The Consequences of the COVID-19 Pandemic for Children in Kenya

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Abstract

Based on survey data for more than 5,000 Kenyan households, this study shows that, despite government efforts to introduce remote learning options, access to education declined markedly during a nine-month-long period of school closures. Remote learning was adopted by only a small minority of students, and disadvantaged children fell further behind. During the first semester of 2021, reports of alterations in children's externalizing and internalizing behavior more than tripled, with one in five children being affected by June 2021. After schools reopened, children learning remotely or through alternative means were more likely to suffer from these disruptions in emotional well-being than those who returned to school. While the medium- and long-term effects on learning outcomes and human capital remain unknown, the findings suggest that girls and children from poorer and less educated households have been disproportionately affected.

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1. Introduction

The COVID-19 pandemic has affected the lives of billions of people worldwide (WHO 2020; World Bank 2020b). In addition to the rise in infection rates and death tolls around the world, incomes, food security and mental health have also been affected by the social and economic shocks that ensued (Javed et al. 2020; United for Global Mental Health 2020; UNSDG 2020a). As governments in many countries closed schools during the period as part of their strategy to contain the spread of the virus, educational outcomes have also taken a hit, which is likely to impact students for generations to come (Kaffenberger 2020).[1] The disruption of education systems affected over 1.6 billion learners – or more than 90 percent of children worldwide and up to 99 percent in low- and lower middle-income countries (UNSDG 2020b). With that in mind, this paper analyzes the consequences of the pandemic (and of the multiple shocks that it has triggered) for children in Kenya.

Despite the relatively short amount of time since the coronavirus was first identified in December 2019, a remarkable amount of research on the socio-economic consequences of the pandemic has already been produced. In terms of the challenges faced by children, for example, it has become clear that the education calamity has far-reaching consequences that are likely to exacerbate the pre-existing learning crisis, inequities and financing gaps (Azevedo et al. 2020; Carvalho and Hares 2020; Engzell et al. 2021; Save the Children 2020; Save our Future 2020; UNSDG 2020b). The sudden need, in many countries, to push education towards distance learning has improved our understanding about the benefits as well as the limitations of remote learning, and also made clear the challenges that stem from the lack of access to technology.[2] Beyond the direct consequences to learning, school closures have also affected the provision of other essential services, such as school meals, vaccinations and childcare, as well as the work schedules and job opportunities of parents, who are now expected to also facilitate and supervise learning at home (UNSDG 2020b; UNESCO 2020b). Considering all of these ramifications, the overall impact of the pandemic is still difficult to grasp (UNSDG 2020b).

Although the coronavirus has spread throughout almost the entire world, developing countries have been disproportionately affected. In these countries, where less than five percent of people can work from home and more than 9 out of 10 are employed in the informal sector, it is substantially more difficult to implement social-distancing policies and quickly roll out new social-assistance programs (Gerard et al. 2020; ILO 2018; Sanchez et al. 2020). With regards to education, only 1 million (out of 500 million) children in Africa have access to edtech, and many schools are unable to provide the suitable support needed for continued learning. Consequently, during the recent closure, the effective out-of-school rate for primary-aged children in countries with a low human development index increased by almost 60 percentage points, affecting 86 percent of this cohort – more than four times the rate in very high human development countries (Carvalho and Hares 2020; UNDP 2020). In Sub-Saharan Africa alone, almost 500 million people now live in extreme poverty. Among the 550 million children, 280 million must deal with food insecurity, and the majority have had learning activities completely halted (UNICEF 2020a).

In Kenya, COVID-related disruptions have created enormous economic and social losses throughout the country, increasing concerns over food provision and access to health care and education. The unemployment rate more than doubled in comparison to its level before the pandemic, as the country's real GDP shrank 0.3 percent in 2020, pushing an additional two million Kenyans into poverty. This was the worst drop in Kenya's real GDP since 1992 (World Bank 2020a). Moreover, in an attempt to slow the virus outbreak, the Kenyan government has adopted a series of policies that included mobility restrictions, and – beginning in March 2020 – school closures, affecting 300,000 teachers and over 18 million students (World Bank 2021).

[1] A major concern is that, without proper support, many of the children affected by the disruption in education may never come back to school (UNSDG 2020b).

[2] Almost a third of all school-aged children worldwide could not be reached by remote learning approaches during the current pandemic (UNICEF 2020b).

Like many other countries, however, Kenya had limited infrastructure set up, prior to the pandemic, making it difficult to carry out a swift transition to remote learning or to ensure that children could safely and quickly return to classrooms (UNESCO 2019).[3] In fact, during the first months of the COVID-19 crisis, early assessments indicate that only 22 percent of Kenyan children had access to digital learning, and that children in private schools were twice as likely to learn remotely than their counterparts in public school. In addition, parents cited poverty as the main challenge to accessing digital learning and reported having difficulties supporting home-based learning. Coupled with increased family expectations and anxiety, this exposed many parents to mental health challenges and had negative effects on child development (Uwezo 2020).

With the goal of drawing a comprehensive picture of the impact of the pandemic on Kenyan children throughout and after school closures, this paper takes advantage of Kenya's rapid-response phone surveys (RRPS) with more than 5,000 households.[4] We examine two sets of questions in particular. First, to what extent the take-up of remote and alternative learning options – as well as the rates of return to school, once the restrictions were lifted – differed according to socio-economic characteristics. Second, how the COVID-19 crisis affected children's emotional well-being, and whether this is mediated by the form of learning – i.e., remotely, community-based, or in-person.

Our empirical analysis is organized in chronological order. The first part encompasses the interviews held between September and November 2020 (wave three of the RRPS), and thus corresponds to the period in which most schools were closed.[5] Given these circumstances, the outcomes of interest in this part are twofold: access to remote learning and to alternative forms of education (in both cases conditional on not attending school). The data from the period between January and June 2021 (waves four and five of RRPS) provide the basis for the second part of our analysis, in which we examine children's return to school as well as potential consequences for their emotional well-being. In both parts, aware of the concerns raised in the recent literature, we assess whether the pandemic has disproportionately affected underprivileged groups of children, including those from poorer and less-educated households, as well as girls, who already faced additional obstacles to continuing their education before the COVID-19 crisis (O'Donnell, Akmal and Hares 2020).

For children from deprived households, the COVID-19 crisis might eventually tip the balance in favor of dropping out of school prematurely, as they are more likely expected to provide additional support at home due to decreased family earnings and less likely to have access to education modalities when schools close. To analyze whether this is the case (at least in the short run), our analysis includes three sets of household characteristics to help identify the most important barriers to accessing (remote) education: (i) poverty and infrastructure, (ii) location and remoteness, and (iii) parent (or head of household) education levels.

We find that the pandemic and the public policies that ensued have widened the gap in access to education in particular along income lines, with poorer children falling further behind during school closures. Girls living in poor households have been especially vulnerable. Moreover, we document a significant increase in the number of reported cases of negative alterations in children's externalizing and internalizing behavior throughout the first term of 2021. After schools reopened, children learning remotely or through alternative means were more likely than those who were back in school to suffer from these disruptions in emotional well-being.

This paper is structured as follows. In Section 2, we review the recent literature on the consequences of school closures and reopening. We provide more background information for the Kenyan context in Section 3 and, in Section 4, describe the data and the methodology. Section 5 presents the findings from

[3] According to UNESCO (2019), almost half of the world's out-of-school children live in Sub-Saharan Africa.

[4] The Kenyan RRPS is implemented by the World Bank, in partnership with the Kenyan National Bureau of Statistics (KNBS), the United Nations High Commissioner for Refugees (UNHCR) and the University of California, Berkeley, since May 2020.

[5] Our analysis does not include waves 1 and 2 of the RRPS because most of the questions related to education and children's well-being only become available in wave 3.

our analysis. In Section 6, we offer concluding remarks and a brief discussion of the policy implications of our results.

2. Literature Review

2.1. Impacts of Closed Schools

Evidence from past crises as well as preliminary studies on recent school closures indicate a challenging road ahead. First, as pandemics are not the only cause of school closures, we can draw important lessons from the impact of school closures caused by natural disasters or even just summer holidays. For instance, after the 2005 earthquake in northern Pakistan, many schools in the surrounding area closed for 14 weeks. Four years later, children in schools affected by these short-term closures were almost 1.5 learning-adjusted years behind their peers enrolled in schools that remained open (Andrabi, Daniels and Das 2020). In the United States, a meta-study on summer learning losses reports that student achievement scores decline by one month of school-year learning while on holiday, and that reading gaps differ based on income level (Cooper at al. 1996).

These concerns are corroborated by initial assessments of the impact of the COVID-19 pandemic on education. Kaffenberger (2020) estimates learning trajectories in low- and middle-income countries and predicts that children could lose more than a full year's worth of learning from only three months of school closures. Azevedo et al. (2020) expect the current pandemic to lead to a loss of up to 0.9 schooling-adjusted years worldwide and predict a 25 percent increase in the share of lower secondary-aged children who will be below the minimum level of proficiency according to test scores. In the Netherlands, which experienced only a "short lockdown, [and provides] equitable school funding, and world-leading rates of broadband access" (Engzell et al. 2021, p. 1), and thus serves as a lower-bound estimate of the negative consequences of children being away from face-to-face education, children suffered an average learning loss equivalent to a fifth of a school year. The authors find that students from less-educated households were the ones hit the hardest by lockdown policies.

In a recent working paper highlighting different learning modalities during the pandemic, the authors found that although test scores declined across the United States during the 2020-21 school year, school districts that sustained higher rates of in-person education throughout this period fared better than those that relied to a larger extent on remote learning (Halloran et al. 2021). The authors estimate that districts with full face-to-face learning would present significantly smaller losses in math and English test scores (10.1 and 3.2 percentage points smaller, respectively) than districts that opted for fully virtual or hybrid education.

More broadly, however, efforts over the past several decades to improve technological access in classrooms have also showed positive signs. Programs such as "One-laptop-per-child" or Information and Technology Communications (ICT) classes have started to be implemented across the developing world to some success. In Peru, increasing children's exposure to technology led to improvements in digital skills (Bet et al. 2014), and, in Kenya, the use of tablets in early grades is linked to better grades in English and Kiswahili (Piper et al. 2016).

What is clear is that most children affected by school closures will struggle, and governments worldwide need to react accordingly. Educational losses may be particularly severe in places that faced longer school closures and lack the appropriate infrastructure to at least mitigate the shock, as it is often the case in most of the developing world. In the spring of 2020, less than one-quarter of all low-income countries offered remote-learning options – and the most frequent offer was still TV or radio solutions. Without alternatives, almost 31 percent of children in school had no access to remote learning (UNICEF 2020b).

Across Africa, the adoption rate of remote learning has been slow. In early 2020, only 19 million of the 450 million children on the continent had access to edtech (Crawford 2020). Though governments throughout Sub-Saharan Africa strived to increase the supply to provide more remote options, only 23 percent of countries offered some combination of remote-learning strategies (radio, TV, Whatsapp,

online, and take-home materials), and not a single country provided training for teachers to learn how to teach remotely (Vegas 2020). This lack of structural support inhibits not only teachers but also children and their families from engaging in remote education.

Although the possibilities of learning remotely are even more restricted in the case of pre-primary students, governments have been trying to increase opportunities also for this cohort. Across Eastern and Southern Africa, the (limited) offer of remote learning options for young children is evenly distributed across different modalities, such as radio, online learning, television, and paper-based materials (UNICEF 2020c). In Kenya, in particular, UNICEF has been supporting the Kenya Institute of Curriculum Development (KICD) to develop new material for remote learning also for children in pre-primary age. The content is then made available to students via television, radio and internet.[6]

All in all, despite the still limited evidence on the effectiveness of remote education, even if second-best, these alternatives can be decisive in times of crisis. Nevertheless, while there have been important strides in this regard, the discrepancies in ownership of remote devices at home are still significantly large, such that disadvantaged groups are expected to fall even further behind during the pandemic (Mundy and Hares 2020).

2.2. Implications for Returning to School

Prior to the COVID-19 crisis, 258 million children were already out of school (with an additional 175 million pre-primary children not enrolled) and 44 percent of children in school were lacking age-appropriate skills (Save our Future 2020; UNSDG 2020b; UNICEF 2019; World Bank 2019). Across low-income countries, only 22 percent of children are enrolled in pre-primary education (UNESCO 2020a). The pandemic is expected not only to worsen this situation, but also to widen learning gaps, as inequalities increase.

Socio-economic status, household location, and gender are three driving factors behind a child's access to schooling and learning outcomes. Across Global Partnership for Education countries, 74 percent of children from the wealthiest households achieve at least minimum reading proficiency compared to only 48 percent of children from the poorest families (GPE 2019). The majority of children already in learning poverty – that is, unable to read or understand a simple text by age 10 – come from poor or rural households. Moreover, despite the gender achievement gap, with girls outperforming boys on foundational learning, fewer girls are progressing to or through secondary school as a result of the many unique barriers they face (UNDP 2015). During school closures, girls face "disproportionate increases in unpaid household work" and then often struggle to re-enter school and resume their studies (Burzynka and Contreras 2020, p. 1968; O'Donnell, Akmal and Hares 2020). In Brazil, parental unemployment in the aftermath of economic shocks increased the likelihood of girls dropping out of school by up to 60 percent (Duryea, Lam and Levison 2007). In Sierra Leone, after the Ebola outbreak, teenage pregnancy increased by 65 percent in some communities and, because of laws against visible pregnancies in school, many girls were forced to give up their education (Bandiera et al. 2019; UNDP 2015). Furthermore, evidence from school closures during the Ebola epidemic saw increased dropout rates, child labor, heightened levels of violence against children, and persisting socioeconomic and gender divides (Bandiera et al. 2019; UNDP 2015).

Children from wealthier, urban and higher-educated families, on the other hand, are usually more likely to go back to school and face less severe learning losses because they more often have access to internet, electricity, tech gadgets, higher-quality teachers and higher-educated parents, who are more likely (to be able) to provide support and to offer a more stimulating environment at home (GPE 2019; Save our Future 2020). Parents' education may not only influence children directly – by improving educational achievement – but also indirectly, as it shapes children's beliefs and aspirations (Davis-Kean 2005).

Finally, the consequences of the outbreak for children are not limited to learning. The pandemic, along with social isolation and the restrictive measures adopted to fight the virus, has substantially increased

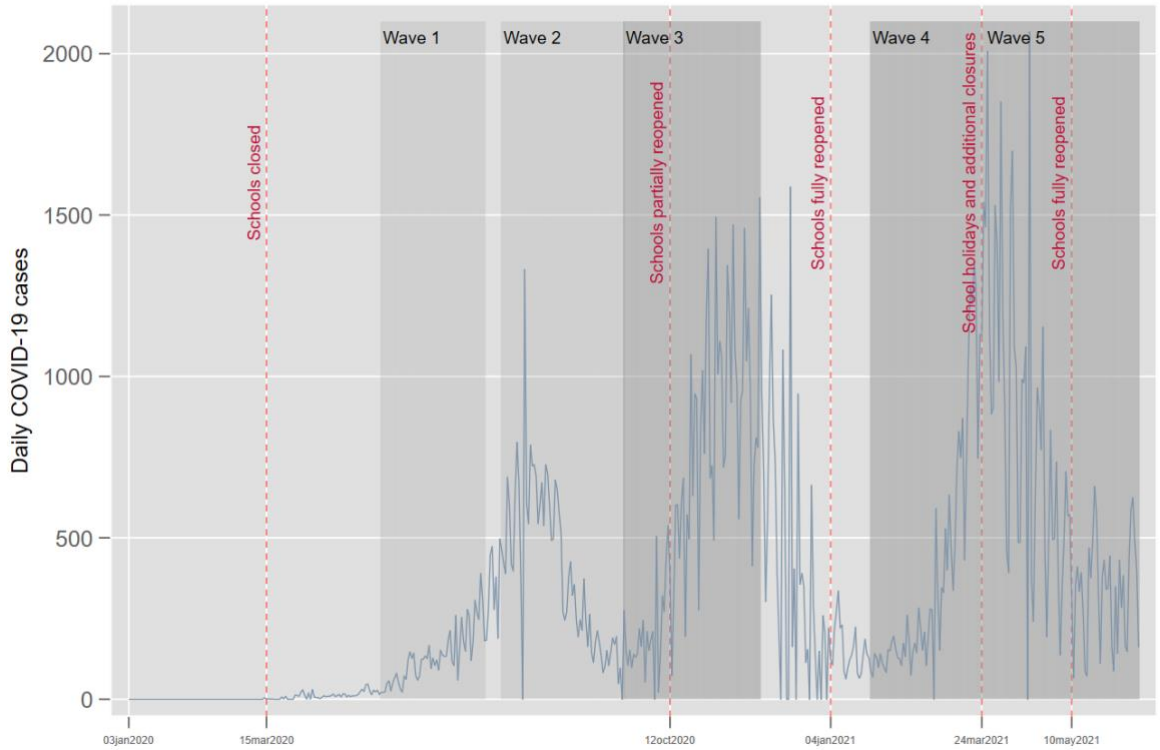
[6] More information about UNICEF's support to KICD is available here.

mental-health issues, anxiety and depression, as well as the number of children experiencing violence (M'jid 2020; Ravens-Sieberer et al. 2020). In addition, access to basic health care has fallen, while food insecurity increased for many children and families. Exposure to these issues – during early years in particular – can severely affect a child's upbringing, and lead to lifelong suffering not only in terms of learning but also of physical and mental health (Shonkoff, Boyce and McEwan 2009; Shonkoff and Garner 2012). If delivered properly, however, education can serve as a shield against some of these threats, and offer a safe and stable environment for children during times of upheaval (Talbot 2013; INEE 2016).

3. Background

In March 2020, in an effort to curb the transmission of the virus, the Kenyan government implemented a series of policies aimed at restricting physical contact. Across Kenya, many people lost jobs or saw a reduction in income, and the unemployment rate more than doubled in comparison to its level before the pandemic. Additionally, food insecurity increased, while access to clean water, routine health appointments and enrollment in education all dropped (World Bank 2020a). As of late October 2021, more than 250,000 infection cases and 5,200 deaths have been attributed to COVID-19 in Kenya.[7]

Figure 1. Timeline of Kenya's COVID-19 Cases from January 2020 until May 2021



Source: Daily COVID-19 cases as reported by the World Health Organization here.

In March 2020, over 90,000 schools were closed, affecting 300,000 teachers and over 18 million learners – of which 1.75 million relied on school meals prior to the closure of schools (World Bank 2021). In May 2020, the Kenyan Ministry of Education implemented a US$ 24 million emergency response plan to ensure continued learning during school closures and in preparation for when learners would return to the classroom.[8]

[7] Data from the Johns Hopkins University CSSE, available here.

[8] The main objectives of the emergency response plan were (i) to provide access to quality, equitable and inclusive education to learners during and after the crisis to ensure continued learning; (ii) to facilitate production of online

Two months later, in July 2020, the government announced that the entire school year, which runs from January to November, would be cancelled and children would be expected to repeat their grade once schools reopened. Education officials later changed plans and allowed schools to partially reopen in October 2020, with priority given to children preparing for national exams in grades 4 and 8 (Dahir 2020; Gikandi 2020). Only in January 2021, nine months after the initial closure, were all Kenyan schools reopened for all grades, making Kenya the last East African country to fully reopen schools (Mlaba 2021; Parsitau and Jepkemei 2020). Thousands of children (mostly girls), however, did not come back to schools once they reopened (Mlaba 2021). For instance, at the beginning of 2021, 8 percent of boys and 16 percent of girls in the target counties (Nairobi, Kisumu, Kilifi and Wajir) did not return to school (Population Council 2021). Figure 1 above offers a timeline of the most relevant policy changes, as well as the interview periods from the first five waves of the RRPS. In this study, we rely mostly on data from waves three to five (September 2020 to June 2021) – that is, before and after school closures.

4. Data and Methodology

To analyze the impact of the pandemic for children in Kenya, we take advantage of the Kenya COVID-19 rapid-response phone survey (RRPS) for households. Conducted by the World Bank in partnership with the Kenyan National Bureau of Statistics (KNBS), the United Nations High Commissioner for Refugees (UNHCR), and the University of California, Berkeley, the RRPS consists of a panel survey that captures the impacts of the COVID-19 pandemic on Kenyan nationals, refugees and stateless people.[9] Since May 2020, households have been contacted by phone every two months and asked a broad set of questions, ranging from basic socio-economic characteristics to knowledge of COVID-19.[10] The questionnaire includes, in addition to most core questions used in the global template of the World Bank and a subsample of questions from the ECD COVID-19 survey monitoring parental support, questions about children internalizing and externalizing behaviors, as well as specific questions designed to better understand the consequences of COVID-19 for the Kenyan population.[11]

The interviews could be conducted in a series of different languages, including Swahili, Luo, Arabic, French, Kirundi, Luganda, Oromo, Somali, Kinyarwanda, Tigrinya, Nuer and Dinka, according to the respondent's preference. By combining a nationally representative sample – randomly drawn from the 2015/16 Kenya Integrated Household Budget Survey (KIHBS) and stratified by county and place of residence – with additional samples of randomly-drawn mobile-phone owners (not stratified) and of refugees and stateless people (stratified by location), the final sample is representative of the Kenyan population using mobile phones, which accounts for 80 percent of the population (KNBS 2019). The RRPS is then re-weighted to make it as representative as possible of the entire Kenyan population.[12]

Since most questions that are specifically about young children have been introduced in the third wave of the survey, between September 18 and November 28, 2020, we take this to be our baseline period. The analysis extends up to June 14, 2021, and thus also includes waves four (between January 25 and

teaching and learning materials, and to expand existing distance-learning programs; (iii) to train teachers to effectively support distance learning, including monitoring and assessment; (iv) to develop, and implement intervention programs targeting the marginalized and most vulnerable learners especially the girls and learners with special needs; and (v) to provide psychosocial support to learners, teachers, education officials and other stakeholders (Republic of Kenya Ministry of Education 2020).

[9] A target respondent in each household has been followed throughout all waves, but as there are cases in which the person could not be reached or stated that no longer wished to be contacted, we end up with an unbalanced panel.

[10] We define households as "a person, or group of people, that eat from the same pot and spend four nights or more in an average week sleeping in the same home." This is comparable to the definition used by the Kenya National Bureau of Statistics (KNBS 2018), but slightly simplified to ease implementation via phone survey.

[11] The questionnaire is available here.

[12] More information about the survey as well as a dashboard to monitor some of the key indicators are available here.

March 25, 2021) and five (between March 26 and June 14, 2021).[13] Therefore, the survey captures distinct periods in terms of implementation of public policies. It starts at a time in which most Kenyan schools were closed and spans the whole reopening phase, such that we are able to observe respondents both during and after lockdown.

In each of the three survey waves analyzed in this study, around 4,000 households, associated with more than 10,000 children, were interviewed. Children are on average 9.1 years old and live mostly in rural areas (60 percent). At baseline (between September and November, 2020), around 7 percent of households reported having at least one child going to bed hungry in the last seven days and 38 percent of those children lived in poor households. Table A0, in the appendix, provides a full list of variables and descriptive statistics.

Throughout this paper, we examine child and household characteristics that potentially impact children's response to the pandemic and help identify whether the pandemic widened pre-existing inequalities. To capture general welfare, we define a binary poverty proxy (*poor*), based on whether children live in a household in which the predominant floor material is dirt (i.e., either earth/sand or dung), and an indicator of child hunger (*childhunger*), defined, also at the household level, by children going to bed hungry at least once in the last seven days.[14] Moreover, we capture remoteness and general infrastructure by including indicator variables for whether the household is located in an urban or rural area (*urban*), whether it has access to the power grid (*powergrid*) and, in analyses from January 2021 (wave four) onwards, to the internet (*internet*).[15] We also take into account the type of school (*public*), private or public, that each child attends.

Given the influence that household heads (who are often the parents) play in the lives of children, we include variables that capture their gender (*headfemale*) and education level based on an indicator for having a tertiary degree (*headtertiary*).[16] Furthermore, as discussed above, (teenage) girls can be disproportionately affected during school closures and times of crisis. We examine to what extent that is the case during lockdowns in Kenya and include a binary variable for child gender (*female*). In addition, we control for the (logarithm of the) number of children in each household (*nchild*), child age (*age*), age squared (*agesq*), for the week of the interview (*weekcount*), and for a binary variable that indicates whether at least one person in the household reported feeling nervous or anxious due to the outbreak (*feelanxious*), as different attitudes to the pandemic may influence children's school attendance.

To measure the adoption of remote learning forms, we create an indicator variable (*remote*) for children who, although not attending school in person, have access to education online, via television and/or attend school, according to the survey, "remotely/from home". While the number of children with access to remote education during the period between September and November 2020 (wave three) is limited, a significantly larger group of children resorted to home or community-based schooling at this time.[17] These "alternative" forms of education (*alternative*) include children being educated by their parents, siblings and other members of their community, as well as self-directed learning. Both variables are

[13] Although our analysis ends with the fifth wave of the survey, two additional RRPS waves have since been implemented.

[14] Alternatively, in Tables A1 and A2, in the appendix, we test the robustness of our results using an imputed measure of household poverty based on a wider selection of characteristics as an alternative.

[15] Information on internet access only becomes available in January 2021 (wave four).

[16] Our data indicate that the benefits of parent (or head) education are mostly driven by those who have a college degree (or higher). Approximately 14 percent of the households in our sample have at least one member who completed at least college education. In robustness tests (not shown), using an indicator of secondary education (or higher) as a replacement does not yield significant coefficients in most cases.

[17] In fact, between September and November 2020 (wave three), the adoption of alternative forms of education is almost 20 percentage points higher among those without access to remote learning, suggesting that community-based and self-directed learning can be seen as the second-best option when schools are closed. Nevertheless, almost 70 percent of children with access to remote learning during this period reported to also make use of alternative forms of learning.

based on survey questions that refer to one randomly-selected child in the household.[18] Finally, we measure in-person school attendance (*inperson*) if children report to be regularly attending school at the time of the interview. This information is available for all children in the household. Therefore, to analyze to what extent the take-up of remote and alternative learning options, as well as the rates of return to school (once the restrictions were lifted), differed according to socio-economic characteristics, we estimate the following (weighted) OLS model:

$$y_{ihct} = \beta_1 female_{ihct} + \beta_2 poor_{hct} + \beta_3 childhunger_{hct} + \beta_4 urban_{hct} + \beta_5 headtertiary_{hct} + \beta_6 headfemale_{hct} + \beta_7 powergrid_{hct} + \beta_8 public_{ihct} + X'_{ihct}\gamma + \delta_c + \phi_t + u_{ihct}$$

where, for child *i*, in household *h*, in county *c*, during wave *t*, the binary dependent variable (y_{ict}) stands for either remote education, alternative education (both between September and November 2020) or school attendance (between January and March 2021). In addition to the explanatory variables of interest, we include a vector (X_{ihct}) containing the control variables previously mentioned as well as county fixed effects (δ_{ct}), which eliminates (unobserved) county-specific characteristics that are common to all households in a given county.[19] Whenever data from more than one wave is included in the analysis (i.e., when we examine well-being), we add also wave fixed effects (ϕ_t) to capture cross-section variation that is common to all households during each wave. The robust standard error (u_{ihct}) is corrected according to the survey design.

Furthermore, to assess the consequences of the pandemic for child well-being, we track changes in children's behaviors across six different dimensions. If parents report that their children have been (i) crying more, (ii) more defiant, (iii) destroying more, (iv) speaking less, (v) more withdrawn and/or (vi) more irritable than usual, we consider this to be a sign of (internalizing and externalizing) changes in behavior (*behavior*), which is our main measure to capture emotional well-being. We also split these six indicators into two different groups: externalizing (i, ii, iii) and internalizing (iv, v, vi) behaviors. Simply put, the former attitudes are directed outwards, "generating discomfort and conflict in the surrounding environment," while the latter manifest inwardly, leading to "distress in the individual" (Forns et al. 2011, p. 1464). The main objective is to understand to what extent the recent increase in mental health issues reported in children is explained by the (change in) exposure to the three different types of learning described above (i.e., remote, alternative, and in-person education).[20]

To account for parent attitudes that are likely to be associated with the probability of children exhibiting changes in behavior, in this part we control for two additional binary indicators: whether parents stimulate and engage with their children (*engagement*), and whether they apply harsh disciplinary methods (*discipline*). Engagement is defined as any of the following activities: playing, reading books, telling stories or singing songs to the child, whereas harsh discipline includes calling the child names (e.g., dumb or lazy), spanking, hitting or beating the child.

As these internalizing and externalizing behavioral questions were only introduced in January 2021 (wave four of the RRPS), we first pool observations from waves four and five and run a (weighted) OLS regression similar to the one described above, but with behavioral changes (*behavior*) as the dependent

[18] In this part of the analysis, as the outcome variables capture formal education (either in-person, remote or alternative learning), we exclude children below pre-primary age (i.e., age three and younger) from the sample, as they are below the age of government-provided education and usually have no access to alternative forms of early learning or childcare. Furthermore, considering the fundamental differences between children in different age cohorts and that remote education in particular is more easily adopted by older children, we split our analysis, whenever possible, between age groups.

[19] Vector X_{ihct} includes: $nchild_{hct}, age_{ihct}, agesq_{ihct}, weekcount_{hct}, feelanxious_{hct}$.

[20] Note that the variable *inperson* can be defined based on two different questions in the survey. One of these questions is available to all children in the sample, while the other is only posed to a randomly-selected child in each household. While the former has the advantage of a larger sample size, the latter can be matched to other characteristics that are also only available to the selected respondent, such as *remote* and *alternative*. As the two approaches yield similar results, we rely on the definition that we believe is most appropriate in each section of this paper. We indicate the use of the full-sample alternative with *inperson (all)*.

variable and with the binary variables for education type as well as *engagement* and *discipline* as additional regressors.[21] Second, to improve identification, we leverage these two time points available and estimate the model with child fixed effects (ψ_i):

$$behavior_{ihct} = \theta educ_{ihct} + W'_{ihct}\lambda + \psi_i + v_{ihct}$$

where *educ* stands for either *remote*, *alternative* or *inperson*. At times, more than one of these variables (e.g., $inperson_{ihct}$ and $remote_{ihct}$) are included simultaneously. Vector W_{ihct} includes all explanatory variables of interest described above as well as the control variables in X_{ihct} (from the previous equation) that vary over time.[22] Finally, we again adjust the (robust) standard error (v_{ihct}) to reflect the survey structure. In this case, we rely only on (within) variation over time for each individual, such that all factors that are constant between September 2020 and March 2021, and could confound our results, are eliminated.[23] Getting rid of the unobserved heterogeneity in this case comes with the additional advantage of mitigating potential issues of reporting bias that could affect the dependent variable, as some groups of the population may be more likely to report changes in their children's behavior.

5. Results

5.1. Closed Schools

Children were sent home from school in March 2020, and most had to wait until early January 2021 to return to the classroom. This section analyzes the consequences of these nine months of closed schools for children, and to what extent students relied on remote and alternative forms of learning during this period.[24]

5.1.1. Remote Learning

RRPS data indicate that less than 40 percent of Kenyan households currently have internet access and around 10 percent reported owning a computer before the pandemic.[25] Moreover, only around 5 percent of children (who were not currently attending school) reported having access to remote learning between September and November 2020.[26] While over 11 percent of children in private schools learned remotely during that period, fewer than 4 percent of their peers in public schools did so (p=0.05).

Regression results corroborate the existence of a digital divide (Table 1). Children (aged three and older) living in poor households are on average 6 percentage points less likely to learn remotely when schools are closed than children living in non-poor households. This seems to be driven in particular by poor girls, who are particularly at risk (column 2).[27] Experiencing food insecurity is also associated with a reduced probability (between 4 and 4.6 percentage points) of having access to remote education.

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[21] In this part, we do not include the variable that accounts for the education of the household head, as it yields mostly insignificant coefficients and, due to limited availability, would reduce the sample by almost half. Results are nevertheless similar with and without this variable.

[22] Vector W_{ihct} includes: $engagement_{hct}$, $discipline_{hct}$, $poor_{ihct}$, $childhunger_{hct}$, $urban_{hct}$, $powergrid_{hct}$, $internet_{hct}$, $public_{ihct}$, $nchild_{hct}$, $feelanxious_{hct}$. Moreover, including county fixed effects is redundant in this case, as very few children moved between waves.

[23] Given that the analysis is limited to two periods, this is equivalent to specifying the model in first differences.

[24] Figure A1, in the appendix, shows the adoption rates of remote and alternative forms of education by different groups of the population.

[25] Data on internet access and computer ownership became available only in January 2021 (wave four), and therefore is not included in the baseline regressions throughout this section. In the 2019 Kenya Population and Housing Census, only 22.6 percent of individuals were reported using the internet and 10.4 using computers (KNBS 2019).

[26] Between September and November 2020 (wave three), almost 60 percent of children who learned remotely did so via the internet.

[27] Including other interaction terms, such as between female and age or female and number of hours spent on house chores, did not yield significant results (not shown).

Table 1. Remote and Alternative Education

	(1)	(2)	(3)	(4)
	Remote Education		Alternative Education	
Female	0.022	0.062**	0.047	0.085
	(0.018)	(0.031)	(0.056)	(0.073)
Poor	-0.060**	-0.007	0.094	0.143*
	(0.028)	(0.017)	(0.058)	(0.084)
Female * Poor		-0.109**		-0.101
		(0.047)		(0.106)
Child Hunger	-0.040**	-0.046**	0.163*	0.157*
	(0.017)	(0.018)	(0.089)	(0.089)
Urban	0.002	-0.003	-0.031	-0.035
	(0.016)	(0.017)	(0.063)	(0.062)
Head Tertiary Education	0.046*	0.048*	0.076	0.078
	(0.027)	(0.026)	(0.079)	(0.079)
Female Head	0.031**	0.029*	0.015	0.013
	(0.016)	(0.015)	(0.054)	(0.053)
Power Grid	-0.033	-0.035*	-0.031	-0.033
	(0.022)	(0.021)	(0.063)	(0.061)
Public School	0.043	0.045	0.081	0.083
	(0.050)	(0.048)	(0.078)	(0.078)
County FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
R2	0.18	0.20	0.26	0.27
N	2005	2005	2005	2005

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. Children younger than 3 years old were excluded from the sample. County fixed effects. Data from wave 3. Control variables: age, age squared, no. children (log), anxious due to outbreak, week count.

On the other hand, children who live in households in which the head is college-educated are almost 5 percentage points more likely to learn remotely.[28] Given that poverty is controlled for, this result shows that the benefit of parents' education for children goes beyond material advantages, and may improve their ability to engage with and influence their children as well as teachers to increase the chances that their children continue to learn even if remotely (Reeves and Venator 2014).[29] These disparities in access to remote learning are not only troubling on its own, but may end up widening other pre-existing inequalities long after the outbreak is contained (Zintl and Melia 2020).

Additionally, if the household head is a woman, children in the household are around 3 percentage points more likely to engage in remote education, consistent with the evidence that women treat the pandemic as a more serious threat than men (Galasso et al. 2020).[30] Considering the rather low mean value of the dependent variable between September and November 2020 (0.047), the magnitude of all of these coefficients is quite substantial.[31]

5.1.2. Alternative Education

Contrary to remote education, the divide in the take-up of alternative education is less severe. This is consistent with community and self-directed learning being more accessible to different segments of the population – almost half of Kenyan children engaged in at least some form of alternative education when

[28] It is important to note that tertiary education in particular matters in this case. Replacing it with an indicator for secondary education yields insignificant results.

[29] In fact, almost one-fifth of households with college-educated heads in our sample are poor, indicating that the benefit of parental education goes beyond income.

[30] In our data, households with female heads do not differ significantly (on average) from those led by men neither in terms of poverty nor level of education.

[31] The findings presented in Table 1 are mostly robust to the use of nonlinear (probit) models (Table A3).

schools were closed. In fact, we find some evidence that more vulnerable children (poor and food-insecure) are more likely to rely on this type of learning. Although we cannot observe the quality of education for any form of learning in this paper, it is important to remark that alternative education may be the one with the highest heterogeneity in this regard, since in this case children depend to a higher degree on the skills of their relatives and/or community members.

Finally, remote and alternative learning do not seem to be substitutes when schools close. Rather, the data suggest that these worked as complementary strategies during times of need, and children that engaged in either of the two were more likely to also take part in the other.

5.2. Return to School

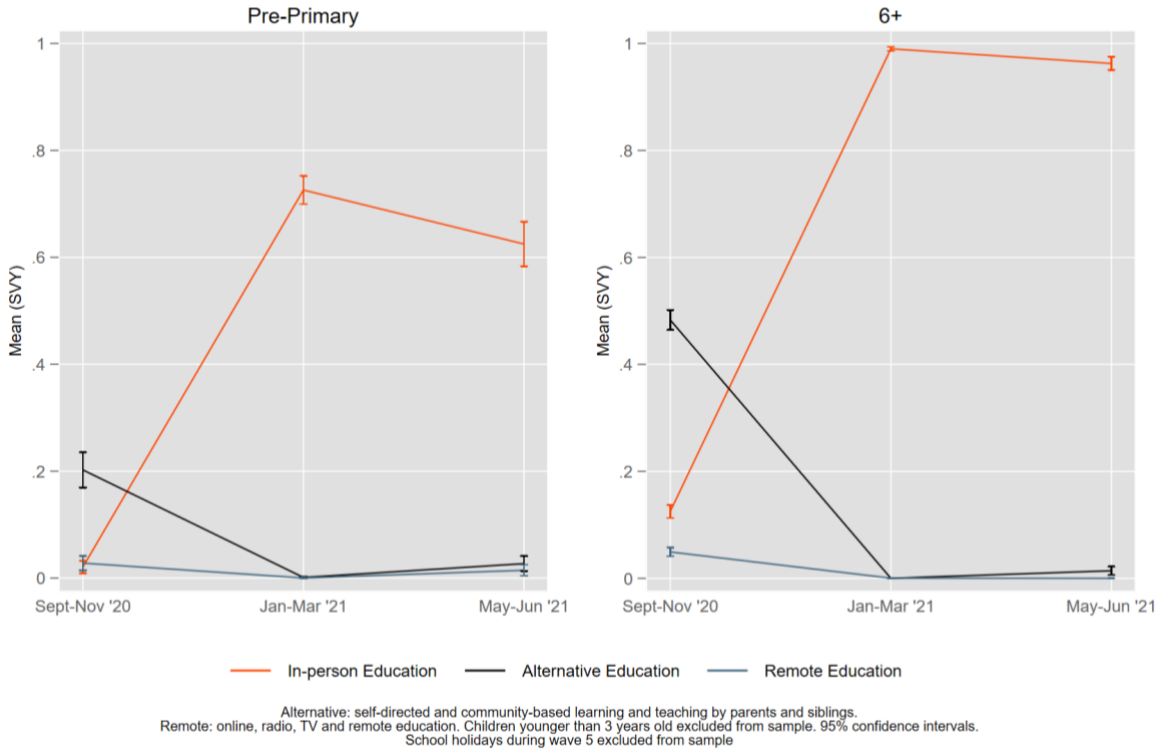
5.2.1. Attendance

Between January 25 and March 25, 2021 (wave four data), approximately 84 percent of Kenyan children attended schools again, while the share of those who relied on either remote or alternative education fell below 1 percent.[32] However, a substantial number of children, especially of pre-primary age did not return to school immediately after the lockdown policies were lifted (Figure 2).[33] To allow for a more nuanced analysis, in this section we split the sample by age group. The explanatory variables remain largely the same.[34]

Starting with children in pre-primary education, we again find significant benefits of living in households with college-educated heads, for which attendance rates are on average 3.3 percentage points higher (Table 2).[35] Also consistent with previous results, households headed by women are less likely to send their young children back to school, which can be interpreted as a more risk-averse behavior in this context (Kowalik and Lewandowski 2021). Although those in urban areas are more likely to return to school (by almost 3 percentage points), children with internet access are 7 percentage points less likely to attend classes, suggesting that, for children in pre-primary age, parents may have been more likely to delay their return to school if remote learning options were available.[36]

[32] For comparison, according to World Bank data, in 2016 (the last year for which information is available) gross school enrollment rates in Kenya were 103 percent for primary- and 76 percent for pre-primary-aged children.
[33] More than 25 percent of children aged between 3 and 6 did not return to school in the first term of 2021 (wave four).
[34] Differently to the previous section, however, from January 2021 (wave four) on we also have information on whether households have internet access, which we include as an additional control variable.
[35] Table A4, in the appendix, reports comparable results when we estimate these models using probit instead.
[36] Approximately 3 percent of children between the ages of 3 and 6 had remote access to education between September and November 2020.

Figure 2. Variation in Modes of Learning



The results are quite different for children above six years of age (columns 3 and 4).[37] First, those living in poor households are more likely (up to 3.1 percentage points) to return to school, and the offer of meals in some schools does not seem to be a strong incentive for (poor) children to come back to the classroom, as children who experience food insecurity are in fact less likely to return. In any case, these results do not rule out (differential) increases in drop-out rates in the future, and the economic conditions in Kenya in the years to come are likely to determine, to a great extent, whether children are able to continue their education once the crisis is overcome.

Although we do not observe a significant overall difference for girls, those (aged six and older) who live in poor households are less likely to return to school. This is in line with the literature on comparable situations of crisis, as it points out that girls often take on additional caregiving and household responsibilities in such times. During this period (between January and March 2021), girls in this age cohort reported spending on average 7.6 hours on household chores in the last seven days, while their male peers reported only 5.6 hours on average (p=0.01). In this case, the head's education is negatively correlated with the probability to attend school, suggesting that highly educated parents, in times of emergency, may be more capable (or willing) to provide learning opportunities at home, and/or (differentially) warier of the virus.[38]

[37] We acknowledge that the large difference in R-squared between the two age cohorts reported in Table 2 might indicate lack of power in the smaller sample of pre-primary-aged children.

[38] Although the data do not allow for a definite answer, an indication of such phenomenon is that college-educated parents were, during the period between January and March 2021 (wave four), almost 30 percentage points more likely to report reading to their children (aged six and older) than other parents: 76 versus 47 percent probability, respectively (p=0.00). Moreover, this difference falls to 11 percentage points and becomes insignificant in wave five (p=0.25).

Table 2. School Attendance

	(1)	(2)	(3)	(4)
	In-person Education (All)			
Female	-0.001	-0.001	0.004	0.019
	(0.013)	(0.017)	(0.006)	(0.013)
Poor	-0.014	-0.014	0.018***	0.031***
	(0.027)	(0.029)	(0.007)	(0.011)
Female * Poor		0.001		-0.026*
		(0.022)		(0.015)
Child Hunger	-0.004	-0.003	-0.062**	-0.063**
	(0.043)	(0.043)	(0.028)	(0.027)
Urban	0.029**	0.029**	0.011	0.012
	(0.014)	(0.014)	(0.008)	(0.008)
Head Tertiary Education	0.033*	0.033*	-0.027*	-0.029**
	(0.018)	(0.018)	(0.014)	(0.014)
Female Head	-0.034*	-0.034*	0.000	0.002
	(0.018)	(0.019)	(0.006)	(0.006)
Power Grid	-0.031	-0.031	-0.007	-0.007
	(0.023)	(0.022)	(0.007)	(0.007)
Internet	-0.070***	-0.070***	0.003	0.005
	(0.022)	(0.022)	(0.009)	(0.009)
Public School	-0.015	-0.015	-0.009	-0.011
	(0.025)	(0.025)	(0.014)	(0.014)
County FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
Age	3-6	3-6	6+	6+
R2	0.62	0.62	0.09	0.09
N	767	767	3210	3210

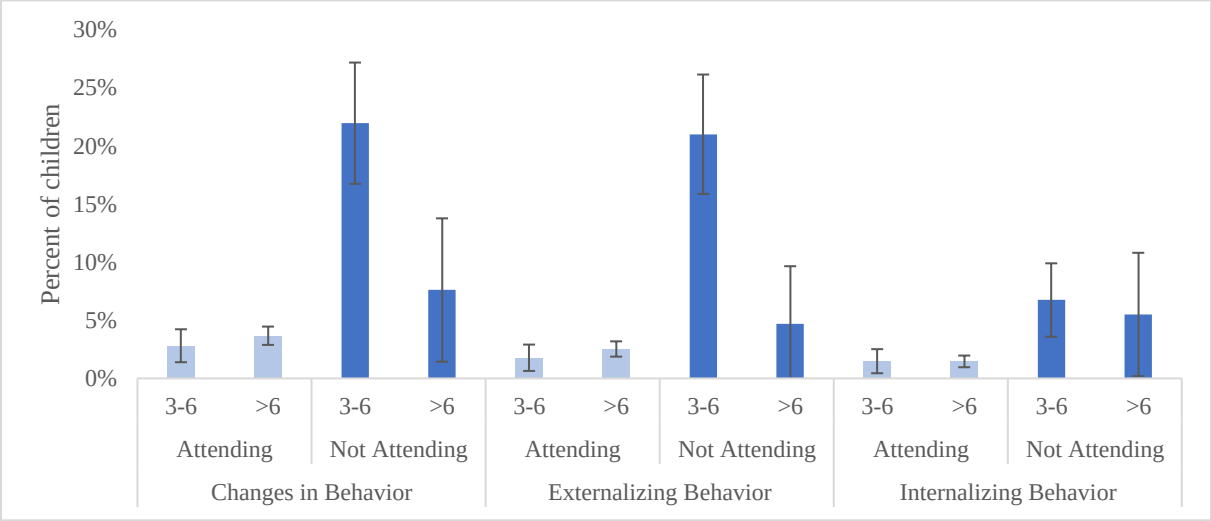
Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. County fixed effects. Data from wave 4. Control variables: age, age squared, no. children (log), anxious due to outbreak, week count.

5.2.2. Well-being

To the extent that the data allow, we now turn our analysis to the impact of the crisis on the emotional well-being of Kenyan children. We devote special attention to those below six years of age, as disruptions to child development at this stage can be particularly detrimental (Shonkoff, Boyce and McEwan 2009; Shonkoff and Garner 2012). A first sign that educations matters for well-being is that, after schools reopened, changes in both internalizing and externalizing behavior were significantly more prevalent in those not attending school: while fewer than 4 percent of children that were back in the classroom experienced changes in behavior, almost one-fifth of those not in school reported some alteration (p=0.01) – and the gap is even larger for children at the pre-primary level across all categories (Figure 3). In the first half of 2021, the cases of behavioral change in children more than tripled, jumping from around 7 percent between January and March to more than 21 percent of children between March and June (p=0.00).[39]

[39] For more details, see Figure A2 in the appendix.

Figure 3. Behavioral Changes and School Attendance (from Jan. - Mar. 2021)



Notes: Sample restricted to children between three and six years old. Behavioral change includes the following six changes in behavior: children who have been (i) crying more, (ii) more defiant, (iii) more destructive, (iv) speaking less, (v) more withdrawn or (vi) more irritable than usual. The first three (i-iii) refer to externalizing behavior, whereas the last three (iv-vi) are classified as internalizing behavior. 95 percent confidence intervals.

In line with Figure 3, regression results show that the different forms of learning are associated with divergent outcomes in terms of child behavior between January and June 2001 (Table 3). First, there is a positive and strong association between alternative education and suffering from behavioral changes: children who adopted this form of learning (and thus, by our definition, were not attending school) were more than 20 percentage points more likely to report issues.

The results for remote education, on the other hand, are more nuanced. The fact the we do not observe a significant coefficient for the full sample (columns 1 to 4) seems to be explained by its heterogeneous role with respect to age. While its adoption is correlated with better behavioral outcomes for older children, the results raise concerns about introducing children to remote forms of learning prematurely. Pre-primary-aged children who engaged in remote education are on average 50 percentage points more likely to report changes in behavior than their peers. Nevertheless, this should be interpreted with a grain of salt, as few children (approximately one percent) engaged in remote education in 2021 (during waves four and five).[40] Moreover, it may also be the case that children who experience changes in behavior are more likely to stay at home (and learn remotely) to begin with.[41] Finally, results from this pooled analysis do not show any significant relationship between attending school and changes in behavior.

Table 3. Well-being (Pooled)

	(1)	(2)	(3)	(4)	(5)	(6)
			Changes in Behavior			
In-person Education	-0.033			0.010	-0.056	0.018
	(0.032)			(0.030)	(0.062)	(0.028)

[40] Since remote education was mostly used during the months of September, October and November 2020 (wave three), we also regress (not shown) behavioral changes (in the subsequent period, i.e., wave four) on lagged remote education (from wave three) as well as on the other (lagged) explanatory variables. For the (small) subsample of pre-primary-aged children, we again find evidence that engagement in remote education is associated with higher probability of reporting behavioral issues.

[41] Potential sources of bias are arguably mitigated by the empirical strategy adopted next, in which we include child fixed effects (Table 4).

Remote Education		0.118		-0.057	0.501***	-0.161**
		(0.078)		(0.098)	(0.136)	(0.082)
Alternative Education			0.205***	0.213***	0.084	0.269***
			(0.060)	(0.062)	(0.122)	(0.054)
Engagement	0.040**	0.041**	0.034**	0.034**	0.052	0.025
	(0.017)	(0.016)	(0.016)	(0.016)	(0.040)	(0.017)
Discipline	0.394***	0.391***	0.380***	0.378***	0.352***	0.399***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.062)	(0.040)
Female	-0.012	-0.012	-0.012	-0.012	0.036	-0.040**
	(0.016)	(0.016)	(0.016)	(0.016)	(0.033)	(0.018)
Poor	-0.005	-0.005	-0.003	-0.004	-0.086**	0.002
	(0.020)	(0.020)	(0.020)	(0.020)	(0.035)	(0.023)
Child Hunger	0.027	0.028	0.028	0.028	-0.069	0.044
	(0.028)	(0.028)	(0.028)	(0.028)	(0.055)	(0.029)
Urban	-0.025	-0.026	-0.027	-0.027	0.011	-0.041*
	(0.020)	(0.020)	(0.020)	(0.020)	(0.032)	(0.024)
Female Head	-0.004	-0.002	-0.004	-0.004	0.018	-0.005
	(0.017)	(0.016)	(0.017)	(0.017)	(0.032)	(0.017)
Power Grid	-0.023	-0.021	-0.023	-0.022	-0.092***	-0.019
	(0.021)	(0.021)	(0.021)	(0.021)	(0.030)	(0.024)
Internet	0.003	0.003	0.007	0.008	-0.043	0.015
	(0.021)	(0.021)	(0.021)	(0.021)	(0.030)	(0.021)
Public School	-0.047	-0.046	-0.045	-0.044	0.080	-0.132**
	(0.043)	(0.042)	(0.043)	(0.043)	(0.050)	(0.053)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes
Age	3+	3+	3+	3+	3-6	6+
R2	0.35	0.34	0.36	0.36	0.43	0.40
N	6397	6397	6397	6397	1184	5213

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. County and wave fixed effects. Data from waves 4 and 5. Control variables: age, age squared, no. children (log), anxious due to outbreak, week count.

Across all specifications, children who experience harsh discipline, regardless of age group, are significantly (up to 39.9 percentage points) more likely to report negative changes in behavior. Nevertheless, since the number of parents adopting these aggressive methods increased in our sample period, this may also be attributed, at least partially, to the current crisis, as parents who are under stress may be more likely to resort to harsh discipline.[42] The fact that children whose parents are more engaged are more likely to report behavioral changes could be explained by the fact that these children require more attention from their caretakers, or that adults who spend more time with these children are more likely to observe these behaviors.[43]

As the magnitude of some of the point estimates reported above may seem worryingly large, we also present results for analogous non-linear (probit) models (Table A6).[44] In this case, although still substantial, the predicted marginal effects are somewhat smaller (Figure 4). Across all models, the largest predicted increase in the probability behavioral changes is 26 percentage points for remote

[42] While approximately 12 percent of parents reported treating their children aggressively between January and March 2021, this figure increased to more than 20 percent between March and June 2021 (p=0.00).

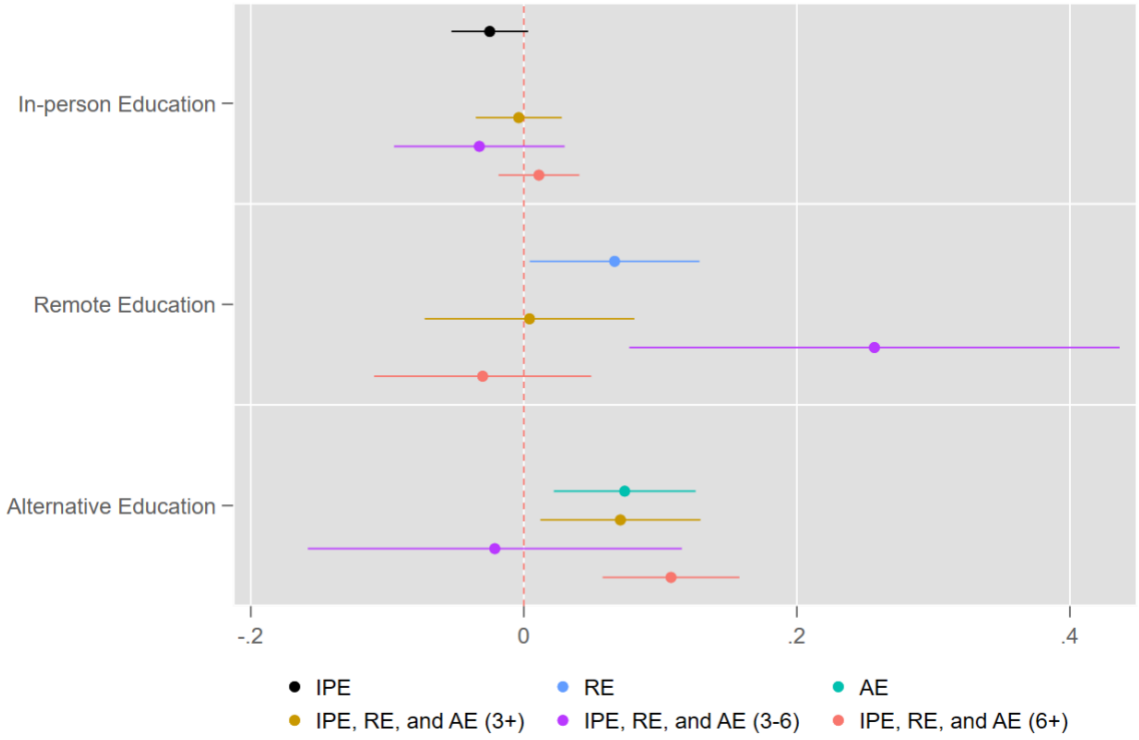
[43] Table A5, in the appendix, confirms the robustness of most results to the exclusion of school holidays (March 29 to May 10 2021) during wave 5, as well as to the use of different sets of control variables.

[44] We do not include fixed effects in the probit models to avoid the potential bias that stems from the incidental parameter problem (Neyman and Scott 1948).

education (children in pre-primary age), and 11 percentage points for alternative education (older cohort).

More importantly, the previous results (Table 3) do not rule out the alternative explanation that children who do not exhibit negative changes in behavior are just more likely to attend school. This concern is at least mitigated by the fact that the more robust models with child fixed (Table 4) effects corroborate our findings above. Children who *switch* to alternative education (between the previous and the current waves) are more likely to experience negative changes in emotional health – in particular for the older cohort. As to remote education, we once again find evidence that (switching to) this mode of learning is associated with the manifestation of behavioral changes at least in the case of children aged between three and six years old.[45]

Figure 4. Marginal Effect on Changes in Behavior



Notes: Predicted marginal effect of in-person, remote and alternative education on changes in behavior based on probit results reported in Table A6. IPE refers to specification with only in-person education (in addition to control variables) reported in Table A6 column 1. RE refers to the model that includes, among the types of learning, only remote education (column 2), and AE to the specification with only alternative education (column 3). IPE, RE, and AE refers to models that include the three forms of education simultaneously. These are displayed, for different age groups, in columns 4 to 6 of Table A6. 95 percent confidence intervals.

In this case, we also observe that switching to in-person education is linked to a 9.9 percentage-point decrease in the probability of reporting changes in behavior, suggesting that face-to-face learning may protect children from experiencing behavioral issues. In fact, this potential benefit of in-person education is the effect that predominates once we include all types of education simultaneously (column 4). These results are robust (and even become stronger) to restricting the sample to children who had at

[45] We consider it unlikely that these results are explained by differential reporting rates of behavioral changes according to learning type. Since most children did not attend school during wave 3, a vast number of parents had already adjusted their expectations during wave 4. It does not, therefore, explain the reporting increase in wave 4 for children who did not (or continued not to) attend school. While this may still affect the results for in-person education, the fact that we control for parent engagement and that most parents already had expectations about their children's behavior while attending school (formed prior to the pandemic) mitigates this concern.

least some form of access to education during this period (Table A7).[46] Finally, additional results (Table A9) indicate that externalizing attitudes seem to be the most affected type of behavior – either favorably, by in-person education, or detrimentally, in the case of remote education.

Table 4. Well-being (Fixed Effects)

	(1)	(2)	(3)	(4)	(5)	(6)
			Changes in Behavior			
In-person Education	-0.099***			-0.072*	-0.197	-0.059
	(0.038)			(0.039)	(0.152)	(0.037)
Remote Education		0.340**		0.180	0.866***	-0.102
		(0.146)		(0.179)	(0.188)	(0.155)
Alternative Education			0.206**	0.131	-0.371**	0.242***
			(0.096)	(0.105)	(0.185)	(0.092)
Engagement	-0.026	-0.017	-0.018	-0.026	0.144	-0.018
	(0.036)	(0.037)	(0.037)	(0.036)	(0.120)	(0.041)
Discipline	0.437***	0.436***	0.416***	0.423***	0.516***	0.414***
	(0.063)	(0.065)	(0.062)	(0.062)	(0.103)	(0.066)
Child FE	Yes	Yes	Yes	Yes	Yes	Yes
Age	3+	3+	3+	3+	3-6	6+
R2	0.32	0.30	0.32	0.33	0.49	0.35
N	4715	4715	4715	4715	857	3858

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. Child fixed effects. Data from waves 4 and 5. Control variables: public, poor, childhunger, urban, powergrid, internet, no. children (log), anxious due to outbreak.

6. Conclusion

The past couple of years brought unprecedented difficulties to billions of people across the world. Children – particularly in developing countries – have had to deal with a heavy load. In Kenya, home to over 20 million children aged 14 and younger, the virus outbreak and the nine-month-long period of school closures have led to disruptions in education and child development that have potentially long-lasting implications. When schools shut their gates in March 2020, few children could resume their education – even if imperfectly – with remote learning, likely increasing pre-existing inequalities, as children from poor and less educated households fell further behind.[47] In particular, girls living in poor households, who were less likely to adopt remote learning when needed and to go back to school after the restrictions were lifted, seem to be particularly at risk.

These early signs of increasing inequality are, to some extent, also reflected in the latest data from the Kenya Continuous Household Survey (KCHS). While school attendance rates remained largely unchanged between 2019 and 2020 for children who live in households with college-educated heads, they fell by almost two percentage points for those living with families whose head is less educated. Over the same period, a similar contrast is observed in terms of place of residence: rates significantly dropped in rural areas, but not in urban centers. Moreover, although we observe a significant reduction

[46] Table A8 in the appendix reports results of probit regressions of changes in behavior on the first differences of in-person, remote and alternative education (in addition to the same control variables), indicating that these findings are robust to nonlinear specifications. We opt for first differences instead of fixed-effects models to avoid the problem of incidental parameters (Neyman and Scott 1948).

[47] As mentioned previously, recent evidence indicates that, even if children do have access to virtual and hybrid education, these alternatives are still less effective than face-to-face learning (Halloran et al. 2021). The heterogeneity in terms of quality may be even larger for remote and alternative education, and this is something that we cannot account for in our analysis.

in attendance rates for both girls and boys, among those not attending school, in 2020 girls (but not boys) became substantially more likely to justify doing so due to the need of helping at home.[48]

Even though most children eventually returned to school when it was possible, it is still too early to tell what the long-term consequences of this period of reduced learning will be. Nevertheless, aggregate results from the latest national exams, such as the Kenya Certificate of Secondary Education (KCSE) – which children sit after four years of secondary education and serves as qualifications for university entrance – provide reasons to be moderately optimistic: so far, at least, there are no conclusive signs of worsening in performance. Similarly to previous years, the number of registered participants continued to increase, and absenteeism rates remained below one percent. In fact, the percentage of children achieving the highest grades, A and A-, even slightly increased, from 0.09 and 0.92 percent, respectively, in 2019, to 0.12 and 0.97 in 2020.[49] However, these results must be interpreted with caution for at least two reasons. First, it is possible that the grading standards have been adjusted to accommodate the special circumstances.[50] Second, children who were sitting exams during the last academic year were prioritized and, in many cases, have been able to return to school sooner than other cohorts, such that the losses that they have experienced are probably smaller than that of children who had to stay out of school for longer periods of time. [51]

In addition to the direct impact on learning, emotional well-being has also taken a hit during the COVID-19 crisis, with almost one in five children reporting at least one sign of a negative change in internalizing or externalizing behavior by June 2021. The chances that children experience these issues, however, varied according to their type of access to education. While alternative and remote learning were linked to worse outcomes (in particular for pre-primary-aged children), attending school in person seemed to protect their emotional well-being from deteriorating. In this sense, our results support the effort put worldwide into swiftly reopening schools whenever it is safe to do so. In this regard, special attention should be given to disadvantaged children, who may fall further behind if support is lacking, and to those still in pre-primary education, since disruptions at this stage can be particularly costly.

[48] Figures A3 and A4, in the appendix, show these differences across groups between 2019 and 2020.
[49] For more details, see the Kenya National Examinations Council website here.
[50] One example of such skewed standardization is available here.
[51] More information is available here.

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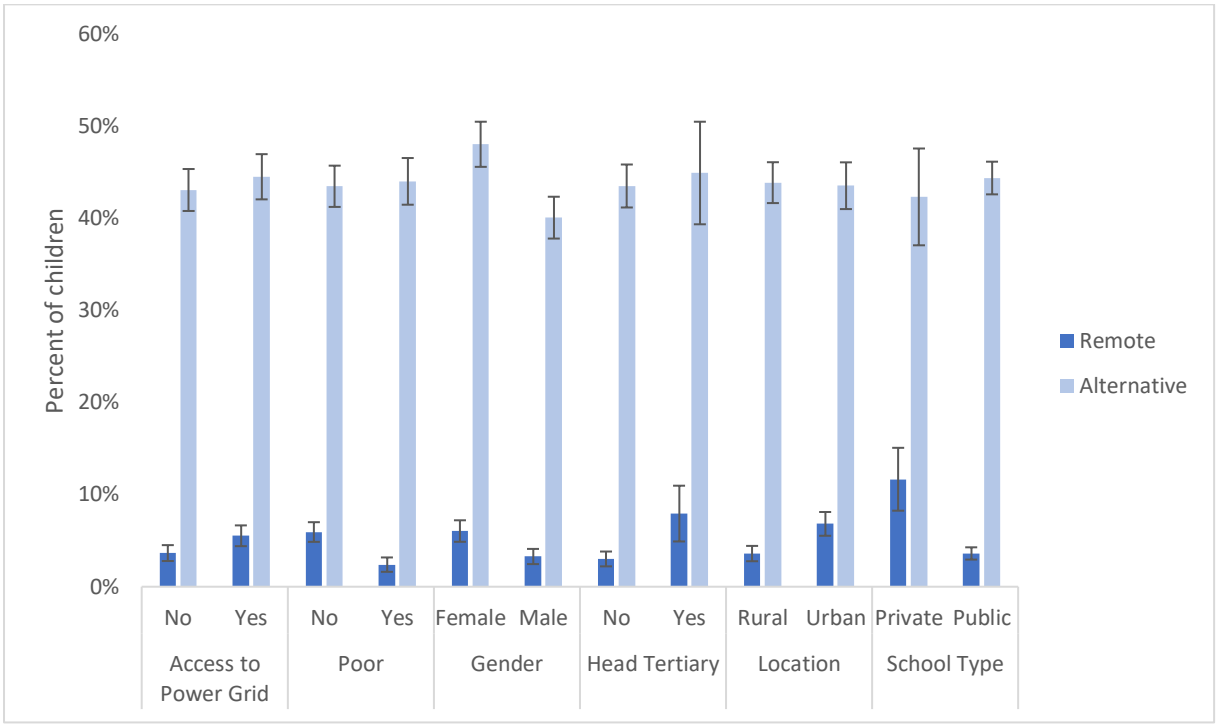
Appendix

Figure A1. Access to Education (Sept. - Nov. 2020)



Notes: Alternative: self-directed and community-based learning and teaching by parents and siblings. Remote: online, radio, TV and remote education. 95 percent confidence intervals.

Figure A2. Changes in Behavior

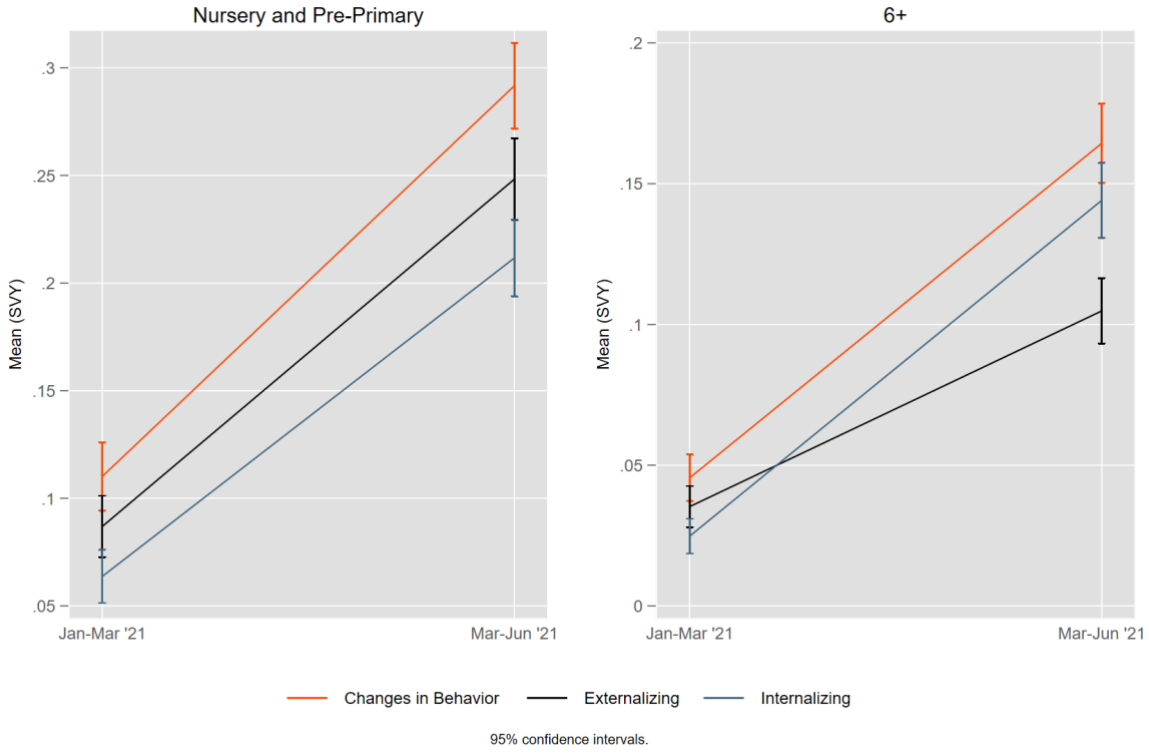
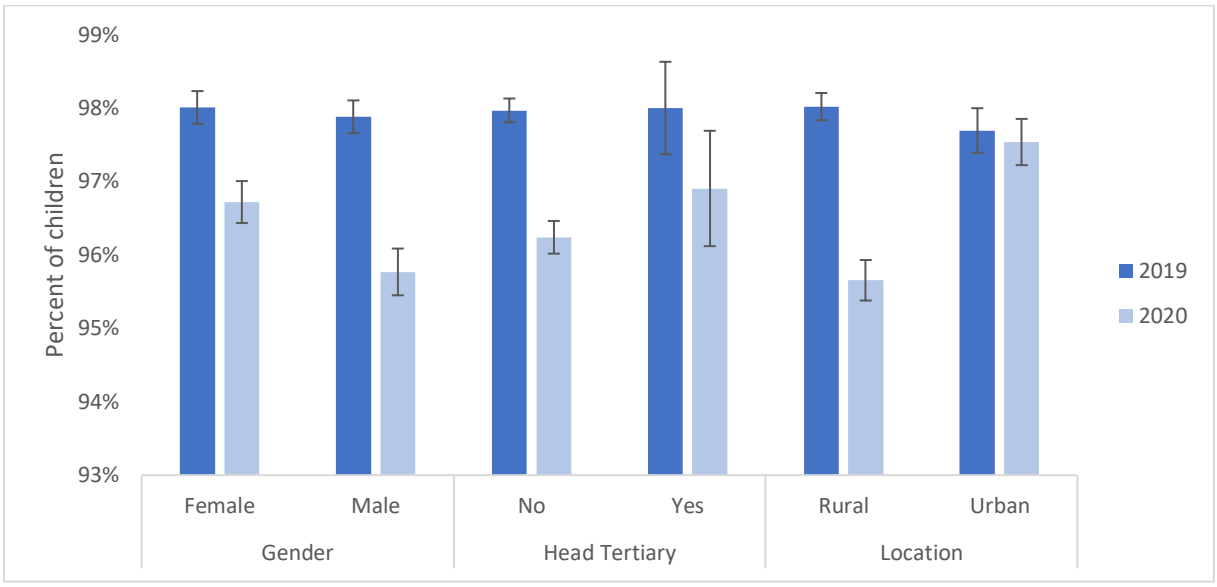
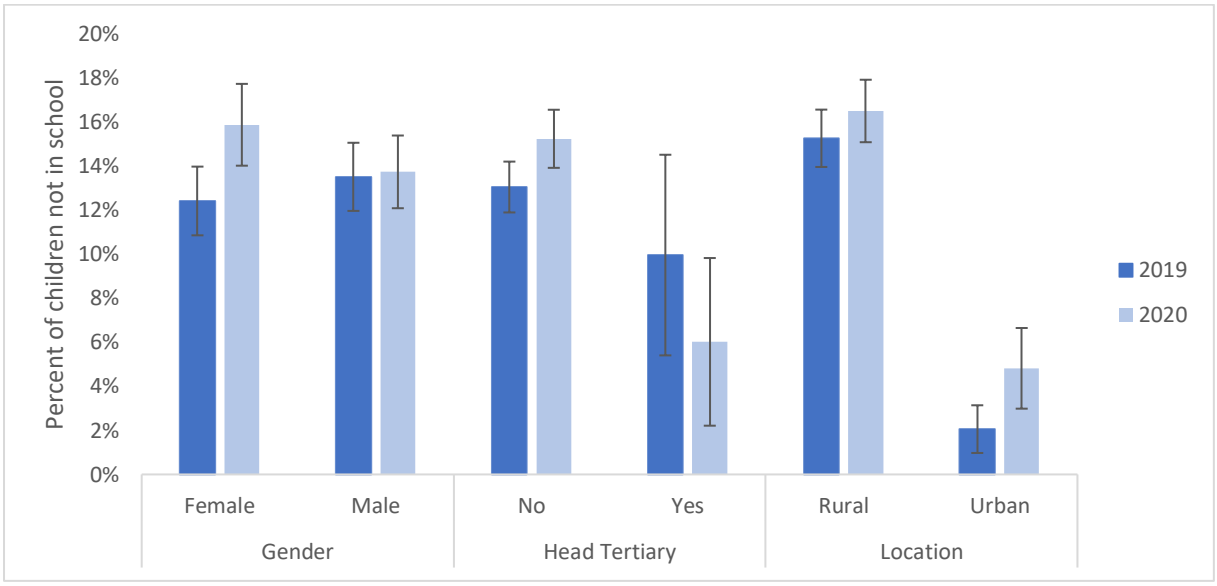


Figure A3. School Attendance (KCHS)



Notes: Percentage of children (aged 17 or younger) attending school in 2019 and 2020, according to sex, head tertiary education, and place of residence. Data from the Kenya Continuous Household Survey (KCHS). 95 percent confidence intervals.

Figure A4. School Interrupted to Help at Home (KCHS)



Notes: Among children (aged 17 or younger) not attending school, percentage who listed working or helping at home as the reason, in 2019 and 2020, according to sex, head tertiary education, and place of residence. Data from the Kenya Continuous Household Survey (KCHS). 95 percent confidence intervals.

Table A0. Descriptive Statistics

Variable	Mean	SD	Min	Max	N
In-person Education	0.47	0.50	0.00	1.00	12,014
In-person Education (All)	0.57	0.50	0.00	1.00	21,236
Remote Education	0.02	0.14	0.00	1.00	12,014
Alternative Education	0.13	0.33	0.00	1.00	12,014
Female	0.48	0.50	0.00	1.00	32,858
Public School	0.89	0.31	0.00	1.00	19,710
Head Tertiary Education	0.14	0.35	0.00	1.00	18,923
Poor	0.50	0.50	0.00	1.00	32,762
Child Hunger	0.09	0.29	0.00	1.00	32,868
Urban	0.40	0.49	0.00	1.00	32,891
Power Grid	0.45	0.50	0.00	1.00	32,891
Female Head	0.42	0.49	0.00	1.00	32,891
Internet	0.36	0.48	0.00	1.00	22,321
Age	9.12	4.83	0.00	17.00	32,858
Age^2	106.51	89.37	0.00	289.00	32,858
No. Children (log)	1.12	0.56	0.00	2.71	32,891
Anxious due to COVID19 outbreak	0.68	0.47	0.00	1.00	32,891
Week Count	19.64	11.80	1.00	37.00	32,891
Engagement	0.82	0.39	0.00	1.00	8,618
Discipline	0.19	0.39	0.00	1.00	8,617

Table A1. Remote and Alternative Education: Poor (SWIFT)

	(1)	(2)	(3)	(4)
	Remote Education		Alternative Education	
Female	0.029	0.041*	0.030	0.042
	(0.019)	(0.023)	(0.059)	(0.064)
Poor (SWIFT)	-0.005	0.037	0.081	0.122
	(0.018)	(0.025)	(0.069)	(0.110)
Female * Poor (SWIFT)		-0.087*		-0.087
		(0.047)		(0.136)
Child Hunger	-0.045**	-0.049**	0.144	0.140
	(0.020)	(0.020)	(0.096)	(0.095)
Urban	0.003	0.007	-0.043	-0.039
	(0.015)	(0.015)	(0.072)	(0.071)
Head Tertiary Education	0.046	0.043	0.067	0.064
	(0.029)	(0.029)	(0.081)	(0.081)
Female Head	0.030*	0.035*	0.038	0.043
	(0.017)	(0.018)	(0.054)	(0.054)
Power Grid	-0.023	-0.024	-0.064	-0.065
	(0.023)	(0.023)	(0.058)	(0.057)
Public School	0.055	0.056	0.123	0.123
	(0.056)	(0.056)	(0.080)	(0.079)
County FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
R2	0.18	0.19	0.28	0.28
N	1817	1817	1817	1817

Significance levels: p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. Children younger than 3 years old excluded from sample. County fixed effects. Data from wave 3. Control variables: age, age squared, no. children (log), anxious due to outbreak, week count.

Table A2. School Attendance: Poor (SWIFT)

	(1)	(2)	(3)	(4)
	In-person Education (All)			
Female	0.002	0.020	0.008	0.008
	(0.017)	(0.021)	(0.007)	(0.009)
Poor (SWIFT)	-0.011	0.032	-0.002	-0.001
	(0.028)	(0.027)	(0.009)	(0.012)
Female * Poor (SWIFT)		-0.094**		-0.002
		(0.044)		(0.013)
Child Hunger	-0.011	-0.010	-0.079**	-0.079**
	(0.049)	(0.049)	(0.034)	(0.034)
Urban	0.032*	0.031*	-0.003	-0.003
	(0.018)	(0.018)	(0.010)	(0.010)
Head Tertiary Education	0.044*	0.042*	-0.003	-0.003
	(0.025)	(0.024)	(0.013)	(0.013)
Female Head	-0.033	-0.036*	-0.009	-0.009
	(0.020)	(0.021)	(0.008)	(0.008)
Power Grid	-0.008	-0.003	-0.008	-0.008
	(0.016)	(0.015)	(0.009)	(0.009)
Internet	-0.086***	-0.084***	0.001	0.001
	(0.027)	(0.026)	(0.011)	(0.011)
Public School	-0.029	-0.026	-0.001	-0.001
	(0.029)	(0.027)	(0.020)	(0.020)
County FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
Age	3-6	3-6	6+	6+
R2	0.64	0.65	0.07	0.07
N	649	649	2658	2658

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. County fixed effects. Data from wave 4. Control variables: age, age squared, no. children (log), anxious due to outbreak, week count.

Table A3. Remote and Alternative Education (Probit)

	(1)	(2)	(3)	(4)
	Remote Education		Alternative Education	
Female	0.184	0.371	0.066	0.200
	(0.202)	(0.248)	(0.174)	(0.241)
Poor	-0.792***	-0.313	0.153	0.319
	(0.285)	(0.254)	(0.247)	(0.331)
Female * Poor		-1.017**		-0.356
		(0.403)		(0.375)
Child Hunger	-0.943**	-0.976**	0.322	0.295
	(0.414)	(0.410)	(0.294)	(0.294)
Urban	-0.099	-0.085	-0.046	-0.058
	(0.197)	(0.203)	(0.188)	(0.186)
Head Tertiary Education	0.623**	0.623**	0.178	0.173
	(0.246)	(0.246)	(0.237)	(0.238)
Female Head	0.532**	0.540**	-0.096	-0.099
	(0.230)	(0.230)	(0.185)	(0.185)
Power Grid	-0.558**	-0.573**	-0.089	-0.095
	(0.266)	(0.272)	(0.220)	(0.217)
Public School	0.130	0.089	0.273	0.276
	(0.311)	(0.319)	(0.320)	(0.323)
County FE	No	No	No	No
Control	Yes	Yes	Yes	Yes
N	2005	2005	2005	2005

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. Children younger than 3 years old were excluded from the sample. Data from wave 3. Control variables: age, age squared, no. children (log), anxious due to outbreak, week count.

Table A4. School Attendance (Probit)

	(1)	(2)	(3)	(4)
	In-person Education (All)			
Female	-0.020	-0.177	0.049	0.275
	(0.299)	(0.343)	(0.196)	(0.256)
Poor	-0.017	-0.197	0.854***	1.187***
	(0.389)	(0.486)	(0.255)	(0.320)
Female * Poor		0.472		-0.740**
		(0.682)		(0.329)
Child Hunger	-0.765**	-0.743**	-1.248***	-1.285***
	(0.386)	(0.370)	(0.270)	(0.269)
Urban	0.509	0.480	0.168	0.227
	(0.329)	(0.334)	(0.258)	(0.242)
Head Tertiary Education	0.435	0.449	-1.031***	-1.056***
	(0.346)	(0.341)	(0.295)	(0.285)
Female Head	-0.788**	-0.813**	-0.014	0.038
	(0.358)	(0.369)	(0.155)	(0.155)
Power Grid	-0.636*	-0.579*	-0.342	-0.339
	(0.367)	(0.327)	(0.223)	(0.214)
Internet	-0.877***	-0.905***	0.093	0.127
	(0.285)	(0.277)	(0.230)	(0.231)
Public School	0.044	0.048	-0.446	-0.461
	(0.320)	(0.325)	(0.368)	(0.364)
County FE	No	No	No	No
Control	Yes	Yes	Yes	Yes
Age	3-6	3-6	6+	6+
N	767	767	3210	3210

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. Data from wave 4. Control variables: age, age squared, no. children (log), anxious due to outbreak, week count.

Table A5. Well-being (Pooled): Additional Robustness Tests

	(1)	(2)	(3)	(4)
	Changes in Behavior			
In-person Education	0.010	-0.019	-0.031	0.033
	(0.030)	(0.033)	(0.048)	(0.059)
Remote Education	-0.057	-0.037	0.275	0.067
	(0.098)	(0.148)	(0.350)	(0.265)
Alternative Education	0.213***	0.128	0.790***	0.803***
	(0.062)	(0.079)	(0.076)	(0.089)
Engagement	0.034**	0.011	0.033**	0.047**
	(0.016)	(0.023)	(0.017)	(0.023)
Discipline	0.378***	0.392***	0.044*	0.293***
	(0.040)	(0.051)	(0.024)	(0.046)
Female	-0.012	0.007	-0.025*	-0.004
	(0.016)	(0.021)	(0.014)	(0.020)
Poor	-0.004	0.003		0.009
	(0.020)	(0.029)		(0.028)
Poor (SWIFT)			0.024*	
			(0.014)	
Child Hunger	0.028	0.063**	-0.015	0.049
	(0.028)	(0.030)	(0.033)	(0.040)
Urban	-0.027	-0.014	-0.028*	-0.049**
	(0.020)	(0.024)	(0.017)	(0.023)
Head Tertiary Education		0.017		
		(0.031)		
Female Head	-0.004	-0.013	-0.023*	-0.011
	(0.017)	(0.024)	(0.014)	(0.020)
Power Grid	-0.022	-0.014	-0.021	0.006
	(0.021)	(0.028)	(0.015)	(0.028)
Internet	0.008	-0.014	0.012	-0.018
	(0.021)	(0.031)	(0.014)	(0.029)
Public School	-0.044	0.038	-0.073**	-0.069
	(0.043)	(0.057)	(0.032)	(0.048)
County FE	Yes	Yes	Yes	Yes
Wave FE	Yes	No	Yes	Yes
Control	Yes	Yes	Yes	Yes
Holidays	Yes	Yes	Yes	No
Age	3+	3+	3+	3+
R2	0.36	0.43	0.18	0.36
N	6397	3439	2361	3935

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. County fixed effects. Data from waves 4 and 5. Control variables: age, age squared, no. children (log), anxious due to outbreak, week count. School holidays from March 29 to May 10 2021. As many RRPS questions refer to the previous seven days, we extend this period until May 17 2021.

Table A6. Well-being (Pooled Probit)

	(1)	(2)	(3)	(4)	(5)	(6)
			Changes in Behavior			
In-person Education	-0.227*			-0.034	-0.290	0.110
	(0.132)			(0.148)	(0.279)	(0.146)
Remote Education		0.603**		0.038	2.285***	-0.302
		(0.295)		(0.361)	(0.751)	(0.400)
Alternative Education			0.681***	0.652**	-0.189	1.078***
			(0.247)	(0.276)	(0.621)	(0.223)
Engagement	0.618***	0.610***	0.558***	0.561***	0.309	0.554**
	(0.197)	(0.195)	(0.197)	(0.196)	(0.335)	(0.228)
Discipline	1.746***	1.713***	1.687***	1.693***	1.651***	1.827***
	(0.148)	(0.145)	(0.149)	(0.149)	(0.274)	(0.160)
Female	-0.182	-0.169	-0.178	-0.179	0.265	-0.394***
	(0.128)	(0.131)	(0.133)	(0.130)	(0.226)	(0.146)
Poor	0.018	0.021	0.045	0.044	0.006	0.042
	(0.164)	(0.162)	(0.163)	(0.164)	(0.376)	(0.183)
Child Hunger	0.122	0.113	0.097	0.099	-0.246	0.216
	(0.190)	(0.192)	(0.187)	(0.186)	(0.359)	(0.213)
Urban	-0.127	-0.116	-0.142	-0.143	-0.023	-0.177
	(0.157)	(0.155)	(0.160)	(0.160)	(0.243)	(0.172)
Female Head	-0.242*	-0.224	-0.238	-0.240*	-0.097	-0.345**
	(0.141)	(0.142)	(0.147)	(0.145)	(0.283)	(0.152)
Power Grid	-0.152	-0.135	-0.144	-0.146	-0.394	-0.133
	(0.159)	(0.155)	(0.158)	(0.160)	(0.329)	(0.180)
Internet	0.066	0.062	0.095	0.094	-0.087	0.181
	(0.148)	(0.148)	(0.150)	(0.151)	(0.233)	(0.165)
Public School	-0.457*	-0.451*	-0.449*	-0.449*	0.174	-0.956***
	(0.240)	(0.239)	(0.246)	(0.245)	(0.312)	(0.272)
County FE	No	No	No	No	No	No
Wave FE	No	No	No	No	No	No
Control	Yes	Yes	Yes	Yes	Yes	Yes
Age	3+	3+	3+	3+	3-6	6+
N	6397	6397	6397	6397	1184	5213

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. Data from waves 4 and 5. Control variables: age, age squared, no. children (log), anxious due to outbreak, week count.

Table A7. Well-being (Fixed Effects): Subsample with Some Form of Access

	(1)	(2)	(3)
		Changes in Behavior	
In-person Education	-0.219**	-0.367***	-0.457***
	(0.089)	(0.077)	(0.097)
Remote Education	0.151	0.786***	-0.304**
	(0.190)	(0.185)	(0.147)
Engagement	0.140*	0.042	0.137*
	(0.076)	(0.125)	(0.083)
Discipline	0.235***	0.352***	0.247***
	(0.075)	(0.133)	(0.087)
Child FE	Yes	Yes	Yes
Age	3+	3-6	6+
R2	0.45	0.92	0.50
N	1752	225	1527

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. County and wave fixed effects. Data from waves 4 and 5. Control variables: received care, aggressive parenting, public, poor, child hunger, urban, power grid, no. children (log), anxious due to outbreak, internet. Sample only includes children who had at least some form of access to education.

Table A8. Well-being (First Differences, Probit)

	(1)	(2)	(3)	(4)
In-person Education FD	-0.138			-0.033
	(0.193)			(0.203)
Remote Education FD		1.112**		0.747
		(0.476)		(0.508)
Alternative Education FD			0.590**	0.544*
			(0.290)	(0.312)
Age	3+	3+	3+	3+
N	2103	2103	2103	2103

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. Data from waves 4 and 5. Control variables: public, poor, childhunger, urban, powergrid, internet, no. children (log), anxious due to outbreak. FD variables are specified as the first difference across waves.

Table A9. Well-being (Fixed Effects): Externalizing and Internalizing Behaviors

	(1)	(2)	(3)	(4)	(5)	(6)
		Externalizing			Internalizing	
In-person Education	-0.065**	-0.210	-0.056**	-0.041	0.004	-0.051
	(0.031)	(0.133)	(0.027)	(0.029)	(0.048)	(0.033)
Remote Education	0.334	0.693***	0.045	-0.144	-0.022	-0.053
	(0.217)	(0.204)	(0.185)	(0.195)	(0.171)	(0.188)
Alternative Education	0.036	-0.127	0.064	0.129	-0.322**	0.203**
	(0.089)	(0.213)	(0.098)	(0.100)	(0.164)	(0.101)
Engagement	-0.013	0.106	-0.007	-0.017	0.224**	-0.014
	(0.026)	(0.140)	(0.028)	(0.034)	(0.094)	(0.038)
Discipline	0.317***	0.520***	0.296***	0.330***	0.288***	0.338***
	(0.058)	(0.122)	(0.066)	(0.059)	(0.078)	(0.067)
Child FE	Yes	Yes	Yes	Yes	Yes	Yes
Age	3+	3-6	6+	3+	3-6	6+
R2	0.25	0.51	0.24	0.26	0.52	0.27
N	4715	857	3858	4715	857	3858

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Standard errors (svy) in parentheses. County and wave fixed effects. Data from waves 4 and 5. Control variables: received care, aggressive parenting, public, poor, child hunger, urban, power grid, no. children (log), anxious due to outbreak, internet.