessibility when devising educational strategies during crises.

Keywords: COVID-19, Homeschooling, Standardized test scores, Education Inequalities.

JEL Classification: I21, I24, O33, J24.

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1 Introduction

The COVID-19 pandemic wreaked havoc on economies worldwide, resulting in unprecedented disruptions across various sectors. As lockdowns and social distancing measures were enforced to contain the virus, the economy suffered, leading to widespread job losses, business closures, and disruptions in the supply chain. By April 2020, the impact was starkly evident, with 5.3 million people losing their jobs, causing a significant reduction in household incomes for 42.6 percent of families (DANE, 2020a). Vulnerable populations, already on precarious ground, bore the brunt of this economic turmoil, amplifying existing inequalities and further widening socioeconomic gaps. (Federico Corredor, 2021, Bottan et al., 2020, and Rodriguez, 2021).

Amidst these economic upheavals, the dynamics of school enrollment underwent significant shifts, reflecting the intertwined relationship between educational access and household financial status. With parents grappling with sudden income shocks, many opted to transfer their children to non-paying schools to alleviate financial strain (Murillo and Garrido, 2017; Prieto-Latorre et al., 2021; Obiakor and Adeniran, 2020). Research, such as that conducted by Elacqua et al., 2023 in Peru, elucidated how parents navigating the uncertainties of the pandemic increasingly turned towards public schools. Prolonged closures, coupled with the unpreparedness of public schools for online education, exacerbated by the financial burden of private school tuition, drove this shift.

Some theoretical approaches have been developed to assess the long-term consequences of this phenomenon. It has been demonstrated that the migration of students between schools disrupts their peer relationships and diminishes investment in human capital, thereby adversely affecting its future accumulation. Research indicates that peers and school environments play pivotal roles in shaping children’s future economic opportunities. However, those from disadvantaged backgrounds are less likely to benefit from this spillover effect, thus exacerbating inequality (Agostinelli et al., 2022; Eckert and Kleineberg, 2021; Blanden et al., 2022). Utilizing a structural life-cycle model, Fuchs-Schündeln et al., 2023 concludes that school closures have profound long-term repercussions for affected children, particularly harming the welfare of those from disadvantaged households (with an average consumption equivalent variation of -0.65%). In this paper, I explore the impact of the pandemic-induced economic crisis on students’ educational processes through school cohort changes and examine how parental decisions to change schools segregate children from vulnerable households.

On the other hand, the implementation of distance learning presented unprecedented challenges for teachers, students, and parents. Some authors found evidence indicating that homeschooling negatively affected academic development, particularly for low-income students, attributed to the availability of ICT tools and internet connection (M. Tomasik et al., 2020; Sanabria et al., 2016; Alvarado et al., 2021). Studies such as Agostinelli et al., 2022 have found that high-school pupils from low-income backgrounds experience a learning loss of 0.4 standard deviations after a year of homeschooling. However, other research, such as that by Sibirskaya et al., 2019 and Allen et al., 2004, demonstrated a positive impact, especially in language courses, due to its personalized nature and access to a variety of providers at lower costs.

This paper also contributes to the literature by measuring the differential effects of COVID lockdowns on schools based on their connectivity characteristics, treating it as a natural experiment. According to several authors, homeschooling resulted in minimal to no progress and lower exam scores, particularly in mathematics and reading (Engzell et al., 2020; Abadia et al., 2022; M. Tomasik et al., 2020; Owusu-Fordjour et al., 2020; Carlana and La Ferrara, 2021). These findings support the idea that the closure of schools was sudden, leaving teachers, students, and parents to improvise due to the educational infrastructure being ill-prepared for remote education (Haelermans et al., 2022; Stelitano et al., 2020).

Also, [Marín Llanes et al., 2023](#) conducted a study in Colombia examining the impact of various characteristics, such as socio-economic level, student ethnicity, school type (private-public), rural versus urban schools, and PDET municipalities, on learning inequality as measured by different Saber 11 score gaps. This paper aims to analyze the causal effects of homeschooling strategies, specifically regarding internet access, on changes in learning inequality.

The objective of this paper is to analyze school closures during the pandemic through two channels: (i) improved internet access, which is associated with more effective skill accumulation within homeschooling, and (ii) how, in response to a negative income shock, parents may choose to transfer their children from public to private schools, thereby limiting opportunities for children from low-income backgrounds to interact with those from higher-income households.

Furthermore, I propose employing a difference-in-differences model as the identification strategy, which controls for observable and unobservable time-varying characteristics of schools. These variables capture the variation in Saber 11 scores and cohort composition resulting from the introduction of homeschooling and categorize them based on measures of internet access. Given the structure of the database and the presence of parallel trends, this approach enables the identification of causal effects of abrupt interruptions on learning outcomes.

The results indicate that even before the implementation of homeschooling during COVID-19 lockdown, students in schools with limited internet access scored lower on the Saber 11 exam compared to those with high internet access. Moreover, during the COVID-19 closure, the disparity between schools with varying levels of connectivity widened further. However, it was observed that despite lacking internet access, private schools achieved higher average scores than public schools due to the migration of more vulnerable households from the latter, thereby altering the composition of the student body.

This document comprises six parts, commencing with this introduction. The second section outlines the evolution of the Colombian education sector during the pandemic. Subsequently, the third section addresses the databases and their sources, while the fourth section elucidates the difference-in-differences methodology. In the fifth section, I present the obtained results. Lastly, the document concludes with some conclusions and policy recommendations.

2 Colombian context

The COVID-19 pandemic has had a profound impact on economic systems around the world, including Colombia. With more than 118,000 positive cases in 114 countries and 4,291 deaths, the World Health Organization declared the disease a global epidemic on March 9, 2020. It made extensive recommendations for preventive measures against contagion, highlighting strict confinement as one of the most effective strategies ([World Health Organization, 2022](#)). Following up on this idea, in March 2020, Presidential Decree No. 476 and Resolution No. 385 established a national economic, social, and ecological emergency strategy. The Ministry of Health decreed four stages of treatment of the pandemic: Strict containment, intelligent isolation, individual and responsible containment, and reactivation.

This policy, while effective in controlling contagion, has led to an economic crisis as work and consumption remain stagnant. According to [DANE, 2022](#), 64% of households with children reported that their economic situation was worse in September than before the pandemic. Consequently, as income fluctuates, investment in children's well-being, entertainment, and education decreases. In terms of education, only 4.1% of students reported dropping out of school, citing the inability to pay school fees as the main reason.

With the pandemic declaration, the Ministry of Education issued Circular 20 to adjust the academic calendar, defining two weeks of consecutive institutional development. Teachers and directors had to make progress in characterizing the conditions of their students, making the curriculum more flexible, and defining the didactic strategies to be implemented. In this way, on April 20, classes resumed remotely using the *Aprende en casa* program.

To support teachers, MinEducación has adapted and designed spaces to strengthen their pedagogical skills, such as 12 virtual classrooms focused on virtual campus management and *Contacto Maestro* with national and international experts who advise on homeschooling tools. For parents, the strategy *¡Juntos en casa lo lograremos muy bien!* offered support and guidance in their new educational role.

However, in developing countries like Colombia, the implementation of the *Aprende en casa* program is difficult because Internet access is unequal among households. Throughout the country, Internet access is precarious, according to government statistics. In 2019, internet coverage only increased to 51.9% nationwide. The situation is even worse in different departments, as Cauca and Vichada reported only 30.8% and 5.2% of their population with internet access (DANE, 2020b).

In this way, some additional media resources based on autonomous learning have been developed to meet the needs of students without a connection. Radio programs such as *Historias en AltaVoz* and TV series such as *Mi Señal*, *Territorio Mágico* and *Profe en tu Casa* have been created for children in preschool, elementary school and high school. Some academic analyses such as [Ayanwale et al., 2023](#) and [Ebubedike et al., 2022](#) have shown that students have mixed experiences with this type of content, as parents report that the radio allows them to be more involved in their children's learning, but students argue that these lessons are not detailed enough. In Colombia, only 56 radios and 396 chapters were broadcast, so some academic content was left out.

Some digital resources were also presented: *Aprender Digital: Contenidos para todos* was a platform with different materials and guides for parents and teachers focused on the educational cycle for 40 weeks of academic work (*Retos para Gigantes* for elementary school and *Secundaria Activa* for secondary school); *Be The 1 Challenge*, an app designed for specific English learning; the *Biblioteca digital*, a digital library with more than 3,000 texts to stimulate reading at home. However, it's important to clarify that even with all these resources, it was up to each school's board of directors to decide on the strategies to be implemented according to the characteristics of its population.

During this period, teachers also utilized tools such as WhatsApp and educational guides to address connectivity issues, particularly in facilitating learning in rural areas. WhatsApp groups involving parents were instrumental in content delivery, communication, and education, enabling teachers to send study materials, and assignments, and conduct virtual classes via text messages and phone calls. Moreover, students were able to bridge the physical distance with their teachers to seek clarification on questions that detailed guides, including explanations, practice exercises, and supplementary materials, could not resolve.

Finally, around May 2021, the government established a progressive return to the stage of individual and responsible confinement. However, by September, less than 30% of schools were back in classrooms ([Observatorio de Gestión Educativa, 2022](#)). As a result, students stayed at home for most of the year while schools remained closed. Therefore, the specific cohorts affected for the purposes of this paper are those of 2020 and 2021.

3 Data

To capture the disparities in the implementation of homeschooling, I used the average Saber 11 scores as an exam that correctly reflects the students' learning processes. Saber 11 is a standardized exam for all secondary school graduates that is given before the end of the academic year. These standardized tests were administered in Colombia during the pandemic, despite the difficulties posed by the health shock.

ICFES, the entity in charge, adapted its processes to make the evaluations electronic. They implemented an automated system that used artificial intelligence algorithms and biometric analysis to ensure the transparency and integrity of the test. More than one million tests were administered using these tools. But for students who didn't have the tools at home, the exam was administered in person, following biosecurity measures. In this way, as the director of the Instituto Colombiano para la Evaluación de la Educación (ICFES) affirmed, the rules and tools were adapted to avoid results contaminated by this change, and they knew it was successfully achieved since the parameters behaved the same (El Espectador, 2021).

The database used in this study collects school-level Saber 11 test scores, student home characteristics, self-reported connectivity measures, and school characteristics. In the analysis, I selected only calendar A schools to achieve greater comparability within the sample, that is, those students who took the test around September of their graduation year. The analysis period spans from 2016 to 2021 encompassing 10,059 schools and resulting in 58,326 observations. Descriptive statistics for these variables are reported in Table 1.

The main outcome variable is the score obtained in the Saber 11 exam. This data comes from the Instituto Colombiano para la Evaluación de la Educación (ICFES), which administers standardized tests at different levels of education throughout the country. Specifically, Saber 11 is designed to evaluate the level of development of the skills of students who are about to graduate from secondary school. The exam consists of five components scored out of 100: reading, mathematics, social science, science, and English. The overall score is defined as the sum of the scores obtained in each component and, for this study, is standardized by cohort. (See panel A of the table 1).

Some covariates act as school controls to capture different socioeconomic characteristics of the student population (see Panel B of Table 1). The school-level variables used as controls are the proportion of students in the middle (3 and 4) and high (5 and 6) strata, the proportion of mothers and fathers with more than a secondary education, and those identifying as ethnic. The data show that, on average, schools have 24% and 3% students from middle and high strata, 10% identify with an ethnic group, and 24% of their mothers have a bachelor's degree (see Panel C of Table 1).

I used the reported data from the Formal Education Form (EDUC - C600) for the heterogeneous effects analysis (see Panel D of Table 1). Each educational institution completed this form and then sent it to the National Statistical Institute (DANE) as an annual census of all public and non-public schools at each level (preschool, primary, middle, and high school). From this form, the size of the teaching staff is taken to capture the personalizing features of homeschooling, the use of computers in the classroom is taken to bring the software skills acquired before the pandemic lockdown, and the nature of the school. The data shows that in 2019, on average, schools had 0.07 teachers per student, 32% of them were private, and 33% of them used computers in the classroom every day.

During the study, I looked at other potential transmission mechanisms. Family size, extracted from the Saber 11 database, and the proportion of families with more than five members explain the demand for devices with connectivity generated within households. On average, schools have 44% of students from large families. In addition, the average Internet speed of the municipality serves as a tool to facilitate synchronous meetings and is obtained from the Ministry's Quarterly ICT Report (MinTIC).

Table 1: Descriptive statistics

Variable	Mean	Median	Std. Desv.	Min.	Máx.
<i>Panel A: Output variables</i>					
Reading score	51.68	51.28	6.30	21.00	100.00
Math score	49.57	49.08	7.59	18.00	84.73
Science score	49.06	48.57	6.73	24.33	100.00
Social sciences score	47.59	46.92	7.27	21.00	83.00
English score	48.77	47.05	8.57	0.00	87.11
Global score	247.09	243.91	34.39	118.00	402.00
<i>Panel B: Internet access</i>					
Proportion of students with internet access	0.52	0.55	0.33	0.00	1.00
<i>Panel C: Controls</i>					
Strata in 2019: Middle (3-4) - proportion-	0.24	0.14	0.24	0.00	1.00
Strata in 2019: High (5-6) -proportion-	0.03	0.00	0.07	0.00	1.00
Mother's education: professional or above -proportion-	0.24	0.17	0.22	0.00	1.00
Father's education in 2019: professional or above -proportion-	0.18	0.12	0.19	0.00	1.00
Ethnicity in 2019 -proportion-	0.10	0.00	0.26	0.00	1.00
<i>Panel D: Heterogeneous</i>					
Teachers per student in 2019	0.07	0.05	0.09	0.00	3.10
Everyday computer use at school in 2019	0.33	0.00	0.47	0.00	1.00
Family with more than 5 members - proportion in 2019-	0.44	0.43	0.16	0.00	1.00
Average internet download speed at municipality (Mbps) in 2019	147.05	28.44	471.63	1.00	11711
Private school	0.32	0.00	0.47	0.00	1.00
Rural school	0.34	0.00	0.47	0.00	1.00
<i>Panel E: Schools composition</i>					
Cohort size	53.62	35.00	56.39	1.00	1007
Mother's education: secondary or less	35.12	22.00	39.00	0.00	674.00
Mothers at home	22.06	15.00	23.20	0.00	422.00

Notes: The data comprises yearly school data between 2016 and 2021. The scores are reported as the average student score obtained on each component of Saber 11. Controls and internet access are defined as proportions of the cohort size only for 2019, as it's the last year before homeschooling. School composition variables are self-reported variables asked at the moment of the exam, transformed as indicators (i.e. = 1 if true). The socioeconomic low level is defined according to the estimates generated by ICFES, which consider strata, tech access, and the family's food supply.

The speed measures have a mean value of 147.05 Mbps for the 1,100 municipalities, as reported in table 1.

Finally, in anticipation of compositional changes within private and public schools, I used some school-level variables from the Saber 11 database to understand the characteristics of households that migrate from private to public schools. These include cohort size, the number of mothers with less than a high school education, and those reported as homemakers. The data show that among the years, the average group size is 53 students, with 35 mothers with up to secondary education and 22 reported as housewives.

4 Empirical Strategy

The proposed identification strategy, known as differences-in-differences, captures the exogenous variation in standardized scores from the implementation of homeschooling during the COVID-19 lockdown, paying particular attention to the effect of connectivity gaps between schools.

In all analyses, I classified schools according to their internet connectivity in 2019. This measure comes from a section of the Saber 11 questionnaire that asks each student whether or not they have internet access, adjusted for cohort size. I then define schools with *low internet access* if this estimate was below the median before the lockdown period, to avoid contextual sensitivity of the treatment variable definition. It’s important to note that the connectivity access survey reflects the actual availability of the service in the community. This is highly correlated with the number of subscribers reported by lenders, making it a useful approach for determining household connectivity (see Appendix A1).

This exogenous classification enables a comparison between schools with low and high internet use and their behaviors during the pandemic, a period when this tool was fundamental for the development of academic activities. It also highlights significant differentiation in the strategies used by each school according to the specific needs of its population, which were determined by their vulnerabilities. Additionally, the difference-in-difference specification allows us to take a nuanced approach to the differential effect of this tool before and after COVID-19, facilitating the interpretation of its causal impact in both groups.

Given the structure of the data, it is possible to track the average performance of schools over the years, allowing for a quasi-experimental analysis around the pandemic shock. To examine the impact of homeschooling on the learning capacity of students from low-connection backgrounds, I constructed a model with the treatment variable described above. The model is formally specified as follows:

$$Y_{it} = \alpha_0 + \beta [COVID - 19_t \times Low - internet_i] + \sum_{j \in T} \gamma_j \mathbf{X}_{i2019} \cdot D_j[t = T] + \mu_i + \mu_t + \epsilon_{it} \quad (1)$$

Where Y_{it} corresponds to the average score obtained by students of school i on the Saber 11 exam in year t , standardized by cohort. $COVID - 19_t$ represents the COVID-19 closure period when homeschooling was adopted (i.e., years after 2019). $Low - internet_i$ indicates, with a value of one, if the school was below the median of the internet access measure in 2019. \mathbf{X}_{i2019} captures the values of the 2019 control variables that interact with the year indicators D_j to capture their changing trend behavior. Controls include the proportion of students with high and middle-class backgrounds, working mothers and fathers, and those identifying with any ethnicity. μ_t and μ_i correspond to period and school fixed effects. Finally, $\epsilon_{i,t}$ is the robust standard error of the model.

The parameter of interest is β , which captures how Saber 11 scores changed during the pandemic years for students in schools with different levels of connectivity. I can interpret this as a causal effect

under the identification hypothesis that, without the introduction of homeschooling, Saber 11 scores would continue a similar trend among all schools, regardless of their level of Internet connectivity. The validation of the parallel trend assumption can be estimated by modeling the dynamic evolution over time as follows:

$$Y_{it} = \alpha_0 + \sum_{j \in T} \beta_j D_j[t = T] \times Low - internet_i + \sum_{j \in T} \gamma_j \mathbf{X}_{i2019} \cdot D_j[t = T] + \mu_i + \mu_t + \epsilon_{it} \quad (2)$$

Where Y_{it} corresponds to the average score obtained by students of school i on the Saber 11 exam in year t , standardized by cohort, $COVID - 19_t$ takes the value of one for the years when homeschooling was adopted during the lockdown. $Low - internet_i$ indicates whether the school was below the median of the internet access measure in 2019. \mathbf{X}_{i2019} captures the values of the 2019 control variables that interact with the year indicators D_j to capture their changing trends. $\epsilon_{i,t}$ is the robust standard error of the model, and μ_t and μ_i correspond to the period and school fixed effects, respectively. In this case, β from equation 1 is decomposed into β_j , which captures the effect over the years.

In addition, since variation in some characteristics across schools can explain some potential mechanisms of how COVID disruption and connectivity affected students' performance on standardized exams, I formalize an extension of equation 1 in a model as follows:

$$Y_{it} = \alpha_0 + \beta [COVID - 19_t \times Low - internet_i] + \phi [COVID - 19_t \times Low - internet_i \times Z_{i2019}] + \sum_{j \in T} \gamma_j \mathbf{X}_{i2019} \cdot D_j[t = T] + \mu_i + \mu_t + \epsilon_{it} \quad (3)$$

The coefficient of interest, denoted as ϕ , captures the difference in the average scores of students from schools with the characteristic Z_{i2019} . These features include the number of teachers per student, the frequency of computer use in the classroom, the proportion of families with more than five members, the nature of the school (public or private), and the average internet speed in the municipality. All characteristics were measured in the year before the COVID-19 lockdown.

Finally, to see if there were changes in the composition of private and public schools during COVID-19 lockdown, I estimated the equation 1 with different outcome variables. Changes in cohort size and the proportion of mothers at home and with less than a high school education were analyzed in private and public schools with low Internet access during the pandemic.

A limitation of this methodology is that it does not capture any individual strategy that students might use on their own. It leaves us with an overestimated effect of connectivity within homeschool environments, since each student could develop alternative tools outside the classroom to access additional academic content. In addition, I cannot identify the specific characteristics of the students who migrate from private to public schools, since the captured effect is an overall result of the education system.

In the following section, I present the results obtained by estimating the differential drop in Saber 11 test scores in those schools with little access to connectivity (according to equation 1), the dynamic persistence of this effect (according to equation 2), some heterogeneous effects (equation 3), and the composition changes in private and public schools.

5 Results

This section consists of two parts. In the first part, I present the effect of the lockdown measures on learning achievement using the Saber 11 scores and explore some potential transmission mechanisms.

In the second part, I focus on the effect of the economic crisis on the composition of cohorts, particularly in private schools.

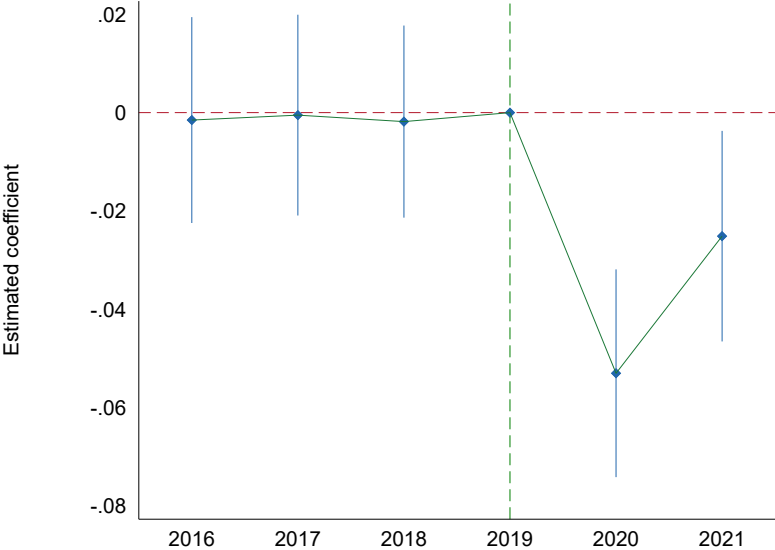
5.1 Academic development

In this section I report the change in standardized scores of Saber 11 exams from the implementation of homeschooling, distinguishing the schools with low connectivity access and following the specifications exposed in the previous section.

The results of the difference-in-differences model are shown in Table 2. In the first column, it is reported that the results obtained on the Saber 11 exam were not affected after implementing the homeschooling strategy for those schools that had the necessary technological tools. Also, without including school fixed effects, schools with lower Internet access score on average 0.26 standard deviations below other schools on standardized assessments. However, after the COVID-19 closure, this score gap between schools with different levels of connectivity increased by 0.03 standard deviations.

Given the difference in the difference specification and the data structure, I can interpret the effect as causal under the hypothesis of identifying parallel trends. To test this hypothesis, following the equation 2, the coefficients are estimated and plotted in Figure 1. It shows that before the introduction of homeschooling, schools above and below the median on the connectivity measures followed a similar trend, so they are comparable. In addition, using a pre-trends test I do not reject the null hypothesis that linear trends were parallel before the pandemic ($F = 0.01 Prob = 0.99$) and the Granger test does not show anticipation of treatment ($F = 0.02 Prob = 0.98$), it is possible to ensure the causality of the results exposed above.

Figure 1: Event study



The figure presents the estimated β_j and their confidence intervals. Estimates were obtained using a linear regression absorbing school and time-fixed effects, following equation 2. The period of analysis comprises between 2016 and 2021. *Low internet* is a treatment indicator that takes the value of one if the school was below the median in the percentage of students with internet access during 2019. Controls are the proportion of students with high and middle strata, professional mothers and fathers, and are identified with any ethnicity. Each control is taken in 2019 and interacted with year indicators to capture the changing trends of each variable.

Table 2: Academic results

	(1)	(2)	(3)
	Global score	Global score	Global score
Low internet \times Homeschooling	-0.0348** (0.0146)	-0.0347** (0.0146)	-0.0382*** (0.0069)
Low internet access (=1 if school is below median in 2019)	-0.2643*** (0.0087)	-0.2643*** (0.0087)	
COVID-19 (=1 after 2019)	0.0202 (0.0147)		
Observations	58,326	58,326	58,309
Number of schools	10059	10059	10059
Number of years	6	6	6
R-squared	0.5853	0.5853	0.9300
FE Schools			✓
FE Year		✓	✓
Controls	✓	✓	✓

Robust standard errors presented in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Estimates were obtained using a linear regression absorbing school and time-fixed effects, following equation 1. *COVID-19* identifies periods after 2019 when education changed because of COVID-19 confinement. *Low internet* is an indicator that takes the value of one if the school was below the median in the percentage of students with internet access during 2019. Controls are the proportion of students with high and middle strata, professional mothers and fathers, and are identified with any ethnicity. Each control is taken in 2019 and interacted with year indicators to capture the changing trends of each variable. Results are consistent with a balanced panel and with the Sant’Anna and Zhao, 2020 estimator (see Appendix A4 and A5).

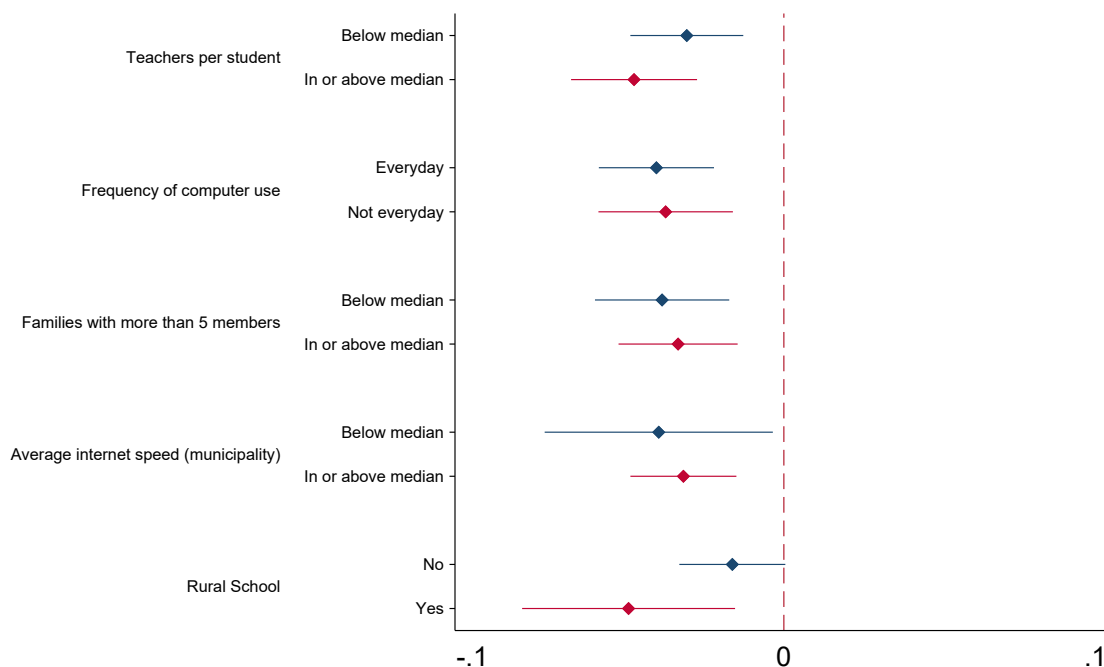
On the other hand, if the results are decomposed by each of the five components within the Saber 11 test, the dynamics described above remain (see Appendix A2). Estimates show that most components experienced an increase in average scores between 0.02 and 0.4 standard deviations during the implementation of homeschooling. However, the reading and social science sections of the exam seem to be more affected by the availability of the Internet than the others, as they each showed an opening of the score gap between schools by -0.05 standard deviations. These results are consistent with the expectations of Abadia et al., 2022, who predicted a drop of 0.4 standard deviations on reading tests after eight months out of the classroom.

5.1.1 Potential transmission mechanisms

This section examines the potential mechanisms through which homeschooling and connectivity affect student performance on these state assessments. It examines the heterogeneous effects of several school, family, and community characteristics, such as the size of the teaching staff, the use of computers in the classroom, family size, and Internet speed. The following results are obtained from the specification exposed in equation 3 and are shown in Figure 2

First, the differential effects of some school characteristics are analyzed. I examined whether the number of teachers per student makes it easier to take advantage of the personalized opportunity of homeschooling and obtain higher scores. No significant differences were found in schools with more teachers, even in areas with lower Internet connectivity. Research has also explored how homeschooling can affect the performance of students and teachers who have the resources and skills to implement it. In 2019, I analyzed the differences between schools that used computers in the classroom every day. However, I did not find any significant differences between these institutions. Finally, as can be

Figure 2: Potential transmission mechanisms



Robust standard errors presented in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Estimates were obtained using a linear regression with school and time-fixed effects. *COVID-19* identifies periods after 2019 when education changed because of COVID-19 confinement. *Low internet* is an indicator that takes the value of one if the school was below the median in the percentage of students with internet access during 2019. *Private school* identifies the nature of the school in 2019. Controls are the proportion of students with high and middle strata, professional mothers and fathers, and are identified with any ethnicity. Each control is taken in 2019 and interacted with year indicators to capture each variable's changing trends.

observed in Figure 2, even though urban schools perceive less of a drop in Saber 11 scores compared to rural schools, these differential effects are not significant.

Second, I examine how family composition can affect learning during the COVID-19 lockdown. Remote processes became the norm as people tried to maintain their daily lives at home, so children and teenagers migrated to the homeschooling strategy, and parents began to work at home. As a result, the effective demand for technology tools increased, and the supply within households remained almost constant. So I analyze the percentage of families with more than five members and their differentiated results on Saber 11. This channel has no differences, as shown in Figure 2.

Third, I examine the impact of the average Internet speed in the community on the students' online learning experience. This factor attempts to account for the possibility that some schools may have high Internet access but poor quality. Lower Internet speed made communication much more difficult, as it was more difficult to establish synchronous meetings between teachers and students. However, it didn't show any relevant effect between communities on their Saber 11 scores (see figure 2).

5.2 Cohort changes

In this part, I analyze the changes in the composition of secondary cohorts in the context of an economic crisis resulting from the COVID-19 pandemic. These results follow the methodology outlined in Equation 1.

Table 3: Composition changes

	(1) Cohort size size	(2) Mothers with less than secondary education	(3) Mothers at home
Panel 1: Private schools			
Low internet \times COVID-19	-6.665** (1.745)	-4.392** (1.177)	-4.723*** (0.750)
Observations	18821	18821	18821
Number of schools	3351	3351	3351
R ²	0.007	0.007	0.008
Mean dep. var.	53.62	35.12	22.06
FE Municipality	✓	✓	✓
FE Year	✓	✓	✓
Controls	✓	✓	✓
Panel 2: Public schools			
Low internet \times COVID-19	2.127** (0.535)	5.211*** (0.413)	1.754*** (0.272)
Observations	39509	39509	39509
Number of schools	6725	6725	6725
R ²	0.222	0.186	0.093
Mean dep. var.	53.623	35.124	22.060
FE Municipality	✓	✓	✓
FE Year	✓	✓	✓
Controls	✓	✓	✓

Robust standard errors presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. *COVID-19* identifies periods after 2019 when education changed because of COVID-19 confinement. *Low internet* is an indicator that takes the value of one if the school was below the median in the percentage of students with internet access during 2019. *Private and Public* identifies the nature of the school in 2019. Controls are the proportion of students with high and middle strata, professional mothers and fathers, and are identified with any ethnicity. Each control is taken in 2019 and interacted with year indicators to capture the changing trends of each variable.

According to [Melo-Becerra et al., 2021](#), the pandemic was a challenging time for education because of the socioeconomic downturn. As a result, they had recorded the transfer of students between public and private institutions. Based on statistics from the [Ministry of education, 2021](#), in 2020, 266,657 students changed institutions, of which 71% moved from private to public institutions. In this way, changes in composition are examined and shown in table 3.

First, according to state statistics, changes in cohort size occurred in both public and private schools. In column 1 of the table 3, it can be observed that the average number of students taking the exam decreases in private institutions, but increases significantly in public ones. This follows the

hypothesis that, in the context of the pandemic lockdown, students who couldn't afford to continue in private schools migrate to public ones.

In addition, the socioeconomic characteristics of the students who migrate are analyzed. In columns 2 and 3 of Table 3, the results show that during the pandemic, students who migrated from private to public schools had, on average, mothers with less than a secondary education and identified themselves as housewives. This is evidenced by the fact that the estimates yield positive and significant coefficients for public institutions in both measures and negative coefficients for private institutions. These results are robust to fixed effects estimations.

This general equilibrium phenomenon was complemented by [Elacqua et al., 2023](#), which showed how parents from Peru requested a transfer to a public school due to factors such as the extended school closures during the first year of the pandemic, the lack of adaptability of private schools to move to online education, and the cost of paying private school tuition during an economic crisis. For Colombia, I showed that there is a change in cohort composition between private and public schools, given that more vulnerable families dropped out of educational institutions because they couldn't afford the associated costs during the COVID-19 lockdown.

In addition, the concept of migration between institutions is consistent with the expected results of the human capital formation model proposed by [Mahler and Yum, 2024](#). Research has shown that school closures during a pandemic, particularly within a substitutability framework, exacerbate inequality and promote mobility between private and public institutions. This is due to the high elasticity of substitution between public and private schools, which leads to aggregate losses in human capital, lower intergenerational mobility, and greater cross-sectional inequality.

When parents decide to change schools, they may unintentionally expose their children to segregation in their new schools, which can result in the loss of the positive peer effect on their future economic opportunities and lower learning outcomes. As [Willms, 2010](#) and [Thrupp et al., 2002](#) have shown, school systems are often segregated both horizontally, among students from different backgrounds, and vertically, across different types of schools. Social interactions in schools are not merely mechanisms but integral to education itself. This tendency to surpass the school effect can significantly influence student learning achievement.

Also, this is not about less effective learning processes in public schools compared to private schools; it's about how they are affected when they receive a higher proportion of vulnerable households, which changes their composition. Studies have shown that for standardized exams such as PISA, school composition has a strong and independent effect on student achievement. Students in schools with higher mean socioeconomic status perform better, even if their individual socioeconomic status isn't high ([Lee et al., 1993](#), [Perry and McConney, 2010](#)). Schools with a vulnerable population not only often face motivation and preparation challenges due to their environment, but they also struggle with hiring and retaining enthusiastic teachers. This makes the influence of family and peers more significant than the overall school effect. ([Robertson and Symons, 2003](#), [Hanushek et al., 2003](#), [Thrupp, 1999](#)).

Finally, I distinguished the effect of homeschooling and connectivity between private and public schools. Estimates show that private schools, even with low Internet access, have better Saber 11 scores than public institutions (see Appendix A6). It is possible to see that before the introduction of homeschooling, private schools had higher scores by 0.51 standard deviations and that this advantage disappeared when the private schools had lower levels of Internet access. Furthermore, during the homeschooling period, although schools with low connectivity experienced an average decrease in their scores of 0.033 standard deviations, private schools received higher scores than public schools.

6 Conclusions

The COVID-19 pandemic drastically disrupted students' educational processes, as confinement became the primary means of preventing contagion. In this context, I examine how the COVID-19 pandemic affected the educational processes of schools with different levels of connectivity.

Using a difference-in-differences specification, the results revealed that schools with limited Internet access had difficulty adapting to homeschooling, subsequently affecting students' performance on the Saber 11 exam, with a noticeable decline in their scores. This decline was particularly significant in reading and social sciences, disciplines that rely heavily on interpersonal interaction in their learning processes. Even after controlling for various factors such as school, family, and community characteristics, no significant aggravating effects on student performance were found.

It is important to consider the long-term implications of these results, as Private institutions achieve different results, with higher average scores compared to public institutions, even in the absence of robust Internet connectivity, due to changes in cohort composition. As a result of the economic strain on households caused by the pandemic, the most vulnerable families, who may face challenges in remote learning environments, shifted to public schools.

The results presented here follow the theoretical approximation to long-term capital accumulation as outlined by Mahler and Yum, 2024 and Fuchs-Schündeln et al., 2023. In addition, based on the model proposed by Zheng and Graham, 2022, we can expect that households that expose their children to public and lower quality schools tend to have lower future earnings than if they remained in private institutions. This self-segregation effect is worrisome because it persists over several generations.

Public policy implication revolves around the management of school closures. Based on the above findings, homeschooling emerges as a viable strategy for maintaining instruction in the event of unforeseen circumstances that interrupt learning (e.g., landslides, health emergencies, etc.). However, it is imperative to consider the socio-economic context of households and their Internet access status before implementing any measures.

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Appendix

A1 Treatment validation

Table A1: Treatment validation analysis: Comparing MinTIC measure with Saber 11

	Internet access (SB11)		
	(1) Time FE	(2) With controls	(3) Controls and FE
Internet household coverage in 2019	2.7896*** (0.0124)	2.7896*** (0.0124)	1.7842*** (0.0126)
Constant	0.1994*** (0.0016)	0.199*** (0.0016)	0.1361*** (0.0014)
Observations	57,824	57,824	57,824
Number of municipalities	1,105	1,105	1,105
R-squared	0.5722	0.5723	0.7768

Robust standard errors presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. *Internet household coverage* is the number of subscribers reported by lenders to the Ministry of Information and Communication Technology (MinTIC) for each municipality at per-cápita levels in 2019. *Internet access (SB11)* is a measure in 2019 for each school of its connectivity access that comes from a section of the Saber 11 questionnaire asking each student if they have or do not have internet access, pondered by cohort size.

Table A2: Treatment validation analysis: Comparing MinTIC measure with Treatment variable

	Low internet		
	(1) Time FE	(2) With controls	(3) Controls and FE
Internet household coverage in 2019	2.78964*** (0.01238)	2.78961*** (0.01238)	1.78422*** (0.01266)
Constant	0.19944*** (0.00156)	0.19944*** (0.00156)	0.13610*** (0.00138)
Observations	57,824	57,824	57,824
R-squared	0.57225	0.57226	0.77680
Number of municipalities	1,105	1,105	1,105

Robust standard errors presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. *Internet household coverage* is the number of subscribers reported by lenders to the Ministry of Information and Communication Technology (MinTIC) for each municipality at per-cápita levels in 2019. *Low internet* is an indicator that takes the value of one if the school was below the median in the percentage of students with internet access during 2019.

A2 Per component analysis

Table A3: Results by component

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Reading	Reading	Math	Math	Science	Science	Social sciences	Social sciences	English	English
Low internet × COVID-19	-0.0480*** (0.0145)	-0.0517*** (0.0079)	-0.0262* (0.0157)	-0.0283*** (0.0077)	-0.0193 (0.0158)	-0.0240*** (0.0078)	-0.0470*** (0.0149)	-0.0501*** (0.0080)	0.0015 (0.0126)	-0.0006 (0.0066)
Low internet access (=1 if school is below median in 2019)	-0.3491*** (0.0086)		-0.2307*** (0.0092)		-0.1906*** (0.0094)		-0.2721*** (0.0087)		-0.2528*** (0.0075)	
COVID-19 (=1 after 2019)	0.0491*** (0.0144)		0.0220 (0.0156)		-0.0137 (0.0158)		0.0374** (0.0149)		-0.0269** (0.0133)	
Observations	58,326	58,309	58,326	58,309	58,326	58,309	58,326	58,309	58,259	58,242
R-squared	0.5949	0.9042	0.5191	0.9110	0.5103	0.9083	0.5757	0.9030	0.6885	0.9328
FE Municipality		✓		✓		✓		✓		✓
FE Year		✓		✓		✓		✓		✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Robust standard errors presented in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Estimates were obtained using a linear regression absorbing school and time-fixed effects, following equation 1. *COVID-19* identifies periods after 2019 when education changed because of COVID-19 confinement. *Low internet* is an indicator that takes the value of one if the school was below the median in the percentage of students with internet access during 2019. Controls are the proportion of students with high and middle strata, professional mothers and fathers, and are identified with any ethnicity. Each control is taken in 2019 and interacted with year indicators to capture the changing trends of each variable.

A3 Schools' behavior over the years

Figure A1: Comparison of exam scores among different connectivity levels

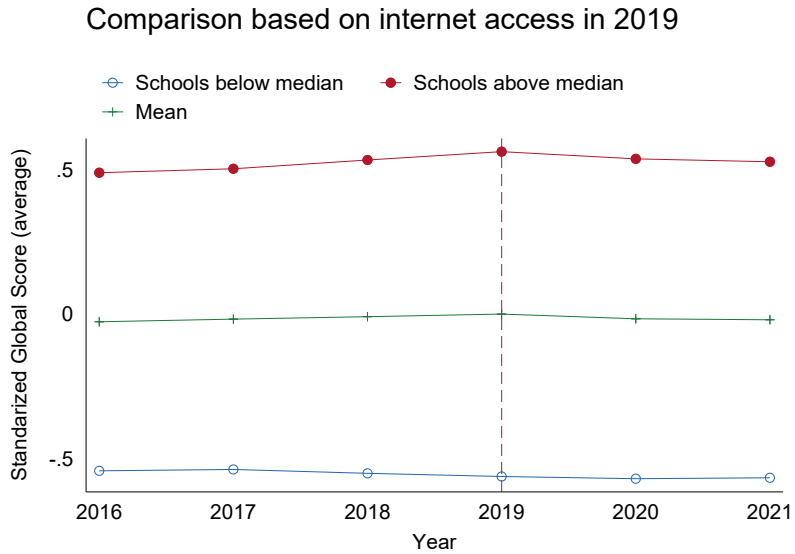


Figure presents the average standardized global score for schools above and below the median in the percentage of students with internet access during 2019. It shows the average scores behavior from 2016 to 2021 of the Saber 11 exam for A calendar students. Periods after 2019 are identified as when education changed because of COVID-19 confinement.

A4 Balanced panel results

Table A4: Principal results using the balanced panel

	(1)	(2)	(3)
	Global score	Global score	Global score
Low internet \times COVID-19	-0.0419*** (0.0148)	-0.0419*** (0.0148)	-0.0419*** (0.0068)
Low internet access (=1 if school is below median in 2019)	-0.2600*** (0.0087)	-0.2600*** (0.0087)	
COVID-19 (=1 after 2019)	0.0197 (0.0148)		
Observations	53,502	53,502	53,502
R-squared	0.5981	0.5982	0.9329
FE Municipality			✓
FE Year		✓	✓
Controls	✓	✓	✓
Number of schools	8917	8917	8917
Number of years	6	6	6

Robust standard errors presented in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Results were obtained with the balanced panel data, with 8917 schools from 2016 to 2021. *COVID-19* identifies periods after 2019 when education changed because of COVID-19 confinement. *Low internet* is an indicator that takes the value of one if the school was below the median in the percentage of students with internet access during 2019. *Private and Public* identifies the nature of the school in 2019.

Figure A2: Event study using the balanced panel



The figure presents the estimated β_j and their confidence intervals. Estimates were obtained using a linear regression absorbing school and time-fixed effects, following equation 2. Results were obtained with the balanced panel data, with 8917 schools from 2016 to 2021. *Low internet* is a treatment indicator that takes the value of one if the school was below the median in the percentage of students with internet access during 2019. Controls are the proportion of students with high and middle strata, professional mothers and fathers, and are identified with any ethnicity. Each control is taken in 2019 and interacted with year indicators to capture the changing trends of each variable.

A5 Doubly robust difference-in-differences estimators

Table A5: Doubly robust difference-in-differences estimator following Sant'Anna and Zhao, 2020

	(1)	(2)
	Global score	Global score
Low internet \times COVID-19	-0.0012 (0.0040)	-0.0410*** (0.0125)
Observations	59,442	58,309
FE Municipality	✓	✓
FE Year	✓	✓
Controls		✓
Number of schools	9907	9718
Number of years	6	6

Standard errors presented in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Results were obtained using the Doubly robust difference-in-differences estimator following Sant'Anna and Zhao, 2020. *COVID-19* identifies periods after 2019 when education changed because of COVID-19 confinement. *Low internet* is an indicator that takes the value of one if the school was below the median in the percentage of students with internet access during 2019.

A6 Heterogeneous effect: Private schools

Table A6: Heterogeneous effect: Private schools

	Average Saber 11 score		
	(1) Time FE	(2) With controls	(3) Controls and FE
Private school			
Low internet access \times COVID-19 \times Private	0.104*** (0.019)	0.104*** (0.019)	0.080*** (0.020)
Low internet \times COVID-19	-0.015** (0.007)	-0.015** (0.007)	-0.033*** (0.008)
COVID-19 \times Private	0.065*** (0.008)	0.064*** (0.008)	0.096*** (0.010)
Low internet access \times Private	-0.832*** (0.040)	-0.831*** (0.040)	
Private school	0.513*** (0.023)	0.513*** (0.023)	
Observations	58,326	58,326	58,326
Number of schools	10,059	10,059	10,059
R ²	0.384	0.384	0.030

Robust standard errors presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Estimates were obtained using a linear regression with school and time-fixed effects. *COVID-19* identifies periods after 2019 when education changed because of COVID-19 confinement. *Low internet* is an indicator that takes the value of one if the school was below the median in the percentage of students with internet access during 2019. *Private school* identifies the nature of the school in 2019. Controls are the proportion of students with high and middle strata, professional mothers and fathers, and are identified with any ethnicity. Each control is taken in 2019 and interacted with year indicators to capture each variable's changing trends.