# Nutrition matters: Numeracy, Child Nutrition and Schooling Efficiency in Sub-Saharan Africa in long-term perspective

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**Abstract:** School enrolment has increased at an unprecedented scale in Sub-Saharan Africa, but test scores from international comparable tests draw a rather pessimistic picture. Therefore, focusing on mathematical skills, we provide estimates for basic numerical abilities of the general population born between 1950 and 2000, and assess the efficiency of the educational system at the regional level. We focus our analysis on children's nutrition, because low-quality diet and insufficient protein in particular might explain the puzzle of increasing schooling inputs resulting in stagnating numeracy skill outputs. Paxson and Schady (2007) and Currie and Vogl (2013) found that low-quality early child nutrition implies a lower efficiency later in life. We confirm this view by using a comprehensive new database of numerical skills in Africa, and by applying an instrumental variable approach. Only if the quality of nutrition of specific groups and regions identified in this study can be improved, self-sustaining long-term growth based on human capital can be achieved in SSA.

**Keywords: numeracy, school efficiency, height, Africa**

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## 1. Introduction

For several decades governments and large development organisations such as the United Nations aimed at providing children access to schools by increasing the availability of schooling and limiting entry barriers such as high school fees. However, while primary school enrolment increased at unprecedented levels in Sub-Saharan Africa, the expected returns to growth at the individual and country-level failed to show. According to Pritchett (2013) and Angrist et al. (2021) this is because schooling does not necessarily translate into learning and the World Bank argued that Africa is facing a severe 'schooling crisis' (Bashir et al., 2018). Many children in developing countries can officially visit a school for several years; yet are then not able to read a simple sentence or solve a basic arithmetic problem (Angrist et al., 2019). Similarly, Hanushek and Woessmann (2008) estimated that once learning outcomes are included into growth regressions alongside years of schooling, an educational input, the explanatory power of the model triples and the size of the coefficient of years of schooling decreases substantially.

Therefore, over the past two decades there has been an increased focus on the quality of schooling instead of its quantity in the field of development both for practitioners as well as in academia. Data from international comparable tests have become an integral part of evaluating the quality of schooling. For Sub-Saharan Africa the *Southern and Eastern Africa Consortium for Monitoring Educational Quality* (SACMEQ) and the *Programme d'Analyse des Systèmes Educatifs de la Confemen* (PASEC) have started to provide test scores for many countries. However, data from these international comparable tests have two important drawbacks. First, they cover only the in-school population and given that many children in Sub-Saharan Africa do not attend school at all or on a regular basis, the test scores will overestimate the overall skills of a given population (Lilenstein, 2020). Second, since both organisations only started operation in the late 1990s it is not possible to assess the long-run development of schooling outcomes.

While measures of literacy are quite frequently available in survey data, numeracy is usually not considered at all. However, Hanushek and Woessmann (2012) showed that math skills are even more important for growth than literacy.[1] Thus, there is still a large gap in the literature measuring mathematical skills. A method to consistently measure numeracy over long periods of time and vast geographic areas is age heaping (A'Hearn et al., 2009). Originally developed in the demography literature to assess the quality of survey data (Bachi, 1951; Myers,

[1] Moreover, indirect effects via violence matter: Gleditsch et al. (2022)

1954), Mokyr (1983) adopted this method in the economic history literature and it is now commonly used to estimate basic numerical abilities (Crayen and Baten, 2010; Manzel et al; 2012; Hippe and Baten, 2012; Stolz et al., 2013). Essentially, the method allows to estimate the share of individuals that report a rounded age with the terminal digit zero or five instead of the exact age which is a strong indicator for a lack of basic numerical skills. The key advantages of this method are first, that the data requirements are comparably low as only the respondent's reported age is necessary and second, this allows to estimate numerical abilities over long time horizons and different geographical areas while remaining comparable.

However, only very few studies that estimate numerical abilities in Sub-Saharan Africa are available. The demography literature provides a few contributions using the age-heaping approach to evaluate the quality of survey data (Bwalya et al., 2015; Lyons-Amos and Stones, 2017; Fayehun et al., 2020). Yet, while these studies employ the age-heaping method, their methodology is not completely comparable, and they do not link their estimates to the numerical abilities of respondents. Hence, the most closely related study is by Cappelli and Baten (2021) who estimate numerical abilities with the age-heaping method for 43 Sub-Saharan African countries between 1730 and 1970 using a panel data model. They find that the type of colonial administration and their respective approach to education had a strong influence on numeracy. Yet their study can only provide insights at the country level and misses most of the post-colonial period. Therefore, this study seeks to fill the gap by providing the first comprehensive overview of basic numerical abilities at the subnational level for the birth cohorts between 1950 and 2000 in Sub-Saharan Africa.

In a second step we investigate the efficiency of schooling for these birth cohorts, because finding methods to improve schooling efficiency are a key policy concern. We argue that nutrition of school children is a decisive factor to improve the effectiveness of schooling, especially for the growth-related numerical abilities. Therefore, we employ our measure for basic numeracy to evaluate the efficiency of the education system. Following the methodology of the human development index, we estimate an indicator to measure the efficiency of time spent in school.

Bryan et al. (2004) finds that without adequate nutrition children lack the necessary concentration to follow classes and store whatever they have learned (on health: Fielding and Torres 2009). However, for a long run analysis there is very limited direct data available on nutrition during the first years of an individual's life. An important indicator to evaluate the quality of nutrition during childhood is adult height (Steckel et al., 2019; Komlos and Baten 2014). While height is highly dependent on genetic factors at the individual level, averaging across individuals within a given group can indicate whether they suffered from malnutrition during childhood. Thus, we can use this to estimate the effect of childhood nutrition on schooling efficiency to contribute long-term evidence to the discussion about the effect of nutrition on educational attainment.

As a preview to our findings, numeracy has in fact changed little during the period of observation. We observe that numeracy is highest in Southern Africa and lowest in Northern Nigeria, Niger, Sudan, and Ethiopia. Thus, policy makers must understand the mechanisms of stagnation to see change in the future. Second, the efficiency of the education system has remained at similar levels over the period of observation as well which suggests that the quality of schooling has not significantly improved over several decades or even decreased given the increase in overall years of schooling. Furthermore, we find that children's nutrition proxied by height is a strong predictor of efficiency of the education system. Employing an instrumental variable approach allows to interpret our findings as causal. Therefore, besides the intrinsic value of improving children's nutrition, it also has the potential to improve long-run educational outcomes.

The contribution of this paper to the literature is twofold. First, it is the first paper to systematically estimate numeracy for sub-Saharan Africa for the second half of the 20th century. We obtain important insights into the spatial development of numeracy in the region. Second, this paper provides evidence that the relationships in efficiency of the educational system persist until today and hence, we also need to consider the long-run drivers of these development and not only short-term fixes to sustainably increase educational attainment.

We also contribute to a large strand of the literature on education efficiency which can be broadly categorised into contributions focusing on estimating education production functions from a retrospective point of view or implementing randomised controlled trials (RCT) to evaluate the impact of various inputs into the educational system on educational attainment. Again, an important drawback of this literature is that it only focuses on the recent past or the present and does not consider long-run development of education in an area or country. Yet, there has been much evidence in the African economic literature that historical episodes, such as missionary activities, have a strong influence on contemporary outcomes such as educational attainment (see Michalopoulos and Papaioannou (2020) for a comprehensive overview). Hence, tracing the efficiency of the education system in sub-Saharan African countries over a longer period of time can provide important insights about determinants and path dependencies for schooling efficiency. The stagnating quality of school effectiveness might explain why more and more inputs into schooling do not lead to economic and human capital's take-off in African countries. The relevance of nutrition for numerical learning has been hypothesized and studied for individual case studies, such as Ecuador (Paxson and Schady, 2007) and England around 1810 when the continental blockade by Napoleon generated hunger and malnutrition (Baten et al., 2014). We are the first to study the relevance of nutrition for the efficiency of the educational sector for a whole world region, Sub-Saharan Africa.

The remainder of this paper is organised as follows. Section 2 presents the background. Section 3 discusses the data sources, the methods to estimate numeracy and as well as our strategy to evaluate the efficiency of the education systems. Section 4 presents the results and Section 5 the robustness checks. Finally, Section 6 provides a concluding discussion.

## 2. Background

As we want to design good policies to raise the overall level of education, it is of utmost importance to first understand the current state of educational achievement and second what factors determine it. The empirical literature or international organizations such as the United Nations' focus is on literacy instead of numeracy (for example the Millennium Development Goals only considered literacy in their targets). However, Hanushek and Woessmann (2012) used a measure of math and science skills based on test scores from numerous international studies between 1964 and 2003 to estimate the effect of numeracy on economic growth. They showed that numeracy is the more important factor compared to literacy that drove economic growth over the past decades.

For a moment, consider that, in fact, we need to process numbers and numerical proportions continuously every day of our lives. Take as an example a farmer that needs to carry 50 stacks of wood to the other end of his field which has a length of 200 meters. He could either carry each stack of wood individually or first walk two kilometres back to his house to get a wheelbarrow and reduce the number of trips he needs to make across his field to four. By first walking back to his house to get the wheelbarrow he can reduce the total distance almost to a quarter and increase his labour productivity substantially. As another example, consider a micro entrepreneur in urban Ghana. Being self-employed, the entrepreneur's revenues are about 2500 Cedi a month whereas she could make only 2000 Cedi as an employee. However, she does not subtract the costs, 1000 Cedi a month, from her revenue, such that after all her income and labour productivity would be higher as an employee.

Both examples illustrate the far-reaching effects basic numeracy skills can have on labour productivity and subsequently on living standards. Thus, an overall increase in numeracy can substantially increase incomes in Sub-Saharan Africa, which can promote pro-poor growth and lower levels of inequality. Crayen and Baten (2010) show an impact of numeracy on GDP growth on a global scale, including many African countries. Whilst literacy naturally remains an essential skill to acquire, more focus on measuring – which the literature so far has mostly neglected – and consequently improving numeracy are of utmost importance to enable populations to lift themselves out of poverty.

Yet the question remains how to achieve higher educational output. Thus, over the past decades many studies investigated which inputs into the schooling system improve its efficiency. This literature has focused both on increasing enrolment and attendance among students as well as improving actual educational output. The theoretical framework for both retrospective and (quasi-)experimental studies in this field is a schooling production function Glewwe and Kremer (2006). Figure 1 presents a stylized version of such an education production function.

[Figure 1 about here]

The achievement of a student is determined by numerous factors including the time spent in school (*S*), the quality of schools and teachers (*Q*), the student's innate ability (*C*), socioeconomic status of the household (*H*).

Much early work has focused on retrospectively estimating the parameters of such an education production function (e.g., Glewwe and Jacoby, 1994; Glewwe et al., 1995 and Tan et al., 1997). However, as most components of this function are highly endogenous this causes severe concerns about the biasedness of the results (Glewwe and Kremer, 2006). Therefore, later research employed experimental or quasi-experimental designs to estimate the influence specific inputs have on attainment and hence, overall schooling efficiency. Several reviews have discussed the findings of this literature (e.g., Kremer et al., 2013; McEwan, 2015; Evans and Mendez Acosta, 2021). Yet, these studies cannot provide a long-run perspective on the schooling efficiency for numeracy which is what our study does.

## 3. Data and Method

### 3.1 Data

Our main data sources are four different types of surveys – censuses provided by the *Integrated Public Use Microdata Series* (IPUMS), *Multiple Indicator Cluster Surveys* (MICS), the *Demographic and Health Surveys* (DHS) and *Afrobarometer* (AB) – which all are representative at the national level. As a caveat, we should note that not all our datasets are designed to be representative at a regional level. Hence, we will assess below whether the regional estimates of education of the different datasets reconfirm each other.

The first data source is IPUMS, which collects census data from countries world-wide and harmonises them. IPUMS has data for 26 Sub-Saharan African countries available. Between one and five censuses are available per country (Table A.1). Moreover, the census data is also representative at the subnational level. The earliest census was conducted in 1960 while the newest one in 2016. The censuses provide information about the age of the respondent as well as several socioeconomic background variables. The second data source are the MICS which are conducted by UNICEF in 118 developing and emerging economies world-wide since the 1990s. MICS are household-based surveys that mainly focus on issues affecting women and children, such as maternal health. However, the MICS team has started to add modules for men in their third and fourth round depending on the country. We only employ surveys that include the module for women and men for the estimation to ensure national representativeness. Table A.2 shows all MICS used in this study. In total, data is available for 21 Sub-Saharan African countries ranging between one and three surveys per country. MICS provides information on age, education, socioeconomic background and female empowerment. The newest round includes reading and math modules for children aged seven to ten which we employ in the later analysis. The third data source are the DHS that have been conducted by USAID since the late 1980s in developing countries across the globe. We employ all surveys for Sub-Saharan Africa for which both a female and male module is available, and which provide geo-coded information which results in overall 34 countries. Table A.3 provides more detail. For each country between one and five surveys are available. The DHS provides a broad range of information on literacy, education, socioeconomic background, health, anthropometric data, and female empowerment. Unfortunately, the age data is not useful for our subsequent analysis of age misreporting, as the enumerators are trained to ensure that the stated age is correct instead of the respondent's estimate. The last data source are the AB surveys which have been conducted since the late 1990s in 37 African countries. They also include information about age and cover questions with regard to public attitude towards governance, democracy, and the economy. To date seven rounds are available with the broadest country coverage in the later rounds. Table A.4 shows all surveys available which is a total of 33 Sub-Saharan African countries. Each country has participated between one to seven times.

One caveat of the data provided by DHS, MICS and AB is that while they are officially representative at the national level, they do not ensure representativeness at the subnational level. To ensure that our aggregation of data based on these sources is very close to the data that has been collected representatively, we compare one of our main variables that is available in several surveys, years of schooling. In particular, we compare the DHS and MICS to IPUMS, which is representative at the subnational level, for those regions for which data is available from at least two sources.[2] The correlation analysis shows that both data sources are highly correlated with the IPUMS data at the subnational level such that we deem the data suitable for aggregation at the subnational level.

[Figure 2 about here]

Figure 3 shows a map indicating for which country which data sources are available with (a) showing the countries for which age data is available and (b) the countries for which height data is available. Overall, the combination of the different sources allows us to cover almost the entire region. We do not have any data on Djibouti, Equatorial Guinea, Eritrea, and Somalia. The only countries that we cannot include for our numeracy estimation besides that are Angola, the Comoros, and the Seychelles. While the AB surveys provide the largest spatial coverage for the estimation, we prefer IPUMS as our main age data source due to its much larger sample size which allows to estimate numeracy and other data at the subnational level much more precisely. Similarly, the MICS sample sizes are larger compared to the AB surveys. Hence, following our preferred data source IPUMS are the MICS and then AB surveys such that each subsequent type of survey fills in the remaining gaps as much as possible. We do not include the remaining age data in our analysis. With regards to years of schooling we unfortunately do not have data for Sudan and South Sudan such that we cannot include them in the efficiency analysis.

[Figure 3 about here]

Moreover, we use data from various sources as geographic and historical control variables in our analysis. A complete list of the controls, their definition and sources are provided in the appendix in Table A.5.

### 3.2 Method

[2] We also compare the age data from the different sources (see section on numeracy estimation).

While data on educational inputs such as enrolment or years of schooling are available for Sub-Saharan Africa for the period between 1950 and 2000, these do not measure educational output, i.e., the skills a student learns in school, as argued above (Pritchett, 2013; Angrist et al., 2021). Therefore, to estimate numeracy we employ the age heaping method. This approach allows us to approximate actual numerical skills rather than mere school attendance over longer time periods and geographical areas.

### 3.2.1 Numeracy

Age heaping is commonly used in the economic history literature to proxy for numerical abilities as statistics on educational attainment are not available for most time periods. Age heaping is the tendency of individuals to round their age to preferred terminal digits such as zero or five. For example, an individual might state 40 as their age when in fact it is 38. While this phenomenon is a serious problem for demographers as these false age statements prove difficult in estimations such as population forecasts, it provides us with an opportunity to estimate the numerical abilities of a given population.

We employ the Whipple Index which is the ratio of the observed frequency of ages that end in zero or five to a uniform distribution where ages ending in zero or five should only constitute one fifth of the entire population. To compare the development of numerical abilities over time and across space, we estimate this index for each birth decade from the 1950s to the 1990s per admin I subnational area in Sub-Saharan Africa[3].

$$W_{it} = \frac{n_{it}^{25} + n_{it}^{30} + n_{it}^{35} + \cdots + n_{it}^{60}}{\frac{1}{5} * \sum_{age=23}^{62} n_{it}^{age}} * 100 \qquad (1)$$

where *i* denotes the subnational area for birth decade *t.* The index ranges from 0 to 500 where a value of 500 indicates all individuals reporting an age that is a multiple of five. A value of 100 indicates no heaping and a value of 0 that no individual in the respective population stated an age ending in zero or five. This implies a five-point increase in the Whipple Index equals to an increase of one percentage point in the share of heaped ages. We employ a simple linear transformation of the Whipple Index, known as the ABCC Index[4], that displays the approximate share of individuals who correctly report their age.

[3] Admin I areas are the largest subnational division of a country. In a few cases the availability of geographic indicators forced us to group some regions together. Moreover, we employ the newest administrative borders currently in place in each country. These boundaries in most cases have changed over time, however, this allows to divide the sample in consistent subareas that are comparable over time and to contemporary statistics.

[4] Named after A'Hearn, Baten, Crayen who published this transformation in 2009 and Greg Clark who suggested it in comment on their paper.

$$ABCC_{it} = \left(1 - \frac{W_{it} - 100}{400}\right) * 100 \; if \; Wh_{it} \geq 100; else \; ABCC_{it} = 100 \qquad (2)$$

We restrict the age range between 23 and 62 for multiple reasons. First, older people tend to overly exaggerate their age which would bias the estimates. Second, individuals younger than 23 are not included as age heaping is much less observed among younger people. As previous studies observed (Crayen and Baten, 2010) that individuals between 23 and 32 are comparably more like to heap on even numbers than older individuals we adjust our results to include this pattern. Third, it is important to consider that also in a regular age distribution there will be less individuals at age 54 than 50 because some people die. To avoid this fact biasing the results, we estimate numeracy separately for age groups from 23 to 32, 33 to 42, 42 to 52 and 53 to 62 and assign each age group the birth decade that most individuals in that age group belong to. If there are several surveys for a birth decade at the subnational level available from one type of source (for example, there is data for the 1960 birth cohort in each Mali census), we calculate the average weighted by the respective sample size.

Before addressing some concerns that have been raised with regards to the method, we would like to provide some further evidence that the method is generally suitable for the Sub-Saharan African context. We compare the age heaping pattern of an older generation to math scores of their children. Ideally, we would like to provide both variables for the same person, but this type of evidence does not exist.[5] However, the intergenerational transmission of education has been widely attested in the literature (Black et al. 2005) and thus we deem the comparison of parents' age heaping and children's test scores still as very useful. For this exercise we employ the latest round of the MICS which includes a short math and reading test for children aged seven to fourteen. In contrast to the analysis in the following sections, this data is cross-sectional and does not include a time component. The math test includes four sections with five to six questions about number reading, discrimination, addition and pattern recognition with a maximum number of points of 21. This data is available for 12 countries.[6] The children can be linked to their caretakers for whom we can calculate the ABCC index of numeracy. Figure 4 compares the children's math score to the ABCC score of their respective

[5] MICS-type numeracy tests for adults have not been recorded for large samples. For much earlier time periods, Baten and Nalle (2022) recently tested this for Inquisition defendants of the 15th to 18th century. The Inquisition performed an indirect math tests by asking the defendants to report their life using year-quantities. For example, a defendant might have reported that he is of age 30; he left home at age 20 and then he worked on a farm for 15 years. Baten and Nalle recalculate these biographies and find a strong correlation between obviously miscalculated biographies and age rounding on multiples of five.

[6] The countries are the Central African Republic, Chad, the Democratic Republic of the Congo, Gambia, Guinea-Bissau, Ghana, Lesotho, Madagascar, Sierra Leone, São Tomé & Principé, Togo, and Zimbabwe.

caretakers for each administrative union. There is a clear positive correlation which is highly significant at the one percent level: regions with low numeracy of parents measured by age misreporting, using rounded numbers, showed also poor performance of the children in explicit math tests in the same region.

[Figure 4 about here]

For countries with low numeracy (i.e., a high degree of age heaping), we can even show that this relationship holds at the micro-level for parent-child dyads. In the three countries with the lowest levels of numeracy – Chad, Sierra Leone, and Togo – we have the largest amount of variability of age heaping, hence we estimate the following OLS model for these three countries.[7]

$$Test_{pi} = \beta_0 + \beta_1 * Heaped_p + \Gamma X + \gamma_i + \varepsilon_p, \tag{5}$$

where $Test$ denotes a child's math test score of dyad $p$ and $Heaped$ is a dummy which equals to one if the caretaker of dyad $p$ reports an age ending in five or zero and zero if else. $X$ is a vector of control variables which includes the age and gender of the child, a wealth index, a dummy for urban residence and the sex of the caretaker. and $\gamma$ are regional fixed effects to control for unobserved heterogeneity. We estimate this equation separately for the three countries. As the test scores are truncated, we also report the coefficients for a Tobit model to account for the data structure.[8]

Table 1 reports the results of the regression. Panel A reports the OLS estimation results and Panel B the Tobit estimation results. Odd numbered columns show the estimate without further controls and even numbered columns add controls. For all three countries the relationship is significant. We can detect the highest correlation in Chad where a child whose caretakers reported a potentially heaped age scores between about one point less on the math test, which is a substantial amount. Once we include the controls the results still remain significant.

[Table 1 about here]

[7] If numeracy is high, the proximity of the 100% border reduces the amount of variability that can be used in regressions.

[8] Obviously, even in areas with substantial heaping not every person reports a false age if the age is ending in five or zero. However, as this issue biases our results downwards, it does not change the qualitative interpretation of the results, only the magnitude which is likely to be larger.

Overall, this provides evidence that age heaping and numerical skills are close correlates and that age heaping based numeracy estimation is a suitable approach for the Sub-Saharan African region.

Nevertheless, as any method the age-heaping approach has several potential caveats which are important to address. First, it might be a concern whether the respondents actually answered for themselves which has been questioned especially with regard to women. However, as the MICS are specifically conducted to gather data on women's and children's situation and the male module has only been added to the surveys later, there is very little doubt that women answered for themselves. The IPUMS and AB surveys are not specifically addressed to either gender, however, if officials and researchers would like to get an insight into gender related questions or how opinions differ by gender, then it is in their best interest to receive the answers from the actual respondent. Yet, to remove any remaining doubts, we compare the estimates of the ABCC index for women only for all countries where there is MICS data and one other data source available. A complete overview of the comparison and results are in the appendix. Table A6 shows that there is no or only a very small difference between women in the MICS and the other data sources.

Second, Földvári et al. (2012) and A'Hearn et al. (2021) wondered whether married women might heap their age less than non-married women. They hypothesize that this is because married women will adjust their response to that of their husband and as men on average have higher levels of numeracy, married women appear more numerate. This concern was invalidated by Baten et al. (2022) for a large Italian census sample who find that there is no systematic difference between married and single women. However, to be sure we show a comparison of married to widowed or separate women and do not find any significant differences (Appendix Table A.7).

Third, there is some concern that individuals heap more as they get older such that the same group of people appears to be more numerate surveyed in their thirties compared to surveyed in their fifties. If this were to be true older birth cohorts would automatically appear less numerate. To check whether we observe this pattern in our data we compare data from the same birth decade but for respondents who differ in age (i.e., individuals from the birth cohort 1960 who were in their thirties if the survey was in the 1990s and in their fifties if the surveys was in the 2010s). Comparing those groups (Table A.8), we find some significant results, yet there is not systematic pattern over time such that there is no clear evidence for an ageing bias.

Similarly, Crayen and Baten (2010) studied this for a global sample of the late 19th and early 20th century and also rejected age group biases.

Fourth, a general issue when using the age heaping method is whether the enumerators counterchecked in any form the age the respondent states. As we have data for many regions from several sources, we can compare the estimated ABCC index of each source with each other to detect a possible upward bias in any of them. The estimation procedure and results are in the appendix. We detect a small upward bias in both the Afrobarometer and MICS data. Hence, we correct the ABCC Index derived from these sources by the amount of the estimated bias. Overall, we cannot completely rule out the possibility that all data sources are biased upwards, hence, the numeracy indicators derived from the age heaping method should generally be considered as an upper bound.

Fifth, a concern raised by A'Hearn et al. (2021) is that the Whipple index cannot detect preference for other digits than zero or five. They investigate a sample from 19th century Italy and find that while there is strong heaping on multiples of ten, there is no strong heaping on numbers with the terminal digit five but six. To check whether this is the case in our data, we inspect histograms from each country and age data source. We find that for the youngest age group there is stronger heaping on multiples of two and hence, as mentioned before, we corrected for that. Moreover, in countries that appear more numerate we find that there is a tendency to not only heap on multiples of five but also on the terminal digits two and eight. As we are concerned with estimating basic numerical skills, this tendency is not of strong importance in this study. Nevertheless, for completeness we calculate the Whipple and ABCC Index for heaping on the terminal digits zero, two, five and eight as shown in the appendix. We find almost a perfect correlation between the two measures. Moreover, the traditional method has a higher correlation with other measures of educational attainment such as years of schooling and literacy and hence remains preferable.

In sum, we assessed the numeracy data in this section in a very systematic way, in order to provide estimates that are as unbiased as possible. For example, we studied whether families whose parents misreported ages had children who also performed poorly in explicit math tests, and we confirmed this intergenerational correlation of low numeracy. We also assessed potential biases, such as whether women were asked as frequently as men by survey-takers. We observed, in general, that the age heaping based numeracy data are quite informative and of a high quality. This allows us to take the next step and to analyse schooling efficiency.

### 3.2.2 Schooling Efficiency

Our measure of schooling efficiency is intended to capture the efficiency of the general education system. Therefore, we do not only want to include the numeracy of children who have ever been to school (to calculate how much they learn per year), but also consider those who have never attended school. This allows us to consider how efficient the overall educational system is in teaching all children.

We calculate our schooling efficiency measure by estimating the ratio of the ABCC index of numeracy (=the educational output) to the average years of schooling (=the educational input) per region and birth decade: [9]

$$ScEff_{it} = \frac{ABCC_{it}^{stand.}}{YrSc_{it}^{stand.}} \tag{3}$$

This ratio between the output in numeracy skills and the year-of-schooling input helps to assess the efficiency of the educational system. Please note that we need a strategy of standardizing both variables, because there is one factor of complication: numeracy does not equal zero for individuals who have not been to school. Basic numeracy is partly acquired in the family and other social environments of young children. Thus, we first standardize both components of our efficiency measure to take this into account. We loosely follow the methodology of the Human Development Index that expresses an indicator between its minimum and maximum setting the former to zero and the latter to one.

$$ABCC_{it}^{stand.} = \frac{ABCC_{it} - ABCC_{min}}{ABCC_{max} - ABCC_{min}} \tag{4}$$

$$YrSc_{it}^{stand.} = \frac{YrSc_{it} - YrSc_{min}}{YrSc_{max} - YrSc_{min}} \tag{5}$$

Another change we need to make is to not employ the observed maximum years of schooling. Basic numerical skills measured by the ABCC index should be achieved latest at the age of finishing primary schooling. The median length of primary schooling in Sub-Saharan Africa is six years and thus we set the maximum number of years of schooling to this. If we would not make this adjustment, regions with very high levels of numeracy and a high number

[9] We do acknowledge that years of schooling as our educational input may not fully capture the educational input in a non-formal environment, i.e., the household. However, the years a child ideally spends in a school are the same in which learning in a non-formal environment needs to take place. Thus, we do believe that using years of schooling is a good approximation for the time a child spends learning, whether in a school or in a non-formal environment. Moreover, the average years of schooling in a region naturally declines the more people never attend school thus reflecting the overall availability of schooling and attendance at schools which are crucial inputs at early stages of educational expansion.

of average years of schooling would appear overly inefficient compared to regions who also have high levels of numeracy but less years of schooling. Yet, the former regions probably achieved basic numeracy years before they ended schooling and moved on to more advanced mathematics. However, we would not be able to capture this in our data without our standardization strategy.

For the schooling efficiency analysis, we focus our attention on countries that overall have not yet achieved high levels of numeracy and thus exclude countries for whom the country average of the ABCC index is below 95. This applies mostly to countries in Southern Africa and Central Africa.[10] For countries in which almost all individuals already mastered basic numerical abilities, a comparison becomes useless as an indicator would be needed that can detect differences at higher levels of mathematical abilities.

Please note that our efficiency measure considers the ratio between inputs and outputs, It does not focus on the underinvestment in school year inputs. For example, a poor region with only one year of schooling might reach a high efficiency even with numeracy output below the overall average. In such a situation, the parents might support the numerical learning in the family, and other factors such as child nutrition might be of sufficient quality. This is not necessarily a region of high development status (because of lacking inputs), but it will inform our analysis why the large increase in inputs in SSA overall did not lead to a corresponding increase in skill output. In other words, we would like to emphasize that we need to understand the issue why the large investment increase of schooling years in Africa did not result in more numeracy output. A potential issue may be the quality of nutrition that we discuss in the following section.

### 3.2.4 Nutrition

As mentioned above, we use average height of a given population as an indicator for nutrition during childhood. Numerous studies have demonstrated that high quality nutrition is key both for the development of cognitive abilities (Bryan et al., 2004) and adult height (Steckel et al. 2019). A child that does not grow enough during childhood due to a lack of adequate

[10] We used an ABCC Index of 95 as our orientation for a cut-off which resulted in a set of country with a few 'southern' outliers. We decided to restrict the sample to keep it more homogenous. This results in the following countries that remain in the sample: Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Ethiopia, Ghana, Guinea, Kenya, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, South Sudan, Sudan, Tanzania, Tchad, Togo and Uganda.

nutrition will not catch up later in life to reach its potential height. Therefore, we use height per admin I area as the main explanatory variable in our model.[11] Our baseline specification is a pooled OLS model in which we adjust the standard errors for spatial and serial autocorrelation.

$$\ln\left(ScEff_{it}\right) = \beta_0 + \beta_1 Height_{it} + Z'_{it}\Gamma + X_{it} + \varepsilon_{it}, \tag{6}$$

where $ScEff_{it}$ is the estimated efficiency of schools per region per birth decade and $Height_{it}$ is height per region and birth decade. $Z_{it}$ is a vector of control variables and $X_{it}$ are birth decade and larger regions fixed effects. Besides the geographic control variables, we include age at first marriage, the share of Muslims and a measure of religious fractionalisation as control variables.[12] We opted not to use a fixed effects panel data model because as we will discuss later schooling efficiency is highly persistent. Thus, there is not enough variation over time to find any effects in a fixed effects model.

A potential caveat could be survivor bias if the healthier individuals survived drought-determined malnutrition periods. Bozzoli et al. (2009) mentioned the potential effects of survivor bias in their comparison of African and South Asian heights (on the following, see also Baten and Maravall, 2020). However, a large number of height studies have found that, survivor bias is less likely to have a substantial distortionary effect (and Bozzoli et al., 2009, p. 663, emphasized that their argument was a possibility rather than an evidence-based reality). For example, Moradi (2010) and Boerma et al. (1992) estimated that the effect of selective mortality on stunting for several developing countries was not substantial based on the height data of children who died or survived. Moradi (2010) found that heights would have decreased (due to the survival of the shorter children) by less than 1% if, instead of the high infant and child mortality in the Gambia during the 1960s, all children had survived up to age 5. Of course, such a dramatic change from a high level of child mortality to zero mortality was not observed anywhere in the developing world. In other words, the complete disappearance of infant and child mortality in a developing country in the 1960s is not plausible. If there were a – quite dramatic -- 10% reduction in infant and child mortality from the level it had been in the Gambia

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[11] The DHS has a good coverage of height data for women, but only very few surveys have data on male heights. Therefore, we opted to only use the female height data to ensure comparability between samples. Moreover, given that women and girls are the more marginalised group compared to their male counterparts, using female height data as a proxy for children's undernutrition might even be the more reliable indicator for undernutrition. If food becomes scarce it is often first redistributed within the household from females to males (Doss, 2013). Hence, female height might be more 'sensitive' to periods of malnutrition during childhood.

[12] We include age at first marriage as a proxy for female empowerment (Baten and de Pleijt, 2018). We include share of Muslims as a control variable as average educational attainment of Muslims is on average lower than that of Christians. Similarly, we include religious fractionalization to control for the homogeneity of the religious community and religious competition has been linked to higher educational outcomes (Gallego and Woodberry, 2010). To calculate religious fractionalization, we follow Alesina et al. (2003).

circa 1960, it would only result in a 0.2 cm lower height due to reduced mortality selectivity. Hence, Moradi (2010) concludes that the effect of survivor bias on height levels was 'too small to explain much'.

A potential problem of the regression above could be an omitted variable bias. Thus, we turn to a quasi-experimental strategy and use an instrumental variable (IV) approach. The instrument we propose for *Height* is the number of months with below average rainfall in the district of residence in the year stated as birth year plus the two years before and after. [13]

There is a large literature around critical period programming (Knudsen 2004) that find that nutritional conditions during early infancy are important determinants of not only child health but also health during adulthood and adult height (see also Barker 1990; Behrman and Rosenzweig, 2004; Black et al., 2007; Alderman et al., 2006; Oereopoulos et al., 2008). Paxson and Schady (2007) and Currie and Vogl (2013) found that a lower early child nutrition implies a lower ability of learning. Underlying determinants can be identified as natural disasters (Beuermann and Pecha, 2020; Groppo and Kraehnert, 2016; Frankenberg et al., 2017), pandemics (Lin and Liu, 2014; Hu and Li, 2019), temperature shocks (Andalón et al., 2016; Agüero, 2014), conflict (Agüero and Deolalikar, 2012; Bundervoet et al., 2009) and famine (Meng and Qian, 2009; Chen and Zhou, 2007; Dercon and Porter, 2014).

We focus on rainfall shocks as our instrument due to its importance in the livelihoods of most people in Sub-Saharan Africa. First, according to the World Bank (2022) more than 60 percent of total employment in Sub-Saharan Africa was in agriculture in 2000 (and this percentage was even higher in the 1950s to 1990s period) meaning that the livelihood of a vast majority of the continent depends on income derived from agriculture. As only very little land is irrigated (Barrios et al., 2010), good rainfall is a key input for a successful harvest period. Schlenker and Lobell (2010) find that rainfall and temperature shocks have a large negative impact on African agriculture. Moreover, following Barrios et al. (2010) insufficient rainfall has a negative effect on overall growth in Africa. For a comprehensive review about the link between climatic conditions and the economy see Dell et al. (2012).

There are several channels through which insufficient rainfall can decrease health and nutrition during infancy. Most obviously, if the harvest is bad due to low rainfall, there is less

[13] We do acknowledge that individuals may have moved over the course of their lives such that the conditions in the district of residence might not resemble conditions in the actual birth district. However, there is only limited information about the district of birth for a small subset of respondents. Thus, we believe that rainfall during pregnancy and infancy in the current district of residence is a good proxy for conditions during birth for the vast majority of respondents who may have not moved outside of their birth district.

food for consumption and lower agricultural income (Hidalgo, 2010; Banerjee et al., 2010; Burlando, 2014) such that the infant does not receive enough food. Another channel that has been investigated in the *foetal origin hypothesis* literature is maternal stress, which may be caused by the prospects of a bad harvest, that can harm foetal development (Aizer, 2016; Black et al., 2016; Lee, 2014; Quintana-Domeque and Ródenas-Serrano, 2017; Torche, 2011; Brown, 2020; Currie and Rossin-Slater, 2013; Camacho, 2008). Moreover, poor rainfall has been linked to conflict (Hsiang et al., 2013) which can be harmful to a child in multiple ways. However, one advantage of lower rainfall might be a reduced disease environment which can decrease the incidence of diarrhoea or malaria among pregnant women and infants (Levy et al., 2016).

We use Version 4 of the Climate Research Unit gridded Time Series by the University of East Anglia (CRU data) for the period 1948 to 2001 (Harris et al., 2020). The dataset provides monthly rainfall data at a 0.5°×0.5° resolution for the entire world except Antarctica. The data is collected from an extensive network of weather station observations and is interpolated using angular-distance weighting. We calculate the mean rainfall per admin I region for each month between January 1948 and December 2001 as well as the long-term average. Next, we create a dummy indicating for each month whether the rainfall in that month is below the district specific long-term mean. Last, for each individual observation we compute the number of months with below average rainfall within the calculated year of birth plus the two years before and after and then calculate the average number of shock months for each district per birth decade.

We add this buffer of two years for several reasons. First, we calculate the year of birth for each individual by subtracting the stated age from the year of interview. Since some individuals round their age, the derived year of birth will also not be accurate for all observations.[14]

Thus, our first stage regression is

$$Height_{it} = \beta_0 + \beta_1 \ln\left(Rainshock_{it}\right) + Z_{it}'\Gamma + X_{it} + \varepsilon_{it}, \tag{7}$$

[14] Assuming that non-numerate individuals heap to the closest number with the terminal digit zero or five, the margin of error is approximately two years. Second, we do not know the month of birth. It might be January or December, thus adding the year before and after ensures that we cover the in-utero period and early infancy for those who stated a correct age as well. Naturally, there are some drawbacks given the wide margin. However, at worst if the true year of birth is in the first year of our margin, we cover more of the infancy period whereas if it is in the last year, we cover the pregnancy and conditions for the mother pre-pregnancy which can be relevant as well for in-utero health exposure. Thus, we believe that overall, we are able to capture a critical period of a child that has lasting impact on adult outcomes.

where *Rainshock* is the negative rainfall shock of region *i* during birth decade *t*.

An omnipresent potential concern with IVs is the validity of the exclusion restriction. However, since rainfall is arguably exogenous and is not serially correlated over time (Paxson, 1992), rainfall at the time of birth is unrelated to rainfall during later ages. Moreover, we only consider within district variation and do not compare rainfall across regions. Therefore, as long as the negative shock caused by insufficient rainfall does not last over several years (other than its long-lasting impact on health), the exclusion restriction is fulfilled. An effect of a negative rainfall shock that could potentially last over several years is if it affects wealth. For example, a household living of subsistence agriculture might have to sell their assets which they accumulated over years of hard work in order to survive. If this shock lasts until the child starts to acquire numerical skills, then this could violate the exclusion restriction. However, for this to be the case the rainfall shock must be very severe. Yet, our data shows more than 70 percent of observations never experienced a negative rainfall shock that is 2 standard deviations below the long-term average of a district and in more than 95 percent of observations the average number of months during pregnancy and infancy is less than one month with a severe negative rainfall shock on average. Thus, while no observational study can ever be sure that the exclusion restriction does not pose a problem, we can be reasonably sure that this problem is not of substantive dimensions here.

### 3.3 Descriptive Statistics

Table 2 provides summary statistics for our main variables for the sample of countries with numeracy less than 95 percent which we use for the efficiency analysis. All estimates are at the subnational region level and per birth decade. On average, the ABCC index is about 81. This suggests that about 80 percent of the sample analysed below have achieved basic numerical skills. However, numeracy varies between less than 30 and 100 percent. Our logarithmized measure of education efficiency is on average about 0.17. Moreover, years of schooling has a mean of 4.5 years in the sample. Average height is about 160 centimetres. The average Muslim share is about 30 percent. Last, religious fractionalisation is about 0.304 on a scale of zero to one but varies strongly between areas.

[Table 2 about here]

Figure 5 displays a bar graph that shows the relationship between the ABCC Index and average years of schooling in our sample. We observe a positive relationship with the largest difference between the categories of two to four years of schooling and four to six years of schooling, resulting in a difference of more than 5 percentage points in numeracy. At higher levels of schooling, the marginal effect of numeracy is smaller. Moreover, the error bars indicate that there is quite some variation in each category which indicates that the efficiency of the education system differs substantially between regions.

[Figure 5 about here]

In Figure 6 we consider the overall trend in numeracy across the continent and some sample countries. Overall, there has been hardly any change in the overall level of numeracy across the continent and the individual countries display a similar pattern. While there is modest change across time there is no strong improvement and Niger even shows a declining trend. This seems to contradict Figure 5, as the increase in school years should have resulted in more numeracy. However, the relationship in Figure 5 depends mostly on cross-sectional variation, while the effect on numeracy over time was quite limited (and similarly the effect on literacy, see Ferber and Fourie 2022). We will explore in the following why this was the case.

[Figure 6 about here]

## 4. Results

### 4.1 Numeracy

The spatial distribution of numeracy has remained highly similar over time and exhibits a strong path dependency. Figure 7 shows the level of numeracy for each region per birth decade. Southern Africa has had achieved high levels of numeracy already for the 1950 birth decade. Thus, our measure is for further investigation in this area not that useful anymore since it cannot detect differences at higher levels of numerical abilities. Other areas with high levels of numeracy are Madagascar, the Congos as well as parts of Mauritania. However, the DR Congo and Madagascar experienced a decrease in numerical abilities over time. In contrast the areas with the lowest level of numeracy are situated in Western Africa, the Sahel area as well as Ethiopia. Northern Nigeria has especially low values in all birth decades. Overall, the spatial distribution does not change much over time and areas that only achieved low values of numeracy for the 1950s birth cohort achieved also low values for the 1990s birth cohort.

[Figure 7 about here]

### 4.2 Schooling Efficiency

Similar to the geography of numeracy, the spatial distribution of schooling efficiency has also remained remarkably stable. Figure 8 shows our estimates for schooling efficiency for each region per birth decade. The countries with the highest efficiency levels according to our measure are Burkina Faso and Chad while at the bottom end we find Nigeria in each period as well as some areas of Ethiopia and Guinea. As before, the variation does not change much over time and the spatial distribution remains very similar over the covered period.

[Figure 8 about here]

Next, we turn to the results of the regression analysis that investigates nutritional status as a driver of schooling efficiency. Table 3 presents the baseline results. The standard errors are adjusted for spatial and serial autocorrelation following Hsiang (2010). We allow for a time lag over two periods which is approximately the age difference between a mother and a child in an environment with early fertility. Our spatial kernel is cut off at 400 kilometres which is the largest minimal distance between two admin I centroids. Column (1) shows the raw correlation between height and our measure of education efficiency. This is significant at the one percent level. Subsequently we add birth decade and African regions fixed effects in column (2), age at marriage, share of Muslims and a measure of religious fractionalization in column (3) and our set of geographic controls in column (4). The results actually increase again once we control for the geographic controls in column (4) and remain statistically significant at the one percent level. Our results suggest that increasing average height by one centimetre, increases schooling efficiency by about 8 percent on average.[15]

[Table 3 about here]

As mentioned before, we need to consider potential endogeneity, arising, for example from measurement error or omitted variable bias. Therefore, we now present the results from our instrumental variable approach in Table 5. Odd numbered columns show the first stage results and even numbered columns the second stage results. The first stage results are in all specifications highly statistically significant and exhibit F-Statistics above ten (Stock and Yogo, 2005). Thus, we do not have to face a weak instrument problem. The instrumental variable results confirm our previous results that height as a proxy for nutrition during early childhood is significantly related to education efficiency. The higher the average height within a population, the more efficient the education system.

[Table 4 about here]

[15] We show in the appendix in Table A.11 the results from the model without adjusting the standard errors for serial and spatial autocorrelation but instead cluster them at the admin I level. The results remain virtually unchanged suggesting that neither spatial nor serial autocorrelation have an important influence.

Overall, we find that height as a proxy for children's nutrition is significantly related to education efficiency in Sub-Saharan Africa. Given that we find this based on an IV approach, we may claim causality. There can be two underlying mechanisms. On the one hand, better nourished and healthier children are more likely to attend in the first place and on the other hand, healthier and well-nourished children in school are better able to learn. We cannot distinguish between these two mechanisms yet provide evidence that improving children's nutrition can be an important contributor to increasing education efficiency in Sub-Saharan Africa.

## 5. Robustness Checks

Our main specification provides estimates for which we use an ABCC index of 95 as a cut-off value. In Table 5 we show that our results are not driven by a sample composition effect and hold if we use a 90 or 85 as our cut-off value. The estimates remain significant and very similar in size.

[Table 5 about here]

Moreover, we provide alternative estimates if we alter our outcome variable slightly. As discussed, we limit years of schooling to six years as this is the median length of primary school education. In Table 6 we show that our results remain virtually unchanged if we use four, five, seven or eight years of schooling.

[Table 6 about here]

## 6. Concluding Discussion

Providing access to high quality education to each child is of utmost importance to achieve sustainable development in the long-run. While in the last decade more children than ever were enrolled in a primary school in Sub-Saharan Africa, the region has not experienced the expected progress in learning outcomes (Angrist et al., 2021). Therefore, policy makers and scholars have been searching for tools to change this.

Our paper is the first to provide long-term evidence on the development of numerical skills at the sub-national level in Sub-Saharan Africa for the birth decades 1950 to 1990. Throughout the observational period we observe high levels of numeracy in Southern Africa and parts of Central Africa compared to the remainder of the region. Moreover, we observe very little progress which is in line with contemporary findings of low educational achievement besides increasing enrolment and years of schooling (Angrist et al., 2021).

Therefore, we contribute to this discussion by taking a long-term perspective. First, we evaluate how schooling efficiency has evolved over the period under observation and find that not much has changed. Again, we find strong regional disparities which persist over time which strengthens the need to understand the underlying mechanisms. Second, we estimate the impact of children's nutrition and health on schooling outcomes using average adult height as our main explanatory variable. Our results show that children's nutrition is an important predictor of schooling efficiency. Moreover, we investigate whether this changes over birth decades, however, we only find that its importance decreases over time yet remains highly important. We furthermore provide evidence using an IV approach. Our instrument is the average number of months an individual was exposed to rainfall below the long-term district rainfall average during pregnancy and infancy. The IV results confirm our findings. Furthermore, our results are robust to several specifications.

How can we improve the nutritional situation of school children? One of the most popular interventions world-wide to incentivise children to come to school and increase their chances of learning something at school are school-feeding programs. The rationale behind this type of intervention is that on the one hand children receive food conditional on attending school and on the other hand well-fed children are better able to concentrate and participate in school. Moreover, given the high level of malnourishment in Sub-Saharan Africa, providing children with extra food can be considered as a goal in itself. Most evidence with regard to school feeding interventions suggests positive effects on enrolment as well as educational outcomes. Yet not all contributions agree (Parker et al., 2015; Alderman et al., 2012) and moreover, the cost-effectiveness compared to other school-level interventions is questioned (see the critical view by Alderman and Bundy, 2012). Yet, we find that better-nourished children indeed acquire better numerical skills which is important for sustainable growth. This can change the cost-benefit analysis of school-feeding programs substantially. Our analysis suggests that school-feeding programs especially for the youngest school-children around age 6 or 7 might be beneficial via the nutrition effect, as at this age, children might compensate earlier malnutrition issues partly. Even better would be pre-school protein supplement programs (Hulett, 2014), although we admit that this might be prevented by financial constraints. [16] However, if these programs would be targeted specifically on the most problematic regions that

[16] Protein would be particularly relevant, as we use height as an indicator of early-life nutritional status. Proteins have been identified as a particular close correlate of height, and Case and Paxson (2008) identified these as predictor of later-life abilities (See also Baten et al. 2014, Baten and Blum 2014).

we identify in the maps of Figure 8 (and on the poorest families within these regions), the programs can contribute to solving the ‘schooling crisis’.

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**Data availability statement**

The data that support the findings of this study are openly available in Development Economics Data Sets at Univ. Tuebingen, https://uni-tuebingen.de/de/18730 , reference name Download Dataset for "Nutrition Matters".

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**Figures**

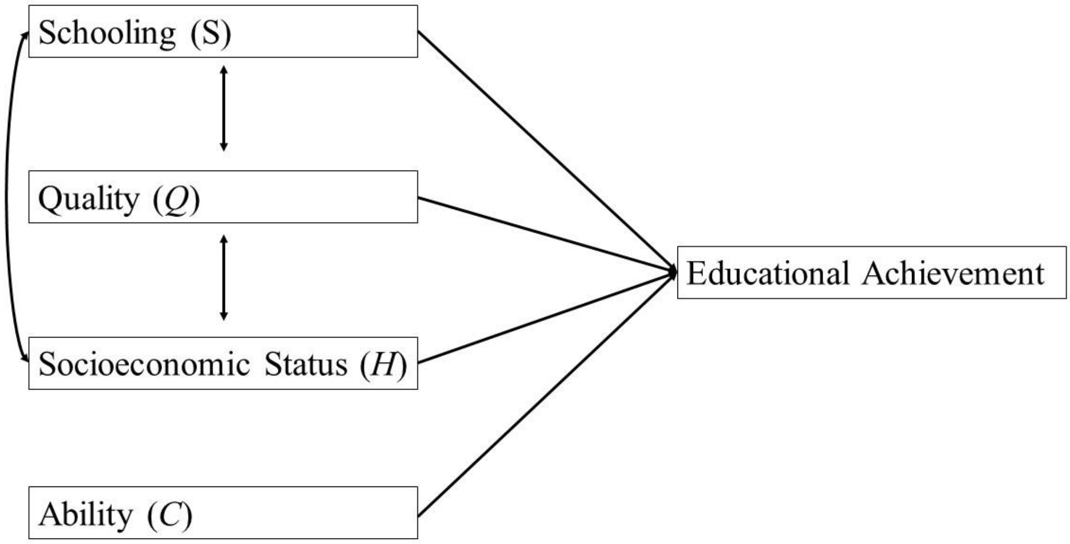
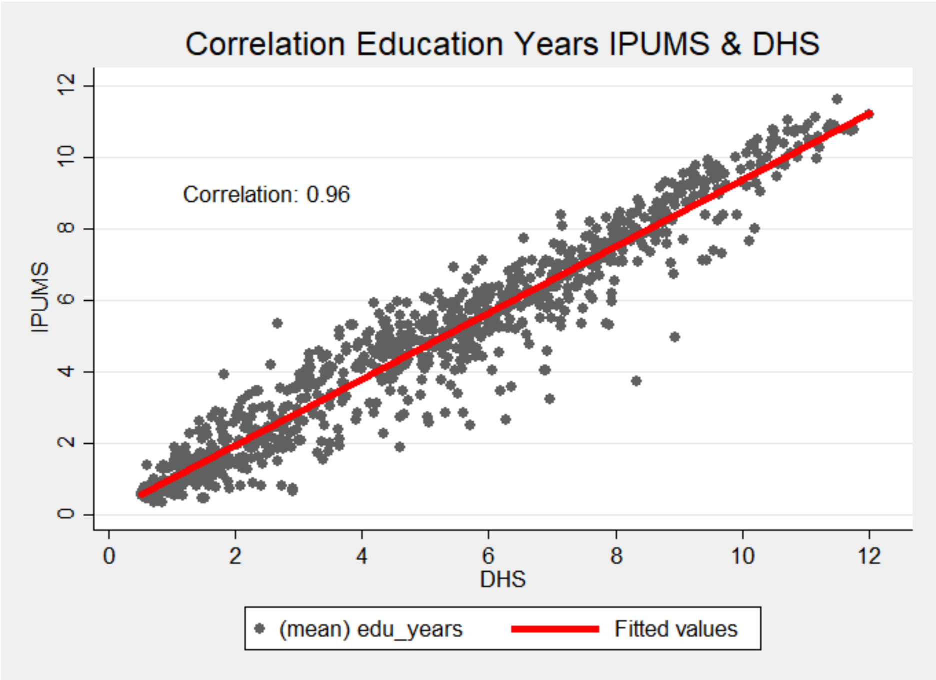



*Figure 1: Stylised education production function following Glewwe and Kremer (2006). Author's own representation.*



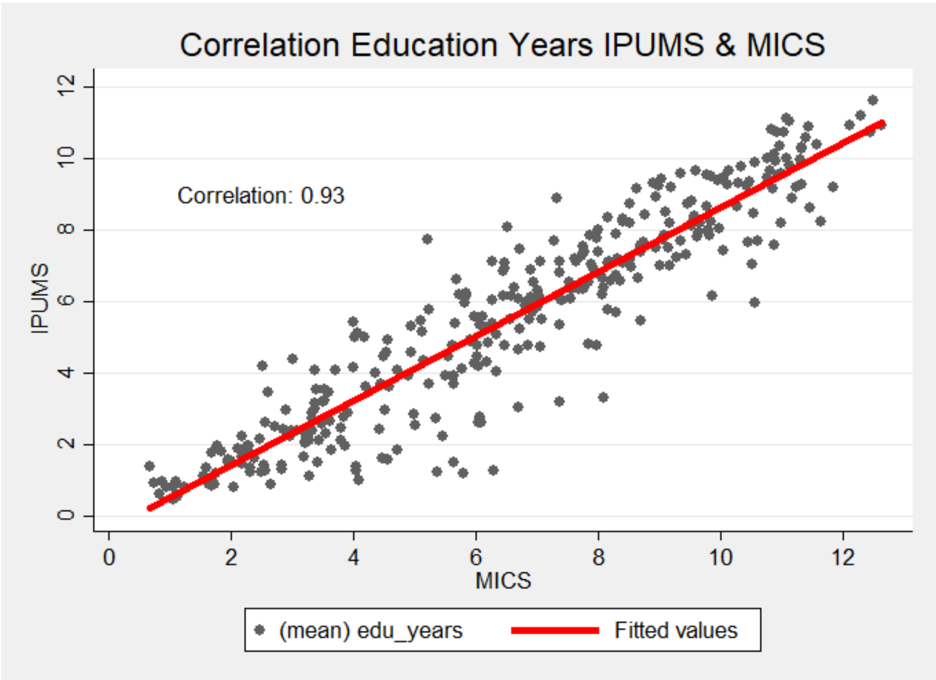
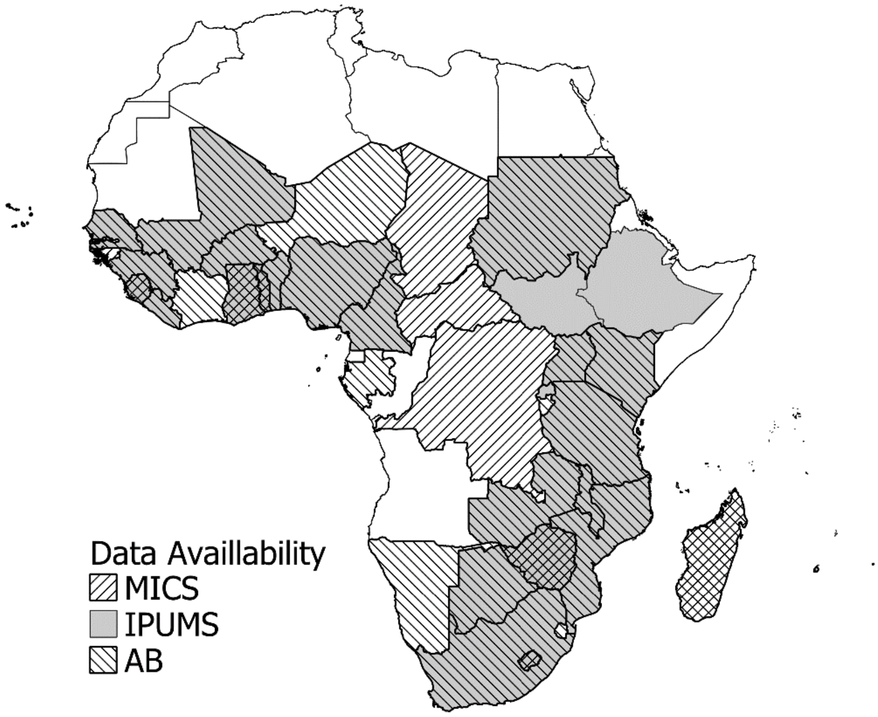




*Figure 2: Correlation of IPUMS data with DHS and MICS data. Authors' own representation.*

(a)




(b)

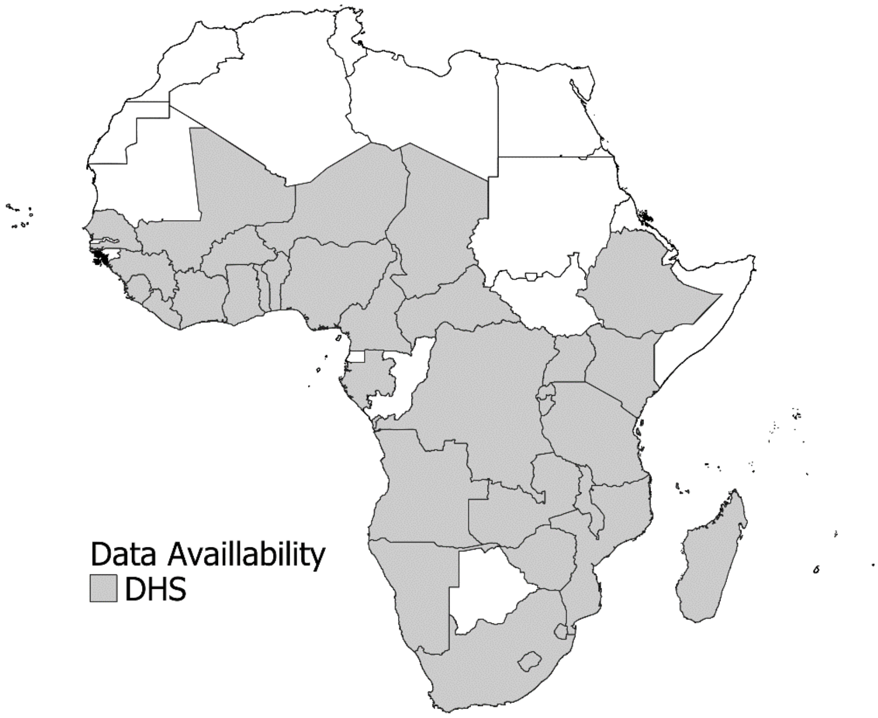



*Figure 3: Data Availability for ABCC calculations (a) and height measures (b). Authors' own representation.*

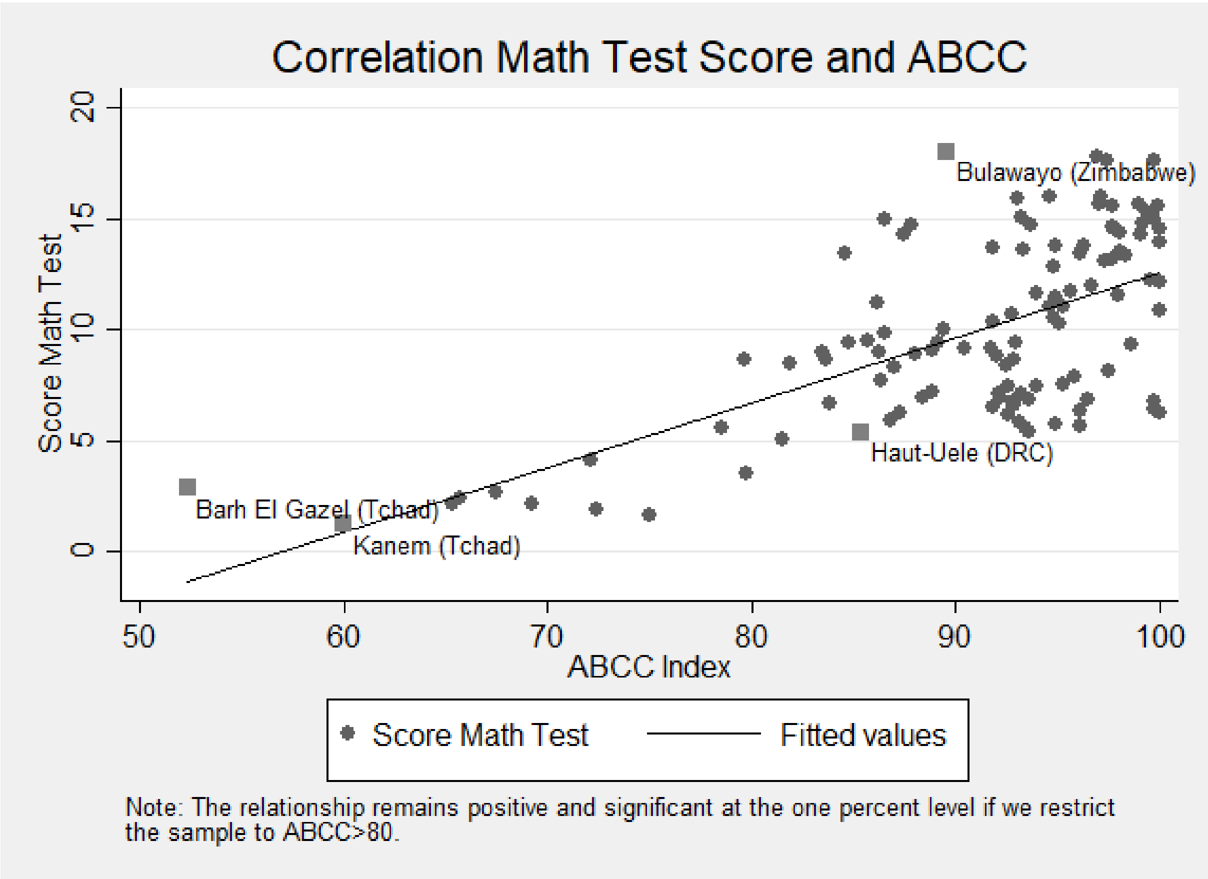



*Figure 4: Correlation of children's math test score and care takers ABCC at the admin I level based on MICS Wave 6. Authors' own representation.*

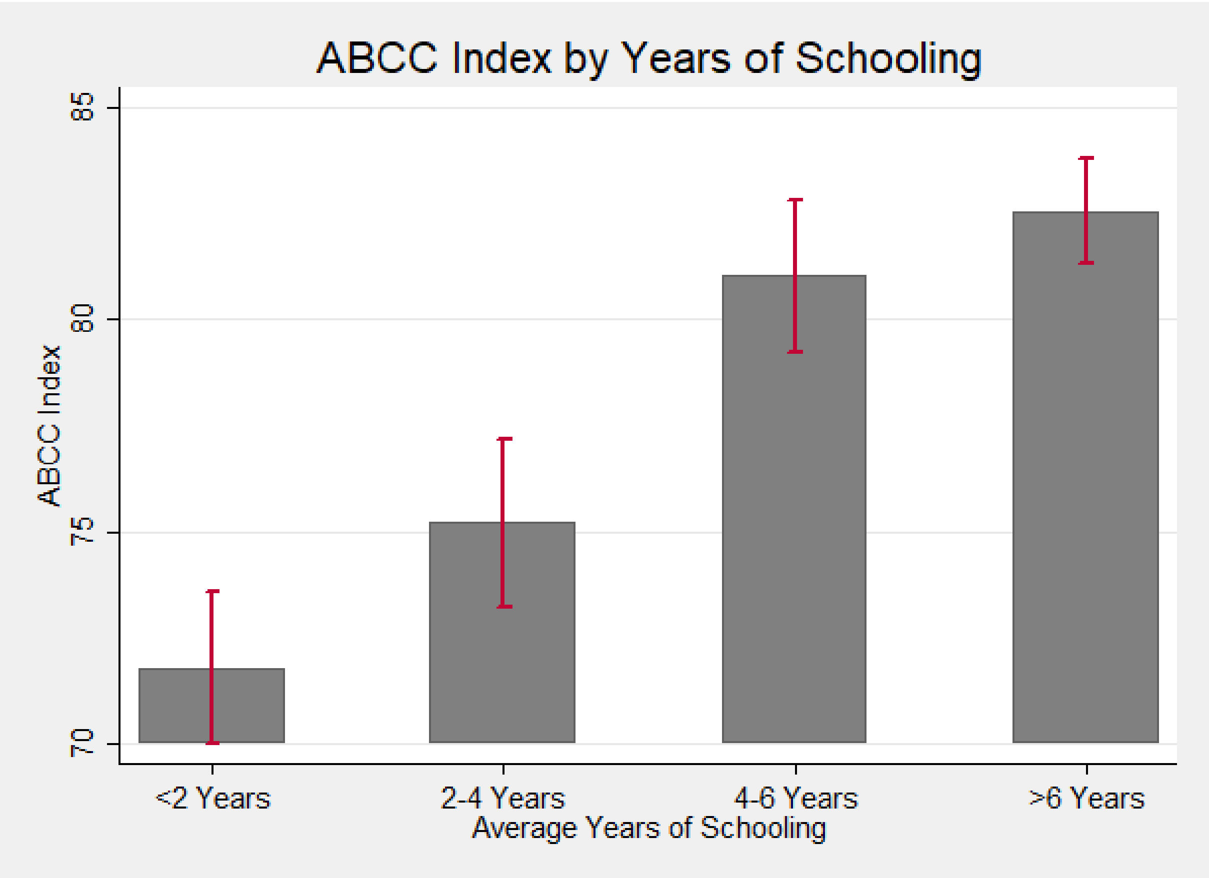


*Figure 5: Relationship of average years of schooling and numeracy (ABCC Index). Data from IPUMS, MICS and Afrobarometer. Authors' own representation.*

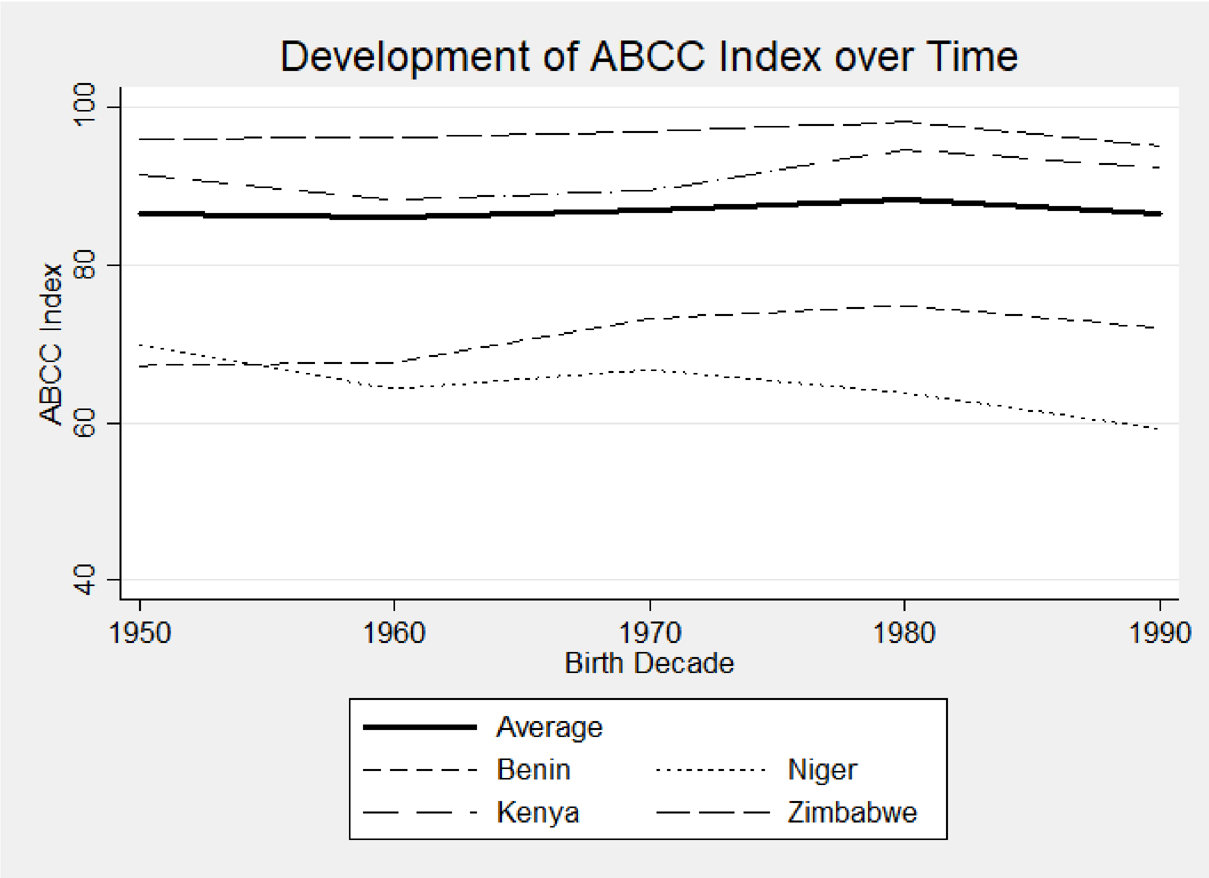



*Figure 6: Development of numeracy (ABCC Index) over Time. Data from IPUMS, MICS and Afrobarometer. Authors' own representation.*

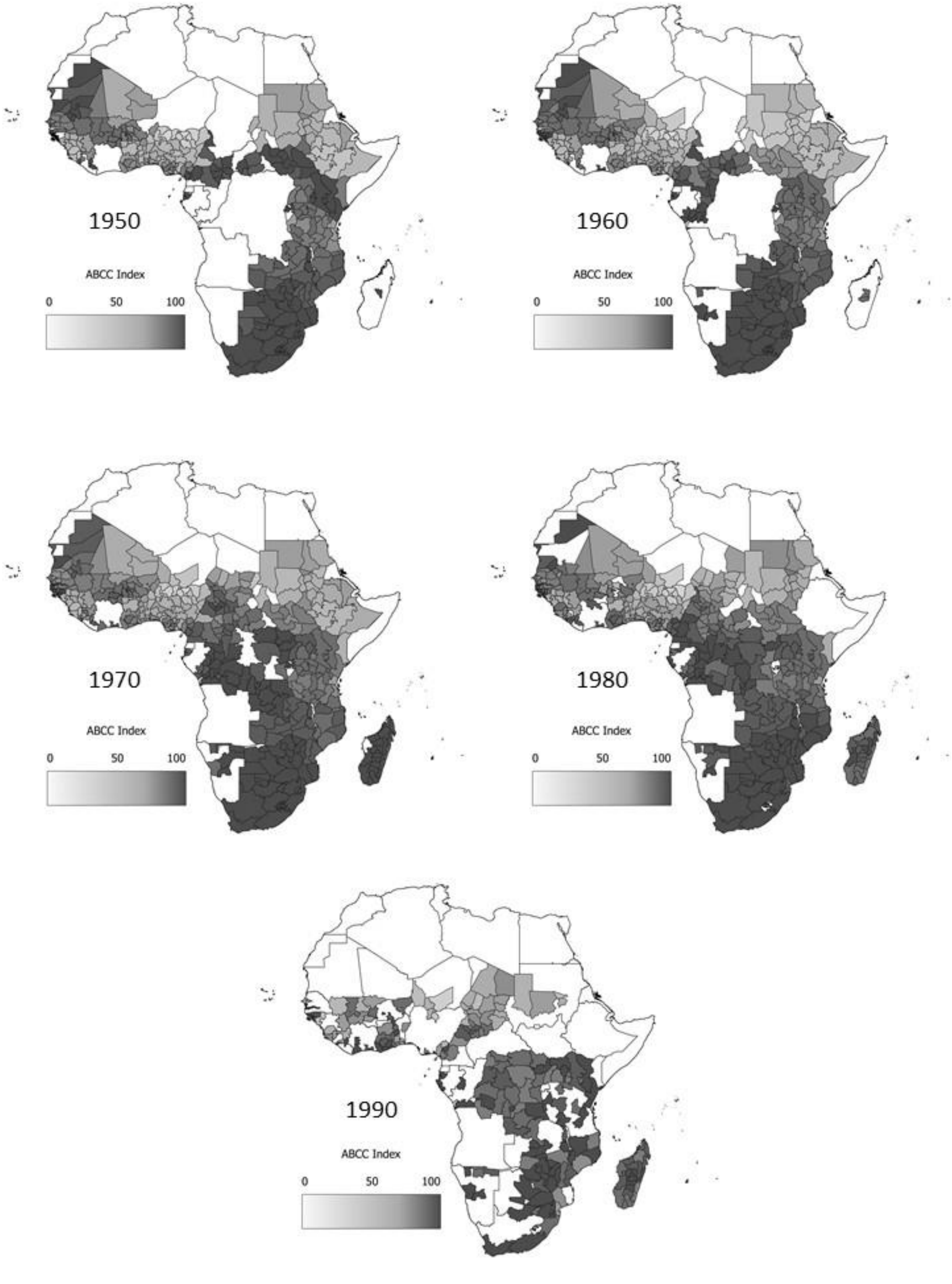



*Figure 7: ABCC Index per admin I level for each birth decade between 1950 and 1990. Data from IPUMS, MICS and Afrobarometer. Authors' own representation.*

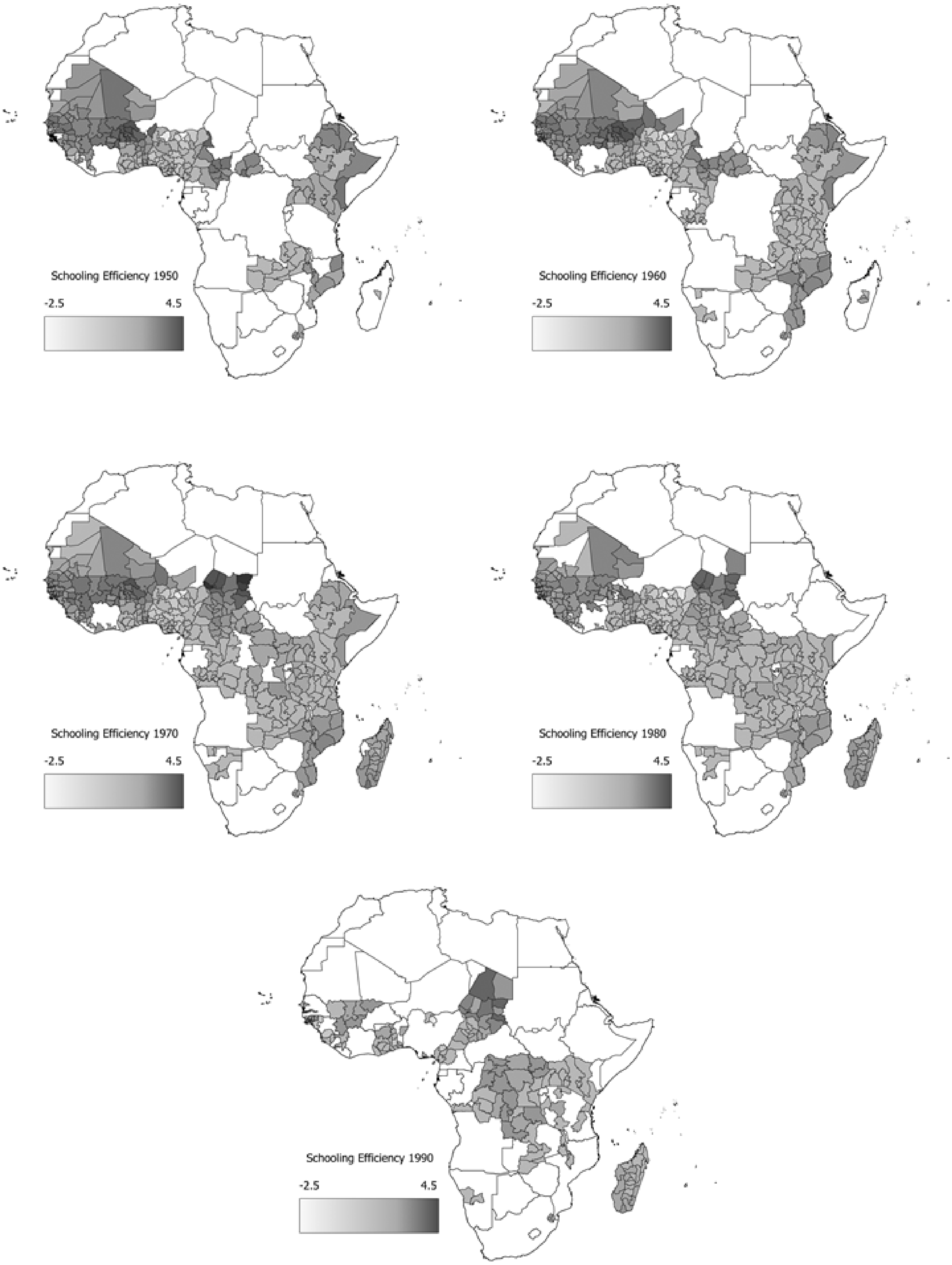



*Figure 8: Schooling efficiency per admin I level for each birth decade between 1950 and 1990. Data from IPUMS, MICS, Afrobarometer and DHS. Authors' own representation.*

# Tables

**Table 1: Individual-Level Correlations - Parents' Age Heaping and Children's Test Scores**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Togo | | S. Leone | | Chad | |
| **OLS** | | | | | | |
| Multiple of Five | -0.678** | -0.538** | -0.598*** | -0.340* | -0.493*** | -0.397*** |
| | (0.288) | (0.248) | (0.205) | (0.179) | (0.157) | (0.140) |
| Regional FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes |
| Observations | 2,790 | 2,790 | 5,929 | 5,929 | 8,136 | 8,136 |
| **Tobit** | | | | | | |
| Multiple of Five | -0.759** | -0.579* | -0.828*** | -0.476* | -1.951*** | -1.689*** |
| | (0.350) | (0.300) | (0.282) | (0.247) | (0.519) | (0.456) |
| Regional FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes |
| Observations | 2,790 | 2,790 | 5,929 | 5,929 | 8,136 | 8,136 |

Notes: These regressions show the correlation between parents age heaping and children's test scores based on MICS Wave 6 data. The dependent variable are children's test scores ranging between 0 and 21 and the dependent variable is a dummy indicating if a parent stated a potentially heaped age. All models control for regional fixed effects. Further controls include wealth, age of the child, gender of the child, urban residence, and sex of the caretaker. Standard errors are clustered at the sampling cluster level. Asterisks denote significance at levels *** p<0.01, ** p<0.05, * p<0.1.

**Table 2: Summary Statistics**

| | Obs. | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| ABCC Index | 1477 | 81.329 | 13.794 | 29.87 | 100 |
| Education Efficiency | 1305 | .269 | .853 | -15.751 | 3.784 |
| Years of Schooling | 1788 | 4.581 | 2.799 | .014 | 12.453 |
| Height | 1525 | 158.732 | 2.793 | 141 | 166.795 |
| Age at Marriage | 1788 | 20.113 | 2.19 | 15.033 | 37.551 |
| Share Muslim | 1619 | .297 | .364 | 0 | 1 |
| Rel. Fract. | 1788 | .304 | .31 | 0 | 1 |

**Table 3: Baseline Regression - Correlation of Schooling Efficiency and Height**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ln(Education Efficiency) | | | |
| Height | 0.095*** | 0.094*** | 0.078*** | 0.085*** |
| | (0.021) | (0.021) | (0.024) | (0.021) |
| Age at Marriage | | | -0.154*** | -0.107*** |
| | | | (0.029) | (0.024) |
| Share Muslim | | | 0.344** | 0.413*** |
| | | | (0.167) | (0.132) |
| Religious Fract. | | | 0.439* | 0.240 |
| | | | (0.232) | (0.157) |
| Constant | -14.925*** | -14.521*** | -8.919** | -12.163*** |
| | (3.280) | (3.433) | (3.938) | (3.696) |
| Birth Decade FE | No | Yes | Yes | Yes |
| Regional FE | No | Yes | Yes | Yes |
| Geographic Controls | No | No | No | Yes |
| Observations | 970 | 970 | 968 | 934 |
| R-Squared | 0.132 | 0.162 | 0.284 | 0.374 |

Notes: These regressions show our baseline model which estimates the relationship between adult height, as a proxy for nutritional status during childhood, and schooling efficiency for the sample of countries with ABCC < 95. The underlying dataset is a panel of African admin I regions for birth decades 1950 to 1990. While column 1 shows the raw correlation, column 2 adds birth decade and regional fixed effects, column 3 sociodemographic controls and column 4 geographical controls. The geographical controls include the length of colonization, colonial railways, diamond mines, explorer routes, nutrient availability, soil toxicity and workability, malaria ecology index, petroleum sites, ruggedness, ancient trade routes, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, population density and area. Standard errors in parentheses and are adjusted for serial and spatial autocorrelation. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

**Table 4: Instrumental Variable Regression – The Impact of Nutrition on Schooling Efficiency**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | ln(Education Efficiency) | | | | | | | |
| | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage |
| Height | | 0.179** | | 0.266*** | | 0.167** | | 0.366*** |
| | | (0.078) | | (0.102) | | (0.074) | | (0.136) |
| Rainfall Shock | 0.111*** | | 0.130*** | | 0.128*** | | 0.066*** | |
| | (0.022) | | (0.026) | | (0.027) | | (0.023) | |
| Age at Marriage | | | | | 0.161* | -0.137*** | 0.246*** | -0.169*** |
| | | | | | (0.086) | (0.044) | (0.082) | (0.050) |
| Share Muslim | | | | | 0.890* | 0.079 | 0.425 | -0.058 |
| | | | | | (0.497) | (0.181) | (0.518) | (0.208) |
| Religious Fract | | | | | 0.956 | 0.802** | 0.641 | 0.228 |
| | | | | | (0.609) | (0.355) | (0.588) | (0.268) |
| Constant | 155.013*** | -28.372** | 155.504*** | -42.148*** | 151.273*** | -23.564** | 149.558*** | -55.855*** |
| | (0.775) | (12.337) | (0.805) | (16.292) | (2.311) | (11.220) | (2.504) | (20.649) |
| Birth Decade FE | No | | Yes | | Yes | | Yes | |
| Regional FE | No | | Yes | | Yes | | Yes | |
| Geographic controls | No | | No | | No | | Yes | |
| Observations | 712 | 712 | 712 | 712 | 712 | 712 | 705 | 705 |
| R-squared | 0.072 | 0.081 | 0.298 | 0.039 | 0.316 | 0.201 | 0.520 | 0.194 |
| F-Statistic (1st Stage) | 26.01 | | 13.21 | | 10.35 | | 14.43 | |

Notes: These regressions show our IV model which estimates the relationship between adult height, as a proxy for nutritional status during childhood, and schooling efficiency for the sample of countries with ABCC < 95. Height is instrumented by rainfall during pregnancy and early childhood. The underlying dataset is a panel of African admin I regions for birth decades 1950 to 1990. The first set of regressions is without further controls, the second adds birth decade and regional fixed effects, the third sociodemographic controls and the fourth geographical controls. The geographical controls include the length of colonization, colonial railways, diamond mines, explorer routes, nutrient availability, soil toxicity and workability, malaria ecology index, petroleum sites, ruggedness, ancient trade routes, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, population density and area. Standard errors are in parentheses and clustered at the admin I level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

**Table 5: Robustness Check with Alternative ABCC Cut-Off**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ABCC < 90 | | ABCC < 85 | |
| | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage |
| Height | | 0.415*** | | 0.513** |
| | | (0.154) | | (0.213) |
| Rainfall Shock | 0.062*** | | 0.061** | |
| | (0.022) | | (0.024) | |
| Age at Marriage | 0.215*** | -0.179*** | 0.242** | -0.192*** |
| | (0.082) | (0.054) | (0.095) | (0.074) |
| Share Muslim | 1.044** | -0.290 | 1.710*** | -0.709 |
| | (0.448) | (0.259) | (0.423) | (0.459) |
| Religious Fract | 1.562*** | -0.144 | 2.445*** | -0.853 |
| | (0.594) | (0.370) | (0.601) | (0.612) |
| Constant | 148.863*** | -63.104*** | 147.199*** | -77.726** |
| | (2.510) | (23.041) | (3.014) | (31.668) |
| Birth Decade FE | Yes | | Yes | |
| Regional FE | Yes | | Yes | |
| Geographic controls | Yes | | Yes | |
| Observations | 613 | 613 | 464 | 464 |
| R-squared | 0.537 | 0.206 | 0.546 | 0.084 |
| F-Statistic (1st Stage) | 17.74 | | 20.85 | |

Notes: These regressions show our IV model which estimates the relationship between adult height, as a proxy for nutritional status during childhood, and schooling efficiency for alternative ABCC cut-offs as a robustness check. Height is instrumented by rainfall during pregnancy and early childhood. The underlying dataset is a panel of African admin I regions for birth decades 1950 to 1990. The first set of regressions uses an ABCC of 90 as a cut-off and the second set uses an ABCC of 85 as a cutoff. Both regressions include birth decade and regional fixed effects, sociodemographic and geographical controls. The geographical controls include the length of colonization, colonial railways, diamond mines, explorer routes, nutrient availability, soil toxicity and workability, malaria ecology index, petroleum sites, ruggedness, ancient trade routes, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, population density and area. Standard errors are in parentheses and clustered at the admin I level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

**Table 6: Robustness Check with Alternative Years of Schooling Cut-Off**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | 4 Years | | 5 Years | | 7 Years | | 8 Years | |
| | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage |
| Height | | 0.332*** | | 0.353*** | | 0.374*** | | 0.370*** |
| | | (0.126) | | (0.132) | | (0.140) | | (0.141) |
| Rainfall Shock | 0.066*** | | 0.066*** | | 0.066*** | | 0.066*** | |
| | (0.023) | | (0.023) | | (0.023) | | (0.023) | |
| Age at Marriage | 0.246*** | -0.118** | 0.246*** | -0.146*** | 0.246*** | -0.185*** | 0.246*** | -0.194*** |
| | (0.082) | (0.047) | (0.082) | (0.049) | (0.082) | (0.051) | (0.082) | (0.051) |
| Share Muslim | 0.425 | -0.233 | 0.425 | -0.125 | 0.425 | -0.011 | 0.425 | 0.017 |
| | (0.518) | (0.187) | (0.518) | (0.200) | (0.518) | (0.213) | (0.518) | (0.212) |
| Religious Fract | 0.641 | 0.041 | 0.641 | 0.158 | 0.641 | 0.280 | 0.641 | 0.318 |
| | (0.588) | (0.245) | (0.588) | (0.259) | (0.588) | (0.274) | (0.588) | (0.275) |
| Constant | 151.595*** | -52.110*** | 151.595*** | -54.952*** | 151.595*** | -58.116*** | 151.595*** | -57.887*** |
| | (1.459) | (11.813) | (1.459) | (12.607) | (1.459) | (13.698) | (1.459) | (13.845) |
| Birth Decade FE | Yes | | Yes | | Yes | | Yes | |
| Regional FE | Yes | | Yes | | Yes | | Yes | |
| Geographic controls | Yes | | Yes | | Yes | | Yes | |
| Observations | 705 | 705 | 705 | 705 | 705 | 705 | 705 | 705 |
| R-squared | 0.520 | 0.155 | 0.520 | 0.176 | 0.520 | 0.206 | 0.520 | 0.226 |
| F-Statistic (1st Stage) | 14.43 | | 14.43 | | 14.43 | | 14.43 | |

Notes: These regressions show our IV model which estimates the relationship between adult height, as a proxy for nutritional status during childhood, and schooling efficiency for the sample of countries with ABCC < 95. We employ alternative numbers of years of schooling in the calculation of the schooling efficiency index as a robustness check. Height is instrumented by rainfall during pregnancy and early childhood. The underlying dataset is a panel of African admin I regions for birth decades 1950 to 1990. The first set of regressions uses an ABCC of 90 as a cut-off and the second set uses an ABCC of 85 as a cutoff. Both regressions include birth decade and regional fixed effects, sociodemographic and geographical controls. The geographical controls include the length of colonization, colonial railways, diamond mines, explorer routes, nutrient availability, soil toxicity and workability, malaria ecology index, petroleum sites, ruggedness, ancient trade routes, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, population density and area. Standard errors are in parentheses and clustered at the admin I level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

## Appendix

Data Sources

### Table A.1: IPUMS data availability per decade

| 1960 | 1970 | 1980 | 1990 | 2000 | 2010 |
|---|---|---|---|---|---|
| Kenya | Benin | Botswana | Benin | Benin | Benin |
| Togo | Cameroon | Burkina Faso | Botswana | Botswana | Botswana |
| | Kenya | Cameroon | Burkina Faso | Burkina Faso | Ghana |
| | Liberia | Ethiopia | Ethiopia | Cameroon | Guinea |
| | Togo | Ghana | Guinea | Ethiopia | Mauritius |
| | | Guinea | Kenya | Ghana | Nigeria |
| | | Kenya | Lesotho | Kenya | Rwanda |
| | | Malawi | Malawi | Lesotho | Senegal |
| | | Mali | Mali | Liberia | South Africa (x2) |
| | | Senegal | Mauritius | Malawi | Tanzania |
| | | Tanzania | Mozambique | Mali | Togo |
| | | | Rwanda | Mauritius | Uganda |
| | | | South Africa | Mozambique | Zambia |
| | | | Uganda | Nigeria(x4) | Zimbabwe |
| | | | Zambia | Rwanda | |
| | | | | Senegal | |
| | | | | Sierra Leone | |
| | | | | South Africa(x2) | |
| | | | | South Sudan | |
| | | | | Sudan | |
| | | | | Tanzania | |
| | | | | Uganda | |
| | | | | Zambia | |

### Table A.2: MICS data availability per wave

| Wave 3 | Wave 4 | Wave 5 | Wave 6 |
|---|---|---|---|
| Centr. African Rep. | Centr. African Rep. | Benin | Centr. African Rep. |
| Ghana | Ghana | Cameroon | Chad |
| Mauritania | Togo | Côte d'Ivoire | DR Congo |
| Malawi | Swaziland | Congo, Rep. | Gambia |
| | | Guinea-Bissau | Guinea-Bissau |
| | | Mali | Ghana |
| | | Mauritius | Lesotho |
| | | Malawi | Madagascar |
| | | Nigeria | Sierra Leone |
| | | São Tomé & Princ. | São Tomé & Princ. |
| | | Swaziland | Togo |
| | | Zimbabwe | Zimbabwe |

**Table A.3: DHS data availability per wave**

| Wave 2 | Wave 3 | Wave 4 | Wave 5 | Wave 6 | Wave 7 |
|---|---|---|---|---|---|
| Burkina Faso | Burkina Faso | Burkina Faso | DR Congo | Burkina Faso | Angola |
| Cameroon | Benin | Benin | Ghana | Benin | Benin |
| Ghana | Centr. African Rep. | Cameroon | Kenya | Burundi | Burundi |
| Niger | Côte d'Ivoire | Ethiopia | Liberia | DR Congo | Cameroon |
| Senegal | Ghana | Ghana | Lesotho | Rep. Congo | Ethiopia |
| | Guinea | Guinea | Madagascar | Cameroon | Guinea |
| | Mali | Kenya | Mali | Ethiopia | Liberia |
| | Niger | Lesotho | Malawi | Gabon | Mali |
| | Senegal | Mali | Nigeria | Ghana | Malawi |
| | Togo | Malawi | Namibia | Guinea | Nigeria |
| | | Nigiera | Rwanda | Kenya | Rwanda |
| | | Namibia | Sierra Leone | Comoros | Siera Leone |
| | | Senegal | eSwatini | Liberia | Senegal |
| | | Togo | Tanzania | Lesotho | Tanzania |
| | | Uganda | Uganda | Mali | Uganda |
| | | Zimbabwe | Zambia | Mozambique | South Africa |
| | | | Zimbabwe | Nigeria | Zambia |
| | | | | Namibia | Zimbabwe |
| | | | | Rwanda | |
| | | | | Sierra Leone | |
| | | | | Senegal | |
| | | | | Tchad | |
| | | | | Togo | |
| | | | | Uganda | |
| | | | | Zambia | |
| | | | | Zimbabwe | |

**Table A.4: Afrobarometer data availability per wave**

| Wave 1 | Wave 2 | Wave 3 | Wave 4 | Wave 5 | Wave 6 | Wave 7 |
|---|---|---|---|---|---|---|
| Botswana | Botswana | Benin | Benin | Benin | Benin | Benin |
| Ghana | Cape Verde | Botswana | Botswana | Botswana | Botswana | Botswana |
| Lesotho | Ghana | Cape Verde | Burkina Faso | Burkina Faso | Burkina Faso | Burkina Faso |
| Malawi | Kenya | Ghana | Cape Verde | Burundi | Burundi | Cameroon |
| Mali | Lesotho | Kenya | Ghana | Cameroon | Cameroon | Cape Verde |
| Namibia | Malawi | Lesotho | Kenya | Cape Verde | Cape Verde | Côte d'Ivoire |
| Nigeria | Mali | Madagascar | Lesotho | Côte d'Ivoire | Côte d'Ivoire | Gabon |
| South Africa | Mozambique | Malawi | Liberia | Ghana | Gabon | Gambia |
| Tanzania | Namibia | Mali | Madagascar | Guinea | Ghana | Ghana |
| Uganda | Nigeria | Mozambique | Malawi | Kenya | Guinea | Guinea |
| Zambia | Senegal | Namibia | Mali | Lesotho | Kenya | Kenya |
| Zimbabwe | South Africa | Nigeria | Mozambique | Liberia | Lesotho | Lesotho |
| | Tanzania | Senegal | Namibia | Madagascar | Liberia | Liberia |
| | Uganda | South Africa | Nigeria | Malawi | Madagascar | Madagascar |
| | Zambia | Tanzania | Senegal | Mali | Malawi | Malawi |
| | Zimbabwe | Uganda | South Africa | Mauritius | Mali | Mali |
| | | Zambia | Tanzania | Mozambique | Mauritius | Mauritius |
| | | Zimbabwe | Uganda | Namibia | Mozambique | Mozambique |
| | | | Zambia | Niger | Namibia | Namibia |
| | | | Zimbabwe | Nigeria | Niger | Niger |
| | | | | Senegal | Nigeria | Nigeria |
| | | | | Sierra Leone | Senegal | Senegal |
| | | | | South Africa | Sierra Leone | Sierra Leone |
| | | | | Sudan | South Africa | South Africa |
| | | | | Swaziland | Sudan | Sudan |
| | | | | Tanzania | Swaziland | Swaziland |
| | | | | Togo | São T. & P. | São T. & P. |
| | | | | Uganda | Tanzania | Tanzania |
| | | | | Zambia | Togo | Togo |
| | | | | Zimbabwe | Uganda | Uganda |
| | | | | | Zambia | Zambia |
| | | | | | Zimbabwe | Zimbabwe |

## Table A.5: Geographic control variables

| Variable | Source | Comments | Access |
|---|---|---|---|
| Length of Colonisation | Henderson and Whatley (2014) | length of colonization of a country in years | Henderson, M., & Whatley, W. (2014), Pacification and Gender in Colonial Africa: Evidence from the Ethnographic Atlas. MPRA Paper No. 61203. |
| Colonial Railways | Nunn (2011) | dummy if colonial railway in admin I | Nunn, N. (2011), The Slave Trade and the Origins of Mistrust in Africa. American Economic Review, 101 (7), 3221-3252. |
| Diamond Mines | Peace Research Institute Oslo (PRIO) | calculated number of diamond mines per admin I area | https://www.prio.org/Data/Geographical-and-Resource-Datasets/Diamond-Resources/ |
| Explorer Routes | Nunn (2011) | dummy if pre-colonial explorer route in admin I | Nunn, N. (2011), The Slave Trade and the Origins of Mistrust in Africa. American Economic Review, 101 (7), 3221-3252. |
| Global Agro-ecological Zones (GAEZ) | Fischer et al. (2008) | mean value of nutrient availability, soil toxicity and soil workability per adminI area | http://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/ |
| Malaria Ecology Index | Kiszewski (2004) | mean value per admin I | https://sites.google.com/site/gordoncmccord/datasets |
| Missions | Cagé and Rueda (2016); Cagé and Rueda (2020), Nunn (2010) | dummy if Christian mission in admin I | https://rdmc.nottingham.ac.uk/handle/internal/8312 https://scholar.harvard.edu/nunn/pages/data-0 |
| Petrolium | Peace Research Institute Oslo (PRIO) | calculated a 0.2 degree (about 20 kilometres at the equator) buffer around each polygon for on- and offshore deposits and the estimated the overlap with admin I areas | https://www.prio.org/Data/Geographical-and-Resource-Datasets/Petroleum-Dataset/Petroleum-Dataset-v-12/ |
| Ruggedness | Nunn and Puga (2012) | mean value per adminI | Nunn, N., & Puga, D. (2012), Ruggedness: The blessing of bad geography in Africa. Review of Economics and Statistics, 94(1), 20-36. |
| Traderoutes | OWTRAD | dummy if ancient traderoute in admin I | http://www.ciolek.com/OWTRAD/DATA/tmcDZm0500.html |
| TseTse Fly Suitability | FAO | mean value of tsetse fly index for morsitans per admin I | https://data.apps.fao.org/map/catalog/srv/eng/catalog.search#/metadata/f8a4e330-88fd-11da-a88f-000d939bc5d8 |
| Ratio nomadic pastoralism to sedentary agriculture | Beck and Sieber (2010) | logarithm of the suitability for nomadic pastoralism to the suitability for sedentary agriculture based on a maximum entropy model | Beck, J., & Sieber, A. (2010). Is the spatial distribution of mankind’s most basic economic traits determined by climate and soil alone? PLoS ONE, 5(5), 2–10. |
| Population Density | HYDE 3.2 | population density per birth decade for each admin I area | Klein Goldewijk, K., A. Beusen, J.Doelman and E. Stehfest (2017), Anthropogenic land use estimates for the Holocene; HYDE 3.2, Earth System Science Data, 9, 927-953. |
| Area | n.a. | area of admin I region in square kilometers | |

Data Validation

**Respondent Bias**: To detect whether there is any bias in the responses given by women in IPUMS or AB surveys we first re-estimate our ABCC results separately by the gender of the respondent from all data sources. Next, we estimate the following regression

$$ABCC_{it} = \beta_0 + \beta_1 * Data_{it} + \beta_2 * Gender_{it} + \beta_3 Gender_{it} * Data_{it} + X_{it} + \varepsilon_{it} \quad (1)$$

where *Data* denotes a dummy that equals to one if the data source is IPUMS or Afrobarometer respectively and zero if it is MICS. *Gender* is a dummy whether the ABCC estimates describe a female or male population. We include country, birth decade and decile fixed effects. The coefficient of interest is $\beta_3$ which if significant would indicate that there is a gender bias in the IPUMS or AB surveys. We do not find any evidence for a respondent bias in the IPUMS, however, a statistically significant result in the Afrobarometer data. Yet, the difference is small enough to be considered economically irrelevant in the later estimation such that we do need to be concerned.

**Table A.6: Respondent bias**

| | (1)<br>ABCC | (2)<br>ABCC |
|---|---|---|
| IPUMS | -5.875*** | |
| | (0.351) | |
| Male=0/Female=1 | -0.057 | -0.067 |
| | (0.337) | (0.327) |
| IPUMS * Female | -0.507 | |
| | (0.426) | |
| Afrobarometer | | -2.957*** |
| | | (0.448) |
| Afrobarometer * Female | | -1.325** |
| | | (0.614) |
| Constant | 26.480*** | 46.723*** |
| | (2.590) | (3.044) |
| Region FE | Yes | Yes |
| Birth Decade FE | Yes | Yes |
| Quartile FE | Yes | Yes |
| Observations | 3,782 | 1,932 |
| R-squared | 0.827 | 0.720 |

Notes: Standard errors are robust. Asterisks denote significance at levels *** p<0.01, ** p<0.05, * p<0.1.

**Marriage Bias**: To detect whether there is an upward bias in the ABCC index for married women as suggested by A'Hearn et al. (2021) we re-estimate the index for married and widowed/separated women separately. We first conduct a simple t-test to compare the results for married and widowed/separated women per age group. While married woman on average have slightly higher levels of numeracy the difference is never statistically significant.

**Table A.7: Marriage bias – T-tests**

| | Married | Wid./Sep. | Diff. | Std. Error | Obs. |
|---|---|---|---|---|---|
| ABCC (23-32 Years) | 82.455 | 80.011 | 2.444 | 3.973 | 52 |
| ABCC (33-42 Years) | 82.718 | 79.852 | 2.866 | 4.004 | 52 |
| ABCC (43-52 Years) | 80.305 | 77.002 | 3.303 | 4.684 | 52 |
| ABCC (53-62 Years) | 86.983 | 83.956 | 3.027 | 4.644 | 40 |

**Ageing Bias**: To detect whether there is a bias with regard to age we separately estimate the ABCC Index for each age group per birth decade. This results in a sample in which we have an estimate for numerical abilities per admin I area for people who were born in the same birth decade but who were asked at different points in life as the surveys were conducted over several decades. Thus, we can compare the ABCC Index of a highly similar group of people at different ages. For this exercise we restrict our sample to the IPUMS data as the sample sizes are large enough to estimate the ABCC index at such a fine level without losing too many observations. Table A.8 shows the results of the comparison. We do observe that we estimate for older age groups a lower ABCC Index on average and we do find some significant differences. However, there does not appear to be a systematic pattern. For example, the difference between the age group 23 to 32 and 33 to 42 is only statistically significant for the 1960s birth decade.

Nevertheless, while there appears to be at least a modest downward trend over the course of life that is important to keep in mind, our data structure is in our favor. In the IPUMS data more than 40 percent of the observations fall into the youngest age group and almost another 30 percent in the second age group. Since we weight the data by age group size in our ABCC calculations, the older age groups with a potential downward bias receive less overall weight. Therefore, we do not believe that this observation causes any real disturbance in our data nor in the subsequent analysis.

**Table A.8: Comparison ABCC by age group per birth decade**

| Birth Decade | ABCC | | | | Differences | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 23-32 Years (1) | 33-42 Years (2) | 43-52 Years (3) | 53-62 Years (4) | (1) - (2) | (1) - (3) | (1) - (4) | (2) - (3) | (2) - (4) | (3) - (4) |
| 1950 | 81.277 | 84.322 | 77.281 | 77.196 | -3.0459 | 3.996 | 4.081 | 7.042 | 7.126 | 0.0849 |
| | (1.664) | (1.296) | (1.270) | (1.311) | (2.209) | (2.430) | (2.462)* | (1.871)*** | (1.898)*** | (18.825) |
| 1960 | 85.502 | 81.048 | 77.47 | *no data* | 4.754 | 8.331 | | 3.578 | | |
| | (1.181) | (1.093) | (1.219) | | (1.641)*** | (1.754)*** | | (3.578)** | | |
| 1970 | 81.478 | 80.183 | *no data* | *no data* | 1.295 | | | | | |
| | (1.056) | (1.052) | | | (1.492) | | | | | |

Notes: Standard errors in parentheses. Asterisks denote significance at levels *** p<0.01, ** p<0.05, * p<0.1.

**Data Source Bias:** As we discussed in the main text using age heaping as a measure for numerical abilities is only feasible if the data is not heavily counterchecked by enumerators. Ideally, we would like these to simply note whatever the respondent has answered without questioning how reasonable the age statement is. However, this is unlikely to always be the case and therefore we provide estimates for a potential bias by which we can correct our estimates.

Since we have age data from different sources that have a geographical overlap, we can compare our estimated ABCC Index within this overlap. For this procedure we use IPUMS as our baseline data as it has lowest ABCC Index on average. We cannot ultimately rule out that there is no upward bias in the IPUMS data due to counterchecking either. Nevertheless, it allows us to countercheck our other two data sources. Therefore, we estimate the following model:

$$ABCC_{it} = \beta_0 + \beta_1 * DataDummy_{it} + X_{it} + \varepsilon_{it}, \qquad (2)$$

where $DataDummy$ denotes a dummy that equals to one if the data for the ABCC Index is sourced from MICS or AB surveys and zero if it is sourced from IPUMS. $X$ is a vector of region, birth decade and quartile fixed effects. Table A.9 shows the results which indicate that there is a small upward bias both in the AB as well as the MICS data. Therefore, we adjust our estimates from these sources by the estimated coefficient to reduce the overall potential bias.

**Table A.9: Bias by data source**

| | (1)<br>ABCC | (2)<br>ABCC |
|---|---|---|
| Afrobarometer Data | 1.921** | |
| | (0.784) | |
| MICS Data | | 4.819*** |
| | | (0.670) |
| Constant | 41.346*** | 41.976*** |
| | (1.226) | (1.455) |
| Region FE | Yes | Yes |
| Birth Decade FE | Yes | Yes |
| Quartile FE | Yes | Yes |
| Observations | 859 | 928 |
| R-squared | 0.794 | 0.777 |

Robust standard errors in parentheses. Asterisks denote significance at levels *** p<0.01, ** p<0.05, * p<0.1.

**Alternative Digit Preference**: First, we manually inspected histograms for each country and survey type to inspect if we can observe any alternative heaping pattern. Below we show to exemplary histograms, one from a country with a high level of age heaping (Sudan) and one with a low level of age heaping (Zambia). We observe that in countries with much age heaping the most popular terminal digits are zero and five. Moreover, in countries with higher numeracy levels the most popular terminal digits remain zero and five, however, two and eight are almost or as popular.

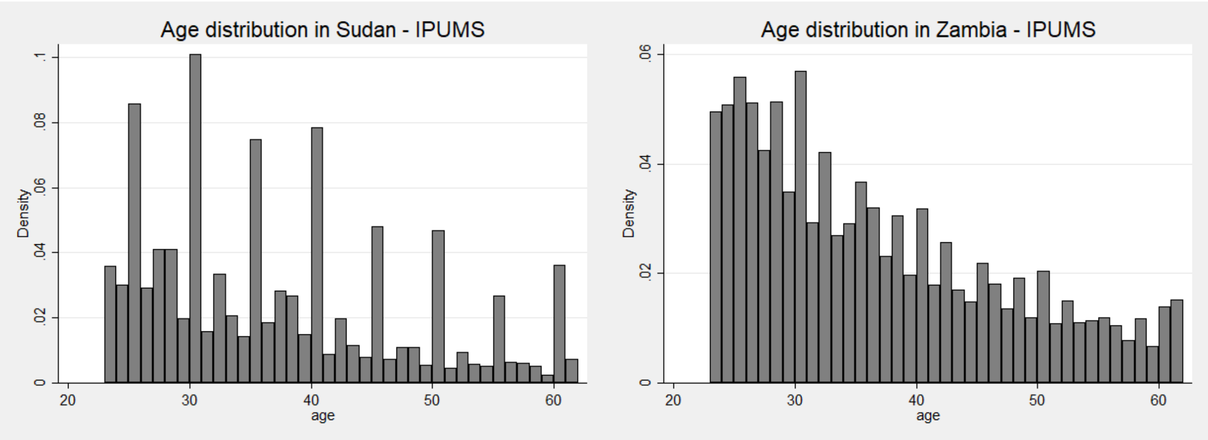



*Figure A.1: Exemplary age distributions from Sudan's and Zambia's censuses based on IPUMS data. Authors' own representation.*

Therefore, we adopt the Whipple and ABCC index such that it additionally becomes sensitive to heaping on two and height.

$$W_{it}^{alt} = \frac{n_{it}^{25}+n_{it}^{28}+n_{it}^{30}+n_{it}^{33}+n_{it}^{35}+\cdots+n_{it}^{62}}{\frac{2}{5} * \sum_{age=23}^{62} n_{it}^{age}} * 100 \quad \text{(A1)}$$

$$ABCC_{it}^{alt} = \left(1 - \frac{W_{it}-100}{150}\right) * 100 \; if \; Wh_{it}^{alt} \geq 100; else \; ABCC_{it}^{alt} = 100 \quad \text{(A2)}$$

As before a value of zero indicates that everyone within a given group heaps their age and 100 indicates that no one heaps.

Next, we compare our original ABCC Index with the newly calculated alternative version. Figure A.2 shows a scattergram of both indices and the high correlation of both measures is clearly visible. The correlation coefficient is about 0.95. Hence, there little difference between our indicators. Moreover, we can show in Table A.10 that our original ABCC index correlates higher with alternative measures of education such as years of schooling and literacy.

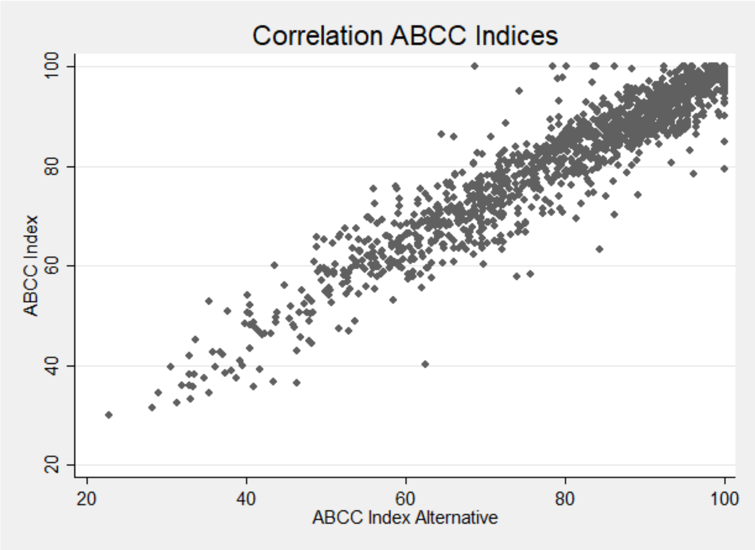



*Figure A.2: Correlation of traditional ABCC Index and alternative ABCC Index. Authors' own representation.*

**Table A.10: Pairwise Correlation ABCC Indices**

| | ABCC Index | Alt. ABCC Index |
|---|---|---|
| Years of Schooling | 0.4287 | 0.3575 |
| Literacy | 0.4875 | 0.4123 |

Baseline OLS Regression without adjustment for serial and spatial autocorrelation

**Table A.11: Baseline OLS Regression - Correlation of Schooling Efficiency and Height**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ln(Education Efficiency) | | | |
| Height | 0.095*** | 0.094*** | 0.078*** | 0.085*** |
| | (0.015) | (0.018) | (0.020) | (0.020) |
| Age at Marriage | | | -0.154*** | -0.107*** |
| | | | (0.026) | (0.023) |
| Share Muslim | | | 0.344** | 0.413*** |
| | | | (0.165) | (0.149) |
| Religious Fract. | | | 0.439* | 0.240 |
| | | | (0.249) | (0.207) |
| Constant | -14.925*** | -14.521*** | -8.919** | -12.163*** |
| | (2.375) | (2.855) | (3.482) | (3.510) |
| Birth Decade FE | No | Yes | Yes | Yes |
| Regional FE | No | Yes | Yes | Yes |
| Geographic Controls | No | No | No | Yes |
| Observations | 970 | 970 | 968 | 934 |
| R-Squared | 0.069 | 0.101 | 0.232 | 0.332 |

Notes: These regressions show our baseline model which estimates the relationship between adult height, as a proxy for nutritional status during childhood, and schooling efficiency for the sample of countries with ABCC < 95. The underlying dataset is a panel of African admin I regions for birth decades 1950 to 1990. While column 1 shows the raw correlation, column 2 adds birth decade and regional fixed effects, column 3 sociodemographic controls and column 4 geographical controls. The geographical controls include the length of colonization, colonial railways, diamond mines, explorer routes, nutrient availability, soil toxicity and workability, malaria ecology index, petroleum sites, ruggedness, ancient trade routes, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, population density and area. Standard errors are in parentheses and clustered at the admin I level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Background to School Feeding Interventions

A policy that is highly popular among policy makers and large organisations such as the United Nations are school feeding programs. They have been implemented by governments and the World Food Programme in more than half of low and lower-middle income countries (Jomaa et al., 2011). The rationale for this policy is that first, it incentivizes children to attend school as they receive a meal or a take home ration conditional on attendance and second, children who are better nourished are better able to concentrate and learn during classes. The importance of adequate nutrition for children's cognitive development is well-established in the literature (see Bryan et al., 2004 for a review). Numerous studies have investigated whether this effect also increases children's enrolment and achievement in schools for the Sub-Saharan African context.

Most evidence on school-feeding programs in Sub-Saharan Africa finds positive impacts of school feeding programs on school performance (Mensah and Nsabimana, 2020; Kazianga et al., 2012; Kazianga et al., 2014; Nikiema, 2017; Aurino et al., 2020; Diagne et al., 2014; Azomahou et al., 2019). Moreover, one intervention has focused on the quality of the meals provided through school feeding programs and finds that the better the nutrient content of the meal, the larger is the positive impact (Hulett et al., 2014). There is also evidence that students who receive meals at school do not receive less food at home as a consequence but overall increase their consumption of calories and nutrients (Jacoby, 2002; Ahmed, 2004; Islam and Hoddinott, 2009). Overall, these findings are supported by studies from other world regions (Powell et al., 1998 for Jamaica; Jacoby et al., 1996 and Cueto and Chinen, 2008 for Peru; Ismail et al., 2014 for Guyana; Buttenheim et al., 2011 for Laos; Cheung and Berlin, 2015 for Cambodia; Afridi, 2010; Jayaraman and Simroth, 2015 and Charkaborty and Jayaraman, 2019 for India).

Nevertheless, other interventions in Sub-Saharan Africa found no evidence for the beneficial effects of a school feeding program (Parker et al., 2015; Alderman et al., 2012). Additionally, some scholars have argued that while school feeding can be a complement to an efficient school system it is neither cost-efficient nor effective enough to provide sustainable solutions to the existing 'schooling crisis' (Alderman and Bundy, 2012). Thus, our paper contributes to this discussion by providing a long-run perspective of the impact of children's nutrition on schooling outcomes.

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