Impact of COVID-19 Pandemic on School Attendance in Kenya

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Abstract

Shocks, whether idiosyncratic or covariate, have been common in many parts of the world and are a development challenge. Shocks ordinarily manifest themselves in many forms, and they affect households and sectors differently depending on the nature and the status in which a household finds itself in when it strikes. Theoretically, shocks of any nature adversely affect human capital development in a country. The COVID-19 pandemic was one of the most recent and severe shocks that brought the entire globe to a halt. This paper was designed to investigate how COVID-19 affected school attendance in Kenya as a form of human capital development. Kenya's gains in human capital development have been adversely affected by the COVID-19 pandemic, which hit the country in March 2020. Arguably, the COVID-19 pandemic worsened the education sector due to closure of schools for a period of at least seven months (March-October 2020). While some learners were able to transition to online studies, most students especially in public schools, stayed at home without any form of learning. The results show that presence of COVID-19 incidences reduced the probability of children attending school. Being a male child and child belonging to a single parent household head had a reduced probability of school attendance. Households with higher incomes had an increased probability of school attendance while controlling for COVID-19 incidences. Children from elderly household heads had a reduced probability of school attendance when controlling for COVID-19 incidences. In future, there is need to put measures that can support public primary schools to cope with such shocks, e.g. acquisition of ICT gadgets, subsidised data bundles and basic media equipment that facilitates remote learning.

Keywords: *Human Capital, COVID-19, Fixed effect, Random effect, Control function*

1. Introduction

Background

The role of human capital in economic growth cannot be over-emphasied. Literature argues that human capital, comprising of education, skills, and health of people, is one of the most important factors for economic development in any country (Angrist and Dercon, 2021). The development of human capital has been recognised by economists to be a key prerequisite for a country's socio-economic and political transformation. Among the generally agreed causal factors responsible for the impressive performance of the economies of most of the developed and the newly industrialising countries is an impressive commitment to human capital formation (Anywnu et al., 2015; Adedeji and Bamidele, 2003; World Bank, 1995). This has been largely achieved through increased knowledge, skills and capabilities acquiredby way of education and training. As such, human capital plays an important role in versions of both neoclassical and endogenous growth models (Mankiw, Romer and Weil, 1992; Sianesi and van Reenen, 2003).

It has been stressed that the differences in the level of socio-economic development across nations is attributed not so much to natural resources and endowments and the stock of physical capital, but to the quality and quantity of human resources (Anywnu et al., 2015; Angrist and Dercon, 2021). Human capital is a critical variable in the growth process and is worthy of development. It is not only a means, but more importantly, the ends that must be served to achieve economic progress. Human capital is the most valuable intangible asset that needs to be mobilised and harnessed (Awopegba, 2003). Capital accumulation and natural endowment constitute the static element of production, which remains largely unutilised without human intervention, while the human capacities represent the dynamic element of production. Admittedly, human capital represents the end and means of every developmental trajectory.

It is for this reason and the need to transform economies that governments all over the world invest in human capital. This has the potential to improve the social and economic outcomes in the future through education and training, learning and experience, or health interventions. Human capital development (HCD) is both multidimensional and dynamic. It can be augmented through investment, or reduced by economic shocks, depreciation, illness or job loss (Raga and Te Velde, 2021; Goldin and Katz, 2020). One of the much talked about shock is the COVID-19, which adversely affected most economies.

This paper evaluates the impact of COVID-19 on the education sector, specifically school attendance as a component of human capital development in Kenya.

In Kenya, despite relatively heavy investment in the education sector, the stock and quality of human capital has remained relatively low. The question of quantity vis-à-vis quality of human capital development is important in addressing the low levels of human capital development index in Kenya. The much-discussed argument is that policies have tended to focus more on quantity than quality, hence creating the learning gap. According to Angrist and Dercon (2021), most African countries have paid attention to schooling as opposed to learning. As a result, investments in the education sector fail to yield the desired human capital outcomes.

The emergence of the COVID-19 adversely affected human capital development in many countries, including Kenya. The pandemic created the most unprecedented economic crisis since the Great Depression of the 1930s, reversing developmental progress made by the African continent in the recent years (African Union, 2020). What started as a health crisis quickly precipitated into a big economic, social, and humanitarian crisis, disrupting millions of people's livelihoods, affecting poor households, and damaging formal and informal businesses and government revenue around the world. Although the number of infections on the continent was lower than in other regions of the world, Africa's exposure to international trade, migration, and global financial markets, and governments' containment and mitigation measures to limit the spread of the COVID-19, outbreak disrupted production systems, plummeted demand, led to capital flow reversals and decline in international trade. To respond to the COVID-19 pandemic, most African countries took decisive measures spanning containment and closure policies, and health system and economic policies to save lives and protect households, business, and national economies (African Union, 2020). These measures undoubtedly affected human capital development and gains that had been realised in the recent past.

For instance, access to education was negatively affected by closures, reduced enrolment and completion, high drop-out rates and deaths. In the health sector, disease surveillance, isolation and supportive care were difficult without external assistance due to weak African health systems, few health workers, inadequate equipment, testing kits, personal protective equipment (PPEs), and poor health facilities (WHO, 2021). Moreover, African countries already affected by HIV, tuberculosis and malaria could experience more deaths and upsurge in infections due to the pandemic. This study is therefore designed to assess how COVID-19 impacted on human capital development, focusing on Kenya.

Research problem

Developing human capital in Kenya requires a massive and coordinated effort to strengthen the quantity, efficiency, and impact of investment on people. This is important in promoting inclusive growth and shared prosperity in line with the Sustainable Development Goals (SDGs).

Kenya's gains in human capital development were adversely affected by the COVID-19 pandemic, which hit the country in March 2020. Arguably, the COVID-19 pandemic worsened the education sector, which is critical in human capital development. This prompted the closure of schools for a period of at least seven months (March-October 2020). While some learners were able to transition to online learning, most students, especially those in public schools, stayed at home without any form of learning. When schools re-opened in October 2020, learning was staggered, and class size reduced to conform to the COVID-19 protocols of social distancing. It is reported by the Ministry of Education that close to 200,000 students never reported back to school due to a variety of reasons related to staying at home during the initial closure owing to COVID-19.

According to UNICEF (2020), COVID-19 affected the way children around the world experience education and, for many, attending school has not even been an option. The longer children are out of school, the greater the risk that the poorest among them will never return. Miguel and Kremer (2024) found that test scores are heavily affected by attendance, in their nobel winning prize paper on impact of worms on education and health.

Although Kenya's schools finally reopened in October 2020 (first with national exam candidates and then in January 2021 for all), a large number of children in the country did not return. This was caused by socio-economic factors, such as a loss of household income, child pregnancy, or early marriage. In Kenya, out of the 15 million children who were expected to return to school, many of them failed to report back to school, with girls forming the larger part of these figures (Global Citizen 2021)).

In line with school attendance, differential status was reported according to school characteristics in terms of whether they were in candidate class or not, rural or urban, public or private schools introduced inequality in school attendance, which was largely not justifiable. The impact of COVID-19 on development is well documented, but there is comparatively less literature on how the pandemic has impacted on specific sectors such as education, which has great implication on human capital development. In addition, most of the studies have been descriptive, but systematic quantitative evidence on the impact of COVID-19 disease on school attendance in Kenya is lacking to the best of our knowledge. Furthermore, as is the case with most aggregated measures, the aggregate analyses conceal the heterogeneity of sub-national situations. Therefore, the need to assess how the pandemic has impacted on learning outcomes and by extension human capital development, cannot be over-emphasised. According to Angrist and Dercon (2021), the pandemic has adversely affected the quality of learning outcomes in Sub-Saharan Africa. This study adds to this literature by analysing the impact of the pandemic on Kenya to understand country-specific dynamics of this issue.

Research questions

The broad question that this study aims to answer is how COVID-19 has impacted on human capital development in Kenya, focusing on the education sector. Specifically, the study seeks answers to the followin questions:

(i) What is the impact of the COVID-19 pandemic on school attendance?

(ii) What is the magnitude of differentials in schooling attendance during COVID-19 in Kenya?

(iii) What are the policy options for Kenya in refurbishing human capital development in the short- and long-run?

Research objectives

The broad objective of this study is to assess the impact of COVID-19 on learning outcomes in Kenya. The specific objectives are:

(i) Analyse the impact of COVID-19 pandemic on school attendance in Kenya.

(ii) Examine the magnitude of differentials in schooling attendance during COVID-19 in Kenya.

(iii) Suggest policy options for Kenya in refurbishing human capital development in the short and long-run within the context of COVID-19 pandemic.

Justification of the study

Economic growth in any country is closely connected with new knowledge drive and quality of human resource. This is obvious from the fact that there have been tremendous achievements in education accompanied with major developments in technological knowledge in all countries that have achieved significant economic growth (Anywnu et al., 2015). The leading economic record for countries such as Japan, Taiwan, and a few more Asian nations, for example, show the importance of human capital development in leading economic growth. Literature suggests that education is one of the critical components closely related to human (resource) capital development. The aim of this study is to examine both the long-run and short-run impact of COVID-19 on human capital development in Kenya.

This study is therefore important for Kenya on account of three issues:

(i) Literature – We contribute to literature on human capital development and COVID-19, which is still scanty

(ii) Methodology – We apply econometric approach in analysing the impact of COVID-19 on education outcome in Kenya.

(iii) Policy – This study makes suggestions on policy interventions to promote human capital development in the context of COVID-19 pandemic.

Structure of the study

Following this introductory section, section two reviews the relevant literature with regard to human capital development and COVID-19. Section three presents the methodology that is used to examine the impact of COVID-19 on learning outcome. Section four analyses the data while section five concludes the study and makes policy recommendations.

2. Review of previous literature

The Impact of COVID-19 disease on education

The COVID-19 pandemic is first and foremost a health crisis that made countries to close schools, colleges, and universities as a measure of mitigating its transmission. Andreas Schleicher (2020) has expressed concern that the crisis has exposed the many inadequacies and inequities in the education system. To this extent, it has deepened inequities in human capital formation among populations, countries, and regions in the world (João Pedro Azevedo, 2021; Human Rights Watch, 2020). Studies have been done to assess the impact of COVID-19 in education (Burgess et al., 2020; Donnelly, 2021; Jelimo, 2021; Human Rights Watch, Azevedo, 2021; Schleicher, 2020, and Blavatnik, 2020, among others), with all supporting the hypothesis of a negative impact of the pandemic on human capital formation, with some linking skills drop to future decline in gross domestic products of many countries.

These studies have used a variety of methods to arrive at various conclusions, ranging from in-depth interviews to modelling. Human Rights Watch (2020) conducted 57 remote interviews between April and August 2020. The interviews were conducted among students, parents, teachers, and education officials across nine African countries to learn about the effects of the pandemic on children's education. Among the key findings were that: the pandemic exacerbated previously existing inequalities; students expressed stress, anxiety, isolation, and depression; parents were burdened by costs associated with new mode of delivery; there were increased risks of child marriage; and students unable to engage in remote learning due to lack of access to necessarygadgets.

Azevedo et al. (2020) used simulation techniques on global data to assess the potential impacts of COVID-19 school closures on schooling and learning outcomes. Their key findings were that the pandemic could result in a loss of between 0.3 and 0.9 years of schooling, culminating in effective years of basic schooling that students achieve during their lifetime from 7.9 years to between 7.0 and 7.6 years. They estimated that close to 7 million students from primary up to secondary education could drop out due to the income shock of the pandemic alone.

Hanushek and Woessman (2020) in Schleicher (2020) used historical growth regressions to estimate the long-run economic impact of the pandemic. Learning loss will lead to skills loss, and the skills people have related to their productivity. Gross domestic product (GDP) could be 1.5% lower on average for the remainder of the century. This implies that countries would continue to face reduced economic well-being, even if their schools immediately return to pre-pandemic levels of performance. Schleicher (2020) alluded that spending on education may be compromised in the coming years because public funds are directed to health and social welfare, implying long-term public spending on education is at risk despite short-term stimulus packages in some countries.

Blavatnik (2020), in estimating the potential long-term losses to children's learning from the temporary shock of school closures, used a calibrated model with "pedagogical production function". She found the following: without mitigation, children could lose more than a full year's worth of learning from a three-month school closure; single mitigation (remedial learning) when children return to school reduces the long-term learning loss by half, but still leaves children more than half a year behind where they would have been with no shock; combined mitigation (remedial learning and re-orientation of instruction alignment) will fully mitigate the long-term learning loss due to the shock and surpass the learning in the counterfactual of no shock by more than a full year's worth of learning.

The learning losses hypothesis was also supported by Eric et al. (2020). They found that a typical current student might expect something on the order of 3% lower career earnings if schools immediately returned to 2019 performance levels. They note that losses will follow students into the labour market, and both students and their nations are likely to feel the adverse economic outcomes. Eric et al. (2020) were quick to mention that nobody can predict perfectly how school closures will affect the future development of the affected children, but past research has investigated how school attendance and learning outcomes affect labour market chances and economic development, and therefore prediction can be made out of this.

Pokhrel and Chhetri (2020) found some literature supporting the possibility of some students' careers benefitting from school interruptions. They gave an example of Norway where it has been decided that all 10th grade students will be awarded a high school degree. They also used a study by Maurin and McNally (2008) who found that abandoning of the normal examination procedures in France in 1968 following the student riots led to positive long-term labour market consequences for the affected cohort.

ACAPS (2020), reviewing secondary academic and grey literature to assesses the impacts of the COVID-19 pandemic, came out with the following findings: school closures could result in up to 24 million dropouts and US$ 10 trillion in lost future earnings for the current cohort of learners (World Bank, 2020). Economic shocks driven by the global pandemic, including reduced funding from governments and donors, may further restrict children's future capacity to attend school and learn.

3. Methodology and data

Theoretical framework

Education is viewed as an investment in human capital, implying a trade-off between enhanced future earnings and foregone earnings during enrolment in the educational system (Nielsen, 2001). It could also be seen as both a consumption and an investment good in that it is valued for its own sake and because it provides future financial returns (Gentler and Glower, 1990). Parents consider whether the utility of taking a child to school exceeds the utility of keeping the child at home. If the expected utility from taking the child to school exceeds the utility of keeping the child at home, then parents enroll their child in school and vice versa. If the supply of schooling is unconstrained (it was constrained by school closures during COVID-19 pandemic), the decision to take a child to school is taken by the household alone and depends on all factors affecting the utility of sending the child to school.

The decision to send a child to school can be modelled using economic models of household behaviour (Strauss and Thomas, 1995). First, we assume that every household has a utility function, which depends on the human capital of its children and the consumption of all other goods and services. An investment in another year of schooling raises a child's human capital at the cost of reduced consumption of other goods and services. This is because the price of sending children to school involves both direct monetary costs and indirect costs of children's time in terms of reduced work (Gertler and Glewwe, 1990).

Following Gulzar and Sara (2016), conditional on deciding to take a child to school, the expected household utility is an indirect utility function, which can be denoted as:

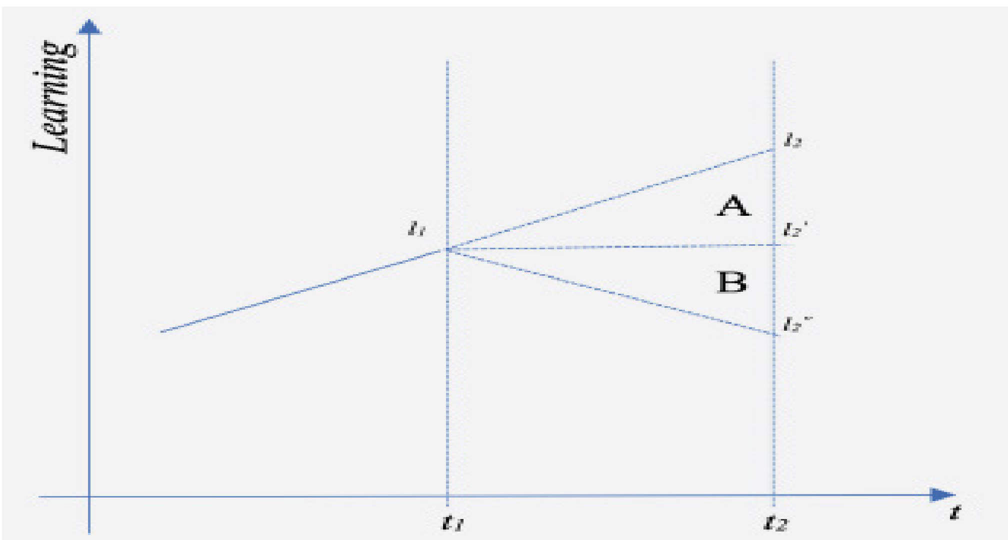
$$U = v(S_1, C(P_i, U_1) + \varepsilon_i \quad (1)$$

Where S_i is the increment to a child's human capital from another year of education from school, C_i is the consumption possible after incurring both the direct and indirect costs/expenditure of sending a child to school *i*. This consumption is dependent on the cost of taking the child to school *P*, and the utility derived from taking the child to school, *U*. ε_i is a random taste shifter.

However, the maximisation of the utility function in (1) was affected by the constrained supply of schooling in the form of school closures to reduce the spread of the virus. Azevedo et al. (2020) conceptualises the learning loss from the COVID-19 pandemic in two ways: (a) as learning that will not take place while schools closed, which is directly linked to schooling adjusted for quality; (b) as the already acquired learning that will be lost or forgotten when students lose their engagement with the educational system. In addition, the framework also captures the impact of school dropouts through the income shock channel.1

The authors conceptualise the current cohort of learners as a panel of students[2] observed just before the crisis, and whom can be observed again the moment after the schools reopened. Figure 1 shows the learning path of the current cohort of students. The framework assumes that for a given level of quality of education, learning (l), for this cohort of students, is a linear function of the amount of time t spent at school. The length of school closures (s), assuming no mitigation, reduces the amount of time students are exposed to learning opportunities from the educational system. Thus, if schools close between t_1 and t_2, and assuming no mitigation, we no longer expect any new learning to take place,[3] and at t_2, the student will in principle at l_2. However, this is not the whole effect. We expect that as students disengage from the educational system, part of the student's stock of learning (l_1) will be forgotten and hence the loss of human capital. This loss will bring students from l_2' to l_2''. Therefore, in Figure 1, the area of the triangle A (bounded by l_1, l_2, and l_2') corresponds to the learning that will not take place while schools are closed s (or $t_2 - t_1$), while triangle B (bounded by l_1, l_2' and l_2'') corresponds to the learning that will be lost due to school disengagement and dropouts.[4] The learning loss due to each one of these mechanisms will be a function of how effective mitigation strategies might be. The total effect is the loss of the human capital.

Figure 1: Analytical framework for an individual student



Source: Azevedo et al. (2020)

The variables

The decision to send or not to send a child to school is influenced by a few factors that affect the expected utility of the decision choice. The four groups of factors are widely debated in the literature (Azevedo et al., 2020; Nielsen, 2001; Gertler and Glewwe, 1990; Bedi et al., 2004 Strauss and Thomas, 1995; Glewwe and Jacoby, 1994). These factors are COVID-19 disease-related ( ); individual child characteristics (I); household (H); community characteristics (C); and education differential factors (D).

Among the individual child characteristics, gender, and whether the child belongs to the household head are important. Age reflects the absolute opportunity cost of education (Nielsen, 2001; Ray, 2000). Gender of the child is potentially important given the possibility of parental preferences for boys over girl's education, which arises from expected lower returns for girls owing to labour market discrimination, lower female participation and lower remittances from daughters than sons. The opportunity cost of sending the girl child to school is also expected to be higher than for the boy child due to expected loss of income and housework from the girl child, though loss of income could be higher for boys schooling.

Important household characteristics include household income, parents' education, parents' age, gender of the household head and household composition. Incomes and assets are important because a poor household may not afford to send a child to school unless there was access to credit. Parental education is expected to have a positive impact on enrolment (Ray, 2000; Gertler and Glewwe, 1990) and is important because it reflects the income potential of the household and probably also the attitude towards education. Educated parents are more able to assist children in learning, as they are likely to recognise the values of their children's education and resist the temptation of pulling them out of school even when they have low income (Ray; 2000; Handa, 1996).

Community characteristics, such as provision of school meals, that reflect the future return to education, are also potentially important. The perceived benefits of attending school also influence enrolment because cognitive skills as measured by performance in school are highly rewarded in the labour market (Gertler and Glewwe, 1990).

Education differential factors represent those attributes that affected the class attendance during the COVID-19 pandemic. The education differentials that impacted school attendance are classified into type of schools (private or public), level of education (no schooling, primary, secondary, etc), whether in examination or non-examination class and the location of the public school (Cameron, 2021; Tomaszewski et al., 2022). Table 1 indicates the variables considered in this paper.

Table 1: Description of variables used in the study

Variable	Description
Dependent	
School attendance	The decision to send or not to send a child to school to learn (1= children between 5-17 years engaged in any education or learning activities and 0=otherwise)
COVID-19 disease explanatory variable	
COVID-19 disease incidences	1=presence of any COVID-19 symptoms such as persistent cough; fever; difficulty breathing (nasal congestion); loss of sense of smell / not being able to taste food; pneumonia; and chronic fatigue; headache 0=Any other symptoms
Individual child characteristics explanatory variables	
Sex of child	1=male child 0=female child
Child of household head	1= The child belongs to the household head 0=otherwise
Household characteristics explanatory variables	
Age of household head	The age of the household head in years
Log of age of household head	The log of the age of the household head in years
Father is employed	1=father of the child employed; 0=otherwise
Mother is employed	1=mother of the child employed; 0=otherwise
Household income	Total earnings from agriculture and pastoralism, family business and wage employment in Kenya shillings
Log of household Income	The log of total earnings from agriculture and pastoralism, family business and wage employment in Kenya shillings
Community characteristics	
School meals	1= presence of school meals sponsored by the government; 0=otherwise
Instrumental Variables	
Public transport	1= any household member using public transport; 0=otherwise
County level COVID-19 incidence	A continuous variable representing the average county COVID-19 incidence is the average of total COVID-19 incidence excluding own county COVID-19 incidence divided by 46 counties. For instance, the average for Nairobi excludes Nairobi County incidence
Education differential factors	
No education	A dummy variable taking the value 1 if the child is not attending any school; 0 otherwise
Preprimary level	A dummy variable taking the value 1 if the child is attending a preprimary school; 0 otherwise
Primary level	A dummy variable taking the value 1 if the child is attending a primary school; 0 otherwise
Secondary level	A dummy variable taking the value 1 if the child is attending a secondary school; 0 otherwise
Type of school	1=Child attending a public school; and 0=child attending a private school
Examination class	1=Child in examination class; and 0=child in non-examination class
Location of public school	1= school located in urban area; and 0=school located in rural area

The model

Let the school attendance be *Ed*, which is a function of an endogenous COVID-19 disease proxied by the presence of symptoms leading to COVID-19 or COVID-19 incidence as used in Upshaw et al. (2021), a vector of exogenous covariates composed of individual child (*I*), household (*H*) and community characteristics (*C*); *and* the unobservable attributes of individuals. In this arrangement, COVID-19 disease is an endogenous determinant of the choice of education variable captured by the education generating function taking the following treatment equation form (Heckman, 2007). A logit model specified in (9) was therefore estimated.

$$Ed_{it}^{*} = \alpha + \lambda C19_{it} + \beta Z_{it} + u_{it} \quad (9)$$

$$Ed_{it} = 1\left[Ed_{it}^{*} \geq 0 \right], i = 1,2,3....N(individuals); t = 1,2,3....,T(years) \quad (10)$$

Where:

Ed_{it}^{*} = The decision to send or not to send a child to school to learn (= children between 5-17 years been engaged in any education or learning activities and =otherwise)

$C19_{it}$ = is an endogenous[5] COVID-19 disease/presence of symptoms leading to COVID-19

Z_{1it} is an $1 \times \left[K - 1 \right]$ vector of exogenous covariates (*I ; H ; C ;* and *D*). The exogenous covariates are: individual (*I*), household (*H*), community characteristics (*C*) and education differential factors (*D*).

u_{it} = the idiosyncratic shocks captures both random terms and unobservable variables that are typically correlated with the endogenous regressors and are are serially uncorrelated error such that $Var\left[u_{it} \right] = 1$

$1\left[Ed_{it}^{*} \geq 0 \right]$ = is an indicator function.

The estimation of the of the parameter, *λ*, indicates the impact of COVID-19 disease on the school attendance and requires robust estimation procedures to obtain. In the estimation of (9), the Ed_{it}^{*} and $C19_{it}$ are likely to be jointly determined by the innate *ability, skills, or intellectual capacity* attributes in the error term (u_{it}), which is likely to correlate with $C19_{it}$, which also influences Ed_{it}^{*} causing endogeneity as a potential problem that should be examined and addressed if present. An appropriate strategy to use in a panel data analysis is the instrumental variables (IV) method. Therefore, a reduced-form of the COVID-19-generating function takes the form of:

$$C19^{*}_{it} = \mu + \beta Z_{it} + \sigma IV_{it} + \varepsilon_{it} \quad (11)$$

Where:

$C19^{*}_{it}$ = Latent COVID-19 disease or presence of symptoms leading to COVID-19 (1=presence of any covid-19 symptom; 0 otherwise)

Z_{it} = vector of exogenous covariates; W_i =Variables that do not change over time (sex/gender); IV_i = a vector of instruments that affect COVID-19 diseases ($C19_{it}$) but have no direct effect on school attendance (Ed^{*}_{it}). The instruments considered in this paper include county-level COVID-19 disease incidences and the use of public transport.

$\varepsilon_{it} = r_i + u_{it}$ = a new composite error term, where *r* is fixed and *u* is an idiosyncratic term.

In addition, unobserved heterogeneity emanating from the inherited traits of responses due to non-linear interaction of COVID-19 disease with unobservable variables could bias the estimated education-generating function. This could affect COVID-19 disease, whose effect on education is captured by the interaction of the COVID-19 disease variable with their respective residuals derived from the reduced form estimates in equation 12. When panel data models contain unobserved heterogeneity and endogeneity (omitted time-varying variables), the control function method (equation 6) is applied to address the two potential issues (Heckman, 1976; Wooldridge, 2002; 2015).

Thus, to purge potential endogeneities and unobserved heterogeneity biases from the estimated parameters, equation (9) can be augmented by including reduced form residuals (both linear and non-linear) and interaction of the linear reduced form residuals with their corresponding endogenous counterparts and expressed as equation 12.

$$Ed^{*}_{it} = \alpha + \lambda C19_{it} + \beta Z_{it} + \gamma C19resid_{it} + \pi(C19resid * C19)_{it} + \varepsilon_{it} \quad 12$$

The residual ($C19resid$) serves as a control function variable that renders C19 exogenous (Wooldridge, 2015). The interaction term $(C19resid * C19)$ addresses the unobserved heterogeneity of the coefficient on C19, keeping it constant across units of analysis; ε_{it} is a composite error term comprising the random and the non-random, fixed part of the of the error term; and $\alpha, \lambda, \beta, \gamma$, and π are vectors of parameters to be estimated. Under weak assumptions, equation 12 yields parameter estimates that are unbiased and consistent (Wooldridge, 2015).

Equation (12) is also useful in choosing between the FE and RE specifications in panel data analysis. It also allows use Durbin–Wu–Hausman (DWH) test to determine whether C19 is endogenous. *C19* is endogenous if the null hypothesis that $\gamma = 0$ cannot be rejected (Wooldridge, 2015). Moreover, the augmented regression test helps distinguish between RE and FE specifications in the actual data by setting $\gamma = 0$ when estimating the RE model; i.e., by assuming that *C19* is uncorrelated with the error term, while FE estimates γ in (12).

The Hausman test, in the choice between RE and FE, is made robust to heteroskedasticity and serial correlation. Intuitively, the Hausman statistic tests whether the difference between FE and RE estimates is equal to zero. If the p-value is large (greater than 0.05), the equality assumption cannot be rejected and the RE estimates (obtained via GLS) are preferred because they have smaller standard errors. However, if the null hypothesis is rejected, the FE estimates (obtained via the panel data procedures) are preferred, because their calculation considers the endogeneity of C19 (the correlation of C19 with the disturbance term).

Data sources

The paper uses the high-frequency phone survey data on the socio-economic impacts of COVID-19 in Kenya, which is implemented by the World Bank, in collaboration with the Kenyan National Bureau of Statistics (KNBS) and the United Nations High Commissioner for Refugees (UNHCR), and the University of California, Berkeley. The sample is composed of three different groups of households. The first group is a randomly drawn subset of the 2015/16 Kenya Integrated Household Budget Survey (KIHBS). This sample covers urban and rural areas and is designed to be representative of the population of Kenya using cell phones. The second sample comprises households selected using the Random Digit Dialing method. A list of random mobile phone numbers was created using a random number generator from the 2020 Numbering Frame produced by the Kenya Communications Authority. The third group consists of camp and non-camp refugees (in urban areas), and stateless people registered by the UNHCR (proGres). As phone surveys can only reach respondents who use a phone with an active subscription in an area with network coverage, statistics are only representative for this part of the population, potentially excluding, to some extent, the poorest households who do not own phones or live in areas with no network coverage. The Kenya COVID-19 Rapid Response Phone Survey uses re-weighting techniques to ensure that statistics are as representative as possible of the entire population of Kenya.

4. Results

This paper analyses the impact of COVID-19 incidences on school attendance in Kenya. School attendance was regressed on COVID-19 incidence and other control variables using Logit estimation technique. To purge the problem of endogeneity and unobserved heterogeneity, a control function is estimated.

Descriptive statistics

Table 2 indicates the descriptive statistics of the variables used to assess the impact of COVID-19 on school attendance in Kenya. It is shown that about 12% of children used different modes of learning during the COVID-19 pandemic. Those in the sample that reported symptoms associated with COVID-19 incidence at the county level were about 7%. Approximately 6% of the sample were males, while 24% of children in the sample belonged to the household head. The average age of the household head in the sample was 37 years. The percentage of fathers employed were 41%, while 30% were employed mothers. The average monthly income of those sampled was about Ksh 1,100. About 16% of children in the sample had meals in school. Those in the sample that had no education were about 0.3% compared with those with different levels of education. The sample percentage of children attending pre-primary education was 5%, primary level 30% and secondary level 40%. About 84% of schools in the entire sample were public, while 16% were private. Of the entire sample, 0.4% was an examination class. In the sample, the percentage of public schools in urban areas was 52% while those in rural areas was 48%.

Table 2: Descriptive statistics of variables used in school attendance generating function

Variable	Mean	Std. Dev.	Min	Max
School attendance	0.1214947	0.326704	0	1
Covid-19 disease incidences	0.0742338	0.2621531	0	1
Gender of child	0.0605969	0.2385915	0	1
Child of household head	0.2410843	0.4277449	0	1
Age of household head	36.6781	15.24078	18	110
Log of age of household head	3.52174	0.3974608	2.890372	4.70048

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Table 2 Continued

Variable	Mean	Std. Dev.	Min	Max
Father is employed	0.4100237	0.4918418	0	1
Mother is employed	0.3016812	0.5416005	0	2
Household income	1100.755	4137.82	0	100000
Log of household income	8.903238	0.9762244	0	11.51293
School meals	0.1615863	0.3680739	0	1
Public transport	0.3408369	0.4739946	0	1
Average temperature for the 47 counties	21.62182	3.343888	15.90389	29.53153
No education level	0.0286273	0.166758	0	1
Pre-primary level	0.046158	0.2098288	0	1
Primary level	0.3008456	0.4586295	0	1
Secondary level	0.4357432	0.495858	0	1
Type of school	0.8376617	0.368764	0	1
Examination class	0.0353621	0.184695	0	1
Location of public school	0.5218423	0.4995269	0	1
Number of observations	59,838			

Source: World Bank dataset

Reduced form: Determinants of COVID-19 incidence

The reduced form first stage regression was done to generate the determinants of COVID-19 incidence and to test the validity of the instruments used in the study (see panel 1 of Table 2). The first stage of regression involves regressing the COVID-19 incidence on instrumental variables and other exogenous variables as shown in Table 3. The predicted residuals of COVID-19 disease incidences, and the interaction of the predicted residual of COVID-19 disease incidences was then obtained from the first stage regressions.

According to Mwabu (2009), a valid instrument must be relevant, strong, and exogenous. The instrumental variables, which include use of public transport, and the county level COVID-19 disease incidence, are both statistically significant (see Table 3, panel 1), indicating that they are relevant and hence valid. Furthermore, the results show that the use of public transport significantly increases the probability of COVID-19 disease incidences by 21%. In addition, an increase in the county level COVID-19 disease incidences increases the national COVID-19 disease incidences 50-fold.

The results also indicates that being a male child significantly reduces the probability of COVID-19 incidences by 5% compared to being a female child. Being a child of the household head significantly increased the probability of COVID-19 incidences by 3.6%. A one-year increase in the age of the household head significantly increased the probability of COVID-19 incidences by 20%. There was a significantly higher increase in the probability of COVID-19 incidences where the father was employed, at 2.3%. Where the mother was employed, there was a 0.2% increase in the probability of COVID-19 incidences. Having meals in school increased the probability of COVID-19 incidences by 0.3%. The children attending the primary school level education significantly increased the probability of COVID-19 incidences by 9.4%. In contrast, children attending secondary school level had a significantly reduced probability of COVID-19 incidences by 3.90%. Children in an examination class significantly reduced their probability of COVID-19 incidences by 7.2%, while those in schools located in urban areas reduced the probability of COVID-19 incidences by 0.5%.

The effect of COVID-19 incidences on school attendance estimates

The Durbin-Wu-Hausman (DWH) Test was used to test for endogeneity of COVID-19 incidences. With the coefficients of COVID-19 incidence residuals (including the squared one) being significant, we conclude that endogeneity is indeed a serious problem, and the estimation of a control function is in order (Table 3). The interaction of COVID-19 incidence and its residual is also significant, which indicates that unobserved heterogeneity is indeed present, justifying the use of the Control Function Approach to control for it. The estimation of the random effects Logit control function accounts for both endogeneity and heterogeneity. The Hausman test specification preferred a Random Effects (RE) model. Table 3, panel 2 presents the estimated results.

Table 3 panel 2 shows that a one-percent increase in the proportion of children with COVID-19 incidences reduces the probability of school attendance by 2.3% assuming other factors constant. COVID-19 caused unprecedented disruption to schooling worldwide. In Kenya, all schools were closed due to COVID-19. Even after opening of the schools, some parents feared taking their children back to school to avoid COVID-19 infections, mainly due to self/family isolation and the effects of COVID-19. This finding is consistent with Children's Commissioner (2022); Department of Education (2021; 2022) and Brontë et al. (2023). Furthermore, the findings are in line with Nathwani et al. (2021), where COVID-19 incidences made children miss out on a substantial amount of schooling. This could be due to the illness itself and self-isolation.

Being a male child reduces the probability of school attendance by 3.5%. These results are in line with Crawfurd et al. (2021) that showed the school participation of boys reduced than those of girls due to COVID-19 pandemic. Other studies suggested that there were no gender disparities in school attendance due to the pandemic (Engzell et al., 2021; Wolf et al., 2021; Sandefur, 2022). Being a child belonging to a household head reduced the probability of school attendance by 0.2%.

Table 3: COVID-19 disease incidence -generating functions

Variables	Estimated model results	
	LPM (Reduced form/ first stage model): Dependent Variable is COVID-19 Disease Incidence (1)	Random-Effects (RE) Logistic Regression (margins)/2SLS/2SRI: Dependent Variable is School Attendance (2)
County level COVID-19 disease incidence (IV)	-0.4062063***	
	(0.0137049)	………
Public transport (IV)	0.2070231***	
	(0.0105549)	……….
COVID-19 disease incidences	……….	-0.0232033***
		(0.0465142)
Gender of child	-0.0500269***	-0.0354179
	(0.0127049)	(0.0644641)
Child of household head	0.0358861***	-0.0024262
	(0.0134877)	(0.0018194)
Log of household income	0.0005456	0.0002856
	(0.0062759)	(0.0006445)
Log of age of household head	0.2046399***	-0.0445963***
	(0.0752888)	(0.0268016)
Mother is employed	0.0017192	0.0027534
	(0.0075617)	(0.0022107)
Father is employed	0.023067**	0.0005304
	(0.0105493)	(0.0014163)
School meals	0.0025506	-0.0417329
	(0.0493515)	(0.0641733)
Pre-primary education level	-0.034985	-0.0354844
	(0.0181879)	(0.0645166)
Primary education level	0.0938358 ***	-0.0408543***
	(0.0319052)	(0.0643322)
Secondary education level	-0.0389194 ***	-0.0366162***
	(0.0106428)	(0.064427)
Type of school public vs private	-0.0170931	-0.0027212***
	(0.0363281)	(0.0024921)
Examination class	-0.0722405 ***	0.0021196 ***
	(0.0104459)	(0.0015821)
Location of public school	-0.0054127	0.0008205***
	(0.0080552)	(0.0011652)

continued next page

Table 3 Continued

Variables	Estimated model results	
	LPM (Reduced form/ first stage model): Dependent Variable is COVID-19 Disease Incidence (1)	**Random-Effects (RE) Logistic Regression (margins)/2SLS/2SRI: Dependent Variable is School Attendance (2)**
Predicted residual of COVID-19 incidences	….	-0.0256769 ***
		(0.0175034)
Predicted residual of COVID-19 incidences squared	…..	-0.0490478***
		(0.0635081)
Interaction of Covid-19 incidences and predicted residual of Covid-19 incidences	….	0.0982348***
		(0.1235648)
Constant	3.271261***	……
	(1.103123)	
F(16,6393)	31.46	…..
Prob > F	0.0000	…...
R-squared	0.0814	……
Adjusted R-squared	0.0788	…….
Root MSE	0.3103	……
Number of observations	55,621	55,621

*** Significant at the 1% level; ** significant at the 5 % level, * significant at the 10% level. Standard errors are in the parenthesis

A one percent increase in the log of the household income increases the probability of school attendance by 0.03% when controlling for COVID-19 incidences. These results are consistent with the studies indicating that children from lower socio-economic status were not likely to be sent to school (Amin et al., 2021; Hevia et al., 2022).

A one-percent increase in the proportion of households' head age reduced the probability of school attendance by 4.5% when controlling for COVID-19 incidences. The employment of mothers in a household increased the probability of school attendance by 0.27% when controlling for COVID-19 incidences. The employment of fathers in a household increased the probability of school attendance by 0.05% when controlling for COVID-19 incidences. Like Jain et al. (2020) and Saenz and Sparks (2020), we found a lower likelihood of sending children to school due to lack of employment of the parents.

Having school meals reduced the probability of school attendance by 4.2% when controlling for COVID-19 incidences. The results are in contrast with Parnham et al., (2020) that found that those attending school were more likely to receive school meals.

The children in the primary level of education had reduced probability of school attendance by 4.1% when controlling for COVID-19 incidences. This is in line with Tuchman and Heyward (2021), where there was lower school attendance as parents opted for home and virtual learning instead.

A one percent increase in the proportion of children in secondary level of education had a reduced probability of school attendance by 3.7% when controlling for COVID-19 incidences. The results echo similar findings that more secondary school-going children did not attend school and especially girls due to the risk of pregnancy (Dessy et al., 2021; Zulaika et al., 2022).

A one percent increase in the proportion of children in pre-primary level of education had a reduced probability of school attendance by 3.6% when controlling for COVID-19 incidences. The children in public schools had a reduced probability of school attendance by 0.27% when controlling for COVID-19 incidences. These results are contrary to Obiakor and Adeniran (2020), where more children were sent to public schools due to financial constraints of their parents as opposed to private schools.

Children in examination classes increased the probability of school attendance by 0.21% when controlling for COVID-19 incidences. The children studying in schools located in urban areas had an increase probability of school attendance by 0.08% when controlling for COVID-19 incidences. These results are in line with UNICEF (2020), where learning continued in the face of college and university closure through distance learning strategies.

5. Summary, conclusions and policy implications

Summary and conclusions

The presence of COVID-19 incidences was found to have significantly reduced the probability of children attending schools. Male children had a reduced probability of school attendance while households with higher incomes had an increased probability of school attendance when controlling for COVID-19 incidences. Children from elderly household heads had a reduced probability of school attendance when controlling for COVID-19 incidences. Children belonging to employed mothers had an increased probability of school attendance compared to the ones belonging to the employed fathers when controlling for COVID-19 incidences. Regarding school differentials, children in secondary schools and those in public schools had a reduced probability of school attendance, while children in public schools had a reduced probability of school attendance when controlling for COVID-19 incidences. Children in examination classes had an increased probability of school attendance. Finally, children studying in schools located in urban areas had an increased probability of school attendance when controlling for COVID-19 incidences.

Policy implications

While school closure was an immediate reaction to the Covid-19 pandemic shock, it failed to address needs of children in different school set-ups. In future, there is need to put measures that can support public primary schools to cope with such shocks. This may include acquisition of ICT gadgets, subsidised data bundles, and basic media equipment that facilitates remote learning. Households in remote rural areas need targeted cash transfers, particularly, those whose household heads are aged. In addition to this, there might be need to educate or create awareness among old people on the need for vaccination to boost immunity.

Notes

1. This second point is in line with the literature on summer 'learning loss' cited above, and the Forgetting Curve, which suggests much of what is taught during the school year can be forgotten, unless reinforced during the summer. The Forgetting Curve pioneered by psychologist Ebbinghaus in the 1880s measures how much we forget over time, and shows that without reinforcement, information can be quickly forgotten. Ebbinghaus experiments have recently been replicated successfully by Murre and Dros (2015), suggesting that his insights hold true today. Extrapolating from his findings to summer learning, we would expect students to forget a large part of what they have learned during the summer, unless that knowledge is used and reinforced during the summer break.

2. This cohort can be students at any grade level, given that schools have been typically closed across all grade levels.

3. Or at the very least, not at the same rate as when schools remained open, in which case the line may also slope slightly upwards.

4. For the purposes here, we do not discuss the long-term effects of these dropouts on learning, which may very well be more dramatic.

5. Generally, model (1) can contain a random vector of endogenous covariate . Modification of our approach discussed in this section to accommodate a random vector of endogenous regressors is straightforward, assuming we have enough instrumental variables.

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