Education in Sub-Saharan Africa: Its Development and Determinants

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A Introduction

A.1 Motivation

The first goal of the United Nations' Sustainable Development Goals (SDGs) is to eradicate poverty. More specifically, target 1.1 aims to "by 2030, eradicate extreme poverty for all people everywhere" (UNDESA, 2024). On a global scale, substantial progress has been made toward achieving this goal. In 1990, approximately 37.9 percent of the world's population lived in absolute poverty, whereas by 2018, this figure had declined to 8.8 percent (World Bank, 2025b).[1] However, this progress has not been evenly distributed across countries. The substantial reduction in absolute poverty has been primarily driven by developments in Asia, particularly in China (Alvaredo and Gasparini, 2015; Chen and Ravallion, 2010). In contrast, progress in Sub-Saharan Africa has been significantly slower. In 1990, 54.9 percent of the region's population lived in absolute poverty; by 2018, this had declined to 36.9 percent (World Bank, 2025b). In absolute numbers, poverty in the region has actually increased by more than 100 million individuals due to population growth. Clearly, eradicating absolute poverty in the near future will require substantial additional progress.

Both large multilateral organizations and national governments consider human capital development a crucial strategy for poverty reduction. As early as 1985, the World Bank emphasized the importance of education for sustained economic growth, arguing that investments in education contribute to long-term development (Psacharopoulos and Woodhall, 1985). Today, the World Bank remains one of the largest financiers of education in developing countries (World Bank, 2025a). Similarly, at the donor-country level, the German Development Cooperation, for instance, includes education components in more than 20 percent of ongoing projects (Deutsche Gesellschaft für Internationale Zussamenarbeit, 2025). In addition, national development plans across developing countries universally highlight the role of human capital (UNESCO, 2024). Given the widespread

[1] Absolute poverty is defined here as the share of the population living on less than \$2.15 per day, adjusted for 2017 Purchasing Power Parity prices.

emphasis on education among policymakers and researchers, significant attention has been devoted to understanding how to increase school enrollment and educational attainment in Sub-Saharan Africa to foster sustainable growth.

In terms of enrollment and years of schooling, Sub-Saharan Africa has seen remarkable progress. Many countries in the region have introduced free primary education (Filmer, 2023). Even before these policy changes, years of schooling had been increasing. Toward the end of the colonial period, individuals born in the 1950s had an average of about four years of schooling. For those born in the 1990s, this had risen to seven years (Ferber et al., 2023). While there is still a considerable number of children that remain out of school, more children than ever before are attending school in Sub-Saharan Africa today (UNESCO Institute for Statistics, 2025). Yet, why has this not led to greater reductions in poverty?

When assessing the output of the schooling system, i.e., the quality of education, the progress appears far less impressive. Le Nestour et al. (2022) provide a global overview of educational quality trends, showing that while unconditional literacy rates have improved in all world regions, particularly for women, expected literacy after five years of schooling has declined. This suggests that a child who completed primary school in the 1950s was more likely to be literate than a child today. Moreover, their findings reveal vast disparities between countries, indicating that years of schooling are neither comparable across time nor across regions. Overall, the quality of education in Sub-Saharan Africa has experienced a significant decline.

To ensure that education contributes to sustainable economic growth, it is crucial to understand the actual levels of educational attainment and their determinants over time. This doctoral dissertation provides a comprehensive analysis of the development of education over the last decades, as well as an investigation of its determinants, from both historical and contemporary perspectives. Before turning to the dissertation's content in greater detail, I first define human capital and how it can be measured to establish a common foundation. Second, I provide a brief review of the theoretical and empirical literature on the education-growth nexus. This is by no means an exhaustive review, but highlights the importance to understand educational development. Third, I outline the different lines of research on the determinants of education. Finally, I summarize the dissertation's objectives and structure.

A.2 Measuring Human Capital

Human capital does not have a universally agreed-upon definition. Adam Smith (1776) described it as the "acquired and useful abilities of all inhabitants or members of society" (p. 298). G. S. Becker (1983) later expanded on this, defining the acquisition of human capital as "activities that influence future monetary and psychic income by increasing resources in people" (p. 1). Similarly, the World Bank (2018) defines human capital as "the knowledge, skills, and health that people accumulate over their lives, enabling them to realize their potential as productive members of society" (p. 14). Some definitions focus exclusively on education, while others also include health. However, all highlight human capital's contribution to both individual and economic productivity. I focus on the education component of human capital and use the terms interchangeably. This does not dismiss the importance of health, but its inclusion lies beyond the scope of this dissertation.

A key distinction throughout this dissertation is between inputs into education, such as school enrollment or years of schooling, and outputs, meaning the skills acquired through education, such as literacy or numeracy. This distinction is crucial, as "schooling ain't learning" (Pritchett, 2013). Completing secondary education, for instance, does not guarantee literacy in Sub-Saharan Africa (UNESCO, 2021). Furthermore, the relationship between educational inputs and outputs varies across countries, regions, and time periods (Le Nestour et al., 2022; Filmer et al., 2020). While in some contexts, particularly in historical studies or data-scarce settings, years of schooling serve as the best available proxy for human capital, a focus on actual skill acquisition provides a more precise assessment of human capital and its determinants.

Several approaches exist for measuring human capital, each with its own advantages and limitations. First, test scores from international assessments provide a detailed analysis of skills in literacy and mathematics at the individual level or, if aggregated, at the regional or national level. These tests include the *Programme for International Student Assessment* (PISA) or for Sub-Saharan Africa the *Programme d'analyse des systèmes éducatifs de la Confemen* (PASEC) and the *Southern and Eastern Africa Consortium for Monitoring Educational Quality* (SACMEQ). In addition, there are national assessments, for instance the *Systemic Test* in South Africa, which I use in the last study of the dissertation. However, there are two important drawbacks to using these test scores. First, tracking educational development before the 21st century in Sub-Saharan

Africa is impossible as the earliest ones were conducted in the 1990s. Second, they only cover children who are attending school, leading to upward-biased estimates in countries with high out-of-school populations (Lilenstein, 2020). An exception to this are houeshold survey-based literacy and numeracy assessments such as those included in UNICEF's *Multiple Indicator Cluster Surveys* (MICS). Although these tests are much shorter, they include all children irrespective of schooling status, offering a more representative picture of educational attainment. The third study in this dissertation relies on this data.

Alternative measures of human capital are literacy and numeracy which allow to cover more countries and longer time periods. Both are fundamental skills which are important for economic production. Literacy as an indicator is more widely available as it is typically included in censuses or household surveys. Moreover, in historical applications the ability to sign documents such as marriage licenses is often used as an indicator of literacy. However, signing a document does not necessarily imply full literacy, as it remains unclear whether the individual can read or write beyond their name. Self-reported literacy measures can also be biased due to cultural factors or social stigma. Modern household surveys, such as USAID's *Demographic and Health Surveys*, address this issue by including a simple reading test, providing a more nuanced assessment of literacy. Despite its importance for monitoring educational progress, literacy measurement methodologies vary, making it difficult to compare estimates across time and space.

Numeracy, measured through age-heaping techniques, provides an alternative approach to estimating human capital. Individuals with lower numeracy skills tend to round their age to multiples of five or ten, allowing researchers to quantify deviations from a uniform distribution of terminal digits across groups (A'Hearn et al., 2009). Captured by the Whipple Index and its linear transformation, the ABCC Index, this indicator is commonly used in economic history to assess numeracy levels over time. While this method is no longer useful once basic numeracy skills become widespread, many Sub-Saharan African countries still struggle to reach this threshold, making age-heaping a valuable tool for tracking human capital development throughout the 20th century. The first two studies of this dissertation rely on numeracy estimates to analyze historical trends in human capital and its determinants across Sub-Saharan Africa.

Beyond these direct measures, economic historians have used a variety of alternative indicators to assess human capital development. The establishment of schools and universities (Cantoni and Yuchtman, 2014; Cagé and Rueda, 2016), the production and consumption of books (Baten and Van Zanden, 2008; Dittmar, 2011; Squicciarini and Voigtländer, 2015), and the number of registered patents (Moser et al., 2014) all serve as proxies for education and knowledge accumulation. The final study in this dissertation incorporates novel data on school locations and performance in the former Cape Colony, drawing from *Cape Colony Education Reports* and other archival sources to assess historical human capital development.

Each of these approaches has its strengths and weaknesses, emphasizing the need to select the most appropriate indicator given the available data and research objectives. The studies included in this dissertation carefully justify the choice of human capital indicators based on the specific context and research question. By employing multiple methods, this dissertation aims to provide a comprehensive analysis of human capital accumulation and its impact on economic outcomes in Sub-Saharan Africa.

A.3 Human Capital for Development

In the second half of the 20th century, economists began systematically investigating the relationship between human capital and economic returns. While the notion that human capital plays a crucial role in the economy had been introduced centuries earlier, for instance by Adam Smith (1776)[2], the formalization of this relationship occurred only two centuries later.

The theoretical microeconomic foundations of human capital's relationship with economic outcomes were laid by the seminal works of G. S. Becker (1983) and Theodore Schultz (1961). G. S. Becker (1983) developed a model illustrating how investment in human capital increases individual income, thereby contributing to economic growth. Schultz (1961) went so far as to argue that "the most distinctive feature of our economic system is the growth in human capital."

These insights were incorporated into endogenous growth models, which assmue that technological progress is determined within the system and can therefore be influenced by human capital

[2]In his seminal work "The Wealth of Nations", Adam Smith identifies three types of capital within a society. The first is capital intended for immediate consumption, such as food or clothing. The second is fixed capital, which includes not only machinery and commercial buildings but also "acquired and useful habits" (p. 298). Since acquiring human capital entails costs, both direct and opportunity costs, and subsequently generates returns, Smith classified it as a form of fixed capital. The third type is circulating capital, which consists of money, shop inventories, and intermediate goods.

accumulation.[3] For instance, Romer (1986) modeled human capital as an essential input to production. In his framework, individuals maximize profits by investing in human capital, thereby accelerating technological progress and fostering overall economic growth. Similarly, Lucas (1988) argued that different countries produce different goods, each requiring varying levels of human capital. In this view, comparative advantage in certain industries is directly linked to a country's human capital development.

Other models aim to understand the decisive role of human capital in economic development in the very long run. For example, Oded Galor's Unified Growth Theory offers a perspective on how human capital contributed to the onset of rapid economic growth across Western Europe in the 18th century. The theory proposes that human capital enabled societies to escape the Malthusian trap, creating a reinforcing cycle between technological progress and human capital growth leading to sustained development in the long run (Galor, 2005; Galor, 2024).

As different as these or other growth models are, they highlight the importance of human capital for economic growth. The predictions made by them have been tested extensively in the empirical literature which provides strong evidence for the positive impact of human capital on economic outcomes.

Cross-country studies consistently show that higher human capital is linked to greater economic growth. Early research primarily used years of schooling as the key explanatory variable (Barro, 1991; Mankiw et al., 1992). However, as data on education quality improved, economists demonstrated that the quality of education is an even stronger predictor of economic growth than the quantity of schooling (e.g., Hanushek and Woessmann, 2015). They also addressed endogeneity concerns, strengthening the causal interpretation of their findings. A recent overview of this literature is provided by Hanushek and Woessmann (2020).

Evidence on the positive individual returns to education further supports these findings. Seminal contributions by G. S. Becker (1983) and Mincer (1974) estimated substantial returns to additional schooling. More recently, Psacharopoulos and Patrinos (2018) found that, on average, one extra year of schooling increases earnings by nine percent, with particularly high returns in Latin America

[3] In contrast, exogenous growth models, such as the Solow (1956) model, posit that technological progress as a key driver of economic growth is exogenous, meaning it is not determined within the system but assumed to occur independently. As a result, these models do not explicitly account for human capital as a direct input into economic growth.

and Sub-Saharan Africa. Studies using (quasi-)experimental methods have also established a causal link between education and income gains across both developed and developing countries. For instance, Oreopoulos (2006) shows that extending compulsory schooling in the United Kingdom by one year led to significant income gains, while Acemoglu and Angrist (2000) report similar findings for the United States. Focusing on education quality, Chetty et al. (2014) provide evidence that higher teacher quality in the US translates into higher future earnings. In developing countries, school construction, for example, has been linked to higher lifetime earnings (Duflo, 2001; Akresh et al., 2023). The meta-analysis by Evans and Yuan (2017) underscores the potential of educational interventions in developing countries to improve economic outcomes. Beyond economic benefits, numerous studies emphasize the positive impact of education on crime reduction, health, and institutional quality (see Lochner (2011) for a review).

Historical evidence further reinforces the link between human capital and economic growth. For example, the establishment of universities stimulated market activity in the Middle Ages (Cantoni and Yuchtman, 2014). Increased book production, a proxy for advanced knowledge, is associated with economic growth in Western Europe from the 15th to 18th centuries (Baten and Van Zanden, 2008). Other studies have highlighted the role of education in industrialization (S. O. Becker et al., 2011; Galor et al., 2009; Squicciarini and Voigtländer, 2015). In the developing country context, research has focused on the long-term economic benefits of early formal education during the colonial period (e.g., Gallego and Woodberry, 2010; Frankema, 2012; Valencia Caicedo, 2019). On a global scale, Crayen and Baten (2010) show that differences in numeracy help explain economic growth disparities.

Both theoretical and empirical findings highlight the critical role of human capital in economic growth and poverty reduction. Theoretical models link education to technological progress, emphasizing its role in sustained economic development. Empirical research, from both macroeconomic and microeconomic perspectives, provides causal evidence that human capital enhances economic returns. To promote sustainable development, it is essential to understand how education evolves and to improve both access to and quality of education.

A.4 Determinants of Human Capital

Given the importance of improving educational outcomes, it is no surprise that economists have examined a wide range of potential determinants. My aim is not to provide an exhaustive list here but to highlight the value of considering multiple perspectives. While some interventions lead to straightforward improvements, such as deworming children increased educational attainment (Miguel and Kremer, 2004), other determinants may have non-linear or less direct effects. Since no single approach serves as a panacea, it is essential to take a holistic view of how different factors can contribute to the broader goal of providing quality education for every child. To this end, I outline various areas of research on educational determinants, accompanied by illustrative examples.

The first area of research focuses on interventions at the child or school level, often evaluated using randomized control trials or quasi-experimental methodologies. These studies examine interventions such as pedagogical training (Banerjee et al., 2007; Taylor and Von Fintel, 2016; Pugatch and Schroeder, 2014), increasing school resources (Glewwe et al., 2009; Evans and Ngatia, 2021; Kazianga et al., 2013), and health improvements (Clarke et al., 2008; Hulett et al., 2014). Findings from these interventions frequently offer concrete policy recommendations and, depending on data availability, allow for cost-effectiveness analyses. Such insights are valuable for policymakers at all levels as they can guide what (not) to use limited resources for. The second study in this dissertation falls within this area, as it investigates the impact of school feeding programs, a health intervention, on educational efficiency.

The second area of research examines how broader structural factors, such as national policies and other economic factors, affect education. Unlike child- or school-level interventions, these factors are typically beyond the control of individuals or local policy makers. Policy changes include the introduction of free primary education (Valente, 2019; Filmer, 2023) or cash transfer programs (Behrman et al., 2011; Kilburn et al., 2017; Benhassine et al., 2015). Broader economic factors include international trade policies (Li et al., 2019; Edmonds et al., 2010), migration (Salas, 2014; Schwank, 2024; Cockx, 2022), and labour market structures (Ahlerup et al., 2020; Shah and Steinberg, 2021) among other things. Many of these factors involve trade-offs: for instance, while free primary education in Sub-Saharan Africa expanded access to schooling, it also led to a decline in quality (Filmer, 2023). Because these structural determinants often have complex effects, they do not always lend themselves to clear-cut policy recommendations. Nonetheless, understanding these factors is crucial in assessing the broader context in which education systems operate. The third study in this dissertation aligns with this area, as it explores the links between child labour, poverty, and educational attainment.

The third area of research investigates the impact of historical and cultural factors on education. Historical determinants include, for example, the legacy of colonial education systems (Gallego and Woodberry, 2010; Frankema, 2012; Valencia Caicedo, 2019) and the influence of pre-colonial political structures (Funjika, 2023; Walters et al., 2023). Cultural influences may stem from religiosity or cultural traits such as patience or risk-aversion (Squicciarini, 2020; Figlio et al., 2019; Hanushek et al., 2022). While these determinants do not directly translate into immediate policy recommendations, they remain essential for informing policy design. A nuanced understanding of these historical and cultural contexts ensures that policies are appropriately tailored and culturally sensitive. The final study in this dissertation contributes to this area by examining the lasting impact of inquality in education in the former Cape Colony on contemporary learning outcomes in South Africa.

By considering these diverse areas of research, we can gain a more comprehensive understanding of the factors that shape educational outcomes. A holistic approach allows for more effective and contextually relevant policy interventions, ultimately advancing the goal of improving education for all.

A.5 Outline of Thesis

This dissertation consists of four chapters, each representing a stand-alone study intended for publication. Hence, these studies are sometimes referred to as papers or articles throughout this work. At the time of submission, two studies have already been published. Chapter B and Chapter C are co-authored with Jörg Baten, Chapter D is single-authored, and Chapter E is co-authored with Johan Fourie. The dissertation concludes with Chapter F.

Chapter B traces the development of human capital in Sub-Saharan Africa at the sub-national level from the 1950s to the 2000s, using birth cohort data. A common issue in demographic data of less numerate societies is age heaping, where a significant proportion of individuals round their ages, for example, stating that they are 40 years old when they are actually 38. This allows for the estimation of numerical skills by measuring deviations of terminal digits from a uniform distribution, known as the ABCC Index. By combining census and household survey data, this study provides coverage for almost all countries in Sub-Saharan Africa. Additionally, the study validates this methodology for Sub-Saharan Africa by assessing potential biases related to respondent gender, marriage, age, enumerator effects, and alternative digit preferences. The findings indicate that biases can either be adjusted for or are not strong enough to affect the overall conclusions. The estimates suggest little improvement in numeracy in Sub-Saharan Africa over time, with significant regional differences—Southern Africa performing best and Western Africa the worst. Some countries, such as Ghana, show positive development, while others, such as Niger, exhibit regression.

Chapter C builds on the previous study but focuses on the efficiency of education systems in conveying numerical skills. Using the same dataset, it estimates how much mathematics is learned per year of schooling and explores factors influencing this process. The findings indicate little change over time, but strong variations between countries and regions. To explore potential determinants of schooling efficiency, the study examines children's health using average height as a proxy. While potential height is largely genetically determined at the individual level, variations across populations reflect childhood nutritional conditions. To establish a causal link, deviations from long-term rainfall during in-utero and early childhood used as an instrumental variable. The results show that children's health significantly influences schooling efficiency, supporting policies such as school feeding programs aimed at improving child nutrition to enhance educational outcomes.

Chapter D shifts the focus to the contemporary economic context, examining the complex interplay between child labour, education, and poverty in Sub-Saharan Africa. While child labour is typically seen as a barrier to education, economic models suggest that in households living close to subsistence levels, additional income from child labour may be necessary to finance schooling. Otherwise, children might remain idle instead of attending school. This study utilizes data on 17 countries from the *Multiple Indicator Cluster Surveys* (MICS) by UNICEF, which provide detailed data on children's work both within (domestic work) and outside (child work) the household, as well as a short mathematics test. The findings reveal no negative association between domestic work and test performance, but a negative association between child work and learning outcomes.

However, when restricting the analysis to the poorest 20 percent of households, participation in work is positively associated with math test performance. Further analysis indicates that as long as the income effect of child work outweighs the substitution effect, work can contribute positively to education. This research does not seek to justify child labour but cautions against outright bans without financial compensation, as education does not necessarily improve in the absence of alternative support mechanisms.

Chapter E aims to understand how historical education systems can contribute to the reproduction of an educational elite in Sub-Saharan Africa, focusing on South Africa. Using novel data from the *Cape Colony Education Reports* (1881-1905) spatially linked with test scores in math and language from the 2018 Systemic Test conducted in the Western Cape, the study shows that mere proximity to a historical school has no consistent impact on contemporary school quality. This is in contrast to previous studies on the legacies of colonial education and suggest that in South Africa there are no broadly accessible benefits from these historic schools. However, the quality of historic white schools, captured by the share of students in attainment Standard 4 or higher, is associated with higher contemporary test scores. In contrast, there appears to be no persistent impact of the quality of black schools. These results are robust to a variety of specifications. Further analyses suggest that the results can be explained by the institutional continuity of high-quality historic white schools. These schools not only have been continuously operating over the last century but also produced a disproportionate share of the country's elite based on data from the *Who's Who of Southern Africa*. These results highlight how historical inequality in educational provision can persist over time and contributes to the inequality in opportunitiy in the contemporary South African education system.

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B Age Heaping Based Numeracy Estimates in African Regions, 1950–1999: New Methodological Advances and Results [4]

Abstract

During the post-colonial period, enrolment and years of schooling have increased substantially in Sub-Saharan Africa. However, this has been accompanied by a decline in the overall quality of education. As a result, it is important to focus on indicators such as numeracy and literacy, capturing the quality of education, rather than the input of schooling alone, to better understand educational attainment. Moreover, these skills have been associated, for example, to higher productivity and health. Numeracy, in particular, has been linked to sustained development. Therefore, measuring and understanding its development is a crucial first step to improve educational quality. Combining data from censuses and household surveys, we estimate numeracy at the subnational level for Sub-Saharan Africa employing the ABCC Index. Additionally, we carefully evaluate the suitability of the index and our data to capture basic numeracy – deeming it to be robust. We find mostly stagnating numeracy for the birth cohorts between 1950 and 1990, although some countries increased (for example, Ghana) and others declined. Moreover, we observe strong regional differences, with Southern Africa performing best and Western Africa worst.

[4]This chapter is based on an article by Ferber and Baten (2025), published in *Economic History of Developing Regions*. The version included in this dissertation is identical in content, with only minor textual differences. I was responsible for approximately 80 percent of the conceptual development and writing, while Jörg Baten contributed the remaining 20 percent.

B.1 Introduction

Education is a precondition for sustainable development (UNESCO, 2023). More educated individuals tend to be more productive (Chang et al., 2016; Kim and Loayza, 2019; Miller and Upadhyay, 2000) and healthier (Conti et al., 2010, Galama et al., 2018). Therefore, economists have taken a keen interest in estimating educational attainment and its determinants. Due to a lack of data availability, the initial focus was on inputs into the education system, such as enrolment and years of schooling. However, these figures are not necessarily very informative – simply being enrolled in or attending school does not guarantee that a child learns much (Pritchett, 2013). The 2021 Global Education Monitoring Report shows that even if an individual completes upper secondary education, they might not be literate. For example, in Benin, less than 70 percent of individuals with secondary education could read two simple sentences (UNESCO, 2021). Moreover, Le Nestour et al. (2022) have shown that the quality of education in Sub-Saharan Africa has substantially decreased over the last few decades, with significant spatial differences. Hence, capturing inputs instead of outputs of the education system has limited informational value in this context.

Both literacy and numeracy are essential outputs and fundamental skills, as reflected in their inclusion in the Sustainable Development Goals (SDG Target 4.6). Effective literacy skills enable individuals to find, consume and comprehend information from a wide range of fields, allowing them to acquire further knowledge (Ippolito et al., 2008). Numeracy skills encompass a diverse set of abilities, from basic computational skills to civic, digital, financial and health numeracy (UNESCO Institute for Lifelong Learning, 2020). While there is some overlap between these two skill sets, they are distinct, and adult numeracy remains under-researched (Gal et al., 2020). Additionally, better numeracy skills have been linked to higher economic growth in a global study (Hanushek and Woessmann, 2008). Therefore, to understand the development of education in Sub-Saharan Africa more holistically, measuring both numeracy and literacy is important. This approach can also help researchers understand the interlinkages of education with other development indicators such as health, civic engagement, or female empowerment.

Today, many countries participate in internationally comparable tests which capture both literacy and numeracy as well as the depth of students' knowledge. In Sub-Saharan Africa the *Programme d'analyse des systèmes éducatifs de la Confemen* (PASEC) and the *Southern and East-*

ern Africa Consortium for Monitoring Educational Quality (SACMEQ) have been conducting such tests since the 1990s. However, they cannot provide an overview concerning the long-run development of educational attainment, nor do they cover the substantial out-of-school population.

Indicators for literacy are more widely available, through either survey questions or proxies such as signature rates on official documents. For example, data on adult literacy is available for all countries in Sub-Saharan Africa except Botswana to measure progress on SDG 4.6. In contrast, data on adult numeracy is only available for South Africa (UNDESA, 2024). As questions on numerical abilities are typically not included in surveys, we need alternative methods to proxy this skill.

A'Hearn et al. (2009) argued that basic numeracy can be captured using the Whipple Index or its linear transformation, the ABCC Index. Its great advantage lies in the fact that the only data requirement is reported ages of individuals. The index calculates the share of rounded age statements (ages ending in 0 or 5) within a group and compares them to a uniform distribution to estimate the share of heaped age statements as a proxy for numerical abilities. The method is popular in economic history and has been applied over a wide range of regions and time periods (A'Hearn et al., 2009; Baten and Juif, 2014; Crayen and Baten, 2010; De Haas and Frankema, 2018; De Moor and Van Zanden, 2010). At the same time, a number of limitations for specific sources need to be taken into account (see below).

Nevertheless, this methodology is the only possibility to estimate numeracy for the birth decades 1950 to 1999, hence it was included also in the United Nations' global education monitoring programme (Baten, 2021a; Baten, 2021b).

The estimates show that there was neither an upward nor a downward trend in numeracy during our observational period. However, individual countries show progress, such as Ghana, or stagnation, such as Niger. We discuss these different developments in greater detail below and provide potential explanations. Moreover, there are strong spatial differences with Southern Africa performing best and Western Africa worst. Yet overall, the results align with research showing while many more children attend school, the expected increase in skills has not yet been realized (Le Nestour et al., 2022; UNESCO, 2021).

Alongside these results we provide a thorough discussion of our methodology, with regards to the link between age heaping and numerical skills as well as potential biases. Ensuring the quality of our data is crucial for the estimation of the ABCC Index. Recent literature has discussed some biases of the age heaping methodology that they find in their respective datasets (A'Hearn et al., 2022a; Beltrán Tapia et al., 2022; Földvári et al., 2012). These biases include the age reporting of women, as others might respond on their behalf or age statements might be adjusted to the husband's age, exaggerated age statements by elderly respondents, and counterchecking of age statements by enumerators, as well as alternative heaping patterns not captured by our index. Hence, after discussing methodological critiques from the literature, we provide evidence that the index is an appropriate proxy for numeracy in Sub-Saharan Africa and that we do not find evidence for these biases in our dataset.

The remainder of the article is structured as follows. Section 2 offers an overview of the literature on educational development in Sub-Saharan Africa and the ABCC Index. Section 3 details the dataset and the age heaping method. Section 4 provides an overview of numeracy trends in the region. Section 5 discusses methodological critiques, evaluates the ABCC Index as a proxy for numeracy and validates the data sources. Section 6 concludes the article.

B.2 Educational Development in Sub-Saharan Africa

The relevance of education for sustainable development has long been recognized. Hence, development economists have been working on evaluating the impact of various policies, for example by exploiting policy changes such as the introduction of universal primary education (e.g., Agüero and Bharadwaj, 2014; Osili and Long, 2008) or implementing randomized control trials focusing on more specific questions (e.g., Duflo et al., 2015; Glewwe et al., 2009) to improve educational outcomes in Sub-Saharan Africa. However, as important as this literature is, it does not provide us with any information about the development of education and its systems in Sub-Saharan Africa, which is crucial to understand the current state.

Little is known about educational levels in Sub-Saharan Africa before European contact, as data is scarce. One notable exception is by Baten and Alexopoulou (2022), who estimated elite numeracy starting in 1400 CE. They found that the rise of Southern African regions started in the eighteenth century, while previously Central and Western African regions were the main development nodes.

Bolt and Bezemer (2009) argue that while there was some formal education in Muslim-dominated areas in Sub-Saharan Africa before the arrival of Europeans, missionary education contributed substantially to the introduction of formal schooling in many other parts of Sub-Saharan Africa. However, the different colonial powers followed different strategies in terms of education. For example, Britain aimed for basic mass education provided by missionary societies, whereas France focused upon elite state-provided education (Cogneau and Moradi, 2014; Frankema, 2012). Most papers investigating the long-term impact of missionary education on today's years of schooling and literacy find an overall positive effect (e.g. Alesina et al., 2021; Cagé and Rueda, 2016; Fourie and Swanepoel, 2015; Gallego and Woodberry, 2010; Montgomery, 2017; Wantchekon et al., 2015; Wietzke, 2014). Concerning French colonial education, Huillery (2009) finds a relationship between colonial investments into education and today's educational outcomes. While the reliability of some of the colonial sources is still under debate (see e.g. Jedwab et al., 2022), the impact of early colonial investment in education appears to be, if anything, positive.

During the post-colonial period, it is undisputed that years of schooling increased very quickly (World Bank, 2018), albeit unevenly across genders (Baten et al., 2021). However, when considering this development, it is of importance to differentiate between the inputs and the outputs of the education system. After all, the acquired skills are what matter for growth (Hanushek and Woessmann, 2012). Yet, years of education are an input and can only provide information on how much time an individual has spent in school – not how much they learned during this time. This is not uniform across either space or time. For example, Singh (2020) shows strong differences between countries. Le Nestour et al. (2022) additionally provide evidence that the quality of education has substantially declined within countries in Sub-Saharan Africa over the past several decades. While in the 1950s the expected literacy rate after five years of schooling was about 80 percent, it declined to about 50 percent in the 1990s. Hence, while many more students started to attend school during this period, increasing overall literacy, literacy output per schoolyear decreased. This underlines the importance of considering output measures to assess the educational development rather than input measures, as even within a given country these might be misleading.

One drawback of the mentioned literature is that it does not consider numerical skills. Whilst literacy is one important component of human capital, numeracy is crucial as well. Higher performance in standardized math tests has been linked to higher growth (Hanushek and Woessmann, 2012; E. A. Jamison et al., 2007). Moreover, including both numeracy (as reflected in science skills) and years of schooling estimates in growth equations, Hanushek and Woessmann (2008) found numeracy to be more important. Further studies have considered effects at the individual level and found that higher numeracy increases agricultural efficiency (D. T. Jamison and Moock, 1984), financial literacy (Indefenso and Yazon, 2020; Villagómez Amezcua and Hidalgo Everardo, 2017) and health behaviour (Kempter and Upadhayay, 2022). Whether an individual is a subsistence farmer or a micro-entrepreneur, these skills are arguably beneficial in either occupation.

Several contributions have estimated numeracy for specific countries in Sub-Saharan Africa. For example, Baten and Fourie (2015) estimate numeracy in the Cape Colony. They observe that early numerical inequalities foreshadowed later inequality patterns. Considering education levels of the Coloured and isiXhosa speaking population of the Cape Colony, Fourie et al. (2014) report numeracy at South African mission stations employing the 1848 census. Several studies consider numeracy in Uganda using Anglican marriage registers (Meier Zu Selhausen and Weisdorf, 2016), census data (De Haas and Frankema, 2018) and mission hospital data (Doyle et al., 2020). Furthermore, Cappelli and Baten (2017) provide evidence on numeracy in Senegal, Gambia and Western Mali using French colonial census data. They studied the interaction of trade, contact between different ethnic groups, and human capital development in West Africa. They found that both the early European slave trade and the later cash crop trade intensified regional differences in numerical skill levels within the West African region under study, favouring the coastal regions and resulting in slower development of interior regions. Maravall et al. (2023) use regional estimates of numeracy to identify political leader selection patterns. Most closely related to our work are Cappelli and Baten (2021) and Ferber and Baten (2024). The former estimate numeracy using the ABCC Index at the national level between 1720 and 1970 for Sub-Saharan Africa and find a positive trend indicating an increasing acquisition of numerical skills. The latter employ the same methodology to estimate numeracy in the post-colonial period, but their focus is on schooling efficiency rather than the numerical skills themselves.

However, there is no comprehensive overview of numerical skills for the post-colonial period, and this paper aims to fill this gap by providing an overview of the development of numeracy in the post-colonial period (1950–1999) and discussing the methodological foundations in the Sub-Saharan African context.

B.3 Data and Method

B.3.1 Data

We draw our data from three distinct sources. The initial source is *Integrated Public Use Microdata Series* (IPUMS), an organization that compiles census data from countries across the globe and harmonizes this information. Our study incorporates data from 25 Sub-Saharan African countries,[5] encompassing one to five census iterations per country (as presented in Table B.10). Notably, this census data maintains representativeness even at subnational levels. The span of available census data ranges from the earliest survey in 1960 to the most recent one in 2016. One potential bias could originate from the use of household roster procedures in which one person responded on behalf of all household members. Although many studies in other temporal and regional units rejected this possibility, we are assessing it here (among others: Manzel et al., 2012; Tollnek and Baten, 2024 rejected this behaviour for census data and also provide a general overview). We cannot be sure for which censuses this might be the case. However, in the Supplementary Material we show that the ABCC Index estimated using only household heads (assuming they would be the primary respondent) and the ABCC Index using the remaining observations correlate almost perfectly (0.983). Hence, while we cannot fully exclude the possibility that not everyone gave a response themselves, we can show that it does not bias our results.

The second data source we leverage is the *Multiple Indicator Cluster Surveys* (MICS), which UNICEF has been conducting in 118 developing and emerging economies globally since the 1990s. MICS are surveys conducted at the household level, primarily focusing on matters impacting women and children, including maternal health. It is worth noting that only in their third and fourth rounds did the MICS team begin incorporating modules for men, dependent on the specific country. To ensure comprehensive national representation, our study exclusively employs surveys that incorporate modules for both women and men. The surveys used in our analysis are outlined in

[5]These 25 countries covered by IPUMS are Benin, Botswana, Burkina Faso, Cameroon, Ethiopia, Ghana, Guinea, Kenya, Lesotho, Liberia, Malawi, Mali, Mozambique, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, South Sudan, Sudan, Tanzania, Togo, Uganda, Zambia, and Zimbabwe.

Table B.11. Our dataset encompasses 21 Sub-Saharan African countries,[6] each with one to three survey waves. Notably, the latest wave (Wave 6) introduces a mathematics module for children aged 7–14, a component we later utilize in our analysis. The math test includes 21 questions. The first six questions ask children to name a printed number, followed by five questions about which of two printed numbers is larger. The third part presents five addition problems, and finally the children must name the missing number in a four-item numerical series. This foundational learning module was examined for its validity and reliability by UNICEF prior to administering the surveys (UNICEF, 2019). The results from these tests can be linked to their caretakers who provided age statements as part of the main survey, such that we can observe their heaping behaviour.

The final data source we tap into is the *Afrobarometer* (AB) surveys, an initiative that has been underway in 37 African countries since the late 1990s. Seven rounds have been conducted, with later rounds providing broader country coverage. Table B.12 lists all available surveys, covering a total of 33 Sub-Saharan African countries.[7] Each country's participation varies between one and seven rounds.

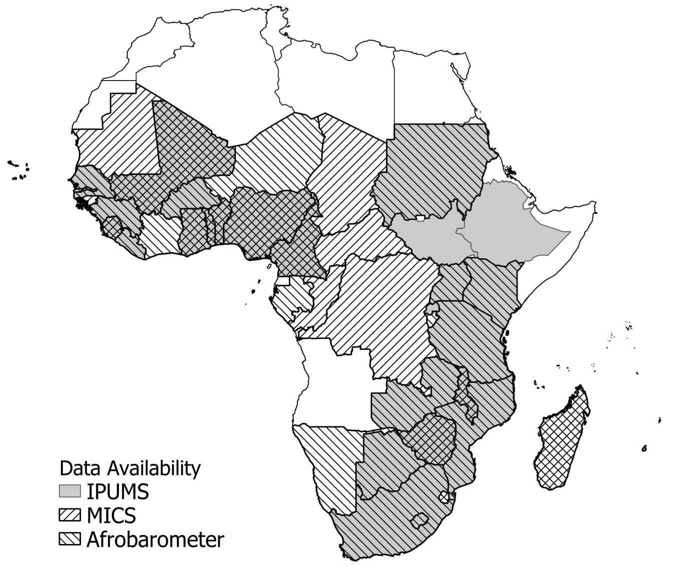
In addition, United States Agency for International Development (USAID)'s *Demographic and Health Surveys* (DHS) have been also conducted across Sub-Saharan African countries. However, the age data from these surveys does not suit our analysis. To ensure data accuracy, DHS enumerators verify respondent-provided ages through cross-checking (e.g. by comparing with birth years). While crucial for demographic statistics, this approach is not viable as a proxy for numerical abilities.

Figure B.1 displays a map depicting the availability of data sources by country. Djibouti, Equatorial Guinea, Eritrea, Somalia, Angola, the Comoros, and the Seychelles lack age data. Overall, the diverse sources combine to cover nearly the entire region.

[6] These 21 countries covered by MICS are Benin, Cameroon, Central African Republic, Chad, Rep. of Congo, Côte d'Ivoire, DR Congo, eSwatini, Gambia, Ghana, Guinea-Bissau, Lesotho, Madagascar, Malawi, Mali, Mauritania, Nigeria, São Tomé and Príncipe, Sierra Leone, Togo, and Zimbabwe.

[7] These 33 countries covered by the Afrobarometer are Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Côte d'Ivoire, eSwatini, Gabon, Gambia, Ghana, Guinea, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritius, Mozambique, Namibia, Niger, Nigeria, São Tomé and Príncipe, Senegal, Sierra Leone, South Africa, Sudan, Tanzania, Togo, Uganda, Zambia, and Zimbabwe.

Figure B.1: Age Data Availability in IPUMS, MICS and Afrobarometer. Authors' own representation.



B.3.2 Method

Turning to our methodology, we employ the Whipple Index to quantify age heaping, comparing observed frequencies of ages ending in 0 or 5 to an expected uniform distribution. This rounding behaviour is the most prominent, linked to humans learning to count on their hands – each with five fingers.

This index is estimated for each birth decade from the 1950s to the 1990s within the largest administrative subnational areas (admin I) of Sub-Saharan Africa. In some cases, geographic indicators necessitate grouping regions. We use contemporary administrative borders, enabling consistent comparisons over time and with current statistics.

The Whipple Index (W_{it}) is calculated as follows:

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

Here, i represents the subnational area for birth decade t. The index ranges from 0 to 500, with 500 indicating complete age heaping. We transform the Whipple Index using a linear adjustment, known as the ABCC Index,[8] to approximate the share of individuals who accurately report their age:

$$ABCC_{it} = \begin{cases} \left(1 - \frac{W_{it}-100}{400}\right) \cdot 100 & \text{if } W_{it} \geq 100, \\ 100 & \text{otherwise.} \end{cases} \quad (2)$$

We focus on ages 23 to 62 for several reasons: to mitigate biases from age exaggeration among older individuals, address the influence of mortality on age distribution, and account for reduced age heaping among younger people. Several studies argued that age awareness is unusual and heterogeneous for the age group 18–22, because these age groups recently reported their ages on the occasion of marriage, election, and military service. Given that marriage ages and the institutional settings of election and military service are heterogeneous across countries, previous work has concluded that including this age group would increase potential biases (Crayen and Baten, 2010). Moreover, as standard in the literature and to ensure comparability, numeracy is estimated separately for age groups (23–32, 33–42, 43–52, 53–62).[9] This allows us to obtain sensible intervals around the rounded numbers. We align each group with the birth decade that dominates it.

The process for constructing the numeracy dataset involves initially calculating the ABCC Index independently from each source before assembling the final dataset. When multiple sources provide data, our primary preference is IPUMS due to its larger sample size. MICS follows as the second choice, offering the next largest sample sizes. Lastly, we incorporate AB surveys. This sequential approach aims to fill gaps progressively with each type of survey. In instances of multiple surveys from one of the sources for a birth decade within a subnational level, we calculate weighted averages based on sample sizes. We omit the remaining age data from our analysis. This approach helps refine our analysis and ensures robust results. Table B.1 presents an overview of the final dataset showing how many regions we can cover per birth decade for each country, the number of underlying observations, which sources we use per country and decade and the ABCC Index.

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

[9]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 (by subtracting 25 percent of the ABCC value, as is standard in the literature; see Crayen and Baten, 2010 or Baten and Hippe, 2018)

Table B.1: Data Overview

Country	No. Reg.	1950				1960				1970			
		No. Reg.	**Obs.**	**Source**	**Co. ABCC**	**No. Reg.**	**Obs.**	**Source**	**Co. ABCC**	**No. Reg.**	**Obs.**	**Source**	**Co. ABCC**
Benin	12	12	165121	IPUMS	71.087	12	194082	IPUMS	69.402	12	202780	IPUMS	69.964
Botswana	14	13	47831	IPUMS	97.131	13	54661	IPUMS	99.55	13	54168	IPUMS	99.789
Burkina Faso	13	13	183252	IPUMS	84.809	13	276440	IPUMS	84.873	13	199190	IPUMS	88.268
Burundi	17									1	49	AB	82.909
Cameroon	10	9	243409	IPUMS/MICS	80.265/94.203	10	170308	IPUMS/MICS	80.138/92.723	10	277108	IPUMS/MICS	82.13/90.312
Cape Verde	22	1	159	AB	95.657	3	586	AB	97.113	3	750	AB	98.604
Central Afr. Rep.	17	12	2085	MICS	93.823	15	5538	MICS	87.392	15	9196	MICS	85.121
Congo, Rep.	12					11	1987	MICS	94.203	12	4398	MICS	92.707
Côte d'Ivoire	19					1	98	AB	93.971	2	285	AB	93.23
DR Congo	26					1	157	MICS	94.203	22	2500	MICS	88.75
eSwatini	4	4	298	MICS	94.203	4	1674	MICS	94.203	4	2993	MICS	91.732
Ethiopia	11	11	926208	IPUMS	53.53	11	1414769	IPUMS	59.323	11	1088309	IPUMS	63.79
Gabon	9	1	47	AB	98.182	1	92	AB	95.738	2	189	AB	95.587
Gambia	6					1	40	AB	78.202	6	1613	MICS	94.203
Ghana	10	10	449149	IPUMS	76.178	10	384376	IPUMS	78.318	10	570020	IPUMS	82.16
Guinea	8	8	185573	IPUMS	71.883	8	171711	IPUMS	71.444	8	97837	IPUMS	70.966
Guinea-Bissau	9					9	1478	MICS	94.203	9	4501	MICS	92.532
Kenya	8	8	455095	IPUMS	98.229	8	522881	IPUMS	87.704	8	604887	IPUMS	86.024
Lesotho	10	10	33208	IPUMS	98.301	10	45930	IPUMS	98.849	10	31025	IPUMS	97.996
Liberia	15	5	11861	IPUMS	97.215	6	22167	IPUMS/AB	85.793/89.198	8	38678	IPUMS/AB	88.541/91.649
Madagascar	22	1	92	AB	95.826	3	279	AB	90.525	22	2648	MICS	94.203
Malawi	3	3	106214	IPUMS	95.429	3	164271	IPUMS	88.634	3	277916	IPUMS	90.338
Mali	9	9	239169	IPUMS	83.616	9	190366	IPUMS	82.628	9	269827	IPUMS	81.25
Mauritania	13	12	2053	MICS	94.203	12	6112	MICS	90.275	12	9438	MICS	88.389
Mauritius	11	11	46863	IPUMS	95.803	11	61134	IPUMS	99.554	11	39300	IPUMS	98.584
Mozambique	11	11	277335	IPUMS	94.124	11	420785	IPUMS	93.98	11	307631	IPUMS	92.399
Namibia	13					4	588	AB	98.782	7	1409	AB	97.834
Niger	8	1	65	AB	70.779	5	491	AB	64.267	6	757	AB	66.711
Nigeria	37	37	25807	IPUMS	63.924	37	39535	IPUMS	61.001	37	52491	IPUMS	64.374
Rwanda	3	3	126072	IPUMS	98.139	3	189795	IPUMS	99.242	3	115607	IPUMS	98.820
São Tomé & Príncipe	2	1	148	AB	100	2	500	MICS	94.203	2	1713	MICS	94.203
Senegal	14	14	333209	IPUMS	85.946	14	503094	IPUMS	87.927	14	486261	IPUMS	81.924
Sierra Leone	4	4	32064	IPUMS	54.321	4	53329	IPUMS	62.346	4	76864	IPUMS	64.972
South Africa	9	9	3342228	IPUMS	99.304	9	4721969	IPUMS	99.86	9	6134501	IPUMS	99.687
South Sudan	10	10	17671	IPUMS	98.606	10	32540	IPUMS	74.63	10	53582	IPUMS	80.464
Sudan	15	14	180524	IPUMS	67.644	14	290099	IPUMS	53.327	14	547668	IPUMS	63.933
Tanzania	30	30	1090429	IPUMS	82.168	30	1939993	IPUMS	84.545	30	2091194	IPUMS	85.45
Tchad	22									21	2347	MICS	85.347
Togo	5	5	43227	IPUMS	62.317	5	77043	IPUMS	70.461	5	119001	IPUMS	75.368
Uganda	4	4	355842	IPUMS	84.756	4	657314	IPUMS	88.283	4	695301	IPUMS	90.808
Zambia	10	10	240117	IPUMS	88.568	10	406701	IPUMS	93.795	10	431430	IPUMS	92.34
Zimbabwe	10	10	27932	IPUMS	96.028	10	37257	IPUMS	96.14	10	69788	IPUMS	96.936

Notes: The column 'No. Reg.' indicates the total number of regions within that country which are the current largest subnational regions. The 'No. Reg.' for the different decades indicates the number of regions for which we have a sufficient number of observations to calculate the ABCC Index (minimum 30 per survey).

Table B.1: continued

Country	No. Reg.	1980				1990			
		No. Reg.	Obs.	Source	Co. ABCC	No. Reg.	Obs.	Source	Co. ABCC
Benin	12	12	155295	IPUMS	72.035	6	255	AB	72.05
Botswana	14	13	39516	IPUMS	99.004	2	219	AB	100
Burkina Faso	13	8	1019	AB	78.692	4	192	AB	84.923
Burundi	17	4	224	AB	83.248				
Cameroon	10	10	4881	MICS	93.98	8	417	AB	79.059
Cape Verde	22	4	812	AB	98.123	3	243	AB	96.035
Central Afr. Rep.	17	14	5470	MICS	84.628				
Congo, Rep.	12	12	5223	MICS	92.33				
Côte d'Ivoire	19	2	405	AB	94.762	3	197	AB	93.694
DR Congo	26	26	6672	MICS	87.843	25	8484	MICS	89.085
eSwatini	4	4	4781	MICS	93.08	4	405	AB	95.605
Ethiopia	11								
Gabon	9	4	511	AB	95.651	3	241	AB	99.379
Gambia	6	6	4263	MICS	92.874	6	5978	MICS	88.858
Ghana	10	10	406912	IPUMS	87.448	8	627	MICS	89.468
Guinea	8	8	152745	IPUMS	72.759	4	192	AB	63.514
Guinea-Bissau	9	9	7585	MICS	91.248	9	4709	MICS	90.215
Kenya	8	8	631970	IPUMS	89.133	7	538	AB	92.395
Lesotho	10	4	773	AB	99.798	2	115	AB	100
Liberia	15	8	57564	IPUMS/AB	91.71/95.131	4	256	AB	94.427
Madagascar	22	22	5569	MICS	89.596	22	7461	MICS	89.75
Malawi	3	3	219591	IPUMS	95.123	3	380	AB	95.412
Mali	9	9	202273	IPUMS	83.574	6	270	AB	73.322
Mauritania	13	10	5272	MICS	85.518				
Mauritius	11	11	20422	IPUMS	100	2	71	AB	88.872
Mozambique	11	11	2543	AB	100	10	820	AB	87.957
Namibia	13	7	1083	AB	95.843	6	361	AB	94.585
Niger	8	6	868	AB	63.784	4	244	AB	59.232
Nigeria	37	37	37300	IPUMS	66.631	4	408	AB	70.288
Rwanda	3								
São Tomé & Príncipe	2	2	2860	MICS	94.08	2	1232	MICS	94.203
Senegal	14	14	341836	IPUMS	86.052	3	184	AB	73.412
Sierra Leone	4	4	8228	MICS	82.587	4	363	AB	75.074
South Africa	9	9	4738007	IPUMS	99.463	6	497	AB	94.653
South Sudan	10	10	81253	IPUMS	81.075				
Sudan	15	14	776544	IPUMS	68.851	4	160	AB	73.371
Tanzania	30	30	1347105	IPUMS	86.905	9	358	AB	90.971
Tchad	22	21	6217	MICS	75.03	21	9529	MICS	76.143
Togo	5	5	175389	IPUMS	76.93	5	388	AB	86.178
Uganda	4	4	508865	IPUMS	93.579	4	399	AB	90.059
Zambia	10	10	309141	IPUMS	93.492	4	201	AB	94.933
Zimbabwe	10	10	110228	IPUMS	98.172	10	4118	MICS	94.203

Notes: The column 'No. Reg.' indicates the total number of regions within that country which are the current largest subnational regions. The 'No. Reg.' for the different decades indicates the number of regions for which we have a sufficient number of observations to calculate the ABCC Index (minimum 30 per survey).

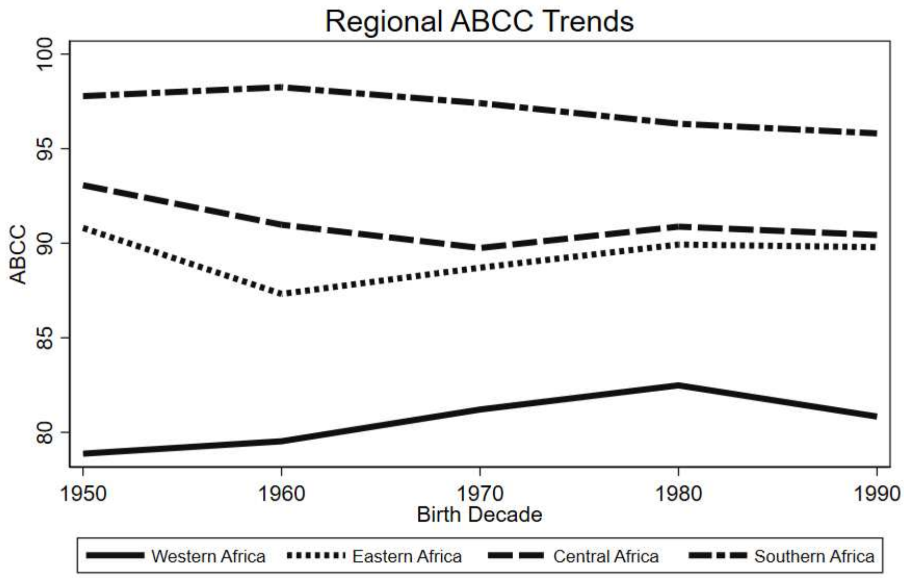
B.4 Results: Numeracy Trends in African Regions

Average numeracy has not changed much over time; however, there are differences across regions. Figure B.2 provides an overview of the ABCC trends by larger region.[10] The region with the highest numeracy throughout the entire period is Southern Africa, with an ABCC Index above 95. This region also has the lowest internal variation, with eSwatini having the lowest average ABCC Index of 93.77 and Botswana the highest value of 99.09. Eastern Africa and Central Africa are close together, with an average ABCC Index of about 90. Especially after 1970 the two trends align very closely. The values for Central Africa range between 82.48 for Cameroon and 96.9 for Gabon. Eastern Africa has a similar distribution but with one outlier to the bottom. The highest value is 98.73 for Rwanda while the lowest value is 65.42 in Sudan. Western Africa comes in last with an ABCC Index of about 80, and it is the region with the strongest variation as well. At the bottom, Niger has a value of 64.95, while at the top, Cape Verde has a value of 97.11.

This pattern is reflected if we disaggregate the data by gender as shown in Figure B.3. Again, Southern Africa is on top, with the ABCC Index for males and females being closely aligned; however, we observe a downward trend for females for the most recent birth cohort. One hypothesis is that this could be attributed to the onset of the HIV pandemic, which affects females more than males (Richardson et al., 2014), as well as the political turmoil that accompanied South Africa's and Namibia's fight against Apartheid (Healy-Clancy, 2017). Central and Eastern Africa both have closely aligned male and female ABCC values with a modest increase in the gaps for the 1990s birth cohort as well. However, while in Eastern Africa we see a slight drop in female numeracy, which widens the educational gap, in Central Africa females overtake males. In Western Africa, we observe an upward trend for males throughout the entire period, while again in the 1990s there is a drop in female attainment. The educational gender gap is also by far largest in Western Africa. A potential reason for this could be the slower overall expansion of the education system, causing a late peak in education gender inequality (Baten et al., 2021).

[10] Western Africa includes Benin, Burkina Faso, Cape Verde, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, and Togo. Eastern Africa includes Burundi, Kenya, Madagascar, Malawi, Mauritius, Mozambique, Rwanda, Sudan, South Sudan, Tanzania, Uganda, Zambia, and Zimbabwe. Central Africa includes Cameroon, Central African Republic, Rep. of Congo, Gabon, and São Tomé and Príncipe. Southern Africa includes Botswana, Lesotho, Namibia, South Africa, and eSwatini. We exclude Ethiopia and Tchad from these regional trends as their data are only available for three periods each and bias the trends. These are simple country averages and are not weighted by population size.

Figure B.2: Regional ABCC Trends Based on IPUMS, MICS and Afrobarometer Data. Authors' own representation.



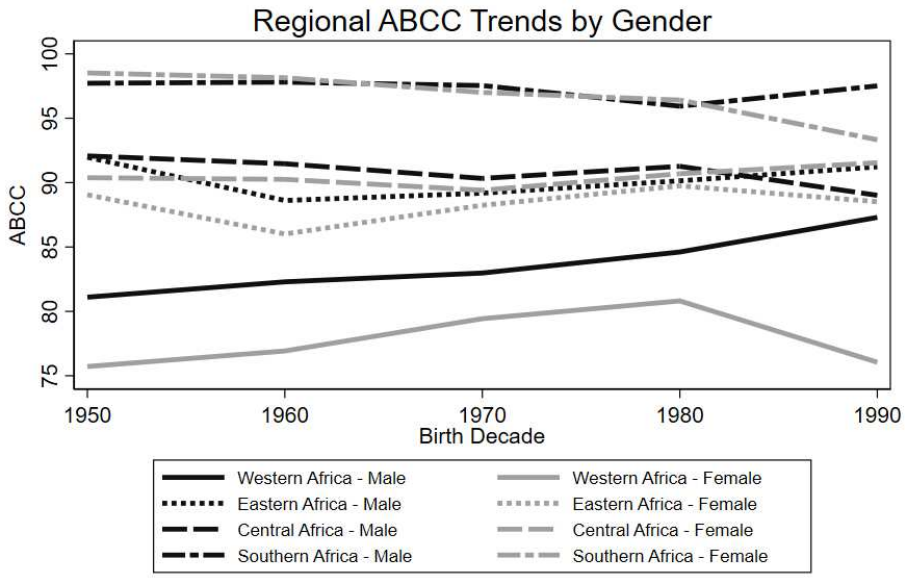
Notes: Western Africa includes Benin, Burkina Faso, Cape Verde, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone and Togo. Eastern Africa includes Burundi, Kenya, Madagascar, Malawi, Mauritius, Mozambique, Rwanda, Sudan, South Sudan, Tanzania, Uganda, Zambia and Zimbabwe. Central Africa includes Cameroon, Central African Republic, Rep. of Congo, Gabon and São Tomé and Príncipe. Southern Africa includes Botswana, Lesotho, Namibia, South Africa and eSwatini. We exclude Ethiopia and Tchad from these regional trends as they are only available for three periods each and bias the trends.

While we observe mostly a stagnation of numeracy in the regions, there are several countries with upward or downward trends.[11] In Figure B.4 we show all country trends in which the mean ABCC value is below 90; the remainder are presented in the Supplementary Materials (Figure B.9). In each of these graphs the bold red line represents the country average, and the light grey lines represent the subnational regions. We refrained from labelling all the subnational regions in the graphs for the sake of clarity. The graphs provide evidence of how large the regional inequality was, for example, in Nigeria, Tchad, and Niger, whereas Tanzania and Burkina Faso had much less regional variation. Moreover, some countries show a clear upward trend while other countries follow a downward trend.

One country with a clear improvement in numerical skills over time is Ghana, as shown in Figure B.5. The regional division shows that already for the 1950s birth cohort the southern regions

[11]Countries that increased their ABCC Index by at least 10 percentage points include Ethiopia, Gambia, Ghana, Sierra Leone, Sudan, and Togo. In contrast, in Mali, Senegal, and Niger the ABCC Index decreased by at least 10 percentage points. However, while Niger faces a steadier decline, in Mali and Senegal the drop only happens in the 1990s.

Figure B.3: Regional ABCC Trends by Gender Based on IPUMS, MICS and Afrobarometer Data. Authors' own representation.



Notes: Western Africa includes Benin, Burkina Faso, Cape Verde, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone and Togo. Eastern Africa includes Burundi, Kenya, Madagascar, Malawi, Mauritius, Mozambique, Rwanda, Sudan, South Sudan, Tanzania, Uganda, Zambia and Zimbabwe. Central Africa includes Cameroon, Central African Republic, Rep. of Congo, Gabon and São Tomé and Príncipe. Southern Africa includes Botswana, Lesotho, Namibia, South Africa and eSwatini. We exclude Ethiopia and Tchad from these regional trends as they are only available for three periods each and bias the trends.

have higher numeracy levels than the northern regions. This pattern continues for all birth decades. Numerous factors could potentially contribute to this spatial pattern as well as the development over time. With respect to the spatial disparities, public goods were distributed unevenly, with the Southern regions receiving greater investments in education, health, and infrastructure (Kambala, 2023). Particularly missions and their schools were largely located in the Southern part of Ghana (Jedwab et al., 2022), such that only these areas could benefit from formal education. Turning to the trend over time, Kwame Nkrumah's post-independence government chose education as one of their foci and, for example, introduced free primary education (Akyeampong, 2007). After Nkrumah's government was overthrown in 1966, the school system faced a decline. However, once Jerry Rawlings came to power in 1981, educational reforms improved, especially primary education outcomes (Akyeampong, 2007). While different governments had different foci with regards to education, the consistent emphasis on education likely contributed to the positive trends in numeracy.

Figure B.4: Development of Numeracy in Countries With an Average ABCC Below 90 at the Subnational Level Based on IPUMS, MICS and Afrobarometer Data.
Detailed information on numbers of regions per country and birth decade, and underlying numbers of observations, can be found in Table B.1. Authors' own calculations.

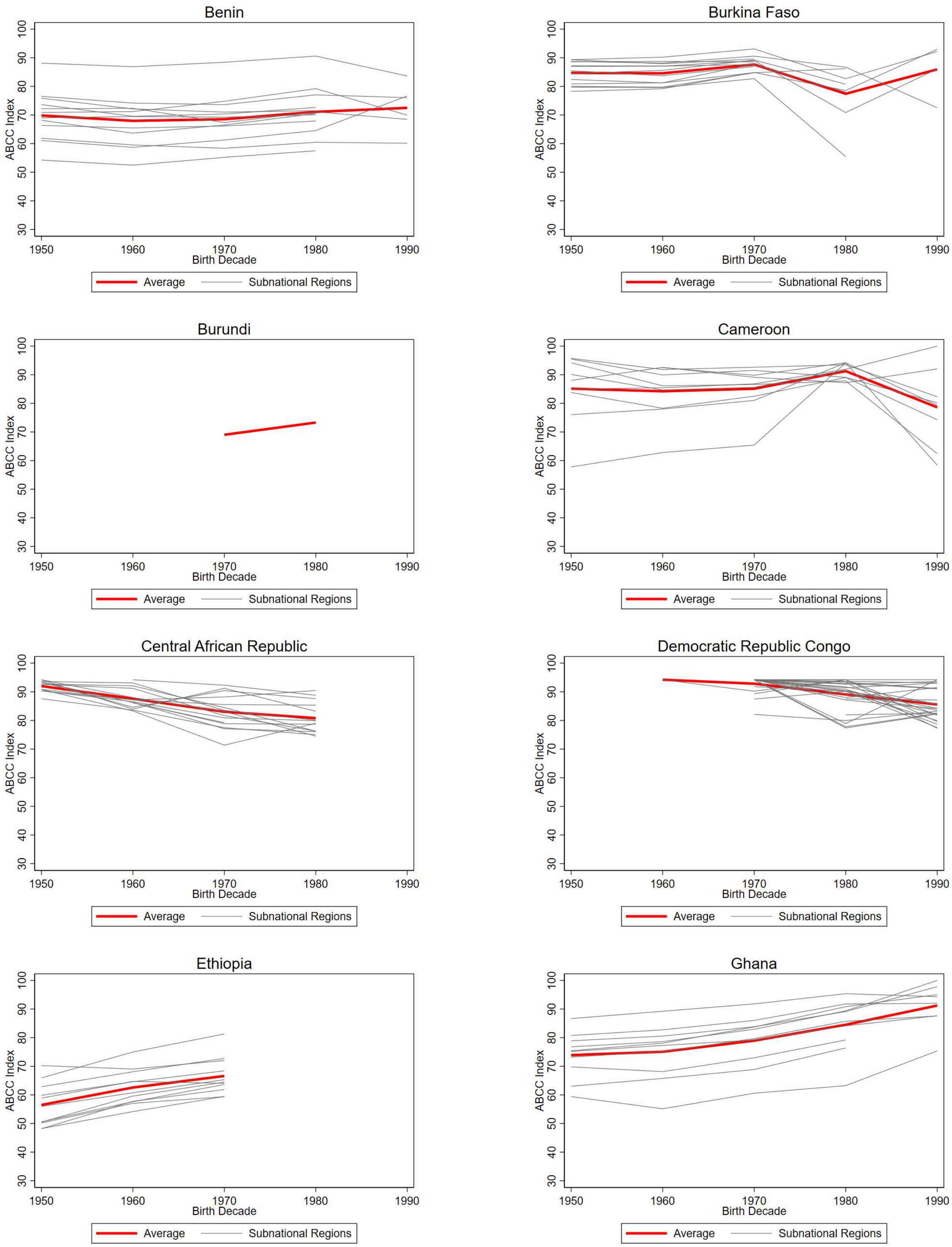


Figure B.4: cont.

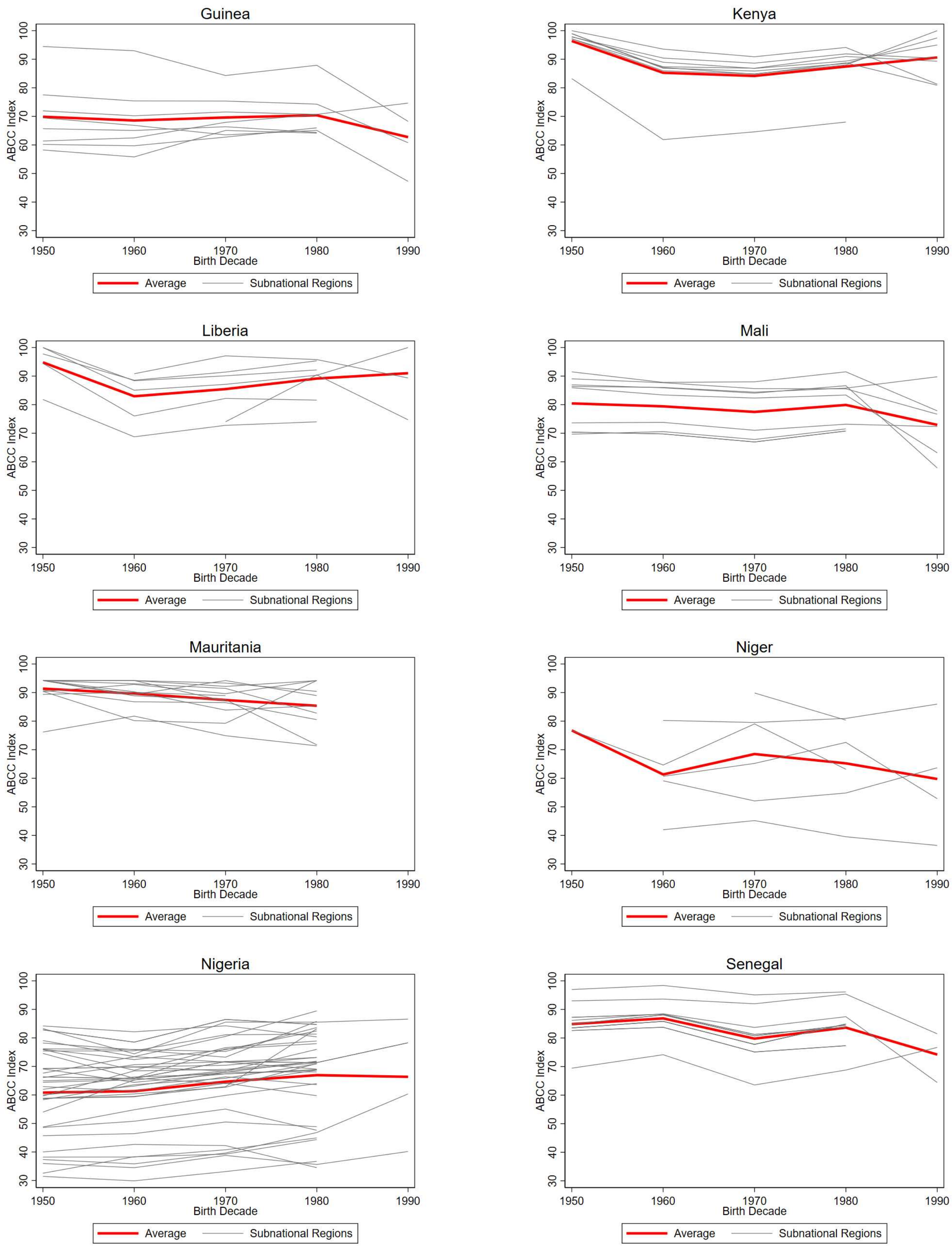


Figure B.4: cont.

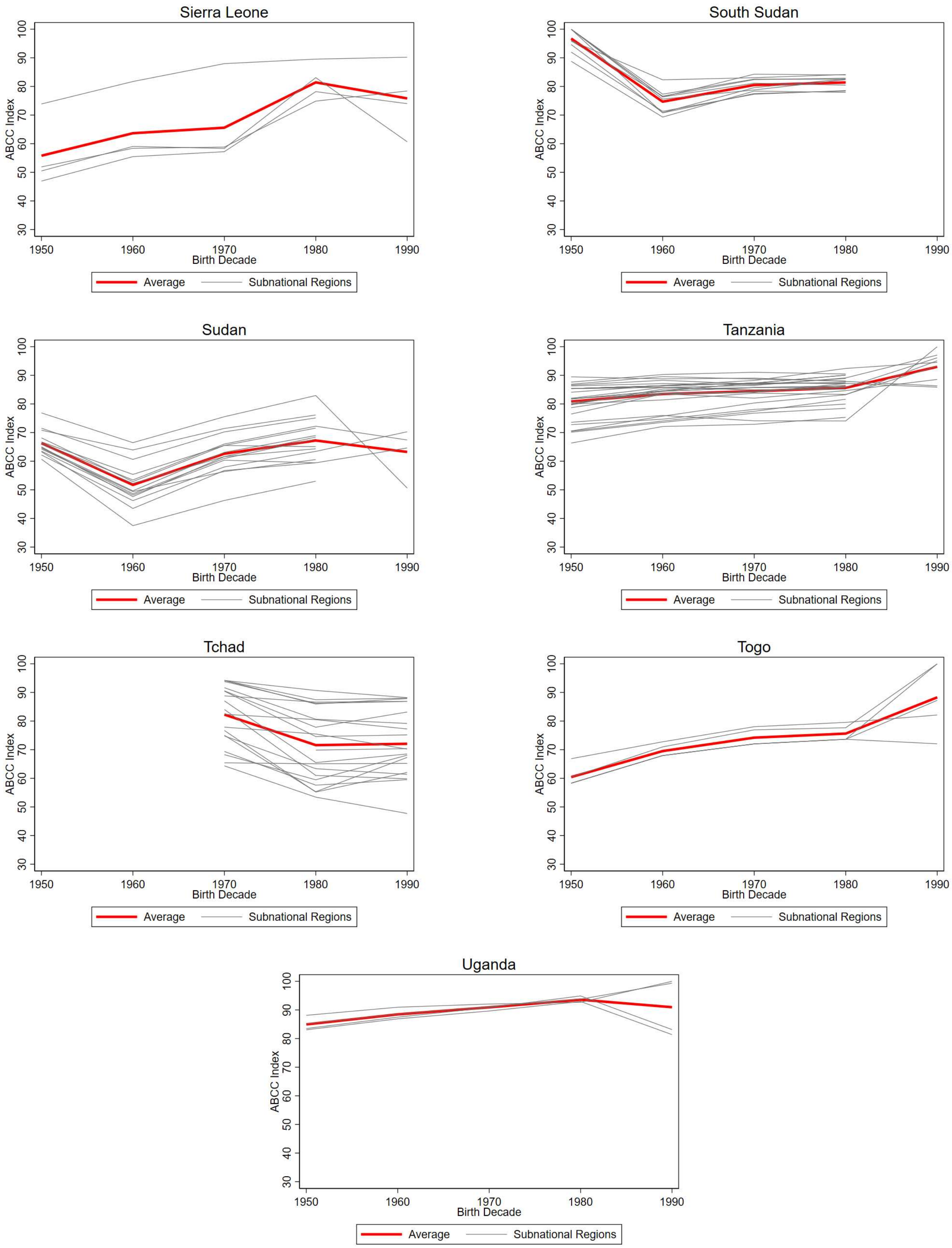
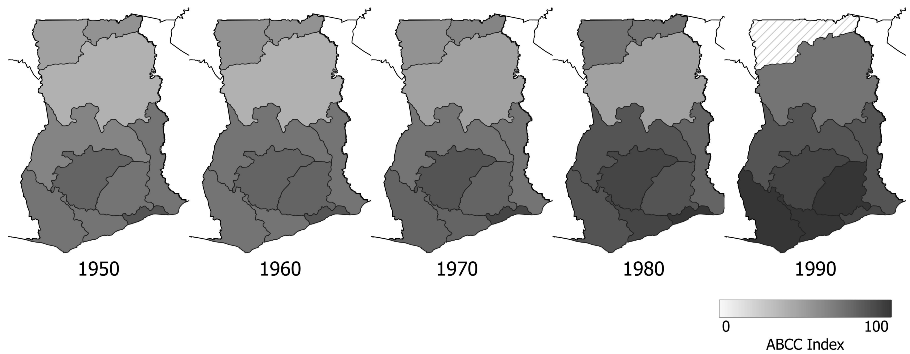
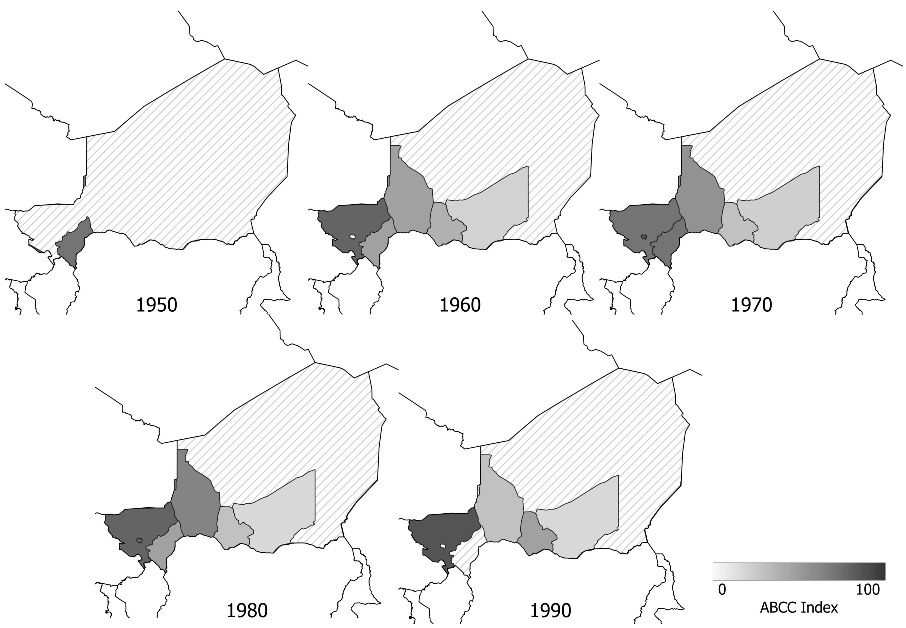


Figure B.5: Development of Numeracy in Ghana at the Subnational Level based on IPUMS, MICS and Afrobarometer Data. Authors' own representation.



In contrast, Niger faced a modest decline in its numerical skills between the birth cohorts of 1950 and 1990 (Figure B.6). After Niger gained independence from France in 1960, Hamani Diori became its first president and ruled the country until a coup d'état in 1974 (Decalo, 1989, p. 174). This period showed an expansion of the education system which is reflected in the increase in numeracy especially in the South-West (Decalo, 1989, p. 95). The South-West is likely to be at an advantage for several reasons. First, it is home to the capital and the area south of the Sahel has higher population density than the north, which eases infrastructure development (Decalo, 1989, p. 2). Second, under Diori's rule the government elite consisted almost exclusively of Djerma, Songhai and Maouri – ethnic groups traditionally residing in the South-West of Niger (Decalo, 1989, p. 7) – who potentially invested more in their 'own' areas (De Luca et al., 2018). However, the following two birth decades witnessed a decline in their numerical skill. The military government following the 1974 coup d'état was popular in its initial years as they focused on drought relief. Yet, calls for a democratic government became louder as oppression and corruption surged again (Decalo, 1989, p. 138). Moreover, while rainfall in the Sahel zone already had started to decline in the 1970s, it reached its historical low in the 1980s. The consequential droughts caused large-scale migrations, much livestock died and access to foodstuffs was problematic (Starr, 1987). Moreover, while Niger experienced a uranium export boom in the 1970s which financed large parts of the fiscal budget, the boom collapsed in the 1980s, causing a fiscal squeeze in the subsequent years (Decalo, 1989, p. 228). In 1993 Niger transitioned to a multi-party democracy; however, the decade was marked by numerous coups and political instability. In addition to these problems, Niger has had one of the highest birth rates in sub-Saharan Africa over the last few decades, with an average population growth rate of above 3 percent (World Bank, 2024). Thus, an expansion of the education system must also keep up with population growth. Hence, gross primary school enrolment only increased from 11 percent in 1970 to 30 percent in 2000 (World Bank, 2024). The outlined reasons are potential explanations for the long-run decline of numeracy in Niger for the birth decades until 2000. In sum, we observe that the numeracy evidence can be used to describe the numerical skill development in these countries. The observed trends are compatible with the educational and economic history of countries such as Ghana and Niger, for example.

Figure B.6: Development of Numeracy in Niger at the Subnational Level Based on IPUMS, MICS and Afrobarometer Data. Authors' own representation.



B.5 Possibilities and Limitations of the ABCC Index

B.5.1 Hypotheses about Potential Limitations

As with any approximate indicator, the ABCC Index is not without limitations and there is a lively debate around these. Hence, we will briefly summarize the main points made in the literature and how we address them.

Most prominently, A'Hearn et al. (2022a) cautioned against relying too heavily on the age heaping methodology to gauge numerical proficiency in Italy. Using late nineteenth-century Italian census data, they assert that age heaping does not accurately measure educational attainment but might rather reflect state capacity and cultural attitudes towards age awareness. First, they illustrate a broad range of age heaping frequencies among the literate and illiterate populations to show that literacy and age heaping were not perfectly correlated. Second, they interpret changes in the index over time as indicative of improved state capacity, leading to more precise census data collection. Third, they demonstrate varying heaping patterns among women based on marital status, suggesting potential societal norms regarding age gaps in marriage. This observation seems to align with findings by Földvári et al. (2012), who, analysing historical census data, found more heaping among widowed and single women compared to married counterparts, even after accounting for socio-economic variables. Similarly, A'Hearn et al. (2022a) and Beltrán Tapia et al. (2022), the latter using Spanish census data, speculate that men might have often reported ages on behalf of women in households, skewing age heaping estimates and neglecting to reflect female human capital accurately. Furthermore, A'Hearn et al. (2022a) also mention the concern that age heaping may increase as individuals age due to exaggeration. Moreover, they argue that the Whipple Index cannot detect preference for digits other than 0 or 5. In their Italian sample they find that while there is strong heaping on multiples of 10, there is no strong heaping on numbers with the terminal digit 5 but heaping on numbers that end in 6. Finally, A'Hearn et al. (2022b) emphasize that while age heaping highlights the external margin (i.e. the extent of age discrepancies), it fails to capture the internal margin (i.e. the actual level of mathematical proficiency it signifies).

Indeed, we acknowledge that not all datasets are suitable for the age heaping methodology. Scholars who consider using it have to assess whether there was substantial counterchecking. For instance, we opted against utilizing age data from USAID's DHS due to enumerator counterchecking of age statements, which might suggest higher statistical capacity. However, this cautionary example does not apply universally to all datasets; rather, it underscores the importance of meticulous data scrutiny before applying any methodology. Consequently, our focus lies in inspecting the key hypotheses posited by these studies and evaluating their relevance to our dataset. Our advantage lies in the availability of data from diverse sources, collected by various entities for distinct purposes. This diversity enables us to cross-reference estimates from these disparate sources, enriching our analytical approach.

Essentially, all these criticisms revolve around questioning the efficacy of the ABCC Index as an accurate measure of numerical proficiency or broader human capital. Hence, as a first step, we will demonstrate a positive correlation between the ABCC Index and years of schooling, as well as an intergenerational correlation between caretakers' age heaping and children's math test scores. Next, we will delve into the additional considerations raised by the aforementioned articles. Firstly, we examine whether there is evidence suggesting that individuals, particularly women, did not provide responses on their own behalf. Secondly, we assess whether heaping patterns differ depending on marital status. Thirdly, we investigate whether age heaping evolves as individuals age. Fourthly, we scrutinize whether diverse surveys yield varying ABCC estimates, potentially indicating differing levels of state or statistical capacity. Finally, we aim to ensure the accuracy of our heaping patterns by checking for alternative heaping patterns.

Before we attend to these concerns, we would like to briefly discuss the comment on the distinction between the internal and external margins of age heaping, as highlighted by A'Hearn et al. (2022a). We concur that age heaping only reflects the external margin, indicating whether an individual provides a heaped age statement or not. However, this limitation applies similarly to any binary literacy indicator, particularly if literacy is inferred from the ability to provide a signature or self-reported status. The depth of an individual's reading or writing abilities, or their comprehension of texts, remains unknown. Furthermore, given the large variety in the quality of education, one might even argue that years of schooling, while not binary, do not provide information about the internal margin. Without more comprehensive test data, this ambiguity is inherent in all simple indicators, whether aimed at measuring literacy, numeracy, or other educational outcomes. While future research may shed light on what level of numerical proficiency corresponds to heaping behaviour, this question unfortunately remains unanswered for now.

B.5.2 ABCC Index and Education

We now turn to provide evidence that the ABCC Index is, in spite of its limitations, a suitable methodology to approximate numerical skills in Sub-Saharan Africa as outlined above.

The first concern relates to the idea that whilst literacy is mostly acquired through formal education, foundational numeracy could be acquired informally and hence cannot capture exposure to formal education. In fact, it is rare that individuals who have never been to school learn to read and write.[12] Nevertheless, the environment outside of formal schooling is also an important contributor to successfully acquiring basic literacy (Buckingham et al., 2014; Piper et al., 2015). These different factors are impossible to disentangle without detailed microdata on the non-school environment.

Nevertheless, we agree that children can develop basic math skills outside of formal schooling. Indeed, some studies provide evidence that individuals can acquire numerical skills through everyday life without ever attending formal schooling, for example by working as a market vendor (Banerjee et al., 2017; Carraher et al., 1985; Guberman, 1996).[13] Research in the field of numerical cognition also provides evidence that children have some sense of numbers and can perform basic addition or subtraction problems given the right framing (Dehaene, 2011, p. 107). Many children proceed to calculate using only these ad hoc methods for simple operations but lack a general reference framework. Thus, they are unable to transfer their skills to other situations that are outside their everyday routines (Dehaene, 2011, p. 124; Luria, 1976, p. 126). The important basic and transferable numerical skills are acquired through formal high-quality education. These skills are also likely to be reflected in the age-heaping behaviour of a person. While an individual with numeracy skills only applicable to everyday routines (such as being a market vendor) is more likely to provide a heaped age statement, an individual with formal transferable numeracy skills is less likely to do so.

We can also show that there is a relationship between formal schooling and numerical skills in our data. Table B.2 shows the results from Ordinary Least Squares (OLS) regressions in which the ABCC Index is the dependent variable and average years of schooling and literacy are the independent variables of interest. All variables are at the regional and birth decade level. All models include country and birth decade fixed effects. Model (1) shows that there is a positive

[12] The MICS by UNICEF provide data on literacy and years of schooling. Among those individuals who have never completed one year of schooling, 3.41 percent were able to read the provided sentences at least partially. Hence, while the vast majority cannot learn to read without formal schooling, there are a few exceptions.

[13] It is important to note that it is not always clear whether people actually perform a mathematical computation in their head or how much is recalled from memory. For example, a farmer with a small herd of cows might have memorized their faces and can realize that one is missing without having to count them. Without an experimental approach to manipulate specific variables, it is impossible to know whether an individual simply memorized faces or a large sum of numbers or whether someone is numerate (Dehaene, 2011, p. 132).

and statistically significant relationship between years of schooling and the ABCC Index. The next column shows the correlation between literacy and the ABCC Index, which is positive and statistically significant as well. Last, Model (3) includes both years of schooling and literacy as explanatory variables. Both years of schooling and literacy remain significant. Therefore, we have confidence that the ABCC Index also reflects exposure to formal education.

Table B.2: The Relationship of the ABCC Index With Years of Education and Literacy

	(1) ABCC	(2) ABCC	(3) ABCC
Years of education	1.314***		0.806**
	(0.255)		(0.394)
Literacy		12.094***	8.573***
		(1.370)	(2.439)
Constant	66.563***	65.107***	64.402***
	(1.152)	(1.902)	(1.779)
Country FE	Yes	Yes	Yes
Birth Decade FE	Yes	Yes	Yes
Observations	1,411	778	778
R-Squared	0.689	0.608	0.618

Notes: These regressions show the correlation of the ABCC Index with years of education and literacy. The dependent variable is the ABCC Index, ranging between 0 and 100, and the main independent variables are years of education and literacy (based on reading cards). All models include country and birth decade fixed effects. Standard errors are robust. Asterisks denote significance at levels *** $p < .01$, ** $p < .05$, * $p < .1$.

These estimates may prompt the question about whether years of schooling could be a good indicator of acquired skills after all. While there is a significant correlation between years of schooling and the ABCC Index, it is far from perfect. As shown in Table B.13, regional estimates for Model (1) across Western, Eastern, Central, and Southern Africa reveal substantial variation in the coefficient of years of schooling, ranging from 0.365 to 1.364. This highlights that the relationship between schooling duration and numeracy skills is not a one-to-one correlation, but there is considerable heterogeneity. Therefore, while the regressions show some degree of association, years of schooling does not provide the same insights as our numeracy indicator.

Next, we turn to the concern whether the ABCC Index captures numerical skills in the Sub-Saharan African context. Ideally, we would like to compare adults' age statements with some type of math test score. However, this type of evidence does not exist, to the best of our knowledge.[14]

[14]MICS-type numeracy tests for adults have not been recorded for large samples. For much earlier time periods,

Thus, we compare the age heaping pattern of an older generation to math scores of their children within the same family as the intergenerational transmission of education has been widely attested in the literature (Black et al., 2005). Hence, we deem the comparison of parents' age heaping and children's test scores a useful analysis.

For this exercise we employ the latest round of the MICS which includes a short math test for children aged 7–14. In contrast to our ABCC data, 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 numerical series with a maximum number of points of 21. This data is available for 12 countries.[15] The children can be linked to their caretakers for whom we can calculate the ABCC Index of numeracy. Table B.3 shows a simple OLS regression with the children's math test score as the dependent variable and their caretakers' ABCC as the independent variable. There is a clear positive and statistically significant correlation which remains after adding country fixed effects: regions with low caretaker numeracy, proxied by the ABCC Index, also show poor performance of children in the administered math tests.

For further illustration, we provide some evidence at the micro level, at which we can mitigate some concerns about omitted variable bias. In countries with low numeracy (i.e., a high degree of age heaping), a significant share of age statements with the terminal digits 0 and 5 cannot be true. Assuming a uniform distribution of terminal digits, 20 percent of age statements should end with 0 or 5. For a share above 20 percent, we can calculate the share of heaped age statements among those ending in 0 or 5. For example, the ABCC Index for Tchad based on the caretakers' age statements is 81.15. This translates to about 35 percent of all age statements ending in 0 or 5, which implies that about 43 percent of age statements ending in 0 or 5 are heaped.[16] In a country such as Zimbabwe, whose ABCC Index based on caretakers' age statements is 100, 20 percent of

Baten and Nalle (2022) recently tested this for Inquisition defendants of the fifteenth to eighteenth centuries. The Inquisition performed an indirect math test 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, 2022 recalculate these biographies and find a strong correlation between obviously miscalculated biographies and age rounding on multiples of five.

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

[16] The calculation is based on the following: Assume that the ABCC Index for Country Z is X. Then the share of age statements ending in 0 or 5 ($Mult5$) is $Mult5 = 1 - \frac{X}{125}$. The share of heaped age statements among $Mult5$ is $Heaped = \left(\frac{Mult5-20}{Mult5}\right) \times 100$.

Table B.3: Regional Relationship of Parents' Age Heaping and Children's Test Scores

	(1) Math score	(2) Math score
ABCC Index	0.338***	0.188***
	(0.029)	(0.034)
Constant	-21.092***	-11.081***
	(2.564)	(3.262)
Country FE	No	Yes
Observations	117	117
R-Squared	0.447	0.739

Notes: These regressions show the correlation between children's math test scores and caretakers' numeracy. The dependent variable is the math test score, ranging between 0 and 21 based on MICS Wave 6 data. The dependent variable is the ABCC Index as a proxy for numerical skills. The 12 countries included are Central African Republic, Tchad, the Democratic Republic of the Congo, Gambia, Guinea-Bissau, Ghana, Lesotho, Madagascar, Sierra Leone, São Tomé and Príncipe, Togo, and Zimbabwe. The second model adds country fixed effects. Standard errors are robust. Asterisks denote significance at levels *** $p < .01$, ** $p < .05$, * $p < .1$.

ages end in 0 or 5 and hence 0 percent of these are heaped. Hence, while a dummy variable that indicates whether an age statement has the terminal digit 0 or 5 for a country like Tchad has some informational value as more than 40 percent of these must be heaped, it holds no informational value in a country like Zimbabwe, where heaping is non-existent.

Therefore, in the following illustrative analysis we focus on three countries with the lowest levels of numeracy – Tchad, Sierra Leone, and Togo. In these countries at least 20 percent of age statements ending in 0 or 5 must be heaped. In countries with higher ABCC values, the information content of an age with the terminal digit 0 or 5 is too low. Naturally, even in areas with substantial heaping not every person is reporting a false age if their age ends in 5 or 0. However, as this issue biases our results downwards, it does not change the qualitative interpretation of the results, only the magnitude. We estimate the following OLS model for these three countries.

$$Test_{pi} = \beta_0 + \beta_1 \cdot TerminalDigit05_p + \Gamma X + \gamma_i + \epsilon_{pi}, \tag{3}$$

where $Test$ denotes a child's math test score in the parent–child-dyad p and $TerminalDigit05$ is a dummy which equals one if the caretaker of dyad p reports an age with the terminal digit 0 or 5 and zero otherwise. 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. γ 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.

Table B.4 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. While the Tobit coefficients for Tchad increase considerably, this can be attributed to the heavily truncated distribution of the dependent variable. Overall, we can find a strong positive correlation between the ABCC Index and children's test scores at the regional level.

Table B.4: Within Household-Level Correlations: Parents' Age Heaping and Children's Test Scores

	(1)	(2)	(3)	(4)	(5)	(6)
	Tchad		Sierra Leone		Togo	
	Math score	Math score	Math score	Math score	Math score	Math score
OLS						
Terminal digit 0/5	-0.493***	-0.397***	-0.598***	-0.340*	-0.678**	-0.538**
	(0.157)	(0.140)	(0.205)	(0.179)	(0.288)	(0.248)
Constant	2.626***	-3.779***	7.903***	-3.111***	13.779***	2.404***
	(0.561)	(0.715)	(0.368)	(0.503)	(0.371)	(0.723)
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	8,136	8,136	5,929	5,929	2,790	2,790
R-Squared	0.136	0.268	0.092	0.300	0.115	0.357
Tobit						
Terminal digit 0/5	-1.951***	-1.689***	-0.828***	-0.476*	-0.759**	-0.579*
	(0.519)	(0.456)	(0.282)	(0.247)	(0.350)	(0.300)
Constant	-14.340***	-31.616***	6.168***	-7.885***	14.007***	0.656
	(2.574)	(2.654)	(0.525)	(0.726)	(0.445)	(0.857)
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	8,136	8,136	5,929	5,929	2,790	2,790

Notes: These regressions show the correlation between caretakers' age heaping and children's test scores based on MICS Wave 6 data. The dependent variable is children's test scores, ranging between 0 and 21, and the independent variable is a dummy indicating whether their caretaker stated an age with the terminal digit 0 or 5. All models control for regional fixed effects, with regions being the largest subnational unit. 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 *** $p < .01$, ** $p < .05$, * $p < .1$.

Overall, these analyses provide evidence that numeracy proxied by the ABCC Index does increase with years of education as well as that the ABCC Index of caretakers' correlates with children's math test scores, both at the regional level including all 12 countries and at the individual level in countries with a high share of heaped ages.

B.5.3 Data Validation

After having provided evidence that the ABCC Index can capture formal schooling and numerical skills in Sub-Saharan Africa, we turn to the other concerns discussed in the literature. While in some cases, these issues might render the dataset unsuitable for the age heaping methodology, we show in the following paragraphs that our data does not fall prey to these biases.

Respondent bias. First, the issue of potential respondent-related biases demands consideration, with specific emphasis on women's participation in the surveys. The concern is that instead of the woman answering questions herself, the husband or another male relative answers on her behalf. However, it is worth noting that the MICS surveys are methodically tailored to capture insights into the circumstances of women and children, thereby bolstering confidence that women respond for themselves. In contrast, the IPUMS and AB surveys do not specifically target either gender. Nonetheless, researchers and policymakers seeking nuanced gender-specific perspectives would naturally favour direct responses from the gender of interest.

To address any remaining doubts, we compare the ABCC Index based on IPUMS and AB data to estimates based on MICS data. This analysis is confined to countries where both MICS data and another data source are available. Hence, we re-estimate the ABCC results separately by gender across all data sources. Subsequently, we estimate the following regression equation:

$$ABCC_{it} = \beta_0 + \beta_1 \cdot Data_{it} + \beta_2 \cdot Gender_{it} + \beta_3 \cdot Gender_{it} \cdot Data_{it} + X_{it} + \epsilon_{it}, \qquad (4)$$

where $Data$ is a dummy variable indicating IPUMS or AB as the data source (0 for MICS) for region i and birth decade t, and $Gender$ is a dummy variable indicating on which gender the ABCC Index is based. Country, birth decade, and quartile fixed effects are included. The coefficients of interest, β_3 ('Respondent bias: IPUMS×Female' and 'Respondent bias: AB×Female'), detect gender bias in IPUMS or AB surveys. Table B.5 indicates no statistically significant evidence of respondent bias in IPUMS, while a small statistically significant finding emerges in the AB data. However, first, the magnitude of this difference is modest (about 1.28 percentage points, relative to a typical numeracy of 82). Second, it is lower than MICS which runs contrary to the hypothesis that women's ABCC might be biased upwards if male relatives respond. Additionally, AB data is only utilized to supplement a limited number of regions.

Table B.5: Test for Potential Female Respondent Bias

	(1) ABCC	(2) ABCC
IPUMS	-6.028***	
	(0.424)	
Male = 0/Female = 1	-0.167	-0.176
	(0.331)	(0.317)
Respondent bias: IPUMS×Female	-0.584	
	(0.396)	
Afrobarometer (AB)		-3.086***
		(0.546)
Respondent bias: AB×Female		-1.281**
		(0.575)
Constant	35.551***	54.929***
	(2.621)	(3.197)
Country FE	Yes	Yes
Birth decade FE	Yes	Yes
Quartile FE	Yes	Yes
Observations	3,743	1,893
R-Squared	0.867	0.759

Notes: These regressions show the potential bias caused by women not answering for themselves in IPUMS and Afrobarometer compared to MICS, a survey targeted at women. The dependent variable is the ABCC score, and the independent variable of interest are the interaction terms. All models control for country, birth decade, and quartile fixed effects. Standard errors are robust. Asterisks denote significance at levels *** $p < .01$, ** $p < .05$, * $p < .1$.

Marriage bias. Second, Földvári et al. (2012) and A'Hearn et al. (2022a) discussed whether married women might heap their age less than non-married women do. Their rationale is rooted in the idea that married individuals may align their reported ages with those of their spouses. Furthermore, considering that men tend to have higher levels of numeracy, this alignment might unintentionally enhance the perceived numeracy levels of married women.

Therefore, we analyse whether there is any upward bias in the ABCC Index for married women in our dataset. Hence, we re-estimate the index separately by gender for the groups of single, in union, separated/divorced and widowed individuals. We restrict the data to IPUMS as the sample sizes are large enough for this finer-level aggregation. We estimate an OLS regression with country and quartile fixed effects by age group, as individuals who are, for example, single in their twenties are most likely different from those who are single in their fifties. Table B.6 reports our results with individuals in union as our base group.

Our results do not support the idea of a marriage bias. There is no robust difference across age groups between women in union compared to their separated counterparts. While there is a small statistically significant difference between married women and widows, it is unlikely that this is caused by the rationale suggested above, as we observe the same effect – and in similar magnitude – for men as well. A more reasonable explanation could be that this is caused by a bereavement effect, as past research has shown that an individual's mental capabilities can decrease after the loss of a loved one (Atalay and Staneva, 2020; Jain et al., 2022; Lee and Ko, 2022; Zhao et al., 2021).

Ageing bias. 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 true, older birth cohorts would automatically appear less numerate. In another study, Crayen and Baten (2010) have already studied this for a global sample of the late nineteenth and early twentieth centuries and rejected age group biases.

To detect whether there is a bias regarding age in our data more specifically, 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. Again, we restrict our sample to the IPUMS data as the sample sizes are large enough to aggregate the data at this fine level. Table B.7 shows the results of the OLS regressions including country and quartile fixed effects.

We do not observe any significant downward trend as people get older. The few results that are significant point in different directions (Column (3) and (6) indicating the older group is more numerate vs. Column (10) indicating the opposite). Thus, we conclude that exaggerated heaping of older respondents is not an issue.

Table B.6: Test for Potential Marriage Bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Men				**Women**			
	23-32	33-42	43-52	53-62	23-32	33-42	43-52	53-62
Union Status								
Never Married	2.899***	0.910**	0.516	0.476	2.260***	-0.168	0.696	-0.507
	(0.430)	(0.455)	(0.552)	(0.544)	(0.426)	(0.412)	(0.505)	(0.555)
Separated	-0.960**	-0.526	-0.535	-0.205	-0.643	-0.989**	-0.328	-0.183
	(0.448)	(0.454)	(0.480)	(0.527)	(0.519)	(0.484)	(0.499)	(0.502)
Widowed	-2.084***	-2.329***	-1.742***	-1.390***	-1.377**	-2.624***	-1.014*	-0.575
	(0.537)	(0.481)	(0.471)	(0.469)	(0.608)	(0.541)	(0.544)	(0.523)
Constant	25.068***	29.630***	29.122***	33.400***	23.590***	31.065***	28.685***	30.775***
	(2.293)	(1.567)	(2.841)	(1.602)	(3.624)	(2.288)	(1.882)	(1.734)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quartile FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,022	1,025	1,018	972	986	1,011	1,019	958
R-squared	0.904	0.908	0.911	0.898	0.877	0.882	0.896	0.880

Notes: These regressions show the potential bias caused by women adapting their age statements to that of their spouse. The dependent variable is the ABCC score, and the independent variables are the different marital statuses with 'in union' being the base category. All models control for country and quartile fixed effects. Asterisks denote significance at levels *** $p < .01$, ** $p < .05$, * $p < .1$.

Table B.7: Test for Potential Ageing Bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)	(10)
	1950						**1960**			**1970**
Age comp. to:	22-32			33-42		43-52	33-42		43-52	43-52
33-42	1.093						0.328			1.197**
	(1.229)						(0.571)			(0.500)
43-52		-1.235		-0.550				-0.419	-0.409	
		(1.024)		(0.576)				(0.681)	(0.558)	
53-62			2.099**		0.699	2.006***				
			(0.952)		(0.682)	(0.613)				
Constant	61.157***	58.539***	40.918***	59.936***	43.533***	42.711***	57.440***	60.911***	60.578***	56.553***
	(1.777)	(2.358)	(1.615)	(2.022)	(1.436)	(1.270)	(2.587)	(2.421)	(1.748)	(1.689)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quartile FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	208	273	265	349	341	406	349	341	406	405
R-Squared	0.898	0.906	0.925	0.911	0.931	0.930	0.903	0.918	0.924	0.930

Notes: These regressions show the potential bias caused by older people exaggerating their age statements. The dependent variable is the ABCC score, and the independent variables are the different age groups compared to one another. We run the model for each birth decade separately to compare highly similar groups of people (i.e. those born in the same decade) at different points in their life. All models control for country and quartile fixed effects. Standard errors are robust. Asterisks denote significance at levels *** $p < .01$, ** $p < .05$, * $p < .1$.

Enumerator bias. Fourth, a general issue when using the age heaping methodology is whether the enumerators counterchecked the age the respondent states. 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. As discussed in the data section in some sources (here, DHS) this bias can be too substantial. However, if it is small, we have the possibility to downward-correct some 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 the lowest ABCC Index on average, and countercheck our other two data sources. Therefore, we estimate the following model:

$$ABCC_{it} = \beta_0 + \beta_1 \cdot DataDummy_{it} + X_{it} + \epsilon_{it}, \tag{5}$$

where $DataDummy$ denotes a dummy that equals 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 country, birth decade and quartile fixed effects.

We detect an upward bias in the MICS data (5.79) but no significant difference in the AB data. Hence, we correct the ABCC Index derived from the MICS by the amount of the estimated bias (Table B.8).[17] 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 an upper bound.

Alternative heaping patterns. Fifth, we check whether we should be concerned about alternative heaping patterns. To check whether this is the case in our data, we inspected the age distribution for each country to see if we can observe any alternative heaping pattern. Figure B.7 shows two exemplary histograms, one from a country with a high level of age heaping (Sierra Leone) and one with a low level of age heaping (Zambia). We can observe in these two age distributions that alongside heaping on the terminal digits 0 and 5, ages with the terminal digits 2 and 8 are given more often as well compared to the other digits.

[17] In other words, we estimate the dummy variable coefficient of the Afrobarometer and MICS data (relative to the constant which represents the IPUMS data). Since, there is a significant result for the MICS dummy, we subtract

Table B.8: Test for Potential Enumerator Bias

	(1) ABCC	(2) ABCC
MICS data	5.797***	
	(0.610)	
Afrobarometer data		-0.393
		(0.322)
Constant	64.950***	66.707***
	(1.676)	(1.279)
Country FE	Yes	Yes
Birth decade FE	Yes	Yes
Quartile FE	Yes	Yes
Observations	553	813
R-Squared	0.814	0.837

Notes: These regressions assess the potential bias caused by enumerator counterchecking. We compare the estimates from IPUMS (Integrated Public Use Microdata Series), producing the lowest ABCC estimates, to Afrobarometer and MICS (Multiple Indicator Cluster Surveys). Robust standard errors are given in parentheses. Asterisks denote significance at levels *** $p < .01$, ** $p < .05$, * $p < .1$.

Figure B.7: Exemplary Age Distributions from Sudan's and Zambia's Censuses Based on IPUMS Data. Authors' own representation

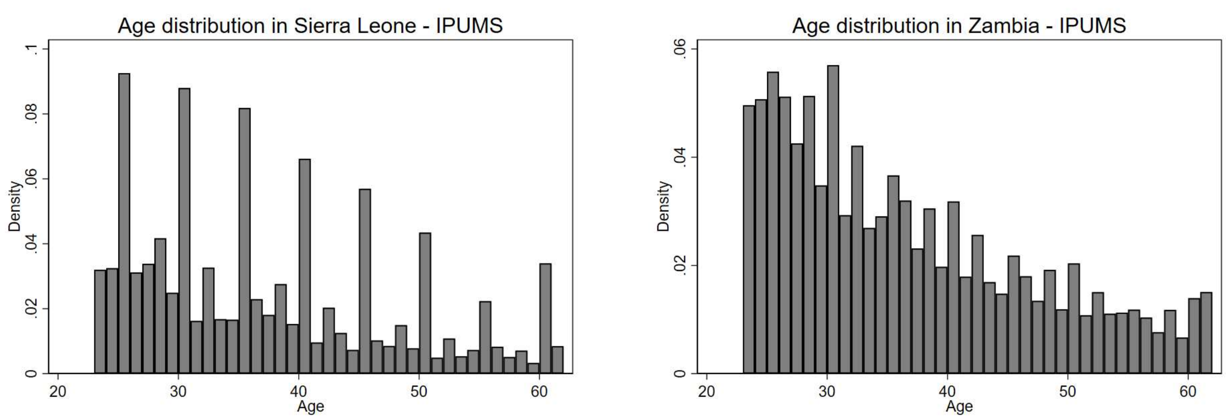


Table B.14 provides a more systematic analysis of these patterns. The table provides an overview of the most frequent terminal digits by country based on the pooled individual-level data from IPUMS, MICS and AB.[18] The table shows that heaping on multiples of 10 is the most frequent pattern in all countries but South Africa, which is the country with the overall highest ABCC. In all countries combined there are 9.20 percentage points more ages with the terminal digit 0 than there should be given a uniform distribution of terminal digits. This is more than a 90 percent increase. In Ethiopia, the country with the lowest overall ABCC, the increase is more than 200 percent. Next, for all countries but Uganda, with an ABCC below 90, heaping on the terminal digit 5 is the second most frequent pattern. However, as countries achieve a higher ABCC Index this pattern changes, andheaping on the terminal digit 2 becomes the second most frequent pattern. Especially, for the countries with an ABCC over 95 the heaping becomes most pronounced on the first four digits (0, 1, 2, 3), which could hint at mortality patterns (i.e. there are more 21-year-olds than 26-year-olds). Yet, heaping on the terminal digits 0 and 2 still remains more pronounced than on 1. The fourth most frequent terminal digit is 8, and it is especially popular among countries with a lower ABCC Index.

Overall, while heaping on the terminal digits 0 and 5 is the most popular, heaping on 2 and 8 is a noticeable pattern. As we are concerned with estimating basic numerical skills, this tendency is not of strong importance. Nevertheless, for completeness we calculate the Whipple and ABCC Index for heaping on the terminal digits 0, 2, 5 and 8. We adapt the Whipple and ABCC indices such that they become sensitive to heaping on 2, 5, 8 and 0.

$$W_{it}^{alt} = \frac{\left(n_{it}^{25} + n_{it}^{28} + n_{it}^{30} + n_{it}^{32} + n_{it}^{35} + \cdots + n_{it}^{62}\right) \cdot 100}{\frac{2}{5} \cdot \sum_{age=23}^{62} n_{it}^{age}} \tag{6}$$

$$ABCC_{it}^{alt} = \begin{cases} \left(1 - \frac{W_{it}^{alt} - 100}{150}\right) \cdot 100 & \text{if } W_{it}^{alt} \geq 100, \\ 100 & \text{otherwise.} \end{cases} \tag{7}$$

the value of this bias coefficient (5.797) from the MICS ABCC estimates to arrive at a standardized estimate.

[18] It is important to note that the age range for the table is 20 to 59 instead of the usual 'ABCC age range' 23 to 62. We had to make this adjustment to ensure that mortality does not bias the frequency of terminal digits as there are, for example, many more 23-year-olds than 62-year-olds. Thus, the terminal digit 3 would appear overly popular compared to the number 2.

As before, a value of zero indicates that everyone within a given group heaps their age and 100 indicates that there is no heaping.

Next, we compare our original ABCC Index with the newly calculated alternative version. Figure B.8 shows a scattergram of both indices. The high correlation of the two measures is clearly visible. The correlation coefficient is about 0.95. Hence, there is little difference between our indicators. Moreover, we can show in Table B.9 that our original ABCC Index has a higher correlation with alternative measures of education such as years of schooling and literacy.

Figure B.8: Correlation of Traditional ABCC Index and Alternative ABCC Index. Authors' own epresentation.

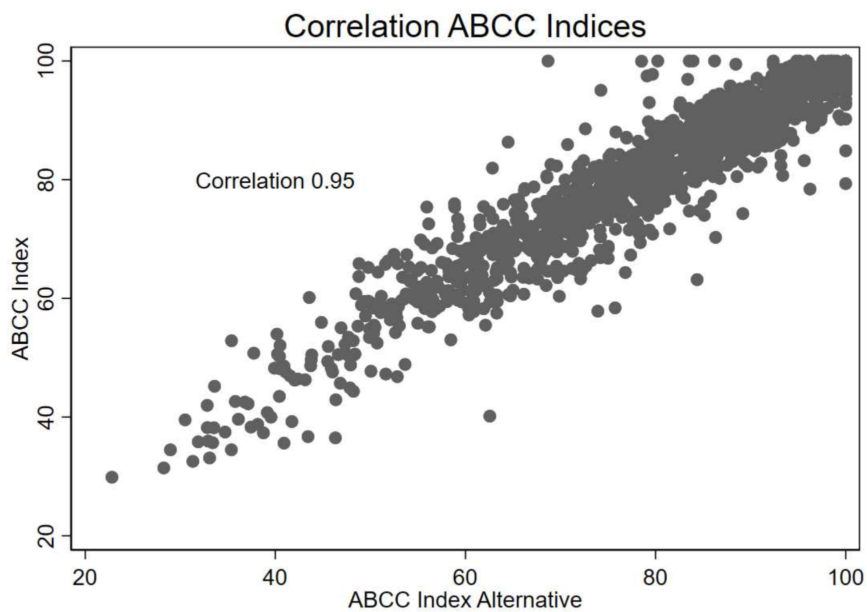


Table B.9: Pair-wise Correlation of ABCC and ABCC Alternative with Education Variables

	ABCC	**ABCC Alt.**
Literacy	0.466***	0.412***
Edu. years	0.262***	0.206***
Observations	1,937	1,937

Notes: t statistics are given in parentheses. Asterisks denote significance at levels * $p < .05$, ** $p < .01$, *** $p < .001$.

Overall, the systematic assessment of our data does not provide evidence that we need to be concerned about the biases discussed in the literature. The only issue we face is enumerator counterchecking in the MICS data – which, however, we can address as data from multiple sources is available.

B.6 Conclusion

Over the past several decades, great improvements have been made in terms of access to education in Sub-Saharan Africa; however, less progress has been made in increasing literacy and numeracy, which are both important foundational skills. While data on literacy is widely available to understand this development, little data is available for numeracy UNDESA (2024). Therefore, focusing on the post-colonial period, we employ the age-heaping methodology to estimate basic numeracy in this world region.

We find that little progress in numeracy has been made on average. However, there are strong regional disparities. Southern Africa has the highest level of numeracy, followed by Eastern and Central Africa. Trailing behind is Western Africa. This region also exhibits the highest variation. Some individual countries have made good progress increasing their educational output, such as Ghana, while other countries have experienced a decline, such as Niger. These results are in line with research by Le Nestour et al. (2022), showing that while inputs into the educational system have increased, the output, i.e. the quality of education skills, has been deteriorating.

The age-heaping methodology has been criticized for not actually capturing numerical skills but rather reflecting culture and state capacity (A'Hearn et al., 2022a; A'Hearn et al., 2022b; Beltrán Tapia et al., 2022; Földvári et al., 2012). Thus, we provide evidence that the ABCC Index is a suitable proxy for numerical abilities in Sub-Saharan Africa. We show that the index correlates well with years of schooling and literacy. Moreover, we studied whether children whose parents misreport their age perform more poorly on explicit math tests, and we confirmed this intergenerational correlation of low numeracy. Hence, we conclude that the ABCC Index is a suitable method for estimating numerical abilities in Sub-Saharan Africa.

Additionally, we show that the data does not fall prey to substantial biases. Only one source had a modest bias, which we can adjust accordingly. We assessed whether women answered for themselves, whether marital status impacts age statements and whether individuals heap more as they get older. We did not find any evidence for these biases. We checked for alternative heaping patterns and find that their incidence is not substantial. Last, we counterchecked our different data sources for enumerators counterchecking age statements. We find that the initial MICS estimates were biased upwards and allow for correction.

Overall, this study provides robust estimates of numerical abilities in Sub-Saharan Africa in the post-colonial period. Given the importance of improving foundational learning skills, understanding their development is essential to explore determinants.

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B.8 Supplementary Material

B.8.1 IPUMS Data Useability

One concern about using the age data from censuses is that they might originate from household rosters in which one household member filled in or named the age of all other members. This could bias the results downwards if the respondent is not sure about every member's age and lists approximations.

Unfortunately, we cannot be certain for which censuses and for which observations within these, this is the case. However, we can check whether there is a downward bias by first estimating the ABCC Index only using the age of the household head (assuming that this person might have responded on everyone's behalf) and then estimating the ABCC Index only employing the remaining household members' ages. We then can compare these two estimates.

The ABCC Index of only using the household heads is 81.0117 and the ABCC Index of the remaining household members is 81.09277. The correlation coefficient is 0.9834 and a simple T-Test shows that the two indices are not statistically significantly different. We further calculated the same indices by gender and the correlation coefficients remain high at 0.9872 for males and 0.9633 for women.

B.8.2 Data Availability by Survey and Country

Table B.10: IPUMS Data Availability per Decade

1960	1970	1980	1990	2000	2010
Kenya (1969)	Benin (1979)	Botswana (1981)	Benin (1992)	Benin (2002)	Benin (2013)
Togo (1960)	Cameroon (1976)	Burkina Faso (1985)	Botswana (1991)	Botswana (2001)	Botswana (2011)
	Kenya (1979)	Cameroon (1987)	Burkina Faso (1996)	Burkina Faso (2006)	Ghana (2010)
	Liberia (1974)	Ethiopia (1984)	Ethiopia (1994)	Cameroon (2005)	Guinea (2014)
	Togo (1970)	Ghana (1984)	Guinea (1996)	Ethiopia (2007)	Mauritius (2011)
		Guinea (1983)	Kenya (1999)	Ghana (2000)	Nigeria (2010)
		Kenya (1989)	Lesotho (1996)	Kenya (2009)	Rwanda (2012)
		Malawi (1987)	Malawi (1998)	Lesotho (2006)	Senegal (2013)
		Mali (1987)	Mali (1998)	Liberia (2008)	South Africa (2011, 2016)
		Senegal (1988)	Mauritius (1990)	Malawi (2008)	Tanzania (2012)
		Tanzania (1988)	Mozambique (1997)	Mali (2009)	Togo (2010)
			Rwanda (1991)	Mauritius (2000)	Uganda (2014)
			South Africa (1996)	Mozambique (2007)	Zambia (2010)
			Uganda (1991)	Nigeria (2006, 07, 08, 09)	Zimbabwe (2012)
			Zambia (1990)	Rwanda (2002)	
				Senegal (2002)	
				Sierra Leone (2004)	
				South Africa (2001, 2007)	
				South Sudan (2008)	
				Sudan (2008)	
				Tanzania (2002)	
				Uganda (2002)	
				Zambia (2000)	

Table B.11: MICS Data Availability per Wave

Wave 3	Wave 4	Wave 5	Wave 6
Cent. African Rep. (2006)	Cent. African Rep. (2010)	Benin (2014)	Cent. African Rep. (2018-19)
Ghana (2006)	Ghana (2011)	Cameroon (2014)	Tchad (2019)
Mauritania (2007)	Mauritania (2011)	Côte d'Ivoire (2016)	DR Congo (2018)
Malawi (2006)	Togo (2010)	Congo Rep. (2014-15)	Gambia (2018)
	Swaziland (2010)	Guinea-Bissau (2014)	Guinea-Bissau (2018-19)
		Mali (2015)	Ghana (2017-18)
		Mauritania (2015)	Lesotho (2018)
		Malawi (2013-14)	Madagascar (2018)
		Nigeria (2016)	Sierra Leone (2017)
		São Tomé & Príncipe (2014)	São Tomé & Príncipe (2019)
		Swaziland (2014)	Togo (2019)
		Zimbabwe (2014)	Zimbabwe (2019)

Table B.12: Afrobarometer Data Availability per Wave

Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Wave 7
Botswana (1999)	Botswana (2003)	Benin (2005)	Benin (2008)	Benin (2011)	Benin (2014)	Benin (2019)
Ghana (1999)	Cape Verde (2002)	Botswana (2005)	Botswana (2008)	Botswana (2012)	Botswana (2014)	Botswana (2019)
Lesotho (2000)	Ghana (2002)	Cape Verde (2005)	Burk. Faso (2008)	Burk. Faso (2012)	Burk. Faso (2015)	Burk. Faso (2019)
Malawi (1999)	Kenya (2003)	Ghana (2005)	Cape Verde (2008)	Burundi (2012)	Burundi (2014)	Cameroon (2019)
Mali (2001)	Lesotho (2003)	Kenya (2005)	Ghana (2008)	Cameroon (2013)	Cameroon (2015)	Cape Verde (2019)
Namibia (1999)	Malawi (2003)	Lesotho (2005)	Kenya (2008)	Cape Verde (2011)	Cape Verde (2014)	Côte d'Ivoire (2019)
Nigeria (1999)	Mali (2002)	Madagascar (2005)	Lesotho (2008)	Côte d'Ivoire (2013)	Côte d'Ivoire (2014)	Gabon (2019)
South Africa (2000)	Mozambique (2002)	Malawi (2005)	Liberia (2008)	Ghana (2012)	Gabon (2015)	Gambia (2019)
Tanzania (2001)	Namibia (2003)	Mali (2005)	Madagascar (2008)	Guinea (2013)	Ghana (2014)	Ghana (2019)
Uganda (2000)	Nigeria (2003)	Mozambique (2005)	Malawi (2008)	Kenya (2011)	Guinea (2015)	Guinea (2019)
Zambia (1999)	Senegal (2002)	Namibia (2005)	Mali (2008)	Lesotho (2012)	Kenya (2014)	Kenya (2019)
Zimbabwe (1999)	South Africa (2002)	Nigeria (2005)	Mozambique (2008)	Liberia (2012)	Lesotho (2014)	Lesotho (2019)
	Tanzania (2003)	Senegal (2005)	Namibia (2008)	Madagascar (2013)	Liberia (2015)	Liberia (2019)
	Uganda (2002)	South Africa (2005)	Nigeria (2008)	Malawi (2012)	Madagascar (2014)	Madagascar (2019)
	Zambia (2003)	Tanzania (2005)	Senegal (2008)	Mali (2012)	Malawi (2014)	Malawi (2019)
	Zimbabwe (2004)	Uganda (2005)	South Africa (2008)	Mauritius (2012)	Mali (2014)	Mali (2019)
		Zambia (2005)	Tanzania (2008)	Mozambique (2012)	Mauritius (2014)	Mauritius (2019)
		Zimbabwe (2005)	Uganda (2008)	Namibia (2012)	Mozambique (2015)	Mozambique (2019)
			Zambia (2009)	Niger (2013)	Namibia (2014)	Namibia (2019)
			Zimbabwe (2009)	Nigeria (2012)	Niger (2015)	Niger (2019)
				Senegal (2013)	Nigeria (2014)	Nigeria (2019)
				Sierra Leone (2012)	Senegal (2014)	Senegal (2019)
				South Africa (2011)	Sierra Leone (2015)	Sierra Leone (2019)
				Sudan (2013)	South Africa (2015)	South Africa (2019)
				eSwatini (2013)	Sudan (2015)	Sudan (2019)
				Tanzania (2012)	eSwatini (2015)	eSwatini (2019)
				Togo (2012)	São T. & P. (2015)	São T. & P. (2019)
				Uganda (2012)	Tanzania (2014)	Tanzania (2019)
				Zambia (2013)	Togo (2014)	Togo (2019)
				Zimbabwe (2012)	Uganda (2015)	Uganda (2019)
					Zambia (2014)	Zambia (2019)
					Zimbabwe (2014)	Zimbabwe (2019)

B.8.3 Trends in Numeracy by Country

The following graphs provide an overview of the numeracy trends, measured by the ABCC Index, for those countries whose average ABCC is above 90. The remainder can be found in the main text. In each of these graphs the bold red line represents the country average, and the light grey lines represent the subnational regions. We refrained from labeling all the subnational regions in the graphs for the sake of clarity. Please refer to the publicly available data set for more details on the subnational regions.

Figure B.9: Development of Numeracy in Countries With an Average ABCC Above 90 at the Subnational Level Based on IPUMS, MICS and Afrobarometer Data. Authors' own calculations.

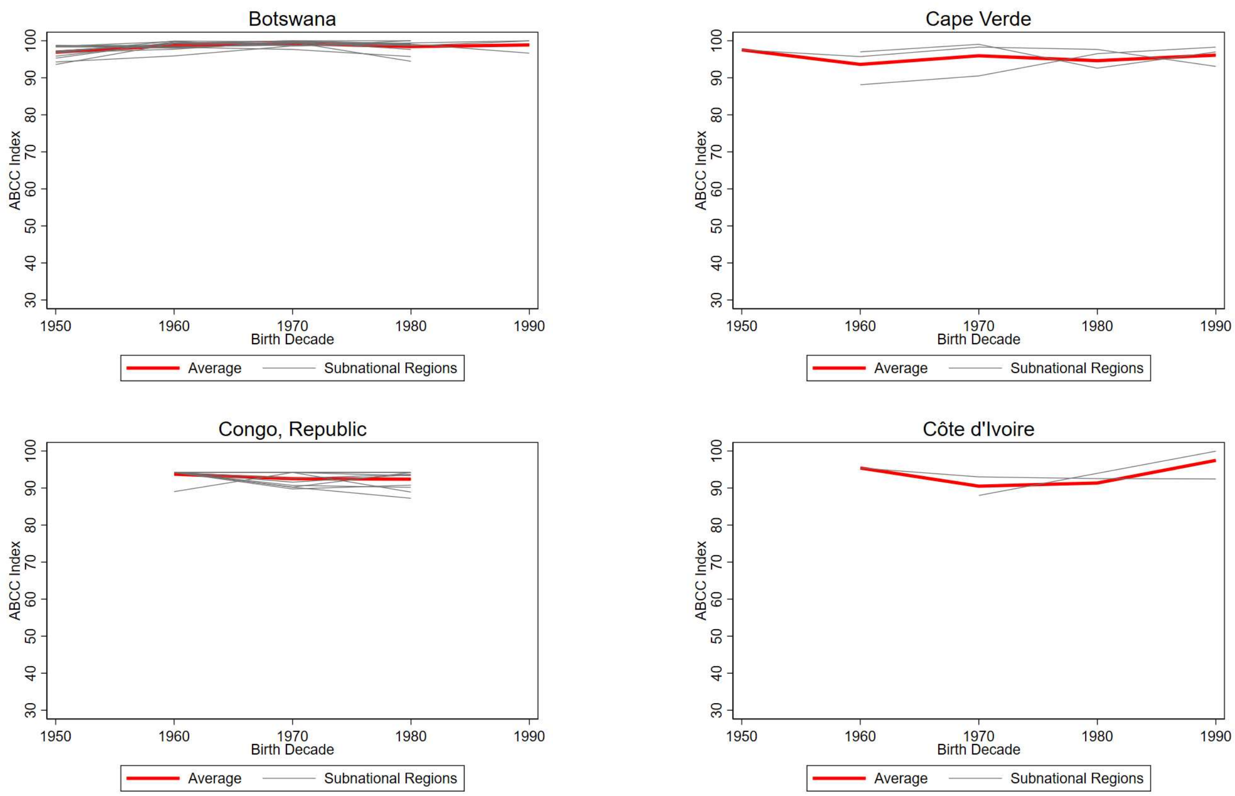


Figure B.9: cont.

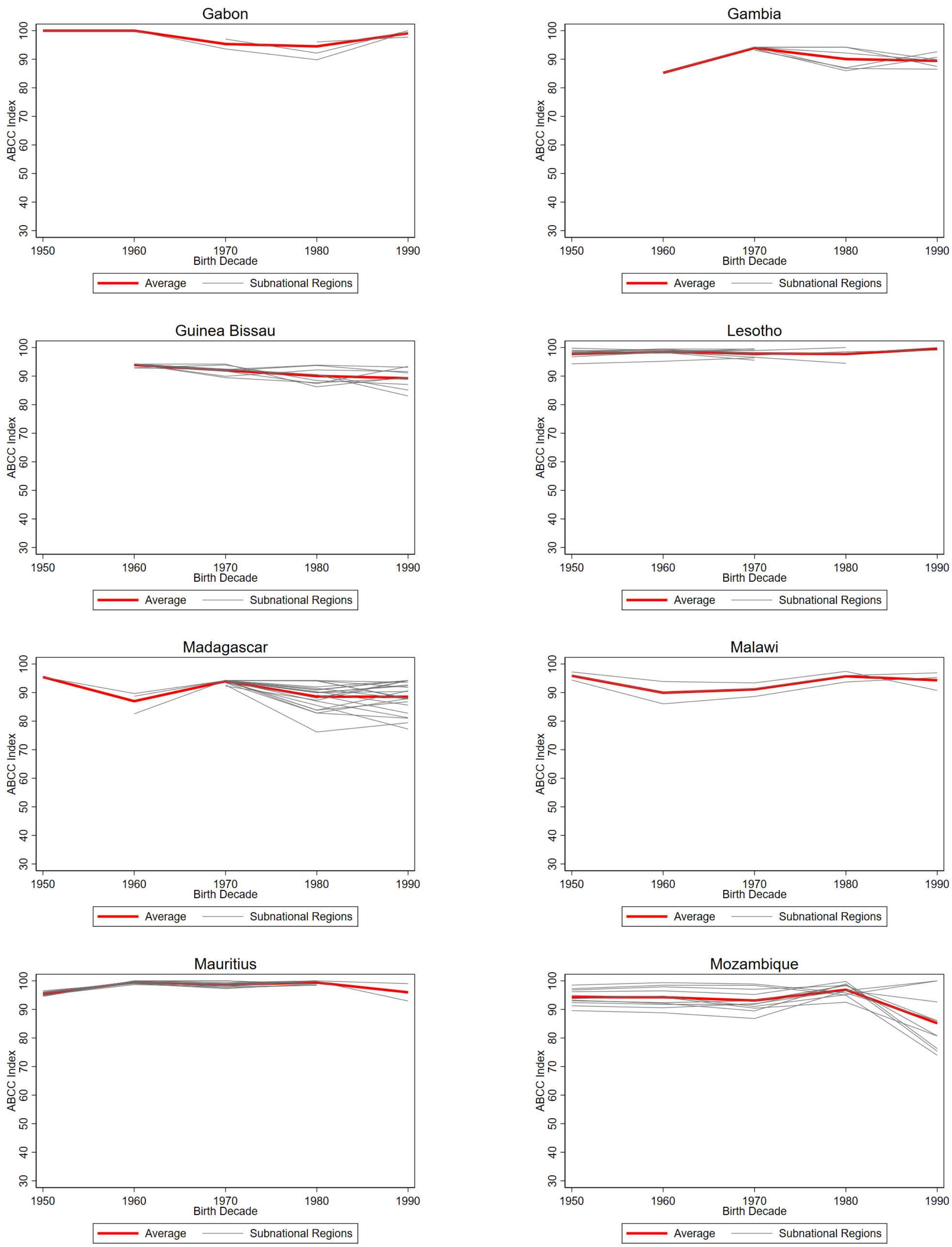
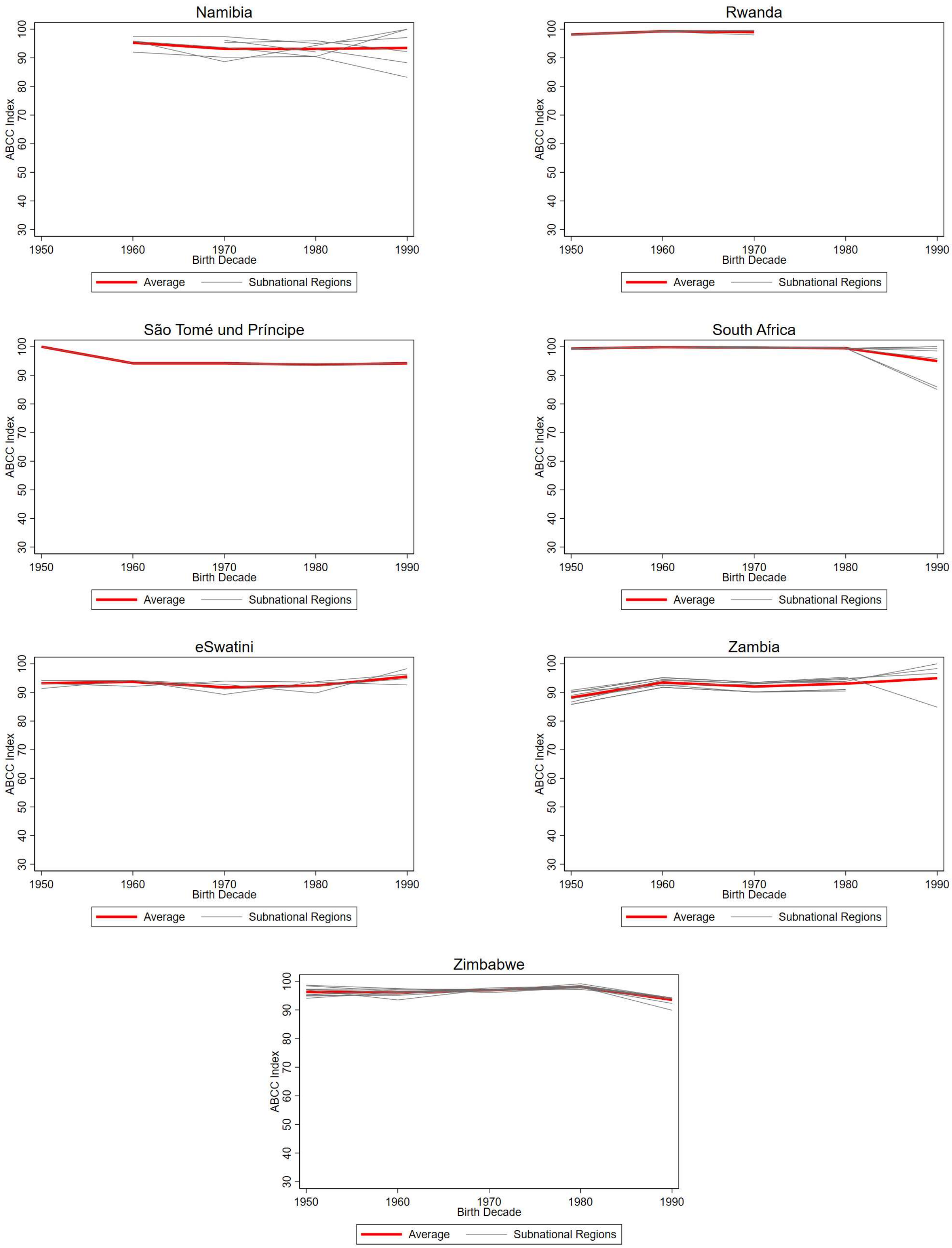


Figure B.9: cont.



B.8.4 The Relationship of the ABCC Index with Years of Education by Region

Table B.13: The Relationship of the ABCC Index with Years of Education by Region

DV: ABCC	(1) Western Africa	(2) Eastern Africa	(3) Central Africa	(4) Southern Africa
Years of Education	1.364***	1.046***	0.840**	0.365***
	(0.412)	(0.251)	(0.419)	(0.137)
Constant	65.718***	80.965***	83.808***	95.768***
	(1.577)	(2.577)	(3.493)	(0.856)
Country FE	Yes	Yes	Yes	Yes
Birth Decade FE	Yes	Yes	Yes	Yes
Observations	557	428	101	149
R-Squared	0.519	0.799	0.143	0.475

Notes: These regressions show the correlation between the ABCC Index with years of education by African region (Western, Eastern, Central, and Southern). The dependent is the ABCC Index ranging between 0 and 100, and the main independent variables are years of education. All models include country and birth decade fixed effects. Standard errors are robust. Asterisks denote significance at levels *** $p < .01$, ** $p < .05$, * $p < .1$.

B.8.5 Frequency of Terminal Digits

Table B.14: Frequency of Terminal Digits

Country	0	1	2	3	4	5	6	7	8	9	ABCC
Ethiopia	0.3002	0.0419	0.0996	0.0562	0.0481	0.2151	0.0609	0.0526	0.0950	0.0305	61.8938
Sudan	0.2827	0.0489	0.1091	0.0646	0.0502	0.2059	0.0537	0.0752	0.0731	0.0368	62.0473
Nigeria	0.2642	0.0552	0.1005	0.0613	0.0545	0.1911	0.0700	0.0637	0.0931	0.0464	63.5033
Niger	0.2349	0.0551	0.1109	0.0653	0.0406	0.2128	0.0614	0.0775	0.0993	0.0422	64.7594
Sierra Leone	0.2419	0.0599	0.0992	0.0623	0.0602	0.2188	0.0664	0.0617	0.0812	0.0483	68.4589
Guinea	0.2394	0.0623	0.0961	0.0685	0.0735	0.1756	0.0789	0.0687	0.0877	0.0493	68.8424
Benin	0.2344	0.0655	0.1133	0.0792	0.0595	0.1856	0.0628	0.0677	0.0854	0.0466	69.7074
Burundi	0.1823	0.0654	0.1352	0.0873	0.0751	0.1391	0.0771	0.0780	0.1066	0.0538	72.4410
Togo	0.2123	0.0708	0.1087	0.0849	0.0685	0.1656	0.0692	0.0739	0.0905	0.0555	73.6116
Tchad	0.2063	0.0697	0.1024	0.0703	0.0858	0.1595	0.0668	0.0811	0.0746	0.0836	75.1429
Mali	0.2060	0.0789	0.1032	0.0816	0.0781	0.1447	0.0783	0.0795	0.0848	0.0649	78.3914
Ghana	0.1980	0.0755	0.1114	0.0802	0.0814	0.1487	0.0850	0.0721	0.0926	0.0550	80.3032
Senegal	0.1820	0.0858	0.1012	0.0896	0.0907	0.1329	0.0780	0.0842	0.0778	0.0778	83.3003
South Sudan	0.2303	0.0619	0.1012	0.0656	0.0697	0.1412	0.0768	0.0725	0.1114	0.0693	83.3262
Tanzania	0.1947	0.0719	0.1232	0.0754	0.0810	0.1339	0.0810	0.0704	0.1030	0.0655	84.2572
Burkina Faso	0.1893	0.0912	0.1038	0.0867	0.0801	0.1261	0.0941	0.0868	0.0779	0.0640	84.3867
Cameroon	0.2103	0.0853	0.0972	0.0871	0.0711	0.1507	0.0795	0.0783	0.0796	0.0609	85.1339
Cen. African Rep.	0.1565	0.0868	0.1112	0.0951	0.0895	0.1231	0.0938	0.0825	0.0944	0.0672	85.6150
Liberia	0.1831	0.0841	0.1083	0.0806	0.0837	0.1274	0.0823	0.0693	0.1065	0.0748	88.1446
Mauritania	0.1445	0.1084	0.1072	0.0965	0.0931	0.1133	0.1092	0.0764	0.0858	0.0657	88.5865
Kenya	0.1775	0.0926	0.1075	0.0869	0.0861	0.1294	0.0832	0.0812	0.0821	0.0734	88.7269
DR Congo	0.1333	0.1128	0.1127	0.0975	0.0959	0.1273	0.0839	0.0834	0.0839	0.0693	89.0853
Uganda	0.1793	0.0862	0.1205	0.0851	0.0940	0.1141	0.0831	0.0758	0.0953	0.0665	89.7712
Madagascar	0.1480	0.0949	0.1071	0.0949	0.0930	0.1104	0.0943	0.0814	0.1021	0.0738	90.2385
Gambia	0.1362	0.1003	0.1069	0.1078	0.0942	0.1181	0.0903	0.0878	0.0836	0.0748	90.8336
Guinea-Bissau	0.1363	0.1072	0.0990	0.1004	0.1079	0.1112	0.0895	0.0741	0.0982	0.0761	91.3084
Zambia	0.1583	0.0956	0.1234	0.0903	0.0914	0.1089	0.0963	0.0751	0.0974	0.0633	91.9979
Congo	0.1214	0.1006	0.1171	0.0863	0.1087	0.0969	0.0967	0.0903	0.0934	0.0887	92.8608
Mozambique	0.1498	0.0879	0.1217	0.0993	0.0814	0.1158	0.0729	0.1065	0.0880	0.0768	92.8800
Swaziland	0.1259	0.1089	0.1129	0.0983	0.1015	0.1011	0.0965	0.0895	0.0914	0.0739	93.3258
Malawi	0.1564	0.0937	0.1127	0.0910	0.0942	0.1157	0.0904	0.0702	0.1045	0.0712	93.3894
Namibia	0.1338	0.1095	0.1166	0.0958	0.0934	0.0940	0.0770	0.0906	0.0985	0.0908	93.5642
Côte d'Ivoire	0.1383	0.0951	0.1063	0.0992	0.0934	0.1077	0.1024	0.0899	0.0897	0.0779	93.9433
São Tomé & Prín.	0.1155	0.1087	0.1143	0.0982	0.1001	0.0983	0.0892	0.0906	0.0952	0.0898	94.8099
Cape Verde	0.1278	0.1026	0.1206	0.1010	0.1004	0.1007	0.0855	0.0833	0.1000	0.0780	95.2203
Zimbabwe	0.1328	0.0967	0.1225	0.0977	0.0959	0.0985	0.0949	0.0859	0.0930	0.0820	96.1832
Gabon	0.1227	0.1102	0.1217	0.1015	0.0802	0.1064	0.0824	0.0938	0.0998	0.0813	96.9056
Lesotho	0.1311	0.1097	0.1124	0.1017	0.1008	0.0979	0.1017	0.0819	0.0890	0.0737	98.1176
Mauritius	0.1114	0.1039	0.1061	0.1031	0.0990	0.1011	0.0971	0.0938	0.0927	0.0917	98.1568
Botswana	0.1183	0.1127	0.1081	0.1026	0.0984	0.1026	0.0950	0.0866	0.0879	0.0877	98.3584
Rwanda	0.1329	0.1160	0.1171	0.1029	0.0974	0.0955	0.0877	0.0849	0.0842	0.0813	98.7983
South Africa	0.1109	0.1134	0.1057	0.1039	0.0971	0.0986	0.0971	0.0927	0.0906	0.0900	98.8329
Total	0.1929	0.0813	0.1096	0.0831	0.0795	0.1416	0.0806	0.0769	0.0904	0.0641	

Notes: This table shows the frequency of terminal digits, i.e., the last number of an age statement, for a pooled individual-level dataset. The "pooled dataset" includes all observations from IPUMS, MICS, and Afrobarometer.

C Nutrition Matters: Numeracy, Child Nutrition and Schooling Efficiency in Sub-Saharan Africa in the Long Run [19]

Abstract

School enrolment has increased at an unprecedented scale in Sub-Saharan Africa but learning and the associated education efficiency have not. Given that resources are limited, the efficient use of inputs is of utmost importance for sustainable development. Hence, we investigate whether improvements in children's nutrition can improve learning and hence efficiency. To assess this relationship, we employ average female height as our proxy for nutrition during childhood. For learning, we estimate numeracy and efficiency using a linearized version of the Whipple Index. Our data is at the subnational level focusing on the birth decades from 1950 to 1999. To deal with the endogeneity of nutrition, we use an instrumental variable approach. Our instrument is negative rainfall shocks during childhood which can adversely affect nutrition. We find that better nutrition increases education efficiency. Therefore, investments in nutrition can advance self-sustaining long-term growth based on human capital in Sub-Saharan Africa.

[19] This chapter is based on an article by Ferber and Baten (2024), published in the *Journal of Development Studies*. The version included in this dissertation is identical in content, with only minor textual differences. I was responsible for approximately 80 percent of the conceptual development and writing, while Jörg Baten contributed the remaining 20 percent.

C.1 Introduction

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 decades, more children than ever have been enrolled in primary school in substantial parts of Sub-Saharan Africa, the region has not experienced the expected progress in learning outcomes (Angrist et al., 2021). The World Bank has even argued that Africa faces a severe 'schooling crisis' (Bashir et al., 2018). For sustainable growth the learning outcomes are essential, not the time spent in school (Hanushek and Woessmann, 2008). Therefore, policymakers and scholars have been searching for tools to increase education efficiency.

We contribute to this discussion by taking a long-term perspective. First, we evaluate how numerical skills and schooling efficiency have evolved at the sub-national level between 1950 to 1999. Second, we investigate the underlying mechanisms focusing on nutritional quality because previous research found that lower nutrition substantially reduces the ability to learn (Bryan et al., 2004; Currie and Rossin-Slater, 2013; Paxson and Schady, 2007). Following this evidence both international organizations and governments have invested in school-feeding programs, which provide children with meals at school, to not only improve nutrition in general but also learning. Hence, we estimate the impact of children's nutrition and health on schooling efficiency, measured as the ratio between acquired numeracy (output) and years of schooling (input). We employ average female height as our main explanatory variable.

Stature is an indicator of the quality of nutrition during childhood (Baten and Blum, 2014). While height is highly dependent on genetic factors at the individual level, averaging across individuals within a given group can specify whether they suffered from malnutrition during childhood. However, we must confine our averages to female height because of constraints in the available data. Nevertheless, we can use this to estimate the effect of childhood nutrition on schooling efficiency.

We use an instrumental variable approach (IV) using negative rainfall shocks as the IV for a causal interpretation. We chose this instrument due to its local variations and its importance in livelihoods as more than half of the population in Sub-Saharan Africa is employed in agriculture (World Bank, 2022) and little land is irrigated (Barrios et al., 2010). Moreover, there are several mechanisms that can link rainfall shocks with adverse child health. First, insufficient rainfall can reduce food supply, agricultural income as well as breastmilk production (Banerjee et al., 2010;

Burlando, 2014; Hidalgo et al., 2010). Second, anticipation of a poor harvest induces maternal stress, harming foetal development (e.g. Aizer et al., 2016; Currie and Rossin-Slater, 2013; Lee, 2014). Lastly, insufficient rainfall is also linked to conflict, posing additional risks to child well-being (Hsiang et al., 2013). We carefully assess the instrumental variable (exclusion restriction and other issues) below.

For our outcome variable "schooling efficiency", we estimate numeracy, because numerical skills are among the most relevant outputs of the schooling process (alongside with literacy). We follow the age-heaping methodology as less numerate people are more likely to misreport their age (A'Hearn et al., 2009).[20] This is visible in censuses and other surveys, as an unusually large number of people mention, for example, "I am 40 years old" when in reality they are 39 or 41. Societies in regions and periods in which many people are innumerate tend to be societies in which many persons do not know their exact age, or they cannot calculate it from existing documents. To quantify this phenomenon, we employ a linearized version of the Whipple Index, the ABCC Index. It compares the frequency of age statements with the terminal digits zero or five to a uniform distribution. We estimate this index for each birth decade from the 1950s to the 1990s per admin I subnational area in Sub-Saharan Africa.

This indicator has been characterized as a reliable proxy for numerical skills. For example, several contributions show the negative correlation of heaped ages with numerical tests (Baten et al., 2022; Baten and Nalle, 2022; Ferber and Baten, 2025). However, a certain degree of measurement error remains, as with any proxy indicator. The key advantages of this method are as follows: First, the data requirements are comparably low as only the respondent's reported age is necessary (compared to a demanding math test); and second, the birth cohort method allows estimating of numerical abilities over long-time horizons and different geographical areas while remaining comparable.[21]

For the numeracy estimation, we combine reported age data from censuses, UNICEF's *Multiple Indicator Cluster Surveys* and the *Afrobarometer* to achieve a large coverage of Sub-Saharan Africa. Thus, this study fills an important data gap about adult numeracy and provides the first

[20] The concept was first used by demographers to assess data quality (Bachi, 1951). It is now commonly used to estimate basic numeracy (Crayen and Baten, 2010; Hippe and Baten, 2012; Stolz et al., 2013).

[21] This holds true if survivor bias is not substantial. Earlier studies found that survivor bias does not invalidate the results (Crayen and Baten, 2010).

comprehensive overview of basic numerical abilities at the subnational level in Sub-Saharan Africa for the birth decades from 1950 to 1990.

As a preview to our findings, we observe that children's nutrition proxied by height is a strong predictor of the efficiency of the education system. The finding is robust across several specifications. This might also explain the stagnation of schooling efficiency, as height has stagnated over this period and declined in several countries of Sub-Saharan Africa (Baten and Blum, 2014). From the 1960s to the 1980s, African heights fell modestly from the range of 169.7-169.9 cm to the one of 169.1-169.0 cm, while all other world regions increased in height.[22]

The contributions of this paper to the literature are twofold. As a first value-added, 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 differences by considering subnational evidence and tracing the development of numeracy in the region. Some evidence on the numeracy of school children exists, but none on adults: 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: They cover only the in-school population and given that many children in Sub-Saharan Africa do not attend school at all or regularly, the test scores will overestimate the overall skills of a given population (Lilenstein, 2020). Moreover, since both organizations only started operation in the late 1990s, assessing the long-run development of schooling outcomes is impossible. Furthermore, only very few studies estimate numerical abilities in Sub-Saharan Africa.[23] 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

[22]Height evidence is from www.clio-infra.eu, reporting male height for 32 Sub-Saharan African countries for the 1960-69 and 34 in the 1980-89 birth periods (based on age groups 20-50). Similarly, the NCD Risk Factor Collaboration (NCD-RisC), 2016 study arrives at 169.7 cm for 45 Sub-Saharan African countries both for 1960-69 and 169.1 cm for the 1980-89 birth periods (including the 17-year age group and no upper limit). For the 1990s, the trend continued down to 167.8 cm. From the birth decade of the 1950s to the 1960s, an increase from 169.0-169.4 to 169.7-169.9 can be observed.

[23]The demography literature provides a few contributions using the age-heaping approach to evaluate the quality of survey data (Bwalya et al., 2015; Fayehun et al., 2020; Lyons-Amos and Stones, 2017). Yet, while these studies employ age heaping, their methodology is not completely comparable, and they do not link their estimates to the numerical abilities of respondents.

using a panel data model. However, their study does not cover most of the post-colonial period.

As a second value-added item, our study contributes to the literature about the efficiency of the educational systems. The relevance of nutrition for numerical learning has been hypothesized and studied for individual case studies, such as Kenya (Hulett et al., 2014), Ecuador (Paxson and Schady, 2007), and England around 1810 (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. In sum, our work uses the educational efficiency of numeracy acquisition for the first time. Using this method broadens data availability considerably. We gain significant insights on the determinants of educational effectiveness, especially nutrition. If the causes of low educational efficiency are fully understood, political decisions can be taken to improve educational efficiency.

The remainder of this paper is organized as follows: Section 2 presents the background; Section 3 discusses the data sources, the methods to estimate numeracy, and our strategy to evaluate the efficiency of the education systems; Section 4 details the results; Section 5 includes the robustness checks; and Section 6 concludes the discussion.

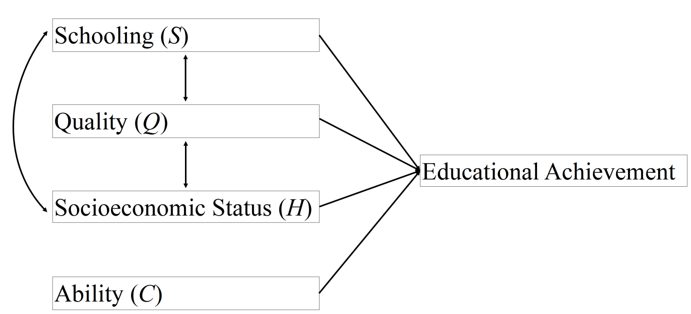
C.2 Background

To design effective policies that raise the overall level of education, understanding the current state and potential determinants of educational achievement is of utmost importance. Many studies and policy reports focused on literacy rather than numeracy until recently (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 revealed that numeracy is an even more important factor than literacy, which drove economic growth over the past decades, although both are necessary.

Even in agriculture, skills for comparing numerical proportions are essential. For example, a farmer might need to carry 50 stacks of wood. The question arises if the farmer should walk home to get a wheelbarrow or walk more often. Another example would be a microentrepreneur who could hire an employee and needs to compare costs and benefits. Both examples illustrate the far-reaching effects of basic numeracy skills on labour productivity and living standards. Thus, an overall increase in numeracy can substantially increase incomes in Sub-Saharan Africa. Crayen and Baten (2010) show the impact of numeracy on GDP growth on a global scale, especially in many African countries. While literacy naturally remains a foundational skill, obtaining numeracy evidence is also relevant to enable populations to lift themselves out of poverty.

The study's second main question pertains to 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 student enrolment and attendance as well as actual educational output. The theoretical framework for retrospective and (quasi-) experimental studies in this field is a schooling production function (Glewwe and Kremer, 2006). Figure C.1 represents a stylized version of such an education production function. The achievement of a student is determined by numerous factors, such as the time spent in school (S), the quality of schools and teachers (Q), the student's innate ability (C), and the socioeconomic status of the household (H).

Figure C.1: Stylised Education Production Function Following Glewwe and Kremer (2006). Authors' own representation.



Much earlier work has focused on retrospectively estimating the parameters of such an education production function (Glewwe and Jacoby, 1994; Glewwe et al., 1995; 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 (Evans and Ngatia, 2021; Kremer et al., 2013; McEwan, 2015) have discussed the findings of this literature. However, these studies lack a comprehensive long-run perspective on the schooling efficiency for numeracy, a gap addressed by our study.

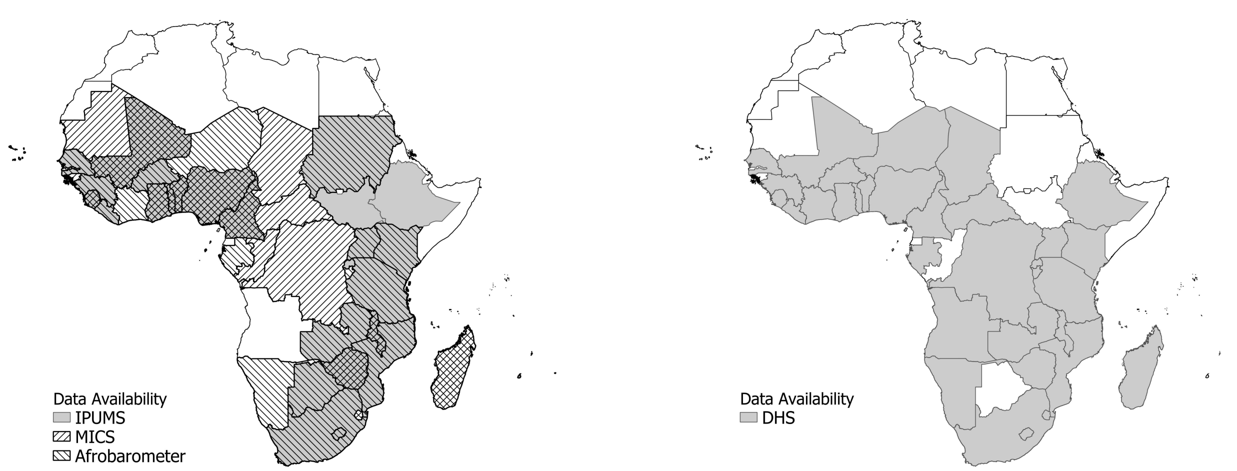
C.3 Data and Method

C.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 are all representative at the national level. As a caveat, we should note that not all our datasets are designed to become representative at a regional level. Hence, we show in the Supplementary Material whether the regional estimates of education of the different datasets reconfirm each other. Our code and data are available in the Supplementary Materials figshare files.

Figure C.2 displays a map indicating for which country which data sources are available with the first showing the countries for which age data is available and the second the countries for which height data is available. Overall, the different sources allow us to cover almost the entire region. A more detailed overview of the surveys can be found in the Appendix (Table C.4).

Figure C.2: Data Availability for ABCC Calculations and Height Measures. Authors' own representation.



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 Table C.5.

C.3.2 Method

While data on educational inputs such as enrolment or years of schooling are available for Sub-Saharan Africa for the period between 1950 and 1999, 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 age heaping.

Numeracy. Age heaping is commonly used in the economic history literature to proxy for numerical abilities as statistics on numeracy are not available for most 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 his or her age when in fact it is 38 (as mentioned before). While this phenomenon is a serious problem for demographers as these false age statements prove difficult in estimations such as population forecasts, it allows us to estimate the numerical abilities of a given population.

We employ the Whipple Index, 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. Admin I areas are the largest subnational divisions of a country. In a few cases, the availability of geographic indicators forced us to group some regions. Moreover, we employ the newest administrative borders in each country. In most cases, these boundaries have changed over time; however, this allows us to divide the sample into consistent subareas comparable over time and to contemporary statistics.

$$W_{it} = \frac{n_{it}^{25} + n_{it}^{30} + n_{it}^{35} + \times + n_{it}^{60}}{\frac{1}{5} \cdot \sum_{age=23}^{62} n_{it}^{\text{age}}} \cdot 100, \tag{8}$$

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 shows no heaping, and a value of 0 means 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, which equals one percentage point increase in the share of heaped ages. To make the index well understandable, we utilize the ABCC Index (which is a simple linear transformation of the Whipple Index).[24] It displays the approximate share of individuals who correctly report their age.

$$ABCC_{it} = \begin{cases} \left(1 - \frac{W_{it}-100}{400}\right) \times 100 & \text{if } W_{it} \geq 100, \\ 100 & \text{else.} \end{cases} \tag{9}$$

We restrict the age range between 23 and 62 for multiple reasons. First, older people tend to exaggerate their age, which would bias the estimates. Second, individuals younger than 23 are excluded as age heaping is much less observed among younger people.[25] Crayen and Baten (2010) observed that individuals between 23 and 32 are comparably more likely to heap on even numbers than older individuals. Hence, we apply their adjustment method for the age group 23–32 (subtracting 25 percent).[26]

It is also important to consider that in a regular age distribution, there will be fewer individuals at age 54 than 50 because some people die. To avoid a potential mortality bias, we estimate numeracy separately for age groups beginning with terminal digit 3 (i.e. from 23 to 32, 33 to 42, 42

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

[25] In earlier studies the age heaping of individuals aged 17–22 was characterized as being impossible to compare with the age heaping of older individuals (Crayen and Baten, 2010). At such young age, just having finished stature growth a few years ago, some individuals tend to round to even numbers (such as 18 or 22), others to 20, others not at all, even if they are not numerate enough to provide an exact age. Prayon (2013) compared this age group (17–22) to other age groups and found a much lower signal-to-noise ratio. This probably depends on the frequency of important life events at this age, such as military service, marriage, and similar events. For all these reasons, a consensus in the literature has emerged to concentrate on the age groups 23–32, 33–42, and so on, as the age heaping-education relationship was much closer for these age groups. This does not imply that rounding on age 20 was negligible, but rounding on 18 and 22 was also very substantial, and the shifts to these ages have not been modelled yet in a way to obtain a reliable indicator. Also taking all round ages such as 18 or 22 as "heaped" does not result in a reliable proxy, that can be compared with other age groups.

[26] Crayen and Baten (2010) have studied a large, global sample for the birth decades of the 1870s to 1940s using a country-decade panel of 1549 observations to identify to which degree individuals of age group 23–32 rounded less on multiples of five, compared to later age groups who were born in the same birth decade, but were interviewed in later censuses. For example, those born in the 1880s, age 23–32 in 1910, were compared to the same persons born in the 1880s, but interviewed in the 1920s, when they were 33–42. Crayen and Baten (2010) estimated an adjustment of the ABCC by -25 percent for the age groups 23–32. This resulted in a quite similar numeracy level for the same birth cohorts, independent of their age during the census. Clearly, the correct adjustment might be -24 percent or -26 percent in some cases, but we cannot identify the subtle differences. The average reduction of 25 percent moves the estimates for this age group closer to the true value.

to 52, and 53 to 62). We 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 (e.g. there is data for the 1960 birth cohort in each of the three Mali censuses), we calculate the average weighted by the respective sample size.

Previous literature (A'Hearn et al., 2022; Földvári et al., 2012) has discussed several potential biases when employing the ABCC Index as a proxy for numerical abilities. These potential biases are a respondent bias (men answering on behalf of women), a marriage bias (wives adapting their age to their husbands' age), an ageing bias (increased heaping as individuals age) and an enumerator bias (counterchecking of age statements by enumerators). Ferber and Baten (2025) validate the African data and check for these potential biases. We provide a summary of their results in the appendix. They provide evidence that the ABCC Index is well suited to capture numerical abilities in Sub-Saharan Africa and does not fall prey to substantial biases. Hence, the conclusion is that the ABCC Index is an appropriate method for our endeavor.

Schooling Efficiency for Numeracy. 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:[27]

$$ScEff_{it} = \frac{ABCC_{it}^{\text{stand.}}}{YrSc_{it}^{\text{stand.}}} \tag{10}$$

This ratio between the output in numeracy skills and the year-of-schooling input helps to assess the efficiency of the educational system. We need a strategy of standardizing both variables because 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 (Benavides-Varela et al., 2016; Niklas et al., 2016). Thus, we first standardize both components of our efficiency measure to consider this. We loosely follow the methodology of the Human Development Index that expresses

[27]We acknowledge that years of schooling as our educational input may not fully capture the educational input in a nonformal environment (i.e., the household). However, the years a child ideally spends in a school are the same in which learning in a nonformal environment needs to take place. Thus, we believe that using years of schooling is a good approximation for the time a child spends learning, whether in a school or a nonformal 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 the early stages of educational expansion.

an indicator between its minimum and maximum, setting the former to zero and the latter to one.

$$ABCC_{it}^{\text{stand.}} = \frac{ABCC_{it} - ABCC_{\text{min}}}{ABCC_{\text{max}} - ABCC_{\text{min}}} \tag{11}$$

$$YrSc_{it}^{\text{stand.}} = \frac{YrSc_{it} - YrSc_{\text{min}}}{YrSc_{\text{max}} - YrSc_{\text{min}}} \tag{12}$$

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; thus, we set the maximum number of years of schooling to this. If we did not make this adjustment—regions with very high levels of numeracy and a high number of average years of schooling would appear overly inefficient compared to regions that also have high levels of numeracy but fewer 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 clarity, we discuss a numerical example. Assume for Equation 11 we only have the following $ABCC_{it}$ values in our dataset:

$5, 33, 42, 69, 88$. So $ABCC_{min} = 5$ and $ABCC_{max} = 88$.

If we plug in our values in the standardization formula shown above, we get:

- For $ABCC_{it} = 5 : ABCC_{it}^{stand.} = \frac{5-5}{88-5} = \frac{0}{83} = 0$

As stated, the minimum value is standardized to zero.

- For $ABCC_{it} = 88 : ABCC_{it}^{stand.} = \frac{88-5}{88-5} = 1$

The maximum value is standardized to one.

- Values in between will be $\in [0, 1]$ e.g.: For $ABCC_{it} = 42 : ABCC_{it}^{stand.} = \frac{42-5}{88-5} = \frac{37}{83} = 0.44$

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 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 a lack of inputs), but it will inform our analysis of 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 of why the significant investment increase in schooling years in Africa did not result in more numeracy output. A potential issue may be the quality of nutrition, which we discuss in the following section.

Nutrition We use the average height of a given population as an indicator of nutrition during childhood. Numerous studies have demonstrated that high-quality nutrition is key for the development of cognitive abilities (Bryan et al., 2004) and adult height (Baten and Blum, 2014). A child that does not grow enough during childhood due to a lack of adequate nutrition will not catch up later in life to reach its potential height (Leroy et al., 2015). Therefore, we use female height per admin I area as the main explanatory variable in our model.[28] Our baseline specification is a pooled OLS model in which we cluster by admin I region.

$$\ln(ScEff_{it}) = \beta_0 + \beta_1 Height_{it} + Z_{it}'\Gamma + X_{it} + \epsilon_{it}, \tag{13}$$

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 ('larger' regions are the regions of East, West, Central, and South Africa). Besides the geographic control variables, we include age at first marriage, the share of Muslims, and a measure of religious fractionalization as control variables (available at the admin I level).[29] We opted not to use a fixed effects panel data model because schooling efficiency is highly

[28] The DHS has 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 marginalized 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.

[29] We include age at first marriage as a proxy for female empowerment (Baten and De Pleijt, 2022). We include the share of Muslims as a control variable as the 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).

persistent. Thus, there is not enough variation over time to find any effects in a fixed effects model.

A potential problem of the regression 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 cumulative monthly negative percentage deviation (Ahmed and Ray, 2018) in the district of residence in the year stated as birth year plus the two years before and after.[30] Another potential issue could be survivor bias of height from cohort data. A survivor bias can occur if some individuals have already died, in this case those of lower stature, and are hence not included in the data biasing the average height upwards. In the Supplementary Materials, we discuss this possibility and find that it is not substantial. In addition, the IV strategy also circumvents potential measurement error issues.

There are two main arguments for the choice of IV. First, there is an extensive literature on critical period programming (Knudsen, 2004) that finds that nutritional conditions during the in-utero period and early infancy are crucial 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; Oreopoulos et al., 2008). Second, according to the World Bank (2022), more than 60 percent of the total employment in Sub-Saharan Africa was in agriculture in 2000, with even higher shares in earlier periods. Little land is irrigated in Sub-Saharan Africa (Barrios et al., 2010) such that sufficient rainfall is a key input for a good harvest (Schlenker and Lobell, 2010). A comprehensive overview of the link between climatic conditions and the economy is provided by Dell et al. (2012). Further information on the reasoning and potential mechanisms is provided in the Supplementary Materials.

We use Version 4 of the Climate Research Unit gridded Time Series by the University of East Anglia (CRU data) for 1948–2001 (Harris et al., 2020). The dataset provides monthly rainfall data at a 0.5×0.5 degrees 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 and the long-term average. Next, we define the rain shock variable as the

[30] We 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 can only calculate the rainfall shock for the current district of residence.

cumulative monthly negative percentage deviation for the year of birth plus the two years before and after (Ahmed and Ray, 2018). We calculate the value for each individual in our dataset before taking the average for each district and birth decade.

We add the two-year buffer for several reasons. First, we calculate the year of birth for each individual by subtracting the stated age from the year of the interview. Since some individuals have rounded their age, the derived year of birth will not be accurate for all observations. If 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, adding the year before and after ensures that we also cover the in-utero period and early infancy for those who stated a correct age. 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 can capture a critical period of a child that has a lasting impact on adult outcomes.

Thus, our first stage regression is

$$Height_{it} = \beta_0 + \beta_1 \ln(Rainshock_{it}) + Z'_{it}\Gamma + X_{it} + \epsilon_{it}, \tag{14}$$

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 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 that it affects wealth. For example, a household living in subsistence agriculture might have to sell their assets accumulated over years of hard work 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 two 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.

Descriptives Summary descriptive statistics for our main variables are provided in Table C.6. All estimates are at the subnational region level and per birth decade. On average, the ABCC index is about 83. However, numeracy varies between less than 30 and 100 percent. Our measure of education efficiency (in logs) is on average about 0.23. Moreover, years of schooling has a mean of 5 years in the sample.

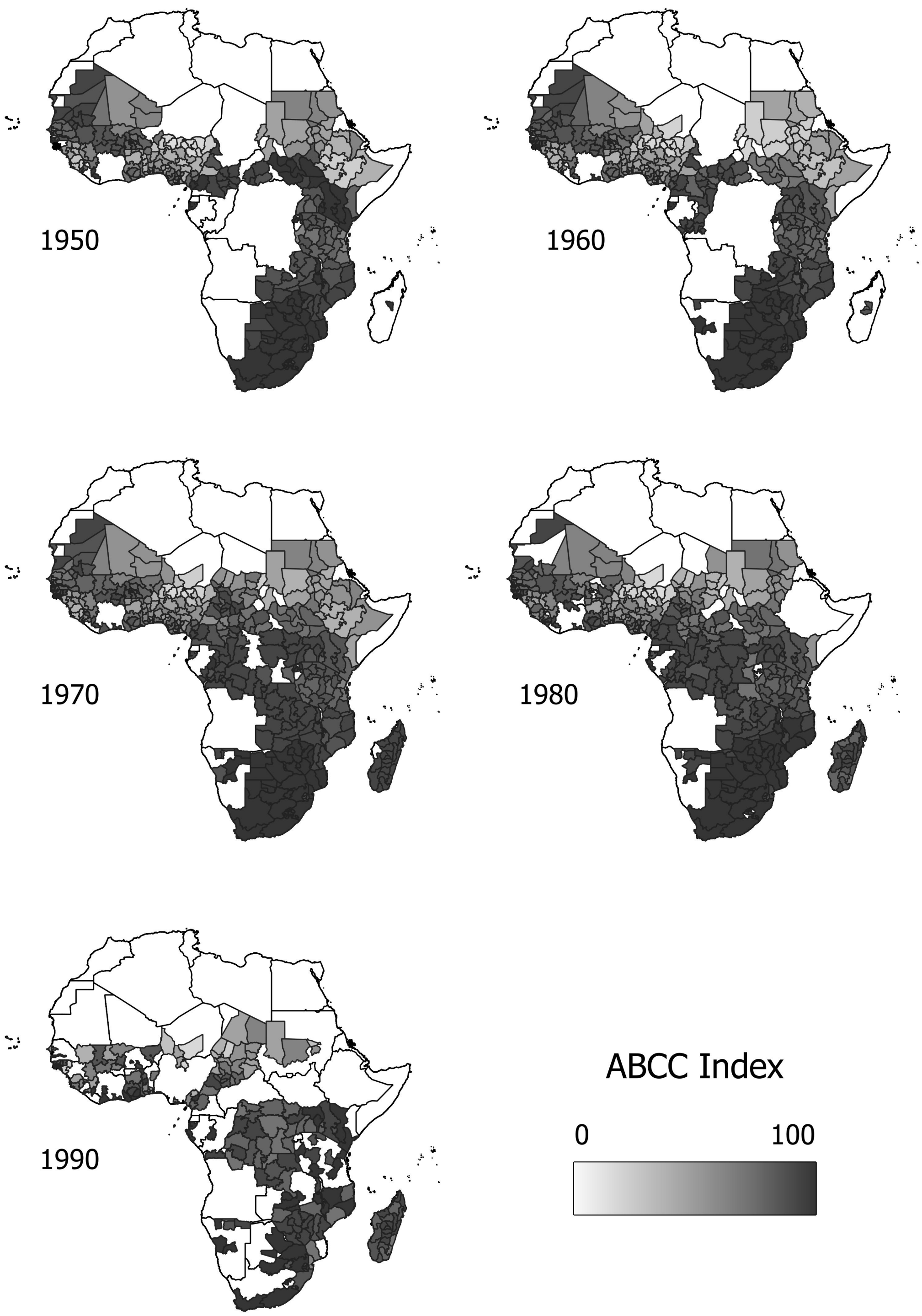
The relationship between the ABCC Index and average years of schooling in our sample is assessed in Figure C.5. We observe a positive relationship indicating that more education does increase numerical skills. However, the error bars indicate that there is quite some variation in each category – the efficiency of the education system differs substantially between regions.

C.4 Results

C.4.1 Numeracy

The spatial distribution of numeracy has remained highly similar and exhibited a strong path dependency. Figure C.3 demonstrates the numeracy level for each region per birth decade. Southern Africa has achieved high levels of numeracy for the 1950 birth decade. Thus, our measure is not that useful anymore for studying this area since it cannot detect differences at higher levels of numerical abilities. Other areas with high levels of numeracy are Madagascar and the DR Congo. However, the DR Congo and Madagascar experienced a decrease in numerical abilities over time. In contrast, we observe the lowest level of numeracy in Western Africa, the Sahel area, and 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 also achieved low values for the 1990s birth cohort.

Figure C.3: ABCC Index per Admin I Level for Each Birth Decade Between 1950 and 1990. Data from IPUMS, MICS and Afrobarometer. Authors' own representation.



C.4.2 Schooling Efficiency

While showing a slight downward trend, given the increase in years of schooling over our observational period, the spatial distribution of schooling efficiency has also remained remarkably stable. Figure C.4 illustrates 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 and some areas of Ethiopia and Guinea. We observe strong and persistent spatial differences over time. A contributing factor to this observation could be increased class sizes and lower average ability in schools as children who were only enrolled in later decades tend to be the weaker students.

Next, we turn to the regression analysis results that investigate nutritional status as a driver of schooling efficiency. Table C.1 synthesizes the baseline results. 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, the share of Muslims and a measure of religious fractionalization in column (3), and our set of geographic controls in column (4). The height coefficient is of substantial size if we include the geographic controls in column (4) and remains statistically significant at the one percent level. Our results suggest that increasing average height by one centimeter increases schooling efficiency by about 6 percent.

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 C.2. 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 10 (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.

Figure C.4: Schooling Efficiency per Admin I Level for Each Birth Decade Between 1950 and 1990. Data from IPUMS, MICS, Afrobarometer and DHS. Authors' own representation.

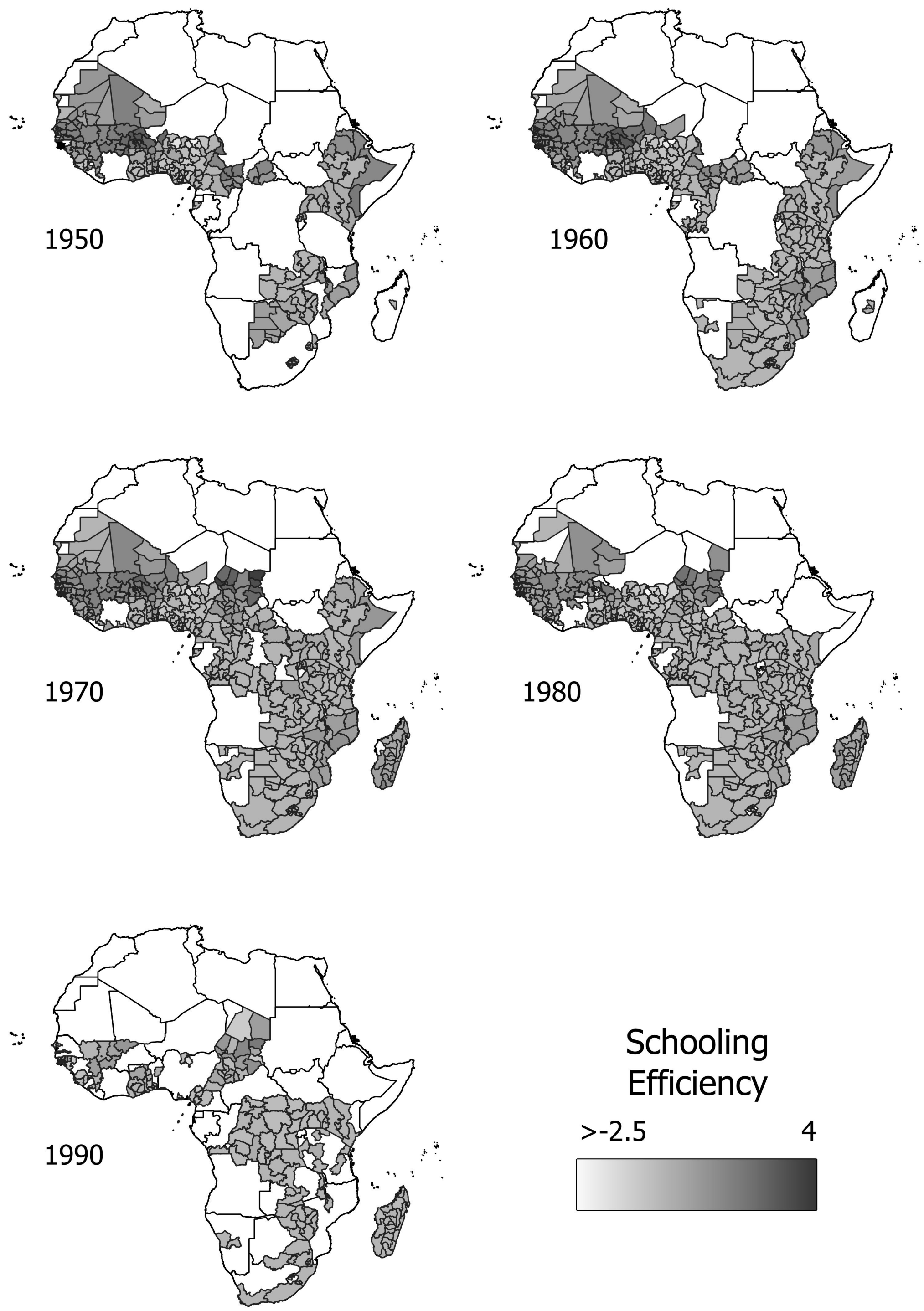


Table C.1: Baseline Regression – Correlation of Schooling Efficiency and Height

	(1)	(2)	(3)	(4)
Height	0.070***	0.078***	0.058***	0.061**
	(0.012)	(0.013)	(0.013)	(0.014)
Constant	-10.925***	-12.011***	-5.643***	-8.799***
	(1.942)	(2.047)	(2.063)	(2.309)
Birth decade FE	No	Yes	Yes	Yes
Regional FE	No	No	Yes	Yes
Sociodemographic controls	No	No	No	Yes
Geographic controls	No	No	No	Yes
Observations	1,234	1,115	1,111	969
R-Squared	0.065	0.117	0.333	0.481

Notes: These regressions show our baseline model which estimates the relationship between adult height (a proxy for health during childhood) and schooling efficiency. The underlying dataset is a pooled panel of African admin I regions for birth decades 1950 to 1999. Due to the modest change over time in our outcome variable, we opted to use our data in a pooled panel format rather than using the panel structure to estimate fixed effects, for example. The fixed effects model would have too little variation over time. 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 sociodemographic controls include age at marriage, share of Muslims, and religious fractionalization. The geographical controls include the length of colonization, colonial railways, ancient trade routes, diamond mines, export routes, missions, nutrient availability, soil workability, malaria ecology index, petroleum sites, ruggedness, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, distance to capital, distance to coast, population density, and area. Standard errors in parentheses are clustered at the admin I level. Asterisks denote significance at levels *** $p < .01$, ** $p < .05$, * $p < .1$.

Table C.2: 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		0.181***		0.179***		0.169***		0.258***
		(0.041)		(0.042)		(0.042)		(0.091)
Rainfall Shock	-0.002***		-0.002***		-0.002***		-0.001***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Constant	154.92***	-24.30**	155.75***	-37.16**	151.49***	-26.12**	149.51***	-53.60***
	(0.751)	(11.414)	(0.731)	(14.517)	(1.883)	(10.246)	(2.427)	(17.639)
Birth Decade FE	No		Yes		Yes		Yes	
Regional FE	No		Yes		Yes		Yes	
Sociodemographic Controls	No		No		Yes		Yes	
Geographic controls	No		No		No		Yes	
Observations	1,225	1,225	1,106	1,106	1,102	1,102	960	960
R-Squared	0.095		0.126		0.262	0.204	0.524	0.277
F-Statistic (1st Stage)	66.79		15.29		18.58		16.67	

Notes: These regressions show our IV model which estimates the relationship between adult height (a proxy for health during childhood) and schooling efficiency. Height is instrumented by rainfall during pregnancy and early childhood. The underlying dataset is a panel of African admin I regions for birth decades 1950–1999. The first set of regressions is without fixed controls, the second adds birth decade and regional fixed effects, the third sociodemographic controls, and the fourth geographical controls. The sociodemographic controls include age at marriage, share of Muslims, and religious fractionalization. The geographical controls include the length of colonization, colonial railways, ancient trade routes, diamond mines, explorer routes, missions, nutrient availability, soil workability, malaria ecology index, petroleum sites, ruggedness, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, distance to capital, distance to coast, population density, and area. Standard errors are in parentheses and clustered at the admin I level. Asterisks denote significance at levels *** $p < .01$, ** $p < .05$, * $p < .1$.

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 school, 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.

C.5 Robustness Checks

Our main specification provides estimates for which we use the whole range of ABCC values. As there is a larger number of top-coded observations in our data, we also provide estimates using an ABCC of 95, 90, or 85 as cut-off values for a robustness check. In Supplementary Table C.11, we show that our results are not driven by a sample composition effect and hold if we use the different cut-off values. The estimates remain significant and similar in size.

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. Supplementary Table C.12 summarizes our results, which are virtually unchanged if we use four, five, seven, or eight years of schooling.

We also assessed the robustness of the instrument by excluding the most arid and rain-intensive part of the distribution (Table C.3). Furthermore, in Table C.3 we provide estimates for predominantly rural and urban areas separately. Interestingly, we do find a significant difference in our estimates for rural and for urban areas indicating that the link between nutrition and schooling efficiency is stronger in rural areas. Since rural regions are on average affected more severely by poverty this could hint that undernutrition is a more severe problem in rural areas. Again, the results of Table C.2 can be confirmed in these alternative specifications. Additionally, Supplementary Tables C.13 and C.14 provide estimates, excluding extreme IV values and using alternative definitions of our IV. We observed that the instrument works in all robustness tests. Lastly, we show in Supplementary Table C.15 that our findings are robust to spatial autocorrelation.

Table C.3: Robustness Checks – Exclusion of the Low or High Extreme Rain Values and by Rural/Urban Areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Exclude Top & Bottom 10% of Rain Distribution		Exclude Top & Bottom 20% of Rain Distribution		Exclude Areas More Than 50% Urban		Exclude Areas More Than 50% Rural	
	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
Height		0.327***		0.359***		0.367**		0.136*
		(0.123)		(0.137)		(0.166)		(0.079)
Rainfall Shock	-0.001***		-0.001***		-0.001***		-0.001**	
	(0.000)		(0.000)		(0.000)		(0.000)	
Constant	156.758***	-50.280***	157.028***	-55.187**	155.576***	-56.258**	154.793***	-20.199*
	(2.100)	(19.188)	(2.178)	(21.437)	(2.205)	(25.682)	(3.700)	(11.959)
Birth Decade FE	Yes		Yes		Yes		Yes	
Regional FE	Yes		Yes		Yes		Yes	
Sociodemographic Controls	Yes		Yes		Yes		Yes	
Geographic Controls	Yes		Yes		Yes		Yes	
Observations	782	782	615	615	778	778	182	182
R-Squared	0.554	0.247	0.577	0.310	0.576	0.090	0.599	0.242
F-Statistic (1st Stage)	14.03		13.76		16.42		43.60	

Notes: These regressions show robustness checks for the IV model of Table C.2 (see notes to Table C.2). The first set of regressions excludes the 10% rainiest and driest regions and the second set the 20% rainiest and driest. All regressions include birth decade and regional fixed effects, sociodemographic controls and geographical controls. The sociodemographic controls include age at marriage, share of Muslims and religious fractionalization. The geographical controls include the length of colonization, colonial railways, ancient trade routes, diamond mines, explorer routes, missions, nutrient availability, soil workability, malaria ecology index, petroleum sites, ruggedness, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, distance to capital, distance to coast, population density and area. Standard errors are in parentheses and clustered at the admin I level. Asterisks denote significance levels at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C.6 Concluding Discussion

Ensuring every child has access to quality education is crucial for achieving long-term sustainable development. Despite increased primary school enrolment in significant portions of Sub-Saharan Africa over the past decade, the region has not witnessed the anticipated improvement in learning outcomes (Angrist et al., 2021). Consequently, policymakers and scholars are actively seeking tools to address this challenge.

Our paper is the first to provide long-term evidence on developing numerical skills at the sub-national level in substantial parts of Sub-Saharan Africa for the birth decades 1950 to 1990. Throughout the observational period, we notice 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 in line with contemporary findings of low educational achievement despite increasing enrolment and years of schooling (Angrist et al., 2021).

Therefore, we contribute to this discussion by adopting a long-term perspective. Initially, we assess the evolution of schooling efficiency over the observed period and observe minimal change. Persistent regional disparities further underscore the importance to comprehend underlying mechanisms. Secondly, we examine the impact of children's nutrition and health on schooling outcomes, using average adult height as the primary explanatory variable. Our findings affirm the significance of children's nutrition as a key predictor of schooling efficiency. Additionally, we employ an instrumental variable (IV) approach, using the average months of exposure to below-average district rainfall during pregnancy and infancy as our instrument. The IV results substantiate our findings, and our results remain robust across various specifications.

While the quantity of education input has increased over the last decades in Sub-Saharan Africa (Baten and Maravall, 2021), this does not necessarily imply that educational efficiency increased. While the input in years of schooling increased from 4.4 to 6.6 (1960s–1990s), the output has increased at a modest rate: For example, numeracy increased only slightly from 82.1 in both the 1950s and 1960s to 84.9 in the 1980s, and 86.2 in the 1990s. Hence, efficiency – which is the ratio between the two – stays at a similar level or shows slightly declining tendencies. Specifically, in some countries, efficiency decreased, while in others, it increased or remained constant. Similarly, Le Nestour et al. (2022) observed a decrease in literacy production efficiency for several African countries, while other countries experienced literacy production efficiency increases. Our results suggest that nutritional quality mattered for these outcomes.

How can we improve the nutritional situation of school children? One of the most popular interventions worldwide to incentivize children to come to school and increase their chances of learning something at school is school-feeding programs (Aurino et al., 2020). 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 able to concentrate and participate better in school. Moreover, given the high level of malnourishment in Sub-Saharan Africa, providing children with extra food can be considered a goal. Most evidence about school feeding interventions suggests positive effects on enrolment and educational outcomes. The recent literature moves toward the view that school feeding is also cost-effective (Aurino et al., 2020; different nuance: Parker et al., 2015). We find that better-nourished children 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 intended for the youngest school children around age 6 or 7 can be beneficial via the nutrition effect, as at this age, children might compensate for earlier malnutrition issues partly. Even better would be preschool protein supplement programs (Hulett et al., 2014), although we admit that this might be prevented by financial constraints. Protein would be particularly relevant, as Case and Paxson (2008) identified these as predictors of later-life abilities (and protein intake correlates with height; see also Baten et al. (2014), Baten and Blum (2014)). If these programs would be targeted specifically at the most problematic regions that we identify in the maps of (and on the poorest families within these regions), they can contribute to solving the 'schooling crisis'.

C.7 References

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C.8 Appendix

C.8.1 Data Sources

IPUMS has data for 26 Sub-Saharan African countries available. Between one and five censuses are available per country (Table C.7). Moreover, the census data are also representative at the subnational level. Age of the respondent and several socioeconomic variables are included.

MICS (by UNICEF) in developing/emerging economies since the 1990s. These household-based surveys mainly focus on issues affecting women and children. MICS has added modules for men (third/fourth round) for some countries. We only employ surveys that include the module for women and men (Table C.8). Data is available for 21 Sub-Saharan African countries (one to three surveys per country). Age, education, socioeconomic background and female empowerment are included.

DHS (by USAID since the late 1980s). We use surveys for Sub-Saharan Africa for which both a female and male module is available, and which provide geo-coded information which results in 34 countries (Table C.9, one to five surveys per country). Information on literacy, education, socioeconomic background, health, anthropometric data, and female empowerment is included. Unfortunately, the age data is not useful for our analysis of age misreporting, as the enumerators are trained to ensure that the stated age is correct instead of the respondent's estimate.

AB surveys (since the late 1990s). Age and cover questions regarding public attitude towards governance, democracy, and the economy. Seven rounds are available with the broadest country coverage in the later rounds (Table C.10, 33 countries; one to seven surveys per country).

See Table C.4 for variables sourced from these 4 surveys. See Table A.2 for geographic and historical variables and their sources.

Table C.4: Data Set Construction Overview

Variable	Primary Source	Secondary Source	Tertiary Source
ABCC	IPUMS	MICS	Afrobarometer
School Years	DHS	MICS	IPUMS
Height	DHS		
Age of Cohabitation	DHS	MICS	IPUMS
Share of Muslims	DHS	MICS	IPUMS
Rel. Fractionalization	DHS	MICS	IPUMS

Table C.5: Sources and Descriptions of 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.
Missions	Cagé and Rueda (2016, 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
Traderoutes	OWTRAD	Dummy if ancient traderoute in admin I	http://www.ciolek.com/OWTRAD/DATA/tmcDZm0500.html
Global Agro-ecological Zones (GAEZ)	Fischer et al. (2008)	Mean value of nutrient availability and soil workability per admin I 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
Petrolium	Peace Research Institute Oslo (PRIO)	Calculated 0.2-degree buffer around deposits and 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 admin I	Nunn, N., & Puga, D. (2012). Ruggedness: The blessing of bad geography in Africa. *Review of Economics and Statistics*, 94(1), 20-36.
TseTse Fly Suitability	FAO	Mean value of tsetse fly index for morsitans and palpalis 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	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, & E. Stehfest (2017). Anthropogenic land use estimates for the Holocene; HYDE 3.2, Earth System Science Data, 9, 927-953.
Distance Coast	n.a.	Distance from centroid of admin I to coast	-
Distance Capital	n.a.	Distance from centroid of admin I to capital	-
Area	n.a.	Area of admin I region in square kilometers	-

C.8.2 Potential Biases of Age-Heaping-Based Numeracy Estimates

The ABCC Index is a popular method in economic history to estimate numeracy. However, the ABCC Index can potentially have biases which are addressed extensively in Ferber and Baten (2025). We provide a comprehensive summary. We conclude that the ABCC Index is a suitable numeracy proxy in SSA without strong biases.

The database as well as the methodology for estimating the Whipple and the ABCC Index are the same as in this study.

Prior to addressing methodological concerns, the study seeks to bolster the ABCC Index's credibility as a numeracy proxy in SSA by comparing age heaping patterns of older generations with math scores of their children. Using the latest MICS round which includes short math tests for children aged seven to fourteen across 12 countries, the authors examine the correlation between children's math scores and their caretakers' ABCC scores, both at the regional and the household level. A positive and highly significant correlation emerges, demonstrating that regions with low numeracy in parents also exhibit poorer math performance in their children. The correlation coefficient is as large as 0.67 (p=0.00). Moreover, for the least numerate countries (Chad, Sierra Leone and Togo) an analysis at the household level shows that caretakers' age statements with the terminal digits 0 or 5 are significantly correlated with lower math test performance of children. These findings confirm the suitability of age heaping-based numeracy estimation in SSA.

We now turn to the potential biases that have been discussed in the literature before.

Respondent bias. A potential concern in surveys is that a husband or male relative might answer questions on women's behalf. However, MICS surveys, designed to capture women's and children's insights, provide confidence in women's self-responses, while IPUMS or AB do not specifically target either gender. To verify, Ferber and Baten (2025) compare ABCC Index based on IPUMS and AB data against MICS data, re-estimating the index separately by gender. A regression equation incorporates data source and gender dummies. The findings show no significant respondent bias in IPUMS, and only a minor bias in AB data.

Marriage bias. Another concern is that married women may adjust their reported ages to match their spouses', potentially leading to an unintentional boost in the estimated numeracy levels of married women due to men's on average higher numeracy. The authors re-estimate ABCC

Index by gender and marital status, comparing single, in union, separated/divorced, and widowed individuals. Contrary to concerns, the results do not support a marriage bias.

Ageing bias. Thirdly, there is some concern that people heap more as they age such that they would appear to be less numerate in their fifties than in their thirties. If this were accurate, older birth cohorts would inherently seem less numerate (and not because they went to school in a period of lower education). To address this concern, the authors estimate the ABCC Index for different age groups within birth decades. Comparing numeracy estimates at various life stages, the results show no significant downward trend.

Enumerator bias. Enumerators' potential age-checking bias is considered by comparing ABCC Index between overlapping IPUMS, AB and MICS data. A model with a data source dummy is estimated to detect bias. Results reveal a small bias in MICS data but not in AB data. Consequently, the MICS-derived ABCC Index is corrected by the estimated bias.

Alternative Heaping Patterns. Concerns about Whipple Index's sensitivity to heaping patterns beyond zero and five are explored. Manual inspection of the data reveals some heaping on the digits two and eight in some countries. The authors estimate an alternative index that accounts for this heaping pattern and compare it to our original one. They only find minor differences between the ABCC Indices and the original ABCC Index also correlates more strongly with education indicators such as years of schooling and literacy.

C.8.3 Descriptives

Table C.6 provides summary descriptive statistics for our main variables. All estimates are at the subnational region level and per birth decade. On average, the ABCC index is about 83. However, numeracy varies between less than 30 and 100 percent. Our measure of education efficiency (in logs) is on average about 0.23. Moreover, years of schooling has a mean of 5 years in the sample.

The relationship between the ABCC Index and average years of schooling in our sample is assessed in Figure C.5. We observe a positive relationship. The error bars indicate that there is quite some variation in each category – the efficiency of the education system differs substantially between regions.

Numeracy across the continent and in some sample countries increased only modestly (Figure

C.6). Niger even shows a declining trend. This seems to contradict Figure C.5, as the increase in school years should have resulted in more numeracy. However, the relationship in Figure C.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 et al. (2023)).

Table C.6: Summary Statistics

	Obs.	Mean	Std.Dev.	Min	Max
ABCC Index	1749	83.369	14.019	29.870	100
Education Efficiency	1544	0.226	0.672	-2.266	3.701
Years of Schooling	2103	5.028	2.879	0.014	12.453
Height	1722	158.709	2.685	141	166.795
Age at Marriage	2007	20.401	2.275	15.033	37.551
Share Muslim	1971	0.252	0.349	0	1
Rel. Fract.	2103	0.274	0.281	0	1

Figure C.5: Relationship of Average Years of Schooling and Numeracy (ABCC Index). Data from IPUMS, MICS and Afrobarometer. Authors' own representation.

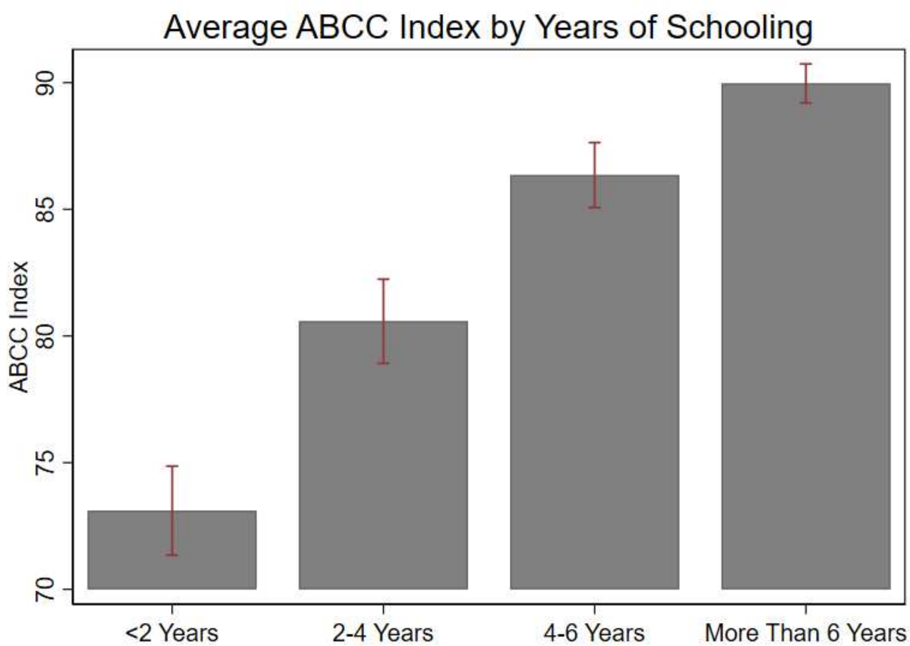
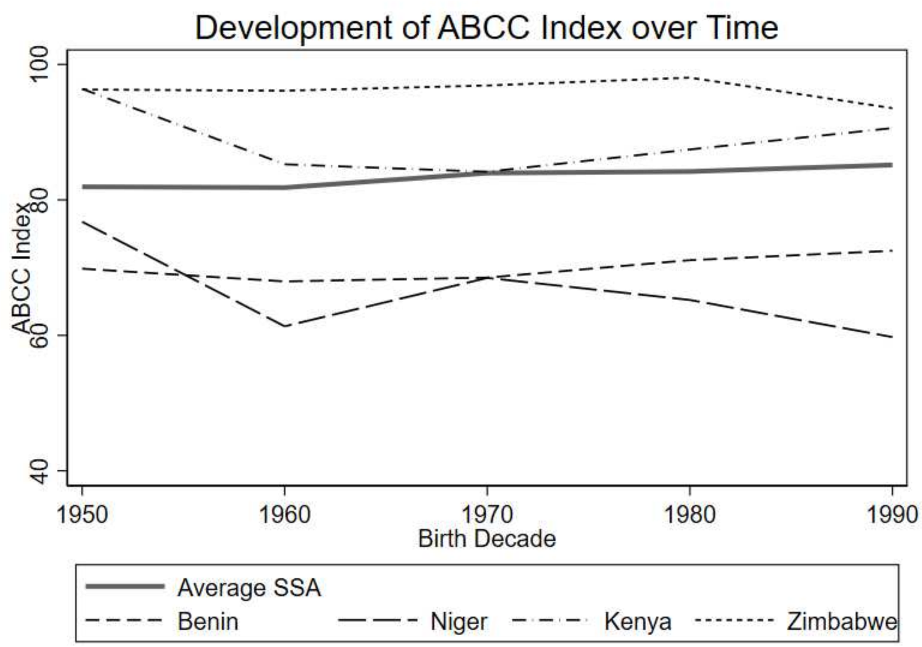


Figure C.6: Development of Numeracy over Time for Selected Countries – Benin, Niger, Kenya, and Zimbabwe. The average refers to all Sub-Saharan African countries included in the data set. Source: IPUMS, MICS and Afrobarometer. Authors' own representation.



C.9 Supplementary Material

C.9.1 Data Sources

Table C.7: IPUMS Data Availability per Decade

1960	1970	1980	1990	2000	2010
Kenya (1969)	Benin (1979)	Botswana (1981)	Benin (1992)	Benin (2002)	Benin (2013)
Togo (1960)	Cameroon (1976)	Burkina Faso (1985)	Botswana (1991)	Botswana (2001)	Botswana (2011)
	Kenya (1979)	Cameroon (1987)	Burkina Faso (1996)	Burkina Faso (2006)	Ghana (2010)
	Liberia (1974)	Ethiopia (1984)	Ethiopia (1994)	Cameroon (2005)	Guinea (2014)
	Togo (1970)	Ghana (1984)	Guinea (1996)	Ethiopia (2007)	Mauritius (2011)
		Guinea (1983)	Kenya (1999)	Ghana (2000)	Nigeria (2010)
		Kenya (1989)	Lesotho (1996)	Kenya (2009)	Rwanda (2012)
		Malawi (1987)	Malawi (1998)	Lesotho (2006)	Senegal (2013)
		Mali (1987)	Mali (1998)	Liberia (2008)	South Africa (2011, 2016)
		Senegal (1988)	Mauritius (1990)	Malawi (2008)	Tanzania (2012)
		Tanzania (1988)	Mozambique (1997)	Mali (2009)	Togo (2010)
			Rwanda (1991)	Mauritius (2000)	Uganda (2014)
			South Africa (1996)	Mozambique (2007)	Zambia (2010)
			Uganda (1991)	Nigeria (2006, 07, 08, 09)	Zimbabwe (2012)
			Zambia (1990)	Rwanda (2002)	
				Senegal (2002)	
				Sierra Leone (2004)	
				South Africa (2001, 2007)	
				South Sudan (2008)	
				Sudan (2008)	
				Tanzania (2002)	
				Uganda (2002)	
				Zambia (2000)	

Table C.8: MICS Data Availability per Wave

Wave 3	Wave 4	Wave 5	Wave 6
Centr. African Rep. (2006)	Centr. African Rep. (2010)	Benin (2014)	Centr. African Rep. (2018-19)
Ghana (2006)	Ghana (2011)	Cameroon (2014)	Chad (2019)
Mauritania (2007)	Togo (2010)	Côte d'Ivoire (2016)	DR Congo (2018)
Malawi (2006)	Swaziland (2010)	Congo, Rep. (2014-15)	Gambia (2018)
		Guinea-Bissau (2014)	Guinea-Bissau (2018-19)
		Mali (2015)	Ghana (2017-18)
		Mauritius (2015)	Lesotho (2018)
		Malawi (2013-14)	Madagascar (2018)
		Nigeria (2016)	Sierra Leone (2017)
		São Tomé & Princ. (2014)	São Tomé & Princ. (2019)
		Swaziland (2014)	Togo (2017)
		Zimbabwe (2014)	Zimbabwe (2019)

Table C.9: DHS Data Availability per Wave

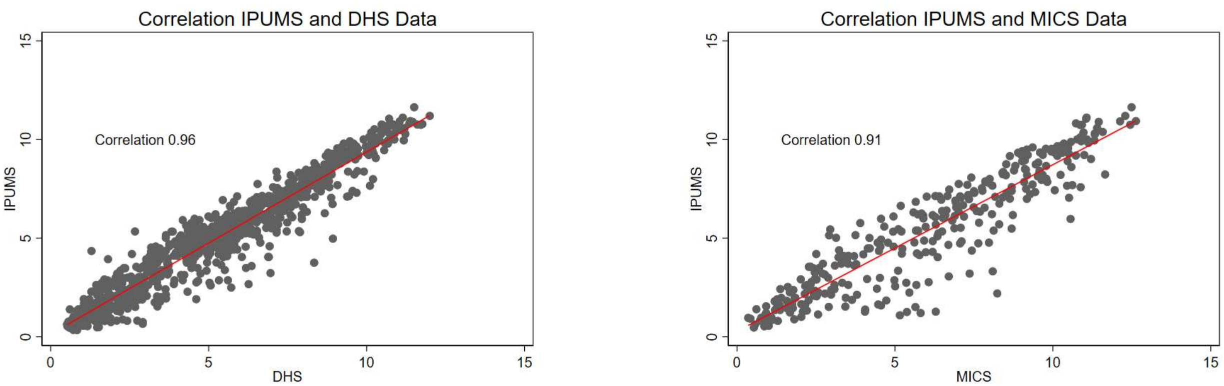
Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Wave 7
Burkina Faso (1992-93)	Burkina Faso (1992-99)	Burkina Faso (2003)	DR Congo (2007)	Burkina Faso (2010)	Angola (2015-16)
Cameroon (1991)	Benin (1996)	Benin (2001)	Ghana (2008)	Benin (2011-12)	Benin (2017-18)
Ghana (1993-1994)	Centr. African Rep. (1994-95)	Cameroon (2004)	Kenya (2008-09)	Burundi (2010-11)	Burundi (2016-17)
Niger (1992)	Côte d'Ivoire (1994-99)	Ethiopia (1992-97)	Liberia (2006-07)	DR Congo (2011-12)	Cameroon (2018)
Senegal(1992-1997)	Ghana (1993-94)	Ghana (2003)	Lesotho (2009-10)	Rep. Congo (2013-14)	Ethiopia (2018)
	Guinea (1999)	Guinea (2005)	Madagascar (2008-09)	Cameroon (2011)	Guinea (2018)
	Mali (1995-96)	Kenya (2003)	Mali (2006)	Ethiopia (2003)	Liberia (2019-2020)
	Niger (1998)	Lesotho (2004-05)	Malawi (2010)	Gabon (2012)	Mali (2018)
	Senegal (1992-97)	Mali (2001)	Nigeria (2008)	Ghana (2014)	Malawi (2015-16)
	Togo (1998)	Malawi (2000)	Namibia (2006-07)	Guinea (2012)	Nigeria (2018)
		Nigeria (2003)	Rwanda (2005-08)	Kenya (2014)	Rwanda (2014-15)
		Namibia (2000)	Sierra Leone (2008)	Comoros (2012)	Sierra Leone (2019)
		Senegal (2005)	eSwatini (2006-07)	Liberia (2013)	Senegal (2016-17)
		Togo (1998)	Tanzania (2009-10)	Lesotho (2014)	Tanzania (2015-16)
		Uganda (2001-01)	Uganda (2006)	Mali (2012-13)	Uganda (2016)
		Zimbabwe (1999)	Zambia (2007)	Mozambique (2011)	South Africa (2016)
			Zimbabwe (2005-06)	Nigeria (2013)	Zambia (2018-19)
				Namibia (2013)	Zimbabwe (2015)
				Rwanda (2010-2011)	
				Sierra Leone (2013)	
				Senegal (2013)	
				Tchad (2014-15)	
				Togo (2013-14)	
				Uganda (2011)	
				Zambia (2013-14)	
				Zimbabwe (2010-11)	

Table C.10: Afrobarometer Data Availability per Wave

Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Wave 7
Botswana (1999)	Botswana (2003)	Benin (2005)	Benin (2008)	Benin (2011)	Benin (2014)	Benin (2019)
Ghana (1999)	Cape Verde (2002)	Botswana (2005)	Botswana (2008)	Botswana (2012)	Botswana (2014)	Botswana (2019)
Lesotho (2000)	Ghana (2002)	Cape Verde (2005)	Burk. Faso (2008)	Burk. Faso (2012)	Burk. Faso (2015)	Burk. Faso (2019)
Malawi (1999)	Kenya (2003)	Ghana (2005)	Cape Verde (2008)	Burundi (2012)	Burundi (2014)	Cameroon (2019)
Mali (2001)	Lesotho (2003)	Kenya (2005)	Ghana (2008)	Cameroon (2013)	Cameroon (2015)	Cape Verde (2019)
Namibia (1999)	Malawi (2003)	Lesotho (2005)	Kenya (2008)	Cape Verde (2011)	Cape Verde (2014)	Côte d'Ivoire (2019)
Nigeria (1999)	Mali (2002)	Madagascar (2005)	Lesotho (2008)	Côte d'Ivoire (2013)	Côte d'Ivoire (2014)	Gabon (2019)
South Africa (2000)	Mozambique (2002)	Malawi (2005)	Liberia (2008)	Ghana (2012)	Gabon (2015)	Gambia (2019)
Tanzania (2001)	Namibia (2003)	Mali (2005)	Madagascar (2008)	Guinea (2013)	Ghana (2014)	Ghana (2019)
Uganda (2000)	Nigeria (2003)	Mozambique (2005)	Malawi (2008)	Kenya (2011)	Guinea (2015)	Guinea (2019)
Zambia (1999)	Senegal (2002)	Namibia (2005)	Mali (2008)	Lesotho (2012)	Kenya (2014)	Kenya (2019)
Zimbabwe (1999)	South Africa (2002)	Nigeria (2005)	Mozambique (2008)	Liberia (2012)	Lesotho (2014)	Lesotho (2019)
	Tanzania (2003)	Senegal (2005)	Namibia (2008)	Madagascar (2013)	Liberia (2015)	Liberia (2019)
	Uganda (2002)	South Africa (2005)	Nigeria (2008)	Malawi (2012)	Madagascar (2014)	Madagascar (2019)
	Zambia (2003)	Tanzania (2005)	Senegal (2008)	Mali (2012)	Malawi (2014)	Malawi (2019)
	Zimbabwe (2004)	Uganda (2005)	South Africa (2008)	Mauritius (2012)	Mali (2014)	Mali (2019)
		Zambia (2005)	Tanzania (2008)	Mozambique (2012)	Mauritius (2014)	Mauritius (2019)
		Zimbabwe (2005)	Uganda (2008)	Namibia (2012)	Mozambique (2015)	Mozambique (2019)
			Zambia (2009)	Niger (2013)	Namibia (2014)	Namibia (2019)
			Zimbabwe (2009)	Nigeria (2012)	Niger (2015)	Niger (2019)
				Senegal (2013)	Nigeria (2014)	Nigeria (2019)
				Sierra Leone (2012)	Senegal (2014)	Senegal (2019)
				South Africa (2011)	Sierra Leone (2015)	Sierra Leone (2019)
				Sudan (2013)	South Africa (2015)	South Africa (2019)
				eSwatini (2013)	Sudan (2015)	Sudan (2019)
				Tanzania (2012)	eSwatini (2015)	eSwatini (2019)
				Togo (2012)	São T. & P. (2015)	São T. & P. (2019)
				Uganda (2012)	Tanzania (2014)	Tanzania (2019)
				Zambia (2013)	Togo (2014)	Togo (2019)
				Zimbabwe (2012)	Uganda (2015)	Uganda (2019)
					Zambia (2014)	Zambia (2019)
					Zimbabwe (2014)	Zimbabwe (2019)

C.9.2 Data Suitability for Sub-National Aggregation

Figure C.7: Data Suitability for sub-National Aggregation. Authors' own representation.



C.9.3 Data Issues: Survivor Bias of Height Cohort Data?

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 (2021)). However, many 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). 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 percent 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 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'.

C.9.4 Instrumental Variable Relevance

Good nutrition is essential for the development of children. For example, Paxson and Schady (2007) and Currie and Rossin-Slater (2013) found that a lower nutrition during early childhood reduces the ability to learn. There are numerous arguably exogenous events that can cause undernutrition such 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 and Bharadwaj, 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 local variation and its importance in the livelihoods of most people in Sub-Saharan Africa. According to the World Bank (2022) more than 60 percent of total employment in Sub-Saharan Africa was in agriculture in 2000 with even higher shares in earlier periods. Moreover, little land is irrigated in Sub-Saharan Africa (Barrios et al., 2010) such that sufficient rainfall is a key input for a good harvest (Schlenker and Lobell, 2010).

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 food for consumption and lower agricultural income (Hidalgo et al., 2010; Banerjee et al., 2010; Burlando, 2014) which increases the likelihood 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 et al., 2016; Lee, 2014; Quintana-Domeque and Ródenas-Serrano, 2017; Torche, 2011; Brown and Pollitt, 1996; Currie and Rossin-Slater, 2013; Camacho, 2008). Malnutrition of mothers during problematic weather periods can also affect the production of breastmilk, with implications for child nutrition. 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).

Therefore, we see negative rainfall shocks during the in-utero and infancy period as a relevant factor influencing childhood health and thereby ultimately the height of individuals.

C.9.5 Robustness Checks

Table C.11: Robustness Checks – Alternative ABCC Cut-Offs

	(1)	(2)	(3)	(4)	(5)	(6)
	ABCC<=95		ABCC<=90		ABCC<=80	
	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
Height		0.264***		0.275***		0.236***
		(0.093)		(0.095)		(0.081)
Rainfall Shock	-0.001***		-0.001***		-0.002***	
	(0.000)		(0.000)		(0.000)	
Constant	155.678***	-40.123***	156.882***	-42.304***	156.489***	-36.271***
	(2.069)	(14.279)	(2.567)	(14.742)	(3.091)	(12.575)
Birth Decade FE	Yes		Yes		Yes	
Regional FE	Yes		Yes		Yes	
Sociodemographic Controls	Yes		Yes		Yes	
Geographic Controls	Yes		Yes		Yes	
Observations	889	889	715	715	538	538
R-Squared	0.521	0.296	0.528	0.407	0.561	0.512
F-Statistic (1st Stage)	15.81		12.60		16.47	

Notes: These regressions show a robustness check for IV model which estimates the relationship between adult height, as a proxy for health during childhood, and schooling efficiency for reduced samples of countries with different ABCC cut-offs. Height is instrumented by rainfall shocks 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 95 as a cut-off, the second one a cutoff of 90 and the last one a cutoff of 85. All regressions include birth decade and regional fixed effects, sociodemographic controls and geographical controls. The sociodemographic controls include age at marriage, share of Muslims and religious fractionalization. The geographical controls include the length of colonization, colonial railways, ancient trade routes, diamond mines, explorer routes, missions, nutrient availability, soil workability, malaria ecology index, petroleum sites, ruggedness, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, distance to capital, distance to coast, 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 C.12: Robustness Checks – Alternative Years of Schooling Cut-Offs

	(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		0.261***		0.260***		0.245***		0.238***
		(0.090)		(0.091)		(0.090)		(0.090)
Rainfall Shock	-0.001***		-0.001***		-0.001***		-0.001***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Constant	155.538***	-40.843***	155.538***	-40.246***	155.538***	-37.032***	155.538***	-35.759***
	(1.912)	(13.730)	(1.912)	(13.936)	(1.912)	(13.822)	(1.912)	(13.729)
Birth Decade FE	Yes		Yes		Yes		Yes	
Regional FE	Yes		Yes		Yes		Yes	
Sociodemographic Controls	Yes		Yes		Yes		Yes	
Geographic Controls	Yes		Yes		Yes		Yes	
Observations	961	961	961	961	961	961	961	961
R-Squared	0.524	0.100	0.524	0.162	0.524	0.261	0.524	0.290
F-Stat. (1st Stage)	16.65		16.65		16.65		16.65	

Notes: These regressions show a robustness check for IV model which estimates the relationship between adult height, as a proxy for health during childhood, and schooling efficiency using different schooling year cut-offs for the schooling efficiency variable. The underlying dataset is a panel of African admin I regions for birth decades 1950 to 1990. All regressions include birth decade and regional fixed effects, sociodemographic controls and geographical controls. The sociodemographic controls include age at marriage, share of Muslims and religious fractionalization. The geographical controls include the length of colonization, colonial railways, ancient trade routes, diamond mines, explorer routes, missions, nutrient availability, soil workability, malaria ecology index, petroleum sites, ruggedness, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, distance to capital, distance to coast, 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 C.13: Robustness Checks – Exclusion of Extreme IV Values

	(1)	(2)	(3)	(4)
	Exclude Top & Bottom 10% of IV		Exclude Top & Bottom 20% of IV	
	1st Stage	2nd Stage	1st Stage	2nd Stage
Height		0.288**		0.169**
		(0.117)		(0.068)
Rainfall Shock	-0.001***		-0.002***	
	(0.000)		(0.000)	
Constant	153.857***	-43.445**	156.223***	-25.578**
	(2.122)	(17.826)	(2.199)	(10.348)
Birth Decade FE	Yes		Yes	
Regional FE	Yes		Yes	
Sociodemographic Controls	Yes		Yes	
Geographic Controls	Yes		Yes	
Observations	778	778	613	613
R-Squared	0.519	0.262	0.553	0.469
F-Statistic (1st Stage)	16.06		16.21	

Notes: These regressions show a robustness check for IV model which estimates the relationship between adult height, as a proxy for health during childhood, and schooling efficiency using a reduced sample. Height is instrumented by rainfall shocks 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 excludes the top and bottom 10% of the rainfall shock variable and the second set the top and bottom 20%. All regressions include birth decade and regional fixed effects, sociodemographic controls and geographical controls. The sociodemographic controls include age at marriage, share of Muslims and religious fractionalization. The geographical controls include the length of colonization, colonial railways, ancient trade routes, diamond mines, explorer routes, missions, nutrient availability, soil workability, malaria ecology index, petroleum sites, ruggedness, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, distance to capital, distance to coast, 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 C.14: Robustness Checks – Alternative IV Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
	Percent Deviation 4 Years		Percent Deviation 3 Years		Below 20th Percentile 5 Years	
	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
Height		0.244***		0.260***		0.610**
		(0.086)		(0.090)		(0.261)
Rainfall Shock	-0.001***		-0.002**		-0.049**	
	(0.000)		(0.000)		(0.024)	
Constant	155.585***	-36.856***	155.494***	-39.312***	153.083***	-92.672**
	(1.909)	(13.230)	(1.912)	(13.826)	(1.930)	(39.749)
Birth Decade FE	Yes		Yes		Yes	
Regional FE	Yes		Yes		Yes	
Sociodemographic Controls	Yes		Yes		Yes	
Geographic Controls	Yes		Yes		Yes	
Observations	960	960	960	960	960	960
R-Squared	0.525	0.305	0.524	0.272	0.510	
F-Statistic (1st Stage)	16.76		16.82		17.78	

Notes: These regressions show a robustness check for IV model which estimates the relationship between adult height, as a proxy for health during childhood, and schooling efficiency using alternative IV specifications. Height is instrumented by different rainfall shocks 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 IV that is the same as the main IV, the accumulated monthly deviation from average rainfall, but for four years instead of five, the second set uses the same IV but for three years. The third set uses and IV which is the average number of months over the five-year period around birth that a person experience rainfall below the 20th percentile. All regressions include birth decade and regional fixed effects, sociodemographic controls and geographical controls. The sociodemographic controls include age at marriage, share of Muslims and religious fractionalization. The geographical controls include the length of colonization, colonial railways, ancient trade routes, diamond mines, explorer routes, missions, nutrient availability, soil workability, malaria ecology index, petroleum sites, ruggedness, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, distance to capital, distance to coast, 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 C.15: Robustness Checks – Spatial and Serial Autocorrelation Adjustment

	(1)	(2)	(3)	(4)
		ln(Education Efficiency)		
Height	0.070***	0.078***	0.058***	0.061***
	(0.018)	(0.017)	(0.017)	(0.016)
Constant	-10.925***	-12.011***	-5.643**	-8.799***
	(2.847)	(2.758)	(2.533)	(2.504)
Birth Decade FE	No	Yes	Yes	Yes
Regional FE	No	Yes	Yes	Yes
Sociodemographic Controls	No	No	Yes	Yes
Geographic Controls	No	No	No	Yes
Observations	1,234	1,115	1,111	969
R-Squared	0.153	0.190	0.387	0.521

Notes: These regressions show a robustness check which estimates the relationship between adult height, as a proxy for health during childhood, and schooling efficiency adjusting the standard errors for spatial and serial autocorrelation following Hsiang (2010). The underlying dataset is a pooled panel of African admin I regions for birth decades 1950 to 1999. 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 sociodemographic controls include age at marriage, share of Muslims and religious fractionalization at the admin I level. The geographical controls include the length of colonization, colonial railways, ancient trade routes, diamond mines, explorer routes, missions, nutrient availability, soil workability, malaria ecology index, petroleum sites, ruggedness, tsetse fly suitability, the ratio of the suitability for nomadic pastoralism to sedentary agriculture, distance to capital, distance to coast, population density and area. Asterisks denote significance levels at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C.10 References

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D It Ain't Easy: The Complex Relationship Between Education, Child Labour and Poverty

Abstract

Public opinion generally holds that child labour deprives children of education and exacerbates inequalities, particularly in the labour market. However, the existing literature remains inconclusive and often fails to account for the vast heterogeneity in children's livelihoods. This study examines the relationship between child labour and education in Sub-Saharan Africa, the region with the highest incidence of child labour globally. Our analysis draws on data from 17 Sub-Saharan African countries, utilizing the most recent wave of UNICEF's *Multiple Indicator Cluster Surveys* (MICS). These household-based interviews enable us to include all children in our study, regardless of their current schooling status. Additionally, the surveys provide detailed insights into working hours and the nature of child labour. Beyond analysing the general relationship between child labour and education, we place particular emphasis on the most deprived population groups. Our findings indicate that, on average, child labour is negatively associated with schooling performance. However, for children from the poorest households, this relationship is reversed. For these children, child labour appears to serve as a means to partially finance their education and meet basic subsistence needs. These findings suggest that outright bans on child labour without accompanying compensation mechanisms may inadvertently cause more harm than good, potentially exacerbating long-term inequalities.

D.1 Introduction

In 1992, United States Senator Tom Harkin first proposed the *Child Labour Deterrence Act* in the US Congress. The bill aimed to prohibit the importation of goods produced using child labour into the United States. Although it was never enacted, its mere proposition had immediate and unintended global consequences. In Bangladesh, for instance, an estimated 50,000 children working in garment factories lost their jobs overnight as factory owners, fearing export restrictions, dismissed them (Rahman et al., 1999). However, instead of going to school, follow-up studies revealed that many of these children were subsequently forced into even worse working conditions or fell into extreme poverty, leading to a decline in overall household income (Rahman et al., 1999). In this case, an initiative intended to protect children and increase education levels ultimately exacerbated their vulnerability.

While such policies may be wellintentioned, they are often based on the flawed assumption that the alternative to child labour is always formal schooling. However, even when education is technically free, various hidden costs—such as transportation, uniforms, books, and most notably, the opportunity cost of lost wages—can make schooling financially inaccessible. For families living at or near subsistence level, child labour may not simply be a barrier to education but rather a necessary means of affording it. Consequently, when children lose access to work without any financial compensation, they may either fall into more exploitative labour conditions or remain idle and out of school altogether.

At the same time, education is widely recognized as a crucial driver of long-term economic development. Higher levels of education are associated with greater earnings potential (Duflo, 2001; Ozier, 2018; Duflo et al., 2021), improved health outcomes (Alsan and Cutler, 2013; Weitzman, 2017; Andriano and Monden, 2019; K. Le and Nguyen, 2020), and higher subjective well-being (Chen, 2012; Cuñado and De Gracia, 2012; Yakovlev and Leguizamon, 2012). Therefore, understanding the complex interplay between child labour, education, and poverty, particularly among the most deprived populations, is essential. Without such insights, well-intended but poorly designed policies such as blanket bans on child labour without financial safeguards could deepen existing inequalities rather than alleviate them.

The relationship between child labour and education has been the subject of extensive research, with most studies finding a negative correlation between the two (e.g., Akabayashi and Psacharopoulos, 1999; Haile and Haile, 2012; Woldehanna and Gebremedhin, 2015; Abou, 2016; Dinku et al., 2019; Lee et al., 2021). However, these studies never investigate the question whether some children engage in labour because they need to finance their education. One notable exception is Luong (2011), who conducted a quasi-experimental study in Vietnam, where families in the treatment group were provided with a cow. Children who were able to generate additional income by selling the cows' manure achieved better educational outcomes. This suggests that in some cases, child labour may serve as a financial enabler of schooling, rather than a direct obstacle to it.

In this paper, we seek to systematically examine this relationship between child labour, education, and poverty, adopting a cross-country approach. Our analysis focuses on Sub-Saharan Africa, which not only has the highest incidence of child labour worldwide but also experiences persistently high levels of poverty. While child labour has been declining globally since 2000, progress has stalled in Sub-Saharan Africa (International Labour Organization, 2017). For instance, in Asia and the Pacific child labour dropped by 1.9 percent between 2012 and 2016. In contrast, during the same period child labour in Sub-Saharan Africa increased by 1 percent. We begin by analysing the general relationship between child labour and education, before exploring the more nuanced interactions between child labour, education, and poverty. Prior theoretical and qualitative studies suggest that for many African children, work is not merely an alternative to education but a necessary means of funding it (e.g., Luong, 2011; Okyere, 2013; Jonah and Abebe, 2019). Thus, a rigid policy approach that criminalizes all forms of child labour may prove counterproductive, particularly for the poorest households.

For our empirical analysis, we use Wave 6 of UNICEF's *Multiple Indicator Cluster Surveys* (MICS), which provides detailed micro-level data on educational attainment, working hours, and the type of labour performed. The household-based nature of these surveys allows us to include all children (7-14 years) in our analysis, regardless of their current schooling status. Furthermore, we disaggregate results by type of work, gender, and economic status, with a particular emphasis on children from the poorest households. Given the structure of our educational attainment data, we adopt a Tobit model, which accounts for censoring in test results. While we do not claim causal inference, our robustness checks provide confidence in the validity of our results.

Consistent with much of the existing literature, we find that child labour is generally associated with lower human capital accumulation, with negative effects observed for both boys and girls. However, when we focus on domestic work, our results show positive and significant effects on the extensive margin, but negative effects on the intensive margin. We hypothesize that engagement in some form of domestic work is the norm for most children, while those exempt from any work may face additional disadvantages (e.g., overall lower ability or weaker family support structures). Additionally, we find that physically demanding or inflexible work schedules have a more detrimental effect on education than less strenuous labour activities. Crucially, when examining the poorest households, we find evidence that additional work hours can be positively associated with schooling outcomes. This suggests that for some of the most economically vulnerable children, child labour serves as a mechanism to finance education, rather than hinder it. These findings highlight the potential risks of imposing out-right bans on child labour without implementing compensatory measures, as such policies could further entrench poverty and limit access to education.

Our contribution to the literature is twofold. As aforementioned, we provide the first systematic analysis of the child labour-education nexus across multiple Sub-Saharan African countries at the household level. Moreover, unlike previous research, which has primarily focused on national or regional averages, we explicitly examine the most deprived population groups. This focus is crucial for policy formulation, particularly as international organizations like the International Labour Organization (ILO) continue to advocate for complete or partial bans on child labour without fully accounting for the complex trade-offs faced by the poorest families.

The remainder of this paper is structured as follows. Chapter 2 discusses the theoretical and empirical literature on the child labour-education nexus and some determinants. Chapter 3 describes our data and outlines the empirical strategy. In Chapter 4, we present our results for both the full sample and the low-wealth sample as well as some robustness checks. Finally, Chapter 5 provides a concluding discussion.

D.2 Background

Before reviewing the empirical literature, we first examine key theoretical frameworks that explore the complex interplay between income, child labour, and education. This provides a foundation for understanding the mechanisms driving these relationships. We then shift our focus to empirical studies, particularly those examining both the determinants and consequences of child labour in developing countries.[31]

D.2.1 Theoretical Considerations

A seminal contribution to the theoretical literature comes from Basu and Van (1998), who argue that poverty is the primary driver of child labour. Their model suggests that banning child labour may reduce overall welfare if the resulting increase in adult wages fails to compensate for the loss of household income previously generated by child labour. Basu (2000) extends this framework by examining the impact of minimum wage legislation. He finds that if a minimum wage leads to higher unemployment, households may need to increase their reliance on child labour to offset lost earnings. These models emphasize that for poverty-stricken households, a reduction in child labour could worsen economic hardship. However, they do not consider the implications for human capital accumulation.

A major advancement came from Baland and Robinson (2000), who incorporated the interaction between child labour and educational attainment. In their two-period model, they demonstrate that even if child labour is inefficient it can arise in equilibrium in the presence of imperfect credit markets. This leads to lower long-term earnings for children. However, their framework assumes that child labour and schooling are strict substitutes, excluding the possibility that they might function as complements.

Fan (2004) challenges this assumption by showing that child labour and education can, under certain conditions, be complementary. His model suggests that when households live at or near subsistence level, they may not be able to afford full-time schooling. In such cases, income generated from child labour can help finance education, leading to higher human capital accumulation, provided that households derive utility from their children's education. In other words, as long as the income effect outweighs the substitution effect, child labour can enhance educational investment rather than diminish it.

[31] The literature also provides various contributions on the impact of child labour on physical health (see Kuimi et al. (2018) for a review) and more recently mental health (e.g., Al-Gamal et al., 2013; Trinh et al., 2020; Peñaherrera, 2021). While the impact on health is no less important than on education, we will refrain from further elaborating on this link given the scope of the research agenda.

Building on this, Luong (2011) introduces a model that explicitly allows for scenarios where children are neither working nor in school (idle children). His findings suggest that as long as some non-school time remains available, the income effect of child labour will always dominate the substitution effect, reinforcing the argument that child labour can support schooling under conditions of extreme poverty.

These theoretical underpinnings are illustrated in Figure D.1. For simplicity, the figure displays a linear relationship. Each child has time available which can be allocated among three activities: leisure (l), work (w), and schooling (s). Work generates income (i), which can be used to cover schooling costs (c). However, households without income-generating child labour only meet subsistence needs, leaving no surplus for education. Initially, as w increases, income also rises, enabling greater spending on education. This results in a positive relationship between w and s up to point $s*$, where the income effect dominates. However, beyond $s*$, the substitution effect takes over, further increases in w lead to reduced schooling because time spent working competes directly with time available for education ($l = 0$). Thus, while child labour initially facilitates schooling by generating income, excessive work time ultimately diminishes educational participation, leading to an inverted relationship beyond a critical threshold.

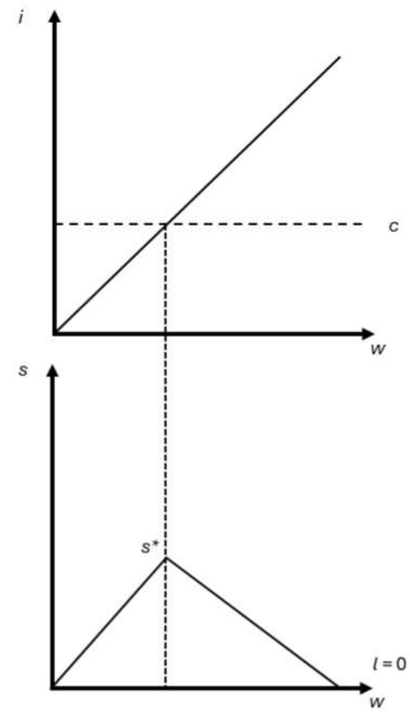
Taken together, these theoretical models highlight an important insight: child labour and schooling are not always mutually exclusive. Under severe financial constraints, reducing child labour without compensatory mechanisms can decrease both household welfare and human capital accumulation.

D.2.2 Child Labour and Education

While the theoretical literature acknowledges the possibility of a positive relationship between child labour and education, most empirical studies find a negative correlation between the two.

Empirical research covering Latin America predominantly reports a negative association between child labour and education, regardless of the specific educational outcome measured, be it school attendance, total years of schooling, or test scores (Psacharopoulos, 1997; Gunnarsson et al., 2006; Bezerra et al., 2009; Zapata et al., 2011; Zabaleta, 2011; Holgado et al., 2014; Emerson et al., 2017; Delprato and Akyeampong, 2019; Vasey, 2020). Similarly, most cross-country studies

Figure D.1: Theoretical Model on the Relationship between Child Labour and Schooling Under Financial Constraints. Authors' own representation.



support this finding (Post and Pong, 2000; Post and Pong, 2009; Ray and Lancaster, 2005; Putnick and Bornstein, 2015). However, Keane et al. (2020), using detailed time-use data from India, Vietnam, Peru, and Ethiopia, find that child labour participation negatively impacts test scores only when work time reduces study time rather than leisure, aligning with theoretical predictions by Fan (2004) and Luong (2011).

The literature on Asia presents a more nuanced picture. While many studies confirm a negative correlation (Amin et al., 2006; Beegle et al., 2009; Khanam and Ross, 2011; H. T. Le and Homel, 2015; Nelson and Quiton, 2018), some report no significant effect or only observe a negative impact when children work more than 20 hours per week (Phoumin, 2008; Kana et al., 2010; Sim et al., 2017). Furthermore, a quasi-randomized study by Luong (2011) in Vietnam finds that children from poor households who received a non-sellable cow as an asset to generate additional income had higher educational attainment than the control group, as the extra income allowed them to perform better in school.

Turning to Sub-Saharan Africa, most quantitative studies also report a negative impact of child labour on education. The majority use schooling inputs such as attendance or schooling-for-age as dependent variables (Akabayashi and Psacharopoulos, 1999; Boozer and Suri, 2001; Haile and Haile, 2012). Only two studies employ an educational outcome variable, both using Ethiopia's *Young Lives Survey* while attempting to address endogeneity concerns through an instrumental variable approach (Woldehanna and Gebremedhin, 2015; Dinku, 2019). However, their instruments likely fail the exclusion restriction, as they do not adequately account for the broader influence of regional affluence and household income on education independent of child labour.

The study most relevant to the present analysis is that of Lee et al. (2021), which examines math and reading test scores from the *Programme d'analyse des systèmes éducatifs de la Confemen* (PASEC) across ten francophone African countries. Using an instrumental variable approach, they find that working outside the household negatively affects test scores. However, their analysis is limited to in-school children and only considers a binary indicator for work outside the household. This approach overlooks two critical factors: (1) the intensity of child labour, which varies significantly, and (2) the prevalence of domestic labour, which is more common and disproportionately burdens girls (International Labour Organization, 2017). Despite the general trend of negative correlations, some studies suggest that child labour does not always hinder education. Dumas (2012), for example, finds a positive relationship between child labour and oral math scores in Senegal. Whereas the effect on literacy is negative, children with work experience perform better in orally administered math tests.

Thus, while most quantitative evidence supports a negative relationship between child labour and education, this correlation is neither universal nor strictly linear. Moreover, all studies, except Luong (2011), fail to explicitly consider the lowest-income segments of the population. Yet, both theoretical models and qualitative literature provide mechanisms through which child labour could positively impact education in extreme poverty settings.

The qualitative empirical literature identifies two primary channels through which child labour can contribute to education. First, when education is not free and poverty limits access, the income generated from child labour may enable children to afford some level of formal schooling (Chant and Jones, 2005; Abebe and Bessell, 2011; Okyere, 2013; Jonah and Abebe, 2019; Maconachie and Hilson, 2016). Second, work itself can serve as a form of learning. In many African societies, children working alongside their parents is part of a socialization process where they acquire skills deemed valuable for their future lives (Admassie, 2002; Krauss, 2017; Busquet et al., 2021). In line with theoretical models, these studies highlight valid reasons why, under conditions of severe poverty, child labour might contribute positively to educational outcomes.[32]

Overall, the existing literature lacks a comprehensive examination of the relationship between child labour and educational attainment in Sub-Saharan Africa, particularly among the poorest populations. This study aims to fill that gap by analysing household survey data with detailed information on children's work participation and educational outcomes. Additionally, it evaluates whether empirical evidence supports the theoretical and qualitative findings regarding the impact of child labour on education for the most impoverished populations.

D.2.3 Determinants of Child Labour

Before turning to the empirical analysis, this section briefly discusses key determinants of child labour, highlighting the complex relationship between household income, wealth, child labour, and education.

Early research primarily focused on poverty as a key driver of child labour, emphasizing that financial hardship forces children into work (Jensen and Nielsen, 1997; Admassie, 2002). However, more recent studies have examined the relationship between household income and child labour in greater depth, yielding mixed findings. On the one hand, income shocks can lead to an increase in child labour, as families rely on children's earnings to buffer against economic downturns (Beegle et al., 2006; Duryea et al., 2007; Dillon, 2013; Bandara et al., 2015). Similarly, seasonal fluctuations and food insecurity can push children into work, as households struggle to maintain a stable livelihood throughout the year (Christian and Dillon, 2018; Shah and Steinberg, 2017; Trinh et al., 2020; Morrow et al., 2017; Marchetta et al., 2019). In contrast, income-smoothing mechanisms such as access to health insurance (Landmann and Frölich, 2015; Strobl, 2017), remittances (Abdul-Mumuni et al., 2019; Boutin, 2014; Alcaraz et al., 2012; Calero et al., 2009; Yang, 2008; Ebeke, 2010; Acosta, 2011), public work programs (Dinku, 2019), and cash transfers (De Janvry et al., 2006; Edmonds, 2006; Edmonds and Schady, 2012; Edmonds and Shrestha, 2014; Del Carpio

[32] By no means we intend to imply that this is a desirable relationship nor idealise child labour. However, given the reality of many African children, this relationship needs to be considered to design effective development policies.

et al., 2016), have been shown to reduce child labour by providing financial security for households.

On the other hand, additional income can sometimes lead to an increase in child labour if it encourages household investments that require extra labour. This has been observed in cases where access to microfinance (Augsburg et al., 2012; Islam and Choe, 2013; Lakdawala, 2018; Hazarika and Sarangi, 2008) or certain cash transfer programs (De Hoop and Rosati, 2014; De Hoop et al., 2019; De Hoop et al., 2020) enables families to expand their economic activities, inadvertently increasing children's workload. Similarly, studies have identified a "wealth paradox" in which the ownership of income-generating assets, such as land or livestock, can lead to greater child labour. Due to imperfect labour markets, families may struggle to hire additional workers, increasing the reliance on children's labour for agricultural and domestic work (Basu et al., 2010; Bhalotra, 2003; Webbink et al., 2012; Oryoie et al., 2017; Kim, 2009).

The macroeconomic context further complicates this relationship. Trade liberalization has the potential to reduce child labour by increasing household incomes (Kis-Katos and Sparrow, 2011; Edmonds et al., 2010; Ranjan, 2001), but it can also have the opposite effect if it expands sectors that heavily rely on low-skilled labour, such as agriculture or informal manufacturing (Abebe, 2015; Atkin, 2016). The establishment of new plantations or production sites can similarly lead to diverging outcomes. While they can provide employment opportunities that raise household income and reduce child labour (Cogneau and Jedwab, 2012), they may also increase child labour if the rising opportunity cost of education discourages school attendance (Kruger, 2007; Xia and Deininger, 2019). Thus, while child labour generally declines as household income rises, the relationship is not strictly linear and depends on the type of assets, economic opportunities, and broader labour market conditions.

Beyond income and wealth, several other factors influence child labour. Household characteristics play a crucial role, as family size and composition affect children's likelihood of working. Studies have found that children in larger families, particularly those with many younger siblings, are more likely to be engaged in labour to support household needs (Patrinos and Psacharopoulos, 1997; Akabayashi and Psacharopoulos, 1999; Emerson and Souza, 2008; Alvi and Dendir, 2011; Seid and Gurmu, 2015). Parental education is another significant factor, with higher levels of parental education being associated with lower child labour rates and higher school attendance (Ray, 2000;

Ersado, 2005; Kurosaki et al., 2006; Emerson and Souza, 2008). Parental health can also play a role, as poor parental health may force children to work to compensate for lost household income (Dillon, 2013; Bratti and Mendola, 2014; Alam, 2015; Dinku et al., 2018). The absence of one or both parents further increases the likelihood of child labour, as single-parent households often struggle to meet basic economic needs (Webbink et al., 2012; Pörtner, 2016).

A child's own characteristics, such as cognitive ability, may also determine labour participation. Children with higher cognitive skills are more likely to remain in school and work less, although empirical research on this relationship remains limited. School characteristics, particularly infrastructure and education quality, are also critical determinants of child labour. Poor schooling conditions can increase the opportunity cost of attending school, making child labour a more attractive alternative for families facing financial constraints (Ray, 2002; Hilson, 2012; Abou, 2016).

While the relationship between income and child labour is often assumed to be negative, the reality is far more complex. The existing literature has primarily focused on the upper end of the income spectrum, where investments and labour market imperfections contribute to child labour. However, little attention has been given to the lowest-income households, where additional work may support educational attainment. This study aims to address this gap by analysing the determinants of child labour, particularly among the poorest populations, to assess whether empirical data supports theoretical predictions regarding the role of child labour in education.

D.3 Data and Methods

D.3.1 Data and Descriptives

The primary data source for this study is UNICEF's *Multiple Indicator Cluster Surveys* (MICS). These surveys, conducted in over 100 developing countries, cover a broad range of topics affecting the lives of mothers and children. This analysis focuses on the sixth wave of MICS, currently available for 17 Sub-Saharan African countries: Benin, the Central African Republic, Comoros, the Democratic Republic of Congo, eSwatini, Guinea-Bissau, Ghana, Gambia, Lesotho, Madagascar, Malawi, Nigeria, Sierra Leone, São Tomé and Príncipe, Chad, Togo, and Zimbabwe.

A distinctive feature of the sixth MICS wave is the inclusion of a short math test administered to children aged 7 to 14. The test consists of 21 questions assessing number recognition, numerical discrimination, addition, and pattern recognition. In theory, any child with basic numeracy skills should be able to answer these questions with ease. The questions have been tested for their validity (UNICEF, 2019). The total number of correctly answered questions serves as the main dependent variable in this study. One significant advantage of this assessment, compared to standardized tests such as PASEC, is that MICS is a household-based survey, meaning it includes the out-of-school population. This is particularly relevant, as approximately 20 percent of children in the sample do not attend school.[33]

Figure D.2 illustrates the distribution of math scores across regions. Sao Tomé and Principe, eSwatini and Zimbabwe stand out as the countries with the highest numeracy levels, followed by Ghana, Lesotho, and Togo. Madagascar, Nigeria, and Chad, however, exhibit notable within-country variation. In Madagascar, the northern region performs almost on par with the top-performing countries, while the southern region lags behind. In Nigeria, the southern regions perform very well, while some of the northern regions show some of the lowest overall outcomes. Similarly, in Chad, the southern regions score significantly higher than the northern regions, which are more rural. Figure D.3 provides an overview of the overall distribution of math test scores. Notably, nearly a quarter of the children in the sample scored zero, despite having agreed to participate in the test, while approximately 15 percent achieved the maximum score.

The primary independent variable in this study is child labour. There is no universally accepted definition of child labour in the literature. The ILO defines child labour based on age thresholds: for children up to 12 years old, engaging in at least one hour of economic activity per week is considered child labour, while for children up to 14 years old, the threshold is 14 hours or more per week. Additionally, for all children under the age of 17, any economic activity is classified as child labour if it involves hazardous work such as carrying heavy loads, exposure to toxic substances, or other physically dangerous tasks or falls under the worst forms of child labour, including bonded labour, forced labour, or involvement in armed conflicts and prostitution. However, the ILO does not pro-

[33] The surveys also provide a literacy test. However, we decided not to use the results due to a strong selection bias. Whereas most children participated in the math test more than a third of children refused to participate in the literacy test. A simple t-test revealed that the children who refused to participate on average have only about half the points in the math test compared to those who did (6.922 vs. 12.532 points). The difference is statistically significant. Therefore, due to this strong positive self-selection into the literacy test we opt not to use them. However, using the literacy test results as our outcome variable leads to the same conclusions.

Figure D.2: Distribution of Math Scores by Region. Calculations Based on MICS Wave 6. Authors' own representation.

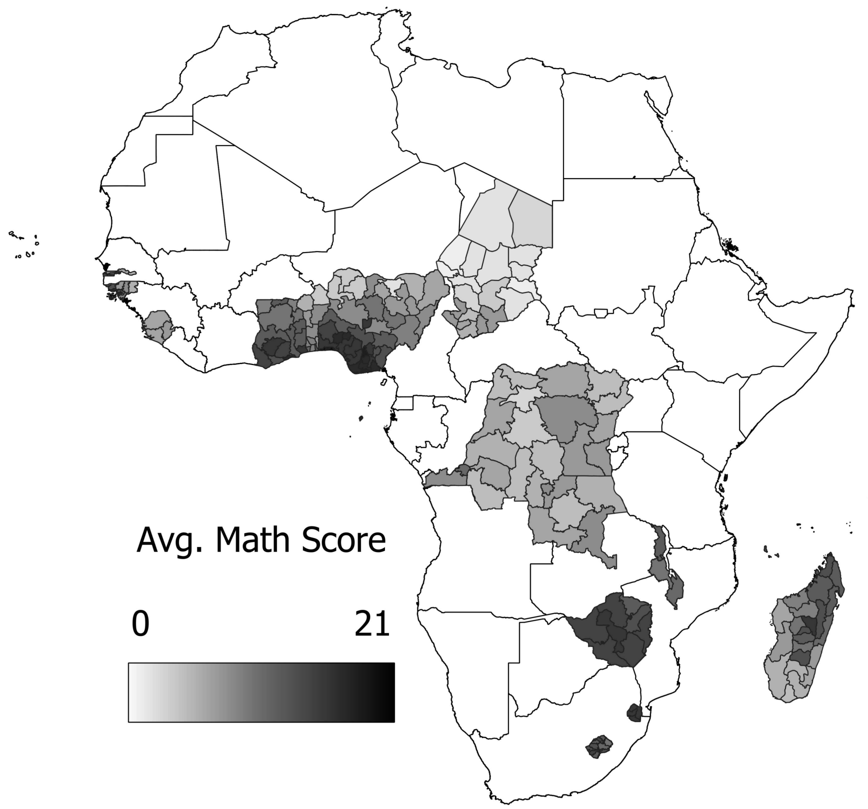
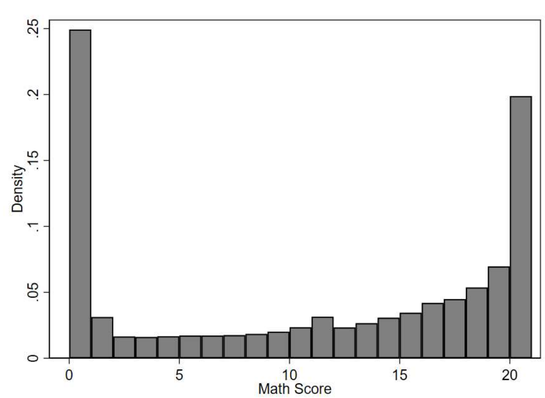


Figure D.3: Distribution of Math Scores. Calculations Based on MICS Wave 6. Authors' own representation.



vide a clear definition regarding limitations on domestic work (International Labour Organization, 1973; International Labour Organization, 1999). The empirical literature varies in its definition of child labour, often depending on data availability and research objectives. Definitions range from binary indicators to detailed time-use data. Some studies only consider economic activities, such as employment outside the household, while others include domestic work and contributions to family farms or businesses.[34]

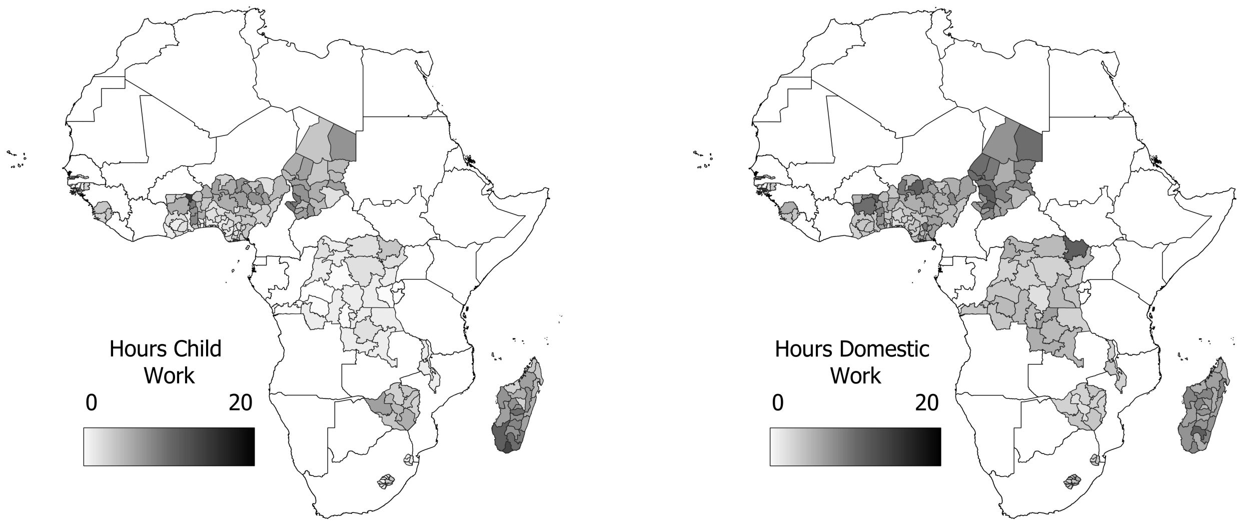
Given the detailed data available in MICS, this study defines child labour as any work carried out by children, whether inside or outside the household, measured in terms of hours worked per week. The MICS dataset also allows for disaggregation by type of work. Time-use data is available for both economic activities (hereafter referred to as "child work") and domestic chores (hereafter referred to as "domestic work"), as well as binary indicators for specific work categories. The economic activities recorded in the survey include assisting on family farms or with livestock, working in a family business, producing or selling goods, and engaging in any other form of work in exchange for income. The survey also provides information on whether any of these activities are considered hazardous. Domestic work categories include fetching water, collecting firewood, shopping, cooking, washing, cleaning, and caring for children or elderly and sick family members.

Figure D.4 provides an overview of the distribution of hours worked in economic activities and domestic work by region. While the overall hours spent on domestic work are much higher the distribution over both types of work is rather similar. Both Chad and Madagascar exhibit high levels of child and domestic work. Interestingly, Zimbabwe has a comparatively high incidence of child work given its performance in the math test. An outlier in terms of child work is the Savanes region in Benin with about 16 hours of child work on average per week.

Figure D.3 provides an overview of the most common types of child work in Sub-Saharan Africa. These categories are not mutually exclusive, as children may engage in multiple forms of labour. More than 30 percent of children in the sample work on family farms, and over 10 percent are

[34] Examples of studies using binary indicators are Delprato and Akyeampong (2019); Sim et al. (2017); Lee et al. (2021) and Emerson et al. (2017). Examples of studies using detailed time data are Dinku et al. (2019); Woldehanna and Gebremedhin (2015); Holgado et al. (2014) and Haile and Haile (2012). Studies that only focus on economic activities outside of the household are, for instance, Lee et al. (2021); Boozer and Suri (2001); Beegle et al. (2009) and Emerson et al. (2017). In contrast, studies that include work inside the household such as chores or labour on the family farm are, for example, Zabaleta (2011); Bezerra et al. (2009); Nelson and Quiton (2018) and Amin et al. (2006).

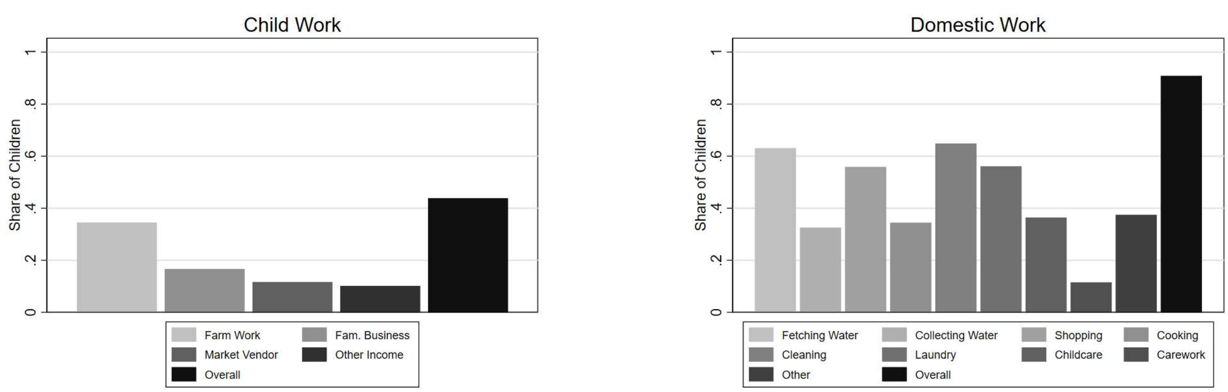
Figure D.4: Distribution of Child Labour by Region. Calculations Based on MICS Wave 6. Authors' own representation.



involved in family businesses. Working outside the household for income is less common, though around 10 percent of children engage in income-generating activities such as producing or selling goods, some of which may involve hazardous or exploitative labour. Overall, approximately 40 percent of children participate in some form of child work, while nearly 90 percent engage in domestic work. The most common domestic tasks include fetching water, shopping, cleaning, and doing laundry, while caring for elderly or sick individuals is relatively less frequent.

Summary statistics for all variables used in the subsequent analysis are provided in Table D.8.

Figure D.5: Prevalence of Different Types of Child Labour: Child Work and Domestic Work. Calculations Based on MICS Wave 6. Authors' own representation.



D.3.2 Method

This study aims to assess the full effect of child labour on math scores while also distinguishing between its external and internal margins. The external margin examines differences in math scores between children who do not work and those who do, while the internal margin evaluates how the intensity of work, measured in hours per week, affects math performance among working children. As illustrated in Figure D.3, a disproportionately high number of children score either zero or the full number of points on the math test. This suggests that the distribution is censored by the number and difficulty of the test questions. A Tobit model is therefore appropriate to account for this censoring and estimate the following equation:

$$math_{icr} = \beta_0 + \beta_1 \cdot labour_i + \beta_2 \cdot sq(labour_i) + \Gamma X_i + \gamma_c + \delta_r + \varepsilon_i, \tag{15}$$

where *math* denotes the math score of child i in country c and region r. The variable *labour* denotes our respective measure of labour for child and domestic work. A squared term is included to account for potential nonlinearities in the relationship between labour and math scores. The estimation strategy differs depending on whether we assess the full effect, the external margin, or the internal margin. In the full model, labour is measured as the total number of hours worked per week. For the external margin, we use a binary indicator that distinguishes between children who work and those who do not, meaning the squared term is excluded. For the internal margin, we analyse the number of weekly working hours, conditional on the child engaging in labour.

To control for confounding factors, we include a range of household- and child-level covariates (ΓX_i). These controls consist of the child's age and gender, a dummy for urban residence, household size, the number of infants in the household, the amount of land owned, a dummy for cattle ownership, and dummies for the household's religious affiliation. Additionally, we incorporate country fixed effects (γ_c) and regional fixed effects (δ_r) to account for unobserved heterogeneity. Country-level fixed effects control for structural factors such as the education system or colonial heritage, while regional fixed effects capture geographic characteristics and, to some extent, variations in school quality within regions.[35] As this econometric approach does not explicitly address

[35] The regional level is the smallest geographical unit which we can assign a household to. Naturally, there is variation in geographic factors within regions, however, unfortunately, we are unable to account for these more

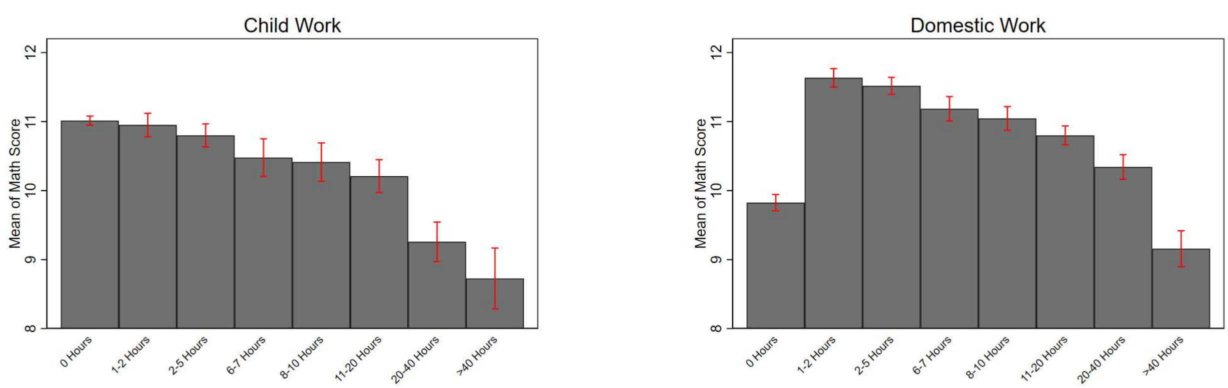
potential endogeneity concerns, the estimated effects should not be interpreted as causal but rather as indicative of associations between child labour and math performance.

D.4 Results

D.4.1 Full Sample

Before presenting the regression results, we first provide a graphical analysis of the relationship between hours worked and average math scores. Figure D.6 illustrates these relationships separately for child work and domestic work. The left graph shows the relationship between weekly hours of child work and average math scores. The graph suggests that there is no significant difference in scores between children who do not work and those who work up to two hours per week. The right graph in Figure D.6 presents the relationship between domestic work and math scores. Interestingly, children who do not contribute to household work score significantly lower than those who engage in domestic chores. Given that the vast majority of children perform some household tasks, those who do not contribute at all may have overall lower cognitive abilities or may be idle rather than engaged in alternative productive activities. Beyond this initial observation, the trend suggests that as the number of hours spent on domestic work increases, math scores tend to decline.

Figure D.6: Relationship of Child Work and Math Score for the Lowest Wealth Quintile. Calculations Based on MICS Wave 6. Authors' own representation.



closely. Moreover, schooling quality can differ between schools, yet, again the data does not allow to investigate its effect in more detail.

Table D.1 presents the main regression results for the relationship between child work and math scores. Panel A reports the baseline regression for the full sample, Panel B examines the external margin (whether a child works at all), and Panel C focuses on the internal margin (the number of hours worked among working children). Column 1 presents the raw correlation, followed by specifications that progressively introduce socio-demographic controls and country and regional fixed effects. In the full model, after accounting for all controls, an additional hour of work per week is estimated to reduce math scores by 0.066 points, with statistical significance at the one percent level. The squared term is small and insignificant, suggesting that the relationship is linear. Turning to the external margin, we find a negative and statistically significant correlation between working and the test score. The results for the internal margin confirm this interpretation. Similar to the full model, an additional hour of work per week reduces the math score. In our preferred specification in Column 5, the coefficient suggests a decline of 0.064 points per additional hour worked.

Next, Table D.2 presents the regression results for domestic work. The full model in Panel A shows an unstable coefficient of the main explanatory variable. First, the coefficient is negative. However, after including socio-demographic controls and fixed effects, the coefficient turns positive and statistically significant. This counterintuitive result can be better understood by examining the external margin results in Panel B. The preferred specification in Column 5 indicates a strong positive relationship between engaging in domestic work and math scores. Given that the vast majority of children perform some form of household work, it is uncommon for a child to contribute no domestic labour at all. As previously suggested, children who do not perform any household tasks may have lower overall cognitive ability, and their exclusion from chores may reflect a lack of engagement rather than an absence of labour burden. The large positive coefficient (1.132) in the external margin regression likely explains the positive coefficient in Panel A. While we cannot directly test this hypothesis, further support comes from the internal margin results in Panel C, where the coefficient is insignificant. This suggests that there is no strong negative effect of domestic work on math performance and that non-participation in domestic chores may be a marker of lower ability rather than an indicator of a reduced workload.

Child labour is highly gendered, as noted in prior studies (International Labour Organization,

Table D.1: Relationship Child Work and Math Score

	(1)	(2)	(3)	(4)	(5)
Panel A: Full Model					
Hours Child Work	-0.152***	-0.314***	-0.106***	-0.113***	-0.066***
	(0.037)	(0.036)	(0.025)	(0.017)	(0.015)
sq(Hours Child Work)	0.001**	0.003***	0.001	0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Age		2.049***	1.826***	1.769***	1.731***
		(0.061)	(0.066)	(0.065)	(0.066)
Sex (1 = Female)		-0.154	-0.172	-0.228	-0.189
		(0.165)	(0.162)	(0.161)	(0.164)
Constant	10.351***	-10.092***	-6.795***	-8.290***	-8.967***
	(0.491)	(0.744)	(0.740)	(1.080)	(0.736)
Observations	91,711	91,654	87,335	87,335	87,335
Panel B: External Margin					
Dummy Child Work	-1.050***	-2.798***	-0.605***	-0.699***	-0.368***
	(0.405)	(0.368)	(0.223)	(0.166)	(0.142)
Age		2.049***	1.805***	1.754***	1.716***
		(0.061)	(0.067)	(0.065)	(0.066)
Sex (1 = Female)		-0.103	-0.125	-0.194	-0.160
		(0.163)	(0.162)	(0.161)	(0.163)
Constant	10.309***	-9.989***	-6.639***	-8.200***	-8.962***
	(0.475)	(0.751)	(0.738)	(1.086)	(0.742)
Observations	91,717	91,660	87,341	87,341	87,341
Panel C: Internal Margin					
Hours Child Work	-0.172***	-0.224***	-0.129***	-0.101***	-0.064***
	(0.039)	(0.037)	(0.027)	(0.020)	(0.019)
sq(Hours Child Work)	0.002***	0.002***	0.001*	0.001**	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Age		2.000***	1.736***	1.637***	1.580***
		(0.059)	(0.054)	(0.046)	(0.047)
Sex (1 = Female)		-0.372*	-0.567**	-0.492**	-0.497*
		(0.207)	(0.199)	(0.195)	(0.200)
Constant	10.508***	-10.436***	-5.045***	-8.258***	-10.494***
	(0.709)	(0.841)	(0.748)	(1.161)	(0.644)
Observations	34,311	34,277	32,322	32,322	32,322
Individual Controls	No	No	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes

Notes: These regressions show our baseline Tobit model which estimates the relationship between child work and children's math score for the full sample. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. Panel A shows the full model, Panel B the external margin and Panel C the internal margin. While column 1 shows the raw correlation, column 2 adds age and sex as controls, column 3 further individual controls, column 4 country fixed effects, and column 5 regional fixed effects. The individual controls include an urban dummy, number of household members, number of infants in the household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table D.2: Relationship Domestic Work and Math Score

	(1)	(2)	(3)	(4)	(5)
Panel A: Full Model					
Hours Domestic Work	0.014	-0.191***	-0.067***	-0.007	0.033**
	(0.040)	(0.035)	(0.024)	(0.017)	(0.014)
sq(Hours Domestic Work)	-0.001	0.002***	0.000	-0.000	-0.001**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Age		2.030***	1.819***	1.733***	1.690***
		(0.062)	(0.067)	(0.066)	(0.067)
Sex (1 = Female)		0.362**	0.034	-0.140	-0.184
		(0.166)	(0.169)	(0.165)	(0.166)
Constant	9.951***	-10.116***	-6.740***	-8.201***	-8.959***
	(0.490)	(0.752)	(0.735)	(1.086)	(0.742)
Observations	91,706	91,649	87,330	87,330	87,330
Panel B: External Margin					
Dummy Domestic Work	2.167***	-0.027	0.690***	1.014***	1.132***
	(0.328)	(0.307)	(0.229)	(0.151)	(0.133)
Age		1.945***	1.752***	1.683***	1.653***
		(0.060)	(0.066)	(0.064)	(0.065)
Sex (1 = Female)		0.040	-0.210	-0.331**	-0.331**
		(0.167)	(0.168)	(0.162)	(0.162)
Constant	8.321***	-9.938***	-6.794***	-8.467***	-9.191***
	(0.519)	(0.756)	(0.730)	(1.085)	(0.740)
Observations	91,717	91,660	87,341	87,341	87,341
Panel C: Internal Margin					
Hours Domestic Work	-0.149***	-0.259***	-0.137***	-0.065***	-0.025
	(0.040)	(0.037)	(0.026)	(0.020)	(0.016)
sq(Hours Domestic Work)	0.001**	0.003***	0.001***	0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Age		1.989***	1.751***	1.626***	1.583***
		(0.060)	(0.063)	(0.062)	(0.062)
Sex (1 = Female)		0.022	-0.164	-0.441***	-0.456***
		(0.185)	(0.176)	(0.169)	(0.171)
Constant	11.415***	-8.869***	-5.296***	-6.247***	-6.445***
	(0.522)	(0.750)	(0.745)	(1.062)	(0.690)
Observations	67,593	67,545	64,227	64,227	64,227
Individual Controls	No	No	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes

Notes: These regressions show our baseline Tobit model which estimates the relationship between domestic work and children's math score for the full sample. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. Panel A shows the full model, Panel B the external margin and Panel C the internal margin. While column 1 shows the raw correlation, column 2 adds age and sex as controls, column 3 further individual controls, column 4 country fixed effects, and column 5 regional fixed effects. The individual controls include an urban dummy, number of household members, number of infants in the household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

2017). Table D.3 presents results disaggregated by gender, with Panel A focusing on child work and Panel B on domestic work. Overall, the results are similar to the main regressions. For child work, in all models the coefficients are highly similar to the main regressions for both genders. For domestic work, the results in Panel B largely mirror previous findings. The full model and external margin coefficients are positive, while the internal margin results are insignificant. Interestingly, the coefficients for girls are smaller than for boys, suggesting that the impact of domestic work on math scores may be less pronounced for girls.

Table D.3: Relationship Child and Domestic Work and Math Score – By Gender

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Model		External Margin		Internal Margin	
	Boys	Girls	Boys	Girls	Boys	Girls
Panel A: Child Work						
Hours Child Work	-0.063***	-0.063***			-0.055**	-0.066***
	(0.018)	(0.018)			(0.023)	(0.022)
sq(Hours Child Work)	0.000	0.000			0.000	0.000
	(0.000)	(0.000)			(0.000)	(0.000)
Dummy Child Work			-0.345*	-0.300*		
			(0.179)	(0.157)		
Age	1.807***	1.656***	1.789***	1.644***	1.489***	1.650***
	(0.069)	(0.068)	(0.068)	(0.067)	(0.055)	(0.054)
Constant	-10.555***	-7.477***	-10.567***	-7.431***	-8.031***	-12.655***
	(0.707)	(0.747)	(0.713)	(0.748)	(0.778)	(0.737)
Observations	43,387	43,948	43,388	43,953	15,173	17,149
Panel B: Domestic Work						
Hours Child Work	0.054**	0.014			-0.026	-0.025
	(0.018)	(0.016)			(0.020)	(0.017)
sq(Hours Child Work)	-0.001**	-0.000			0.000	0.000
	(0.000)	(0.000)			(0.000)	(0.000)
Dummy Domestic Work			1.190***	0.954***		
			(0.150)	(0.174)		
Age	1.758***	1.628***	1.722***	1.593***	1.619***	1.559***
	(0.069)	(0.069)	(0.066)	(0.068)	(0.064)	(0.065)
Constant	-10.599***	-7.415***	-10.784***	-7.794***	-6.942***	-6.484***
	(0.707)	(0.754)	(0.707)	(0.760)	(0.589)	(0.753)
Observations	43,836	43,944	43,388	43,953	28,379	35,848
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show our Tobit model which estimates the relationship between child labour and children's math score disaggregated by gender. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. Panel A shows the relationship for child work and Panel B for domestic work. Columns 1 and 2 present the results for the full model, Columns 3 and 4 the external margin, and Columns 5 and 6 the internal margin. Odd-numbered columns refer to the boy sample and even-numbered columns to the girl sample. All regressions include individual controls, country, and region fixed effects. The individual controls include an urban dummy, number of household members, number of infants in household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The rich data structure of MICS allows us to analyse the effects of different types of child work separately. Since work activities are not mutually exclusive, we estimate separate regressions for each type of child work at the internal margin. Table D.4 presents these results. Among various types of child work, working on family farms or in gardens appears to have the most detrimental effect on math scores. In contrast, helping in a family business mitigates the negative effects of child work, and in fact, for children working up to seven hours per week, the effect is even positive. A possible explanation is that agricultural labour is physically demanding and often inflexible, particularly during peak farming seasons, leading to school absenteeism or fatigue that hinders academic performance. In contrast, family business work may be more adaptable to school schedules and could even contribute to numeracy skills, as children may engage in tasks involving basic arithmetic, such as handling transactions (Reed and Lave, 1979; Carraher et al., 1985; Jurdak and Shahin, 1999; Banerjee et al., 2017). As expected, the dummy variable indicating whether a child engages in hazardous work is negative and statistically significant. As defined by ILO guidelines (International Labour Organization, 1999), hazardous labour is generally understood to harm children's education and well-being.

Table D.5 examines different types of domestic work. Most variables indicating work type are significant, except for fetching water, caring for the elderly or sick and engaging in miscellaneous household chores. Caring for others is relatively uncommon in the sample, with only 11.47 percent of children performing this task, while the heterogeneity of "other household chores" may make it difficult to detect a clear effect. Only one domestic task—collecting firewood —shows a negative relationship with math scores. As with child work, the explanation likely lies in the physical demands and inflexibility of these tasks. Collecting firewood can be time-consuming and require long-distance travel (Brouwer et al., 1997). In contrast, other domestic tasks, such as shopping, cooking, washing, and cleaning, exhibit a positive relationship with math scores. This aligns with the earlier findings that children who do not engage in any household work tend to score lower, possibly because performing domestic chores is a social norm, and nonparticipation signals a broader disengagement. Thus, lighter household tasks may not necessarily be detrimental to academic performance, while physically demanding or timeconsuming tasks may have more significant negative effects.

Table D.4: Relationship Child Work and Math Score - By Type of Work

	(1)	(2)	(3)	(4)	(5)
Hours worked in past week	-0.061***	-0.065***	-0.064***	-0.064***	-0.060***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
sq(Hours Child Work)	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Worked or helped on garden/farm (=1)	-0.979***				
	(0.203)				
Helped in family business (=1)		0.459***			
		(0.171)			
Produced or sold articles (=1)			0.165		
			(0.222)		
Engaged in any other activity for income (=1)				-0.328	
				(0.215)	
Hazardous Labour (=1)					-0.373*
					(0.199)
Constant	-9.999***	-10.670***	-10.442***	-10.661***	-10.486***
	(0.654)	(0.631)	(0.638)	(0.643)	(0.648)
Observations	32,310	32,295	32,298	32,296	32,244
Individual Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show our Tobit model which estimates the relationship between child work and children's math score controlling for the type of work. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. All regressions include individual controls, country, and region fixed effects. The individual controls include age, sex, an urban dummy, number of household members, number of infants in household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table D.5: Relationship Domestic Work and Math Score – By Type of Work

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total Hours Domestic Work	-0.025	-0.015	-0.030*	-0.035**	-0.029*	-0.035**	-0.024	-0.025	-0.027*
	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
sq(Total Hours Domestic Work)	0.000	0.000	0.000	0.000*	0.000	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fetched water (=1)	-0.150								
	(0.139)								
Collected firewood D(=1)		-1.549***							
		(0.127)							
Did shopping (=1)			0.653***						
			(0.140)						
Did cooking (=1)				0.669***					
				(0.120)					
Did washing dishes or cleaning (=1)					0.620***				
					(0.164)				
Washed clothes (=1)						0.969***			
						(0.137)			
Cared for children (=1)							-0.073		
							(0.138)		
Cared for old or sick (=1)								0.030	
								(0.219)	
Did other household tasks (=1)									0.213
									(0.158)
Constant	-6.409***	-6.379***	-6.867***	-6.091***	-6.685***	-6.122***	-6.452***	-6.490***	-6.410***
	(0.692)	(0.693)	(0.680)	(0.660)	(0.724)	(0.663)	(0.692)	(0.691)	(0.691)
Observations	64,203	64,171	64,196	64,200	64,213	64,209	64,206	64,177	64,168
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show our Tobit model which estimates the relationship between domestic work and children's math score controlling for the type of work. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. All regressions include individual controls, country, and region fixed effects. The individual controls include age, sex, an urban dummy, number of household members, number of infants in household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Taken together, these results suggest that while child labour generally has a negative impact on math scores, the effect varies significantly depending on the type and intensity of work. Domestic work, in particular, appears to have a more complex relationship with academic performance, where moderate participation is associated with better outcomes, while excessive burdens, especially those involving physically strenuous tasks, can hinder learning.

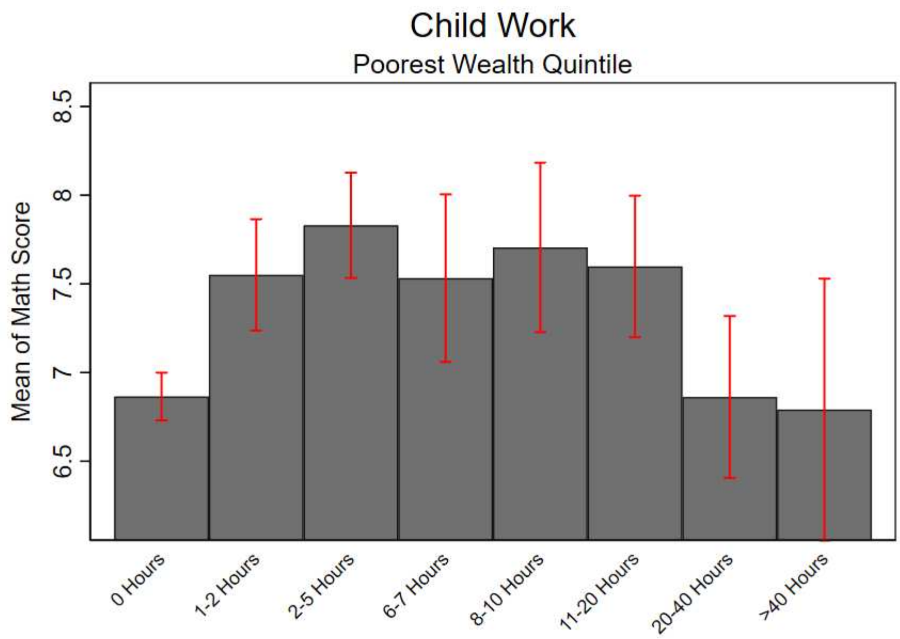
D.4.2 Low Wealth Sample

So far, in line with previous literature, the analysis has considered all children, regardless of their ability to afford schooling. In this section, we focus specifically on children in the lowest wealth quintile, for whom work may be a necessity to meet basic household needs. This focus is particularly relevant, as the theoretical literature suggests that for children living at or below subsistence level, income generated through child labour could facilitate school attendance. Given that economic activities are more directly tied to household income, we restrict our analysis to child work, excluding domestic work. While children's domestic labour can free up adult household members to engage in income-generating activities, domestic work itself does not contribute directly to household income. Moreover, labour markets in many developing regions are imperfect, meaning that freed-up time does not necessarily translate into additional earnings (Basu et al., 2010).

Before presenting the regression results, we first examine the descriptive relationship between hours worked and math scores. Figure D.7 illustrates this relationship for children in the lowest wealth quintile. The pattern suggests a non-linear, inverse U-shaped relationship. The highest average math scores are observed among children who work between two and five hours per week, while the lowest scores are found among those who work 40 hours or more. However, children working zero hours have on average a lower math test score compared to children working up to 20 hours. This finding aligns with theoretical predictions, which suggest that for children from the poorest households, engaging in a moderate amount of work can enhance educational outcomes by making schooling financially viable.

Table D.6 provides a more detailed examination of this relationship using the same regression framework as in previous sections but restricting the sample to the lowest wealth quintile. The results offer further suggestive evidence that some degree of work may be beneficial for children's

Figure D.7: Relationship of Child Work and Math Score for the Lowest Wealth Quintile. Calculations Based on MICS Wave 6. Authors' own representation.



educational attainment in the poorest households. Panel A presents the full regression model, and in the preferred specification (Column 5), the coefficient is small and statistically insignificant suggesting that there is no universal negative relationship between child work and educational outcomes for this subsample. In addition, the external margin results in Panel B indicate a positive and statistically significant effect at the five percent level. The coefficient suggests that children who engage in work score, on average, 0.458 points higher on the math test compared to those who do not work at all. This finding is consistent with both theoretical predictions and the descriptive evidence from Figure D.7. Nonetheless, the internal margin results in Panel C paint a different picture. The coefficient for hours worked per week is negative and statistically significant throughout (-0.069). This suggests that while some level of work may be beneficial, excessive working hours ultimately hinder educational attainment. Overall, these results indicate that working a small number of hours is associated with better academic performance, but beyond a certain threshold, additional work hours reduce math scores.

While these findings provide empirical support for the theoretical models and qualitative evidence suggesting that some work may be beneficial for children in extreme poverty, they also

Table D.6: Relationship Child Work and Math Score - Poorest Wealth Quintile

	(1)	(2)	(3)	(4)	(5)
Panel A: Full Model					
Hours Child Work	0.012	-0.164***	-0.065**	-0.038	-0.016
	(0.039)	(0.039)	(0.033)	(0.025)	(0.024)
sq(Hours Child Work)	-0.001	0.002***	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Age		2.199***	2.051***	1.937***	1.919***
		(0.087)	(0.093)	(0.088)	(0.089)
Sex (1 = Female)		-0.347	-0.182	-0.298	-0.278
		(0.224)	(0.209)	(0.215)	(0.220)
Constant	3.766***	-17.523***	-12.894***	-16.032***	-22.969***
	(0.662)	(0.842)	(0.922)	(1.516)	(1.077)
Observations	22,644	22,622	21,569	21,569	21,569
Panel B: External Margin					
Dummy Child Work	0.963**	-1.028**	0.167	0.341	0.458**
	(0.440)	(0.416)	(0.326)	(0.232)	(0.210)
Age		2.172***	2.009***	1.898***	1.882***
		(0.088)	(0.095)	(0.087)	(0.088)
Sex (1 = Female)		-0.287	-0.099	-0.233	-0.215
		(0.226)	(0.210)	(0.218)	(0.222)
Constant	3.323***	-17.385***	-12.749***	-15.933***	-22.900***
	(0.650)	(0.841)	(0.917)	(1.518)	(1.080)
Observations	22,647	22,625	21,572	21,572	21,572
Panel C: Internal Margin					
Hours Child Work	-0.123***	-0.186***	-0.142***	-0.102***	-0.069***
	(0.031)	(0.029)	(0.028)	(0.027)	(0.025)
sq(Hours Child Work)	0.001***	0.002***	0.001***	0.001**	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Age		2.015***	1.826***	1.725***	1.703***
		(0.059)	(0.060)	(0.054)	(0.052)
Sex (1 = Male)		-1.053***	-0.832***	-0.801***	-0.797***
		(0.260)	(0.255)	(0.234)	(0.227)
Constant	5.124***	-15.112***	-8.561***	-13.988***	-27.469***
	(0.290)	(0.668)	(0.734)	(0.957)	(3.542)
Observations	10,306	10,294	9,718	9,718	9,718
Individual Controls	No	No	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes

Notes: These regressions show our baseline Tobit model which estimates the relationship between child work and children's math score for the poorest sample, i.e., the lowest wealth quintile. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. Panel A shows the full model, Panel B the external margin, and Panel C the internal margin. While column 1 shows the raw correlation, column 2 adds age and sex as controls, column 3 further individual controls, column 4 country fixed effects, and column 5 regional fixed effects. The individual controls include an urban dummy, number of household members, number of infants in household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

indicate that only a very limited amount of child work contributes positively to educational outcomes. To further explore these dynamics, we conduct two additional analyses. In the first model, we exclude children who attend school and do not work. The rationale behind this exclusion is that these children can afford school attendance without engaging in labour, meaning their inclusion may obscure the relationship between child work and academic performance for those who rely on work to access education. The remaining sample consists of children for whom work is likely necessary to afford school. In the second model, we exclude "idle" children—those who neither work nor attend school. These children represent cases where the income effect would always dominate the substitution effect if they were to enter the workforce. By excluding them, we refine the analysis to compare only children for whom there can be a meaningful trade-off between work and education. Table D.7 presents the results from these two models. Column 1 reports the estimates excluding the "In-School & No Work" population. Here, the coefficient for child work is positive and highly statistically significant. The results indicate that an additional hour of work increases math test scores by an average of 0.244 points. For this subset of children, the income effect clearly dominates the substitution effect, meaning that working enables them to perform better academically by securing access to schooling. In contrast, Column 2 presents results excluding idle children. In this specification, the effect of child work becomes negative and statistically significant. This suggests that among children who are both in school and working, additional work hours lead to lower math scores, even within the lowest wealth quintile. Thus, while work may be necessary for some children to afford schooling, it does not improve educational outcomes once they are in school.

Taken together, these findings highlight a critical policy consideration: preventing children from working at the lower end of the wealth distribution will not automatically improve their educational attainment unless alternative financial support mechanisms are put in place. If schooling remains unaffordable without child labour, restricting work may result in lower school participation and poorer academic outcomes for the poorest children. These results emphasize the importance of targeted policies that address the financial barriers to education for the most disadvantaged households.

Table D.7: Relationship Child Work and Math Score - Poorest Wealth Quintile: Variations

	(1) Exclude In-School & No Work	(2) Exclude Idle Children
Hours Child Work	0.244***	-0.187***
	(0.039)	(0.026)
sq(Hours Child Work)	-0.004***	0.002***
	(0.001)	(0.000)
Age	1.872***	1.889***
	(0.074)	(0.094)
Sex (1 = Female)	-1.024***	-0.079
	(0.276)	(0.201)
Constant	-33.279***	-18.528***
	(0.946)	(1.138)
Observations	13,376	17,911
Individual Controls	Yes	Yes
Country FE	Yes	Yes
Region FE	Yes	Yes

Notes: These regressions show our Tobit model which estimates the relationship between child work and children's math scores for the poor sample, i.e., the lowest wealth quintile. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. Column 1 excludes children who are in school and not working, assuming that they can afford school without child work. Column 2 excludes idle children. All regressions include individual controls, country, and regional fixed effects. The individual controls include an urban dummy, number of household members, number of infants in household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

D.4.3 Robustness Checks

To ensure the validity of our findings, we test the robustness of our results using alternative model specifications and outcome variables. The results confirm that our main conclu-sions hold across different estimation frameworks and measurement approaches.

First, we account for the discrete count structure of our outcome variable by employing a negative binomial regression framework rather than focusing on the censored nature of our outcome variable. Table D.9 presents estimates for the relationship between child work, domestic work, and math scores using this approach for the full sample, while Table D.10 applies the same methodology to the poorer subsample. The results remain consistent with our primary analysis, reinforcing the robustness of our findings.

Second, we use an alternative dependent variable commonly employed in the literature: an age-adjusted years of schooling measure based on the methodology of Psacharopoulos and Yang (1991), as used in previous studies (Ray and Lancaster, 2005; Phoumin, 2008; Kana et al., 2010; Haile and Haile, 2012). This variable is calculated as the highest grade completed, divided by the child's age minus the school entry age, and then multiplied by 100. This adjustment accounts for differences in educational attainment that may arise due to variations in school entry age and grade progression. Table D.11 reports the results for the full sample using this alternative outcome measure, while Table D.12 focuses on the poorer subsample. In both cases, our core findings remain robust. The relationship between child work and educational attainment follows a similar pattern, confirming that moderate levels of work may support school participation for the poorest children, while excessive work hours negatively impact educational outcomes.

Third, to further address concerns of endogeneity, we incorporate survey cluster fixed effects into our model. This allows us to control for unobserved heterogeneity at a more granular level. For instance, while school quality may vary significantly across regions, it is less likely to exhibit substantial variation within a single cluster. Similarly, opportunities for child labour are more likely to be uniform within a cluster compared to an entire region. However, this approach comes with certain limitations, as the unit of fixed effects should ideally contain at least ten observations. In our dataset, approximately 45 percent of survey clusters have fewer than ten observations. Consequently, including survey cluster fixed effects reduces our sample size by nearly half. Table D.13 presents balance tests for all variables comparing the smaller and larger clusters. On average, children in larger clusters score lower on math tests, work more hours, live in more rural areas, and come from larger families. This suggests that the subsample is not entirely comparable to the full dataset, a factor that should be considered when interpreting the results. Tables D.14 and D.15 report the estimates for the full sample and the poorer subsample, respectively. Despite the differences in the sample, the findings remain consistent with our main results.

Overall, these robustness checks provide further confidence in the validity of our conclusions. The persistence of our findings across different statistical frameworks and educational outcome measures underscores the importance of considering the nuanced effects of child labour, particularly among the most disadvantaged populations.

D.5 Concluding Discussion

Our study contributes to the ongoing debate on the relationship between child labour and educational attainment, with a particular focus on income and wealth constraints. Consistent with previous literature, we find that children who work tend to have lower educational outcomes. However, our results also reveal a more complex relationship, particularly regarding domestic work. Children who do not engage in any household chores tend to have lower test scores compared to those who perform some domestic work. This suggests that participating in household tasks may be the norm, and children who are not assigned any responsibilities may have lower overall ability, leading to lower academic performance. While this hypothesis aligns with existing literature, further research is needed to validate this finding. Additionally, we observe that the negative correlation between child labour and math scores is stronger for girls, while the positive correlation between domestic work and academic performance is more pronounced for boys.

Beyond these general findings, our study makes a significant contribution by specifically examining the poorest children for whom child labour may be a necessity to meet subsistence needs. While excessive work hours undoubtedly reduce time and energy for schooling, the absence of work does not necessarily translate into increased school attendance. Our results indicate that, among the lowest wealth quintile, children who work perform better academically than those who do not. This pattern becomes even clearer when we exclude children who attend school without working, as these children appear to have access to education without requiring additional income. Among the remaining children, an additional hour of work is associated with higher test scores, suggesting that income from child labour enables schooling rather than replacing it. This finding carries important implications for policy design, as interventions should aim to improve overall welfare rather than merely addressing child labour in isolation.

While economic theory has long suggested that outright bans on child labour may do more harm than good, our study provides the first empirical evidence from Sub-Saharan Africa supporting this claim. Luong (2011) previously demonstrated in a quasi-experimental study that providing children with a productive asset can lead to higher human capital accumulation, as long as the income effect outweighs the substitution effect. Our findings suggest that similar dynamics may be at play in many African countries, where a significant number of children remain idle rather than attending school. Providing productive assets or alternative income sources could help transition these children from inactivity to part-time schooling.

In another part of the world, working children have taken it upon themselves to advocate for their right to dignified labour. In Peru, the *Movimiento Nacional de Niños, Niñas y Adolescentes*

Trabajadores Organizados del Perú actively challenges the notion of children's passivity by demanding a voice in decisions that affect their lives and communities (Taft, 2019). Their efforts offer a powerful illustration of children's agency and how they understand the value of their economic contributions. At the same time, their activism serves as a reminder to question Western-centric ideals of childhood and to genuinely listen to those whose lives are most directly impacted – regardless of their age.

That being said, we do not intend to idealize child labour. In an ideal world, no child should have to sacrifice educational opportunities for economic survival. However, the reality is that for many children, work is a necessity rather than a choice. Policies that aim to simply ban child labour without addressing its underlying economic causes are unlikely to improve children's well-being. The experience of Bangladesh following the introduction of Harkin's Law (Rahman et al., 1999) has already demonstrated that such bans can have unintended negative consequences. To successfully reduce child labour while promoting education, policies must be designed with a nuanced understanding of the economic constraints facing poor households.

First, any policy aimed at reducing child labour, particularly among those working to meet basic needs, must offer a viable alternative source of income. Conditional cash transfer programs that cover the cost of schooling have proven effective in both reducing child labour and increasing school attendance when well implemented (De Janvry et al., 2006; Edmonds, 2006; Edmonds and Schady, 2012; Edmonds and Shrestha, 2014; Del Carpio et al., 2016). Similarly, policies aimed at increasing household income through employment opportunities for adults, such as public work programs, have successfully reduced child labour (Dinku, 2019). Income-smoothing mechanisms, including health insurance, have also been shown to lower child labour rates by reducing the need for children to compensate for economic shocks (Landmann and Frölich, 2015; Strobl, 2017).

Second, the structure and content of education must align with children's realities. Several scholars have pointed out that Western-style education models often fail to address the needs of African societies (Kanu, 2007). Furthermore, anthropological research has shown that children and adults engaged in informal market activities demonstrate strong numeracy skills when solving real-world problems but struggle with abstract mathematical concepts taught in schools (Reed and Lave, 1979; Carraher et al., 1985; Jurdak and Shahin, 1999; Banerjee et al., 2017). A curriculum that incorporates practical applications and connects to children's everyday experiences could enhance both educational outcomes and future employability.

Third, it is essential to recognize that children face more than just a binary choice between school and work. Many children in developing countries remain idle, neither attending school nor working (Biggeri et al., 2003; Bacolod and Ranjan, 2008). If schooling is not accessible, work may provide a better alternative than doing nothing at all (Aufseeser, 2014). In such cases, allowing children to engage in manageable work while ensuring they receive some level of education may be a more realistic policy approach.

Despite the valuable contributions of this study, some limitations must be acknowledged. First, our labour data captures only a single point in time, while math scores reflect cumulative learning over several years. Ideally, a longitudinal dataset tracking child labour and educational outcomes over time would allow for a more precise analysis, including seasonal variations in work patterns. However, no such dataset currently exists for multiple Sub-Saharan African countries. Second, due to selection biases, we are unable to analyze literacy outcomes and instead rely solely on numeracy scores. While numeracy is a critical skill, it would be valuable to explore whether the relationship between child labour and education differs between literacy and numeracy. Finally, our study does not establish causal relationships. Previous research attempting to identify causal effects has relied on instrumental variables, but many of these approaches fail to satisfy the exclusion restriction. As a result, our findings should be interpreted as correlational rather than causal.

Nonetheless, this study makes an important empirical contribution by covering multiple Sub-Saharan African countries, including out-of-school children in the analysis, and focusing on the most economically disadvantaged populations. Our findings generally align with existing literature, but they also highlight the nuanced role of child labour in the educational attainment of the poorest children. While reducing child labour remains a critical goal, policy-makers must recognize that simply prohibiting child work may not automatically lead to better educational outcomes. In many cases, child labour partially finances education, and restricting it without providing alternative income sources could ultimately reduce human capital accumulation.

To effectively combat poverty and inequality, policies must prioritize support for the most vulnerable households. This includes designing educational systems that accommodate working children and developing curricula that reflect the realities of their lives. By acknowledging the complex trade-offs that poor families face, policymakers can design interventions that both reduce child labour and enhance educational opportunities, ensuring that children are better prepared for future economic participation. Since our study provides only correlational evidence, further research—particularly using longitudinal and experimental methods—is needed to validate and expand upon these findings.

D.6 References

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D.7 Supplementary Material

D.7.1 Summary Statistics

Table D.8: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Education					
Math Score	91717	10.806	8.202	0	21
Math Score (Recognition)	91717	3.494	2.533	0	6
Math Score (Discrimin.)	91717	2.846	2.159	0	5
Math (Addition)	91717	2.459	2.2	0	5
Math Score (Row)	91717	2.008	2.03	0	5
Ever Schooled	91706	.85	.357	0	1
Current Schooled	91702	.794	.404	0	1
Highest Grade	91695	3.327	2.512	0	14
Child Work					
Hours Child Work	91419	.438	.496	0	1
Child Work (Dummy)	91590	.345	.475	0	1
Worked Farm/Animals	91593	.166	.372	0	1
Worked Fam. Business	91643	.116	.321	0	1
Worked Prod./Vendor	91599	.101	.302	0	1
Worked Other Income	91636	.232	.422	0	1
Worked Hazardous Occ.	91711	.103	.304	0	1
Idle	91419	.438	.496	0	1
Domestic Work					
Hours Domestic Work	91706	5.689	9.031	0	81
Domestic Work (Dummy)	91632	.908	.288	0	1
Fetched Water	91669	.63	.483	0	1
Collected Wood	91636	.325	.469	0	1
Shopping	91668	.558	.497	0	1
Cooking	91675	.344	.475	0	1
Cleaning	91668	.648	.477	0	1
Laundry	91662	.561	.496	0	1
Childcare	91670	.364	.481	0	1
Cared for Old/Sick	91636	.115	.319	0	1
Other Domestic Work	91616	.375	.484	0	1
Controls					
Sex (1 = Female)	91717	.504	.5	0	1
Age	91660	10.237	2.307	7	14
Urban Residence	91717	.307	.461	0	1
No. Household Members	91717	6.229	2.888	1	20
No. Infants	88998	.953	1.032	0	20
Land (in Acres)	90073	4.999	13.513	0	95
Household Owns Cattle	91717	.159	.366	0	1
Christian	91717	.309	.462	0	1
Muslim	91717	.032	.177	0	1
Traditional/Animistic	91717	.034	.181	0	1
Other	91717	.077	.267	0	1
No Religion/Missing	91717	.307	.461	0	1

D.7.2 Robustness Checks

Table D.9: Robustness Check - Child Work and Domestic Work (Negative Binomial)

	(1)	(2)	(3)	(4)	(5)	(6)
	Child Work			Domestic Work		
	Full	External	Internal	Full	External	Internal
Hours Child Work	-0.004***		-0.005**			
	(0.001)		(0.002)			
sq(Hours Child Work)	0.000		0.000			
	(0.000)		(0.000)			
Dummy Child Work		-0.016				
		(0.013)				
Hours Domestic Work				0.002*		-0.002
				(0.001)		(0.001)
sq(Hours Domestic Work)				-0.000		0.000
				(0.000)		(0.000)
Dummy Domestic Work					0.084***	
					(0.014)	
Constant	0.808***	0.812***	0.632***	0.812***	0.789***	1.005***
	(0.057)	(0.057)	(0.072)	(0.057)	(0.058)	(0.055)
Observations	87,335	87,341	32,3222	87,330	87,341	64,227
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show a Negative Binomial model which estimates the relationship between child and domestic work and children's math score for the full sample. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. While column 1 to 3 shows the results for child work, column 4 to 6 shows the results for domestic work. All regressions include individual controls, country, and regional fixed effects. The individual controls include age, gender, an urban dummy, number of household members, number of infants in household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table D.10: Robustness Check - Child Work for Poorest Wealth Quintile (Negative Binomial)

	(1) Full	(2) External	(3) Internal	(4) Exclude In-School & No Work	(5) Exclude Idle Children
Hours Child Work	0.000		-0.004	0.036***	-0.018***
	(0.003)		(0.004)	(0.005)	(0.003)
sq(Hours Child Work)	0.000		0.000	-0.001***	0.000
	(0.000)		(0.000)	(0.000)	(0.000)
Dummy Child Work		0.043			
		(0.028)			
Constant	-0.851***	-0.831***	-1.757***	-2.822***	-0.232**
	(0.101)	(0.101)	(0.125)	(0.134)	(0.095)
Observations	21,569	21,572	9,718	13,376	17,911
Individual Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show a Negative Binomial model which estimates the relationship between child work and children's math score for the poorest wealth quintile. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. While column 1 to 3 shows the results for child work, column 4 to 5 shows the results for domestic work. All regressions include individual controls, country, and regional fixed effects. The individual controls include age, gender, an urban dummy, number of household members, number of infants in household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table D.11: Robustness Check - Child Work and Domestic Work (Schooling-for-Age)

	(1)	(2)	(3)	(4)	(5)	(6)
		Child Work			Domestic Work	
	Full	External	Internal	Full	External	Internal
Hours Child Work	-0.338***		-0.396***			
	(0.080)		(0.091)			
sq(Hours Child Work)	0.003**		0.004**			
	(0.001)		(0.002)			
Dummy Child Work		-2.048***				
		(0.694)				
Hours Domestic Work				-0.024		-0.153**
				(0.058)		(0.068)
sq(Hours Domestic Work)				0.001		0.003**
				(0.001)		(0.001)
Dummy Domestic Work					1.003*	
					(0.548)	
Constant	173.304***	173.321***	138.870***	173.515***	173.235***	168.894***
	(4.001)	(3.989)	(4.243)	(3.993)	(4.020)	(3.762)
Observations	87,315	87,321	32,310	87,310	87,321	64,211
R-Squared	0.292	0.291	0.294	0.291	0.291	0.291
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show an OLS model which estimates the relationship between child and domestic work and children's schooling-for-age for the full sample. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. While columns 1 to 3 show the results for child work, columns 4 to 6 show the results for domestic work. All regressions include individual controls, country, and regional fixed effects. The individual controls include age, gender, an urban dummy, number of household members, number of infants in household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table D.12: Robustness Check - Child Work for Poorest Wealth Quintile (Schooling-for-Age)

	Full (1)	External (2)	Internal (3)	Exclude In-School & No Work (4)	Exclude Idle Children (5)
Hours Child Work	-0.098		-0.335**	1.294***	-1.278***
	(0.127)		(0.166)	(0.195)	(0.142)
sq(Hours Child Work)	-0.000		0.003	-0.020***	0.017***
	(0.002)		(0.003)	(0.004)	(0.002)
Dummy Child Work		1.102			
		(1.017)			
Constant	99.578***	99.825***	89.573***	46.186***	146.137***
	(5.081)	(5.079)	(5.865)	(5.264)	(5.216)
Observations	21,565	21,568	9,714	13,372	17,907
R-Squared	0.257	0.257	0.283	0.273	0.284
Individual Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show an OLS model which estimates the relationship between child work and children's schooling-for-age for the poorest wealth quintile. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. While columns 1 to 3 show the results for child work, columns 4 to 5 show the results for domestic work. All regressions include individual controls, country, and regional fixed effects. The individual controls include age, gender, an urban dummy, number of household members, number of infants in household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table D.13: Balance Test for Cluster Sizes

Variable	Obs. SC	Obs. LC	Mean SC	Mean LC	Diff.	Std. Err.	t-value	p-value
Education								
Math Score	40934	50783	12.182	9.697	2.485	.054	46.15	0
Math Score (Recognition)	40934	50783	3.865	3.194	.671	.017	40.25	0
Math Score (Discrimin.)	40934	50783	3.130	2.616	.514	.014	36.1	0
Math (Addition)	40934	50783	2.828	2.161	.666	.015	46.15	0
Math Score (Row)	40934	50783	2.359	1.726	.633	.013	47.5	0
Ever Schooled	40931	50775	0.889	.819	.071	.003	29.75	0
Current Schooled	40929	50773	0.835	.762	.072	.003	27.05	0
Highest Grade	40924	50771	3.678	3.045	.632	.017	38.2	0
Child Work								
Hours Child Work	40933	50778	3.404	3.914	-.511	.059	-8.65	0
Child Work (Dummy)	40805	50614	0.415	.458	-.043	.004	-13.1	0
Worked Farm/Animals	40885	50705	0.315	.369	-.054	.003	-17.15	0
Worked Fam. Business	40886	50707	0.161	.171	-.011	.003	-4.2	0
Worked Prod./Vendor	40902	50741	0.102	.128	-.026	.002	-12.4	0
Worked Other Income	40886	50713	0.094	.107	-.013	.002	-6.7	0
Worked Hazardous Occ.	40903	50733	0.204	.255	-.051	.003	-18.1	0
Idle	40934	50777	0.083	.12	-.037	.002	-18.4	0
Domestic Work								
Hours Domestic Work	40932	50774	5.425	5.902	-.478	.06	-7.95	0
Domestic Work (Dummy)	40894	50738	0.908	.908	-.001	.002	-.3	.757
Fetched Water	40908	50761	0.604	.652	-.049	.003	-15.25	0
Collected Wood	40895	50741	0.298	.348	-.05	.003	-15.9	0
Shopping	40911	50757	0.553	.563	-.009	.004	-2.7	.007
Cooking	40918	50757	0.349	.34	.009	.003	2.75	.006
Cleaning	40918	50750	0.679	.624	.056	.003	17.7	0
Laundry	40905	50757	0.571	.552	.018	.004	5.7	0
Childcare	40914	50756	0.345	.38	-.035	.003	-10.9	0
Cared for Old/Sick	40902	50734	0.106	.121	-.015	.002	-7.15	0
Other Domestic Work	40896	50720	0.352	.393	-.04	.003	-12.5	0
Controls								
Sex (1 = Female)	40934	50783	0.505	.503	.002	.004	.5	.603
Age	40898	50762	10.289	10.195	.094	.015	6.15	0
Urban Residence	40934	50783	0.361	.264	.097	.003	31.9	0
No. Household Members	40934	50783	6.003	6.41	-.407	.019	-21.25	0
No. Infants	39403	49595	0.869	1.02	-.15	.007	-21.65	0
Land (in Acres)	40141	49932	4.738	5.21	-.472	.09	-5.2	0
Household Owns Cattle	40934	50783	0.143	.173	-.03	.003	-12.35	0
Christian	40934	50783	0.248	.358	-.111	.003	-36.25	0
Muslim	40934	50783	0.034	.03	.004	.001	2.95	.003
Traditional/Animistic	40934	50783	0.036	.033	.004	.001	2.9	.004
Other	40934	50783	0.099	.06	.04	.002	22.35	0
No Religion/Missing	40934	50783	0.505	.503	.002	.004	.5	.603

Notes: SC is the abbreviation for "small cluster" meaning survey cluster with less than ten observations. LC is the abbreviation for "large cluster" meaning survey cluster with ten or more observations.

Table D.14: Robustness Check - Child Work and Domestic Work (Cluster Fixed Effects)

	(1)	(2)	(3)	(4)	(5)	(6)
		Child Work			Domestic Work	
	Full	External	Internal	Full	External	Internal
Hours Child Work	0.013		-0.019			
	(0.019)		(0.028)			
sq(Hours Child Work)	-0.001		-0.000			
	(0.000)		(0.000)			
Dummy Child Work		0.357**				
		(0.145)				
Hours Domestic Work				0.061***		-0.004
				(0.016)		(0.019)
sq(Hours Domestic Work)				-0.001***		0.000
				(0.000)		(0.000)
Dummy Domestic Work					1.278***	
					(0.150)	
Constant	-13.091***	-12.941***	-64.782***	-12.914***	-13.402***	-12.777***
	(0.982)	(0.976)	(2.031)	(0.987)	(0.978)	(0.927)
Observations	48,732	48,737	18,937	48,728	48,737	36,058
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show a Tobit model which estimates the relationship between child and domestic work and children's math score for the subsample including survey cluster with ten or more observations. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. While column 1 to 3 shows the results for child work, column 4 to 6 shows the results for domestic work. All regressions include individual controls, country, regional and survey cluster fixed effects. The individual controls include age, gender, an urban dummy, number of household members, number of infants in household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table D.15: Robustness Check - Child Work for Poorest Wealth Quintile (Cluster Fixed Effects)

	(1) Full	(2) External	(3) Internal	(4) Exclude In-School & No Work	(5) Exclude Idle Children
Hours Child Work	-0.011		-0.012	0.211***	-0.138***
	(0.029)		(0.049)	(0.050)	(0.030)
sq(Hours Child Work)	0.000		-0.000	-0.003***	0.002***
	(0.001)		(0.001)	(0.001)	(0.001)
Dummy Child Work		0.478*			
		(0.285)			
Constant	-67.232***	-67.319***	-60.912***	-66.540***	-64.263***
	(2.114)	(2.102)	(2.220)	(2.135)	(2.164)
Observations	13,278	13,281	5,994	8,425	10,847
Individual Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Cluster FE	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show a Tobit model which estimates the relationship between child work and children's math score for the poorest wealth quintile for the subsample including survey cluster with ten or more observations. The underlying dataset is based on MICS Wave 6 and includes children aged 7 to 14. While column 1 to 3 shows the results for child work, column 4 to 6 shows the results for domestic work. All regressions include individual controls, country, regional and survey cluster fixed effects. The individual controls include age, gender, an urban dummy, number of household members, number of infants in household, acres of land owned, a dummy indicating cattle ownership, and dummies for religious affiliation. Standard errors are clustered at the regional level. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

E Colonial Legacies and Elite Reproduction: The Role of Education in South Africa's Inequality [36]

Abstract

This study examines how historical education systems contribute to the reproduction of elites in Sub-Saharan Africa, using South Africa as a case study. We link newly digitized data from the *Cape Colony Education Reports* (1881-1905) with results from the 2018 *Systemic Tests* conducted in the Western Cape. We investigate whether the location or quality of historic schools, differentiated by whether they served the white or black population, matters for current educational outcomes. Using a grid-cell approach, we find no evidence that the mere presence of a historic school predicts present-day performance implying there are no broadly accessible benefits. However, when focusing on school quality, using inverse distance weighting to link historic and contemporary school qualiy, we find a robust positive relationship for historic white schools, but no consistent effect for black schools. These results hold across multiple specifications. We argue that this asymmetry reflects the legacy of systematic neglect of black education during the 20th century, in contrast to the institutional continuity afforded to white schools. Many high-performing historic white schools continue to operate and produce a disproportionate share of the country's educational and professional elite. By tracing the enduring effects of historical schooling, this study contributes to understanding how inequality of opportunity is reproduced over time in one of the most unequal societies in the world.

[36] This chapter is based upon joint work with Johan Fourie. I was responsible for approximately 80 percent of the conceptual development and writing, while Johan Fourie contributed the remaining 20 percent.

E.1 Introduction

The persistently high income inequality in many developing countries is a concern for policy makers as there is a clear link between high inequality and reduced social mobility, largely due to unequal access to opportunities (Durlauf et al., 2022). As a consequence, those at the top of the distribution are also more likely to maintain their privileged status, often over several generations. Since elites have disproportionate power in economic, political and social decision-making, it is important to understand whether they are persistent and how they stay at the top. While previous research on elite persistence has mainly focused on Western countries (see Kalsi and Ward (2025) for a recent overview), relatively little is known about patterns of elite persistence in African contexts (Dupraz and Simson, 2024). Simson (2025) provides suggestive evidence, that in the Sub-Saharan African context, the elite appears to be an educational one, but we know little about how they secure this high level of education.[37]

South Africa offers a unique context to study elite persistence in Sub-Saharan Africa. While the political elites were exchanged at the end of Apartheid, the economic power largely remained in the same hands (Gruijters et al., 2024). In return, there have been almost no improvements in wealth inequality over the last 30 years (Chatterjee et al., 2022) and South Africa remains the most unequal country in the world (World Bank, 2024). Education starkly mirrors this inequality. Schools formerly reserved for the white population under Apartheid still perform much better than the remainder (Spaull, 2013) and serve a disproportionate share of the white population (Gruijters et al., 2024).[38,39] In the resulting dual education system, about 20 percent of schools perform

[37]Simson (2025) argues that in Sub-Saharan Africa there are four ways to reach the top: traditional authority (e.g. chieftaincy), ethnicity, private wealth ownership and human capital formation. Comparing household characteristics of the top 1 percent to the bottom 99 percent, she finds particularly large differences in the share of university education. Moreover, parental education is highly predictive of making it to the top 1 percent.

[38]During Apartheid, the government classified the population into four racial groups: White, Black/African, Coloured and Indian. The lines between these categories were arbitrary and some individuals were reclassified throughout their lives. However, these categories are still commonly employed, for example, by Statistics South Africa and are culturally significant. Therefore, we follow this terminology. We use the term white in this study to refer to the population of European descent. We use the term black to refer to all other groups. If we specifically refer to one of the groups, we use the term African to refer to the native South African Bantu-speaking population (e.g. Xhosa) and Coloured refers to descendants of the Cape Malay, the indigenous Khoi-San population and other "mixed" individuals.

[39]For example, the top three percent of schools generate more students with distinctions in mathematics than the remaining 97 percent of schools which are predominantly black (Spaull, 2019). The inequality is further exacerbated by high dropout rates. Many students do not reach the end of high school, with a particularly sharp decline after grade ten. In 2023, the Department of Basic Education released statistics that of 1,000 students starting school, only 579 finish grade twelve (Department of Basic Education, 2023). However, the returns to education are low for

well, while the remaining 80 percent are dysfunctional (Spaull, 2013). This inequal access to opportunities reinforces educational and income inequality.

In this article, we explore the historical roots of this segregated education system and how it contributes to the reproduction of elites over time. While the legacy of Apartheid's unjust and racially discriminatory education policies is undisputably part of the reason for the dual education system, educational inequality and segregation began much earlier in the late 19th century Cape Colony. Using novel georeferenced data from the *Cape Colony Education Reports*, we link historical and contemporary schools' location and quality as well as data on elites. This data allows us to explore whether historic schools' locations and their quality matter for contemporary educational outcomes and elite reproduction. By doing so we aim to understand how early educational inequality laid the foundation for the educational inequality in contemporary South Africa limiting social mobility.

Our research contributes to two different strands of research. The first strand of literature focuses on the reproduction of elites through the education system. For example, attending an elite school in the UK significantly increases the chances of entering an elite occupational group (Reeves et al., 2017). Similarly, attending an Ivy-Plus college in the US increases chances of reaching the top of the earning distribution and secure jobs with prestigious firms and universities (Chetty et al., 2023). Michelman et al. (2022) show that even within an elite university, those having attended a prestigious private school before college, on average earn more and are more likely to become member of exclusive social clubs. Findings from Chile support these results (Zimmerman, 2019). In contrast, there is very little evidence on how Africa's elite uses human capital accumulation to retain their status (Simson, 2025). While there is research on educational mobility in Sub-Saharan Africa (Alesina et al., 2021; Dendir, 2023) and South Africa (Louw et al., 2007), it typically focuses on the lower educational qualifications, such as completing primary school. Given the high share of children without primary schooling, this approach is sensible but tells us little about how education can contribute to elite persistence. A recent exception is Gruijters et al. (2024) who analyze the racial composition of elite South African high schools. They find that white children, who were part of the *de jure* elite under Apartheid, continue to be overrepresented in elite public high schools (62

secondary education and only increase significantly with higher education (Salisbury, 2016).

percent of students, despite making up only 3.8 percent of all students), reinforcing their position within the *de facto* elite in post-Apartheid South Africa.

Second, we contribute to the literature on the persistent effects of colonial education for contemporary development on the African continent. The presence of these historic schools has been linked with contemporary outcomes such as higher wealth (Boateng et al., 2019), better education (Baten et al., 2021; Funjika and Getachew, 2022; Montgomery, 2017; Cogneau and Moradi, 2014; Wietzke, 2014; Gallego and Woodberry, 2010), higher political involvement (Cagé and Rueda, 2016) and lower levels of polygamy (Kudo, 2017; Fenske, 2015) but also with lower social capital (Wuepper and Sauer, 2016; Wuepper and Sauer, 2017), a higher likelihood of HIV (Cagé and Rueda, 2020) and increased anti-LGBTQ attitudes (Ananyev and Poyker, 2021). While these findings are not without critique (see for example, Jedwab et al. (2022) and Conley and Kelly (2025)), the overall literature comes to the consensus that exposure to historic education can have a long-term impact on contemporary outcomes. The context of the former Cape Colony, however, differed from that in other Sub-Saharan African colonies. Given the favorable disease environment, a large number of European settlers actually moved to the Cape Colony in contrast to most other Sub-Saharan African colonies (Green, 2022). After starting out as a small trading post by the Dutch East India Company, by the mid-19th century more than 180,000 individuals of European descent lived in the Cape Colony – about a third of the total population at the time. Hence, alongside the missionary provision of education a (state-driven) demand for non-denominational education for the white population developed (Malherbe, 1925, p. 50). Whether there is any type of persistent effect of colonial education in South Africa has been largely unexplored, especially in combination with the aspect of segregation. The only exception to this is by Fourie and Swanepoel (2015) who find that districts which had a mission in 1848 have better educational outcomes today for African and Colored residents.

As a preview to our findings, we do not find evidence that the proximity to historic schools matters for contemporary school quality, irrespective of whether these were reserved for the white or black population which suggests there is no equalizing impact of early exposure to education across population groups. However, if we consider the quality of these historic schools, we do find evidence of the persistence of the quality of historic white schools, while we do not find robust evidence for historic black schools. This suggests that elite schools of the past were successful in sustaining their quality and thereby status over time. While the black education system suffered from purposeful neglect and restrictions, the white education system benefited from much more resources and support by the government. Moreover, we find that historic white schools that performed better are more likely to still be under operation today and have educated a disproportionate share of the country's elite compared to the remaining schools in our sample. Thus, these historically advantaged schools still contribute to the reproduction of the elite today.

The remainder of this paper is structured as follows. Section 2 provides the historical background on the Cape Colonial education system. Section 3 gives an overview of our data sources and explains our methodology for the subsequent analyses. Section 4 presents our results. Section 5 discusses potential mechanisms. Section 6 concludes.

E.2 Historical Background

The history of formal education in the Cape Colony dates back to the 17th century. The first school was established in Cape Town in 1656 for the education of enslaved children. However, it was soon forced to close as students fled to escape colonial oppression (Malherbe, 1925, p. 30). In general, educational development in the Cape Colony progressed slowly until the early 19th century. Since the Dutch East India Company had not originally intended to develop a colony, there was little incentive to establish a structured schooling system. Consequently, until the British took control of the Cape Colony in 1806, the church remained the primary provider of education (Malherbe, 1925, p. 19).

Following the British takeover, efforts were made to unify and coordinate the various educational initiatives. This culminated in the establishment of the Education Department in 1839, overseen by a Superintendent General of Education (SGE), who was responsible for the development and oversight of the entire education system in the Cape Colony (Malherbe, 1925, p. 71). For the first two decades, the system was relatively liberal and did not formally discriminate based on race (Ludlow, 2017). However, in 1858, Langham Dale was appointed SGE and began shaping a secular schooling system for the white population, while missionary organizations continued to provide education for the black population (Malherbe, 1925, p. 50). Further reinforcing this structure, the

Education Act of 1865, introduced by SGE Dale, laid the foundation for schooling in the colony for the subsequent decades (Malherbe, 1925, p. 95). Under this system, non-denominational public schools—intended for the white population—were financed through a pound-for-pound system, while mission and native schools received grants-in-aid for teacher salaries, with the remaining costs to be covered by local communities.[40]

The first available *Cape Colony Education Report* from 1881 falls into the period at which point the education system began its rapid expansion. Three types of public schools were supposed to serve the white population. First class public schools were located in the main divisional towns. They provided the most extended curriculum and later also prepared students for matriculation, the university entrance exam. Second class public schools were in all other towns and larger villages and covered an extended primary curriculum. Last, third class public schools were in smaller villages and larger agricultural settlements and covered a primary curriculum (Cape Colony, 1881). Nevertheless, many white children continued to attend mission schools, which were more affordable compared to the non-denominational public schools, which relied on voluntary local contributions (Cape Colony, 1882). To extend education to the rural and impoverished white population, two additional types of schools were introduced. In 1885, private farm schools began receiving capitation grants if they provided instruction to at least five children of school-going age (Cape Colony, 1885). These schools, offering only rudimentary education, were short-lived, with an average lifespan of three years (Cape Colony, 1911). In 1893, the first poor school was established to provide free education to poor white children. These students had previously often been educated alongside black children in mission schools—a practice that colonial officials aimed to phase out (Cape Colony, 1893). By 1912, poor schools were either integrated or transformed into third-class public non-denominational schools (Cape Colony, 1912).

For the black population, mission schools were the sole providers of education (Cape Colony, 1906). Operated and partially funded by various missionary societies, these schools generally

[40] Pound-for-pound system means that for each pound raised locally towards teacher salaries, for example through school fees, the government matches that amount. All other expenditures had to be raised locally. The maximum sum in 1865 was 200 Pounds for a first class public school, 75 Pounds for a second class public school, and 30 Pounds for a third class public school. In contrast, the grants-in-aid for mission schools were fixed sums between 15 and 75 pounds were paid out to the schools to finance teachers' salaries. All other expenses had to be raised locally (Malherbe, 1925, p.95). Over time, the financial resources for schools catering to the white population grew much faster than those for the schools catering to the black population.

followed the public school curriculum but often included modifications and abbreviations (Loram, 1917, p. 94). Their primary goal was to provide basic literacy and arithmetic instruction to as many black children as possible, rather than fostering academic talent (Cape Colony, 1884). The Cape Colonial government viewed missionary education as a means of producing a more skilled industrial and agricultural workforce and of assimilating the black population into the colonial social structure (Cape Colony, 1887). However, mission schools suffered from chronic underfunding and significantly lower instructional quality compared to public schools.

To support the education system and monitor student progress, inspectors were expected to visit each school at least once a year. During these visits, students were given brief individual assessments and placed into so-called Standards, defined benchmarks used to measure children's academic achievement (Cape Colony, 1883, p. 10). The distribution of students across Standards can thus serve as a proxy for human capital within and across schools. While some larger schools organized children into separate classes based on their Standard level, most were single-teacher schools where students of all levels were taught together (Cape Colony, 1924). In 1881, the system included only Standards I through IV, but additional levels were added over time, eventually reaching Standard X. The full primary curriculum officially concluded at Standard VII. As shown in Figure E.1, very basic literacy and numeracy were expected by Standard II, which required students to read a short passage and solve arithmetic problems using basic operations (Cape Colony, 1883). Higher Standards introduced additional subjects such as geography, history, and elements of the natural sciences.

Following Langham Dale, Thomas Muir served as SGE from 1892 to 1915. Muir, even more than Dale, prioritized the development of white education, overseeing a near-exponential increase in the number of white schools. Conversely, he left black education entirely in the hands of missionary societies (Elliott, 2021, p. 24). Despite being aware of the poor quality of instruction in mission schools, Muir made no efforts to improve conditions (Elliott, 2021, p. 36). An illustrative example of this is that, throughout his diaries documenting visits to schools across the Cape Colony, he never once recorded a formal meeting with a black individual to discuss missionary education (Elliott, 2021, p. 20). While *de facto* segregation already existed in many schools, Muir played a crucial role in codifying racial segregation in education. The School Board Act of 1905 legally permitted

Figure E.1: Requirements for Standards I - IV in 1983. Source: *Cape Colony Education Report* 1893.

Requirements.	Standard I.	Standard II.	Standard III.	Standard IV.
Reading	Narrative in Monosyllables.	Narrative from an Elementary Reading Book.	Any ordinary Narrative.	Any ordinary Narrative fluently and correctly.
Writing	Writing on Slate, Figures, and Monosyllables.	Write short Sentences to Dictation, and transcribe Passages from a Printed Book.	Write an ordinary Passage, dictated slowly.	Write freely to dictation.
Arithmetic ..	Simple Addition and Multiplication table.	Any example in Simple Rules.	Compound Rules (Money).	Practice, Proportion, and Vulgar Fractions.
Geography....			Outlines of Political Geography.	Political Geography generally.
Grammar.				Elements of Grammar, Parts of Speech, Composition of a Sentence, &c.

public schools to exclude black students and introduced compulsory education for white children.

By 1915, under SGEs Dale and Muir, a segregated education system was firmly in place, laying the institutional foundation for the *Bantu Education Act* of 1953 and the *Coloured Persons Education Act* of 1963. White public schools (hereafter referred to as white schools) received more funding, employed better-qualified teachers, and benefited from closer oversight by the Department of Education. In contrast, most missionary-run schools for black students (black schools) provided a lower-quality education, with many pupils leaving school before acquiring basic literacy or numeracy skills. A more detailed account of the expansion of the education system up to 1920 is available in the Supplementary Materials.

E.3 Data and Method

E.3.1 Data

Our primary data source are the *Cape Colony Education Reports* from 1881 to 1905. While these reports are available until 1985, only those up to 1905 contain detailed school-level information. We digitized district-level data for all reports from 1881 to 1905 and captured detailed school-level information for the years 1881, 1896, and 1905. The 1881 report provides school-level data on school types, enrollment numbers, and subjects taught. The 1896 and 1905 reports are particularly significant as they are the first and last reports, respectively, that offer information on school quality by reporting the distribution across Standards at the individual school level. We use this data on Standards to proxy for the quality of education by calculating the share of students in Standard IV and above for each school. Beyond detailed statistics on enrollment, attendance, and Standards achieved, these reports include general information about the education system and its development summarized by the SGE.

Based on the schools' names, we successfully georeferenced approximately 90 percent of the school locations for 1881 (90.59 percent), 1896 (89.43 percent), and 1905 (86.86 percent). School names were in most cases simply the name of the town or locality. In the 1896 and 1905 report, the schools were sorted by district which helped to narrow the geographical search area. Where school locations could not be determined, this was typically due to one of three issues: either no locality with the school's name existed within the district, multiple localities shared the same name within the district, or the school was named after a river, leading to ambiguity. When comparing observable characteristics of located and non-located schools, we find that located schools generally enrolled more students. Furthermore, while white schools with known locations tended to be of higher quality, no significant quality difference was observed for black schools (Table E.6). Given the high overall coverage of schools, we believe this limitation has only a minor impact on our subsequent estimates. However, this is a small caveat to our data that must be acknowledged. Additionally, we chose not to geolocate farm schools due to their short-lived nature and the overall low proportion of students attending these schools. The share was 5.8 percent in 1896, decreasing to 4.4 percent in 1905, and by 1920, only 1 percent of children were enrolled in farm schools.

Our dataset offers a level of detail on schools in the Cape Colony that surpasses previous studies. Jedwab et al. (2022) noted that mission atlases such as Beach (1900), Roome (1924), and Streit (1929) typically overlook more than 80 percent of mission stations in Sub-Saharan Africa. Similarly, we found that these atlases documented only 135 mission stations in the Cape Colony, whereas our dataset identifies 692 mission schools in 1905.[41] Moreover, these atlases do not account for the substantial number of public schools in the Cape Colony. In 1905 alone, we located an additional 951 public schools. Therefore, while we cannot map the expansion of the education

[41] We assume for simplicity here that each observation is unique. If there is overlap in the missions reported by the different sources, our estimations would show an even higher share of omitted mission stations in the atlases.

system beyond 1905 at the school level, our novel geo-referenced data significantly enhances the accuracy of mapping colonial education in the Cape Colony.

To explore potential persistence in educational outcomes, we collected contemporary school data from the *Education Management Information System* (EMIS), which provides a comprehensive list of all schools in 2018, including background information and GPS coordinates. We linked these schools with their performance in mathematics and language in the 2018 *Systemic Test* - an internationally benchmarked assessment administered annually in the Western Cape province. The test evaluates students in the Grade 3, 6 and 9. Maximum scores are 39 points in mathematics and 44 in language for Grade 3, 50 and 67 points for Grade 6, and 47 and 68 points for Grade 9, respectively. We use these test scores as the outcome variables in our models.

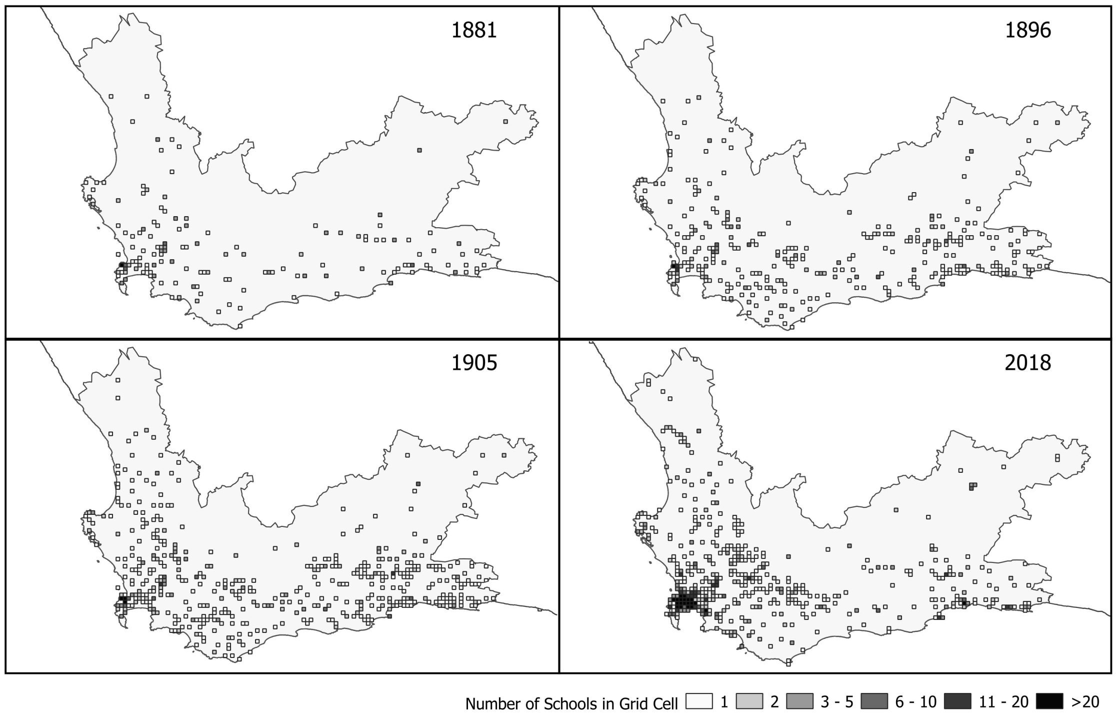
Figure 1 illustrates the distribution of both historical and contemporary schools in the Western Cape. In 1881, most schools were concentrated around Cape Town, but by 1896 and 1905, the distribution expanded along the coastline and into the interior. The 2018 distribution remains remarkably consistent, with many schools still located in Cape Town, a city that has nearly doubled in size since the end of Apartheid. Overall, schools continue to operate in the same areas as they did over a century ago.[42]

We complemented these data sources with a range of geographical and historical control variables, following the methodology of Jedwab et al. (2022). Geographic controls include average rainfall and temperature, altitude, terrain ruggedness, distance to the coast, and soil quality. Historical controls encompass colonial railways, historical explorer routes, ethnic groups based on Murdock (1967), and distances to Cape Town, Gqeberha (formerly Port Elizabeth), and Kimberley. Unlike Jedwab et al. (2022) and similar studies, we did not include malaria or tsetse fly prevalence, ancient cities, or navigable rivers, as these variables are not relevant to the Cape Colony context.

We provide detailed summary statistics for all variables and the sources of our control variables in Supplementary Materials.

[42]We can also show econometrically that schools are more likely to be located in areas which had schools in the past using the same raster grid cell approach outlined in the methodology section. This pattern is rather unsurprising for urban areas, but we also find some further anecdotal evidence for small rural schools as some are still located on the same farmlands as a century earlier (and hence still have the same name).

Figure E.2: Location of Schools in 1881, 1896, 1905 and 2018. Historic school locations are based on Cape Colony Education Reports. Contemporary school locations are available from the EMIS. Authors' own representation.



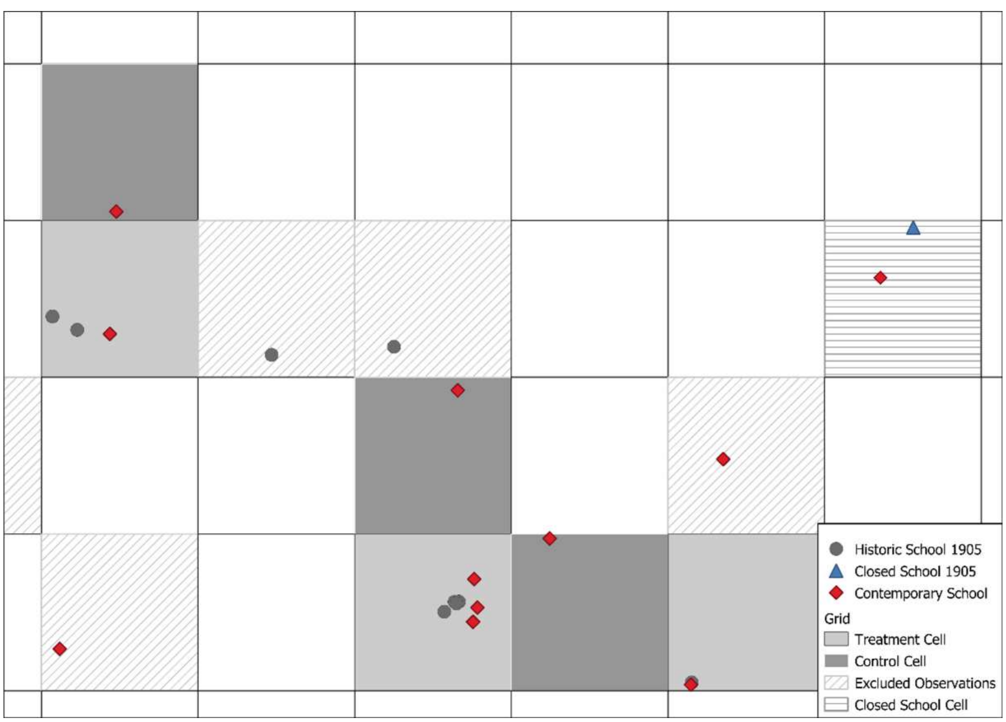
E.3.2 Location-Quality Analysis

To better understand the institutional reproduction of elites, our first step is to examine whether schools located in close proximity to a historical school are associated with higher educational outcomes today ("location-quality analysis"). Previous research on the legacies of colonial education suggests that such a benefit could exist (e.g., Gallego and Woodberry, 2010; Wietzke, 2014; Wantchekon et al., 2015), despite recent criticisms (Jedwab et al., 2022).

If proximity to any historical school positively influences today's educational outcomes, this would suggest that the legacy of elite or in general white historical schools does not play a unique role in elite reproduction. Instead, the benefits of historical schooling would appear to be broadly accessible, regardless of a school's historical status or quality. Conversely, if there is no significant relationship between the proximity to historical schools and contemporary school quality—or if this relationship is only evident for historically elite (white) schools—this would imply that the legacy of the colonial education system may still contribute to elite reproduction. In other words, if only historically elite schools continue to influence present-day school quality, it could indicate that historical advantages are being perpetuated, thereby maintaining elite status across generations through the education system.

For our location-quality analysis, we created a raster with grid cells measuring 0.05×0.05 degrees, approximately five by five kilometers. For each grid cell, we identified whether it contained a historical school, a white school, a black school, and/or a contemporary school. Figure E.3 illustrates this approach. The grey circles represent historical schools, and the red diamonds denote contemporary schools. Cells containing both a historical and contemporary school are considered treated cells. Control cells are those with only a contemporary school in an adjacent cell. We focus on these adjacent cells to increase comparability between the grid cells. All other grid cells are excluded from the analysis. Additionally, we calculated the average values of geographic and historical control variables for each grid cell. To incorporate sociodemographic characteristics such as population density, occupational structure, and related variables, we assigned each grid cell to its corresponding 1891 census division, allowing us to control for divisional fixed effects in our models.

Figure E.3: Illustration of Raster Grid-Cell Approach for Location-Quality Analysis. Authors' own representation.



Formally, we estimate the following OLS model:

$$TestScore_{i,d} = \beta_0 + \beta_1 \cdot HistoricSchool_i + \Gamma X_i + \delta_d + e_{i,d} \tag{16}$$

where $TestScore$ indicates the average score achieved in the *Systemic Test* per cell i and division d. $HistoricSchool$ indicates the presence of a historic school. The vector X_i includes geographic and historical control variables and δ_d are 1891 division fixed effects. To account for spatial autocorrelation in our data, we use Colella et al.'s (2023) Stata package. Since the *Systemic Test* is only available for the Western Cape, we have to restrict our sample to this region.

A potential challenge with this estimation is the endogenous placement of schools. Jedwab et al. (2022) demonstrated that mission schools in the former Gold Coast were more likely to be established in areas with better infrastructure and lower disease burdens. Consequently, comparing contemporary outcomes for areas with and without historical schools could lead to misleading results due to omitted variable bias. However, our analysis shows that schools in the Cape Colony were not necessarily located in more advantageous areas. In the Supplementary Materials, we compare observable geographical and historical characteristics of grid cells containing historical schools versus those without anywhere in the Cape Colony and adjacent cells without a historic school. We find minimal differences between these cells. Additionally, comparisons between cells containing white versus black schools reveal no significant locational advantages for white schools. These findings suggest that adjacent cells containing only contemporary schools serve as a suitable counterfactual.

To further address the issue of endogenous placement, we adopted a methodology similar to Valencia Caicedo (2019). We identified schools that operated in 1896 but were closed by 1905.[43] The blue triangle in Figure E.3 illustrates a closed school. We use cells containing a closed and a contemporary school as our counterfactual, comparing them to cells with schools that remained open in 1905. When a cell contains both an open and a closed school, we classify the cell as "open."

Table E.1 presents evidence that there are no substantial differences in historical or geographical control variables between treated and control cells. Panel A provides T-test results for all schools,

[43] We also checked which school were operational in 1881 and 1896. However, the school closure rate between 1881 and 1896 is smaller, such that our control group (closed school grid cells) is not large enough for the analysis. Therefore, we restrict ourselves to the 1905 sample in this case.

Panel B for white schools, and Panel C for black schools. For both all schools and white schools, we observe that cells with closed schools are slightly farther from Cape Town and closer to Kimberley. However, these cells are also nearer to historical explorer routes, which have been associated with positive long-term development outcomes. There are no statistically significant differences between mission school groups. These findings suggest that cells with closed schools were not at a clear disadvantage compared to those with open schools. Therefore, we rerun our regression analysis using cells with closed schools as the counterfactual instead of adjacent cells.

E.3.3 Quality-Quality Analysis

As a next step, we examine whether the quality of a historic school is linked to contemporary educational outcomes. A positive relationship would suggest that proximity to a historically high-performing school continues to offer access to better educational opportunities, thereby increasing the likelihood of attending an elite institution today. In the context of the Cape Colony's education history, the distinction between historically black and white schools is especially relevant: historically white schools offered better resources, teaching, and oversight, and many of their institutional successors now make up a large share of South Africa's elite schools.

To match the quality of historic schools to that of contemporary schools we use an inverse distance weighting (IDW) interpolation methodology which estimates the historic school quality at unknown points by computing a weighted average of the historic school quality from known points. This allows us to match contemporary schools to the weighted average of historic school quality surrounding them. Figure E.4 provides an exemplary representation of this process.

We calculate the IDW interpolation for school quality in 1896 and 1905 for all schools, white schools, and black schools separately. For the IDW interpolation, we set the power parameter of the interpolation to four. Instead of determining the value of our control at the raster cell level, we now take their value at the location of the contemporary schools.

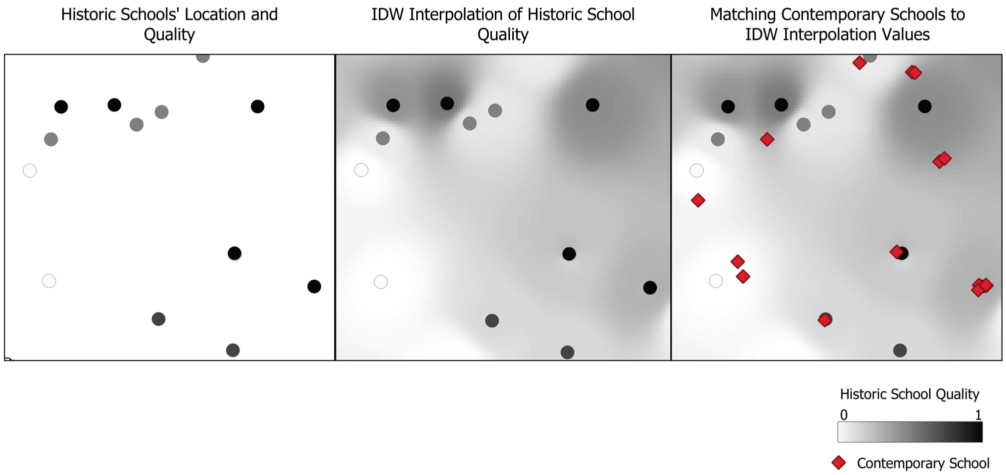
There are several advantages to using this methodology. As historic and contemporary schools are not a one-to-one match, we need some strategy to match them. Assigning the schools to grid cells allowed us to do so before. However, it has several drawbacks that we can circumvent with the IDW interpolation as our independent variable in the quality-quality analysis is continuous. First,

Table E.1: Balance Tests - Grid Cells with 1905 Open School vs. Closed Schools

Variable	No. Open	No. Closed	Mean Open	Mean Closed	Diff.	Std. Err.	t Value	p Value
Panel A: All Schools 1905 vs. Closed								
Distance Coast (km)	224	76	44.398	46.482	-2.084	5.341	-0.4	0.697
Average Rainfall	224	76	50.248	58.578	-8.329	6.371	-1.3	0.192
Average Temperature	224	76	20.409	20.444	-0.035	0.127	-0.25	0.783
Average Altitude	224	76	329.591	375.273	-45.682	37.806	-1.2	0.228
Ruggedness	224	76	103.232	82.751	20.481	10.52	1.95	0.052
Soil Quality	224	76	3.584	3.831	-0.247	0.21	-1.2	0.241
Dist. to Cape Town (km)	224	76	209.671	248.614	-38.944	18.607	-2.1	0.037
Dist. to Gqeberha (km)	224	76	486.032	446.351	39.681	20.594	1.95	0.055
Dist. to Kimberley (km)	224	76	698.65	675.051	23.6	12.96	1.8	0.07
Dist. to Colonial Railway (km)	224	76	27.879	31.221	-3.341	3.677	-0.9	0.364
Dist. to Explorer Route (km)	224	76	376.56	361.948	14.613	7.3	2	0.046
Panel B: White Schools 1905 vs. Closed								
Distance Coast (km)	180	67	49.244	49.711	-0.468	5.936	-0.1	0.938
Average Rainfall	180	67	53.229	60.027	-6.798	6.849	-1	0.322
Average Temperature	180	67	20.467	20.492	-0.026	0.134	-0.2	0.85
Average Altitude	180	67	351.05	398.769	-47.72	41.62	-1.15	0.253
Ruggedness	180	67	101.465	84.046	17.418	11.345	1.55	0.126
Soil Quality	180	67	3.603	3.831	-0.228	0.232	-1	0.328
Dist. to Cape Town (km)	180	67	222.429	264.295	-41.866	19.723	-2.1	0.035
Dist. to Gqeberha (km)	180	67	469.043	433.884	35.159	21.706	1.6	0.106
Dist. to Kimberley (km)	180	67	687.173	663.384	23.79	13.849	1.7	0.087
Dist. to Colonial Railway (km)	180	67	26.525	32.099	-5.574	3.724	-1.5	0.136
Dist. to Explorer Route (km)	180	67	370.481	357.262	13.219	7.711	1.7	0.088
Panel C: Black Schools 1905 vs. Closed								
Distance Coast (km)	119	11	35.963	24.264	11.699	11.527	1	0.312
Average Rainfall	119	11	40.224	46.327	-6.104	14.005	-0.45	0.663
Average Temperature	119	11	20.322	20.176	0.146	0.306	0.5	0.634
Average Altitude	119	11	261.748	245.227	16.521	75.665	0.2	0.828
Ruggedness	119	11	104.528	83.261	21.267	24.829	0.85	0.394
Soil Quality	119	11	3.41	3.465	-0.054	0.463	-0.1	0.907
Dist. to Cape Town (km)	119	11	166.745	173.27	-6.526	42.535	-0.15	0.879
Dist. to Gqeberha (km)	119	11	533.091	541.154	-8.063	46.387	-0.15	0.863
Dist. to Kimberley (km)	119	11	730.555	735.341	-4.787	28.972	-0.15	0.869
Dist. to Colonial Railway (km)	119	11	28.73	40.62	-11.89	10.281	-1.15	0.249
Dist. to Explorer Route (km)	119	11	393.346	395.349	-2.002	16.416	-0.1	0.903

Notes: The table shows t-tests for the comparison of grid cells which include a school that is open in 1905 versus grid cells which included a school in 1896 but that was closed by 1905. If both an open and a closed school are in a grid cell, the cell is assigned as open. Panel A shows the results for all schools, Panel B restricts the sample to schools reserved for the white population and Panel C restricts the sample to schools reserved for the black population. The grid cells are of the size 0.05×0.05 degrees (about 5kmx5km). All distances are calculated from the centroid of the cells and for the remainder the average value of the cell is calculated.

Figure E.4: Illustration of IDW Interpolation Approach for the Quality-Quality Qnalysis. Authors' own representation.



a historic school in an adjacent cell might be very close to the contemporary school in the target cell but is not matched as they are in different cells. Indeed, Figure E.3 provides an example of such a case. Thus, the raster approach does not always ensure that the schools with the highest proximity to another get matched. Second, the IDW interpolation allows us to capture the influence of several historic schools on a contemporary school with those further away receiving less weight mimicking a spatial autoregressive (SAR) model. We cannot estimate a regular SAR model as it requires a one-to-one match of the dependent and independent variable. Thus, the IDW interpolation enables us to circumvent these two issues and, hence, is our preferred strategy. Nevertheless, we also provide results using a grid cell approach in the Supplementary Materials.

Our baseline estimation using the IDW interpolation is the following OLS model:

$$TestScore_{i,d} = \beta_0 + \beta_1 \cdot IDWStd_i + \Gamma X_i + \delta_d + e_{i,d} \tag{17}$$

where $TestScore$ is the average test score achieved at contemporary school i in division d. $IDWStd$ is the interpolated value of the historic school quality at the location of contemporary school i. As mentioned before, at the historic school level, this is the share of students in Standard 4 or higher. The vector X_i includes the geographic and historical control variables and δ_d are 1891 division fixed effects. In our main specification we limit our sample to contemporary schools whose distance to the closest historic school is at maximum ten kilometers. We provide the results with the full sample in the robustness checks. Again, we adjust the standard errors for spatial autocorrelation using the Stata Package by Colella et al. (2023).

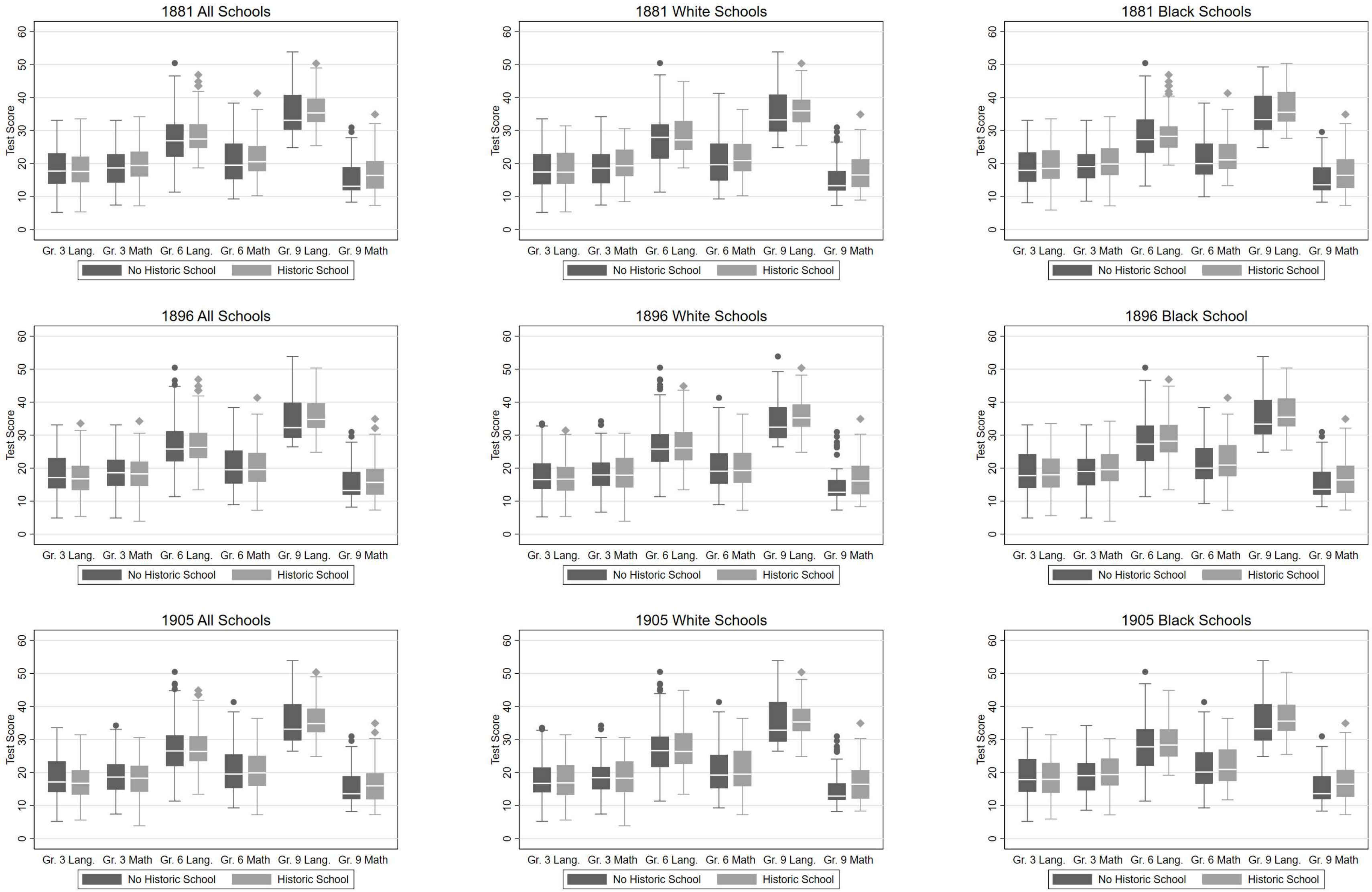
E.4 Results

E.4.1 Location-Quality Analysis

Before turning to the results of the regressions, we first consider the unconditional relationship between the proximity of a historic school and contemporary school quality. Figure E.5 provides boxplots for all, white and black schools for 1881, 1896 and 1905 and the contemporary math and language test scores. In 1881 the median test score for a cell with a historical school is slightly higher in the majority of cases, but for Grade 9 test scores this difference is larger. Similarly in 1896, while there are only small differences across school types in Grade 3 and 6 test scores, Grade 9 contemporary schools in grid cells with a historic school perform better in both language and math. The same holds for the unconditional correlations between the 1905 schools and contemporary test scores. Thus, the analysis of these unconditional correlations provides limited evidence that the proximity of historic schools is important across for educational outcomes as suggested by previous work.

We now turn to our baseline regression results of the location-quality analysis presented in Table E.2. The first three panels provide the estimates for 1881, the next three for 1896 and the remaining three for 1905. In columns (1) and (2) the outcome variables are the Grade 3 test scores for math and language. In columns (3) and (4) these are Grade 6 test scores and in (5) and (6) Grade 9 test scores. Our baseline estimates suggest that there is a positive correlation between 1881 all historic schools and contemporary scores across all three grades. The estimate is largest for grade nine. In 1896 and 1905, the only estimtes which are consistently significant are the Grade 9 test scores. This is also reflected for white and black schools, if considered separately, who only show consistent positive and statistically significant estimates for grade nine.

Figure E.5: Unconditional Relationship of Existence of Historic School in Raster Cell with Contemporary School Quality Disaggregated by Type of School. Authors' own representation.



Yet, these estimates are not robust to our alternative specification using cells with closed schools as our counterfactual. Table E.3 shows that there is only a positive and statistically significant relationship between the historic white schools and Grade 9 math and language test scores. Moreover, these estimates appear to depend on the chosen grid cells size. If we increase the size of the grid cells to 0.1×0.1 degrees (about 10km×10km), the results differ as shown in Table E.13. In contrast to before, the estimates suggest a positive relationship between white historic schools and Grade 3 test scores as well as between black historic school and Grade 3 and 6 test scores. Similarly, if we move the grid either by 0.025 degree to the top or 0.025 degree to the right, the estimates are different both in size and significance (Tables E.14 and E.15). The inconsistency of these results lets us conclude that there is no robust persistent effect of the mere presence of a historic school and contemporary test scores. These findings are similar to those by Jedwab et al. (2022) who also conclude that once all mission schools in Ghana are taken into consideration – instead of only those listed in missionary atlases – there remains no persistent effect. Not finding any persistent effect of historic school presence implies there are not lasting benefits of historical schooling that are broadly accessible irrespective of other characteristics of these schools such as their historical quality.

E.4.2 Quality-Quality Analysis

Results from the previous section show that there is no persistent effect of historical school locations on contemporary quality. However, this does not imply that specific characteristics of schools cannot have a lasting legacy, such as their quality. If there is a legacy of historic school quality, then the persistence of school quality can potentially contribute to elite reproduction over time. Hence, we will now focus on exploring whether historic school quality influences contemporary school quality.

Figure E.6 provides the unconditional correlations of past school quality – proxied by the share of students in Standard 4 and higher in 1896 and 1905 and the contemporary test scores. For all 1896 schools, there appears to be no correlation between past and present quality but a small positive trend for Grade 9 math and language. However, if we look at white schools, we can observe a positive correlation for all contemporary test scores and past quality. Considering 1896 black schools, we can also observe a positive correlation. This positive correlation holds if we

Table E.2: Location-Quality Analysis - Baseline (Raster 0.05)

	(1)	(2)	(3)	(4)	(5)	(6)
	Grade 3		Grade 6		Grade 9	
	Math	Language	Math	Language	Math	Language
Panel A: All Schools 1881						
Historic School in Raster Cell	1.307**	0.803	1.611*	1.619*	2.863**	2.030**
	(0.607)	(0.887)	(0.979)	(0.926)	(1.279)	(0.964)
Observations	201	201	199	199	119	119
R-Squared	0.364	0.379	0.359	0.392	0.360	0.360
Panel B: White Schools 1881						
Historic School in Raster Cell	0.881	0.071	0.759	0.757	2.331*	0.750
	(0.677)	(0.770)	(0.572)	(0.826)	(1.218)	(1.157)
Observations	146	146	141	141	87	87
R-Squared	0.377	0.417	0.387	0.433	0.407	0.386
Panel C: Black Schools 1881						
Historic School in Raster Cell	1.619**	1.441*	2.161*	2.003**	4.045***	3.117***
	(0.692)	(0.776)	(1.115)	(0.786)	(1.053)	(0.987)
Observations	168	168	167	167	110	110
R-Squared	0.393	0.400	0.371	0.401	0.437	0.399
Panel D: All Schools 1896						
Historic School in Raster Cell	0.486	0.122	0.657	1.253	2.362**	2.542***
	(0.639)	(0.518)	(1.002)	(0.890)	(0.974)	(0.772)
Observations	264	264	256	256	134	134
R-Squared	0.327	0.330	0.357	0.388	0.261	0.323
Panel E: White Schools 1896						
Historic School in Raster Cell	0.586	0.619	0.923	1.540	3.427***	3.040***
	(0.826)	(0.704)	(1.028)	(0.990)	(1.064)	(0.772)
Observations	226	226	218	218	111	111
R-Squared	0.354	0.367	0.367	0.400	0.264	0.317
Panel F: Black Schools 1896						
Historic School in Raster Cell	1.543*	1.037	1.458	2.051*	2.784**	2.081**
	(0.832)	(0.885)	(1.294)	(1.114)	(1.192)	(1.050)
Observations	181	181	179	179	113	113
R-Squared	0.378	0.411	0.378	0.444	0.433	0.454
Panel G: All Schools 1905						
Historic School in Raster Cell	0.220	-0.253	0.418	0.976	2.260***	1.921**
	(0.735)	(0.667)	(0.690)	(0.723)	(0.852)	(0.762)
Observations	232	232	226	226	123	123
R-Squared	0.379	0.373	0.378	0.411	0.266	0.313
Panel H: White Schools 1905						
Historic School in Raster Cell	0.823	0.654	1.029	1.654*	2.859***	2.373***
	(0.840)	(0.796)	(0.990)	(0.994)	(1.093)	(0.608)
Observations	196	196	189	189	102	102
R-Squared	0.401	0.399	0.388	0.423	0.261	0.312
Panel I: Black Schools 1905						
Historic School in Raster Cell	0.831	0.260	1.104	1.604*	2.742**	1.944*
	(0.842)	(0.797)	(1.046)	(0.967)	(1.215)	(1.048)
Observations	166	166	164	164	105	105
R-Squared	0.360	0.405	0.367	0.434	0.438	0.456
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show our baseline model for the location-quality analysis, i.e., the relationship between historic school locations and contemporary school performance captured by the mean test score achieved in the *Systemic Test*. The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 matched to a 0.05x0.05 degree raster grid. The sample is limited to the Western Cape. Odd numbered columns show the correlation of the respective school's location and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table E.3: Location-Quality Analysis – Closed School Locations as Counterfactual

	(1)	(2)	(3)	(4)	(5)	(6)
	Grade 3		Grade 6		Grade 9	
	Math	Language	Math	Language	Math	Language
Panel A: All Schools 1905						
Open School in Raster Cell	-0.939	-1.868	-0.150	0.402	0.690	-0.985
	(1.687)	(1.758)	(1.671)	(1.929)	(1.748)	(2.648)
Observations	143	143	138	138	78	78
R-Squared	0.467	0.452	0.470	0.476	0.389	0.456
Panel B: White Schools 1905						
Open School in Raster Cell	1.936	1.015	2.643	2.852	5.122**	6.073**
	(1.754)	(1.859)	(1.872)	(2.170)	(2.526)	(2.566)
Observations	107	107	103	103	59	59
R-Squared	0.511	0.530	0.522	0.559	0.420	0.541
Panel C: Black Schools 1905						
Open School in Raster Cell	-1.967	-3.235	-3.269	-2.659	-0.293	-4.071*
	(1.904)	(2.178)	(2.797)	(3.045)	(1.459)	(2.242)
Observations	92	92	91	91	63	63
R-Squared	0.539	0.545	0.525	0.514	0.591	0.610
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show our counterfactual model for the location-quality analysis, i.e., the relationship between historic school locations and contemporary school performance captured by the mean test score achieved in the *Systemic Test*. The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 matched to a 0.05x0.05 degree raster grid. The counterfactual are grid cells that included a school in 1896 but was closed by 1905. The sample is limited to the Western Cape. Odd numbered columns show the correlation of the respective school's location and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote signifi-cance levels at *** p<0.01, ** p<0.05, * p<0.1.

exclude the outliers. Turning to the 1905 schools, we again only find a positive correlation between all historic schools' quality and contemporary test scores for Grade 9. We observe the same pattern for 1905 white schools. Black schools show some positive correlations for Grade 3 language and math test scores and Grade 9 math test scores. In contrast to 1896 there are no clear outliers in the black schools which could drive this trend. Overall, there is no clear indication based on the unconditional trends analysis whether there is a persistent effect of colonial school quality on contemporary outcomes across white and black schools.

We now turn to the regression results to explore this relationship in more detail. Table E.4 presents the baseline estimates, with all regressions including controls and division fixed effects. Overall, we find a positive association between historical school quality and contemporary school performance for both black and white schools. For example, in white schools, a 10 percentage point increase in the share of students reaching Standard IV or above is associated with an average increase of 1 point in Grade 6 math scores today. Given an average test score of 23.24, this corresponds to an improvement of over 4 percent. Notably, the estimated effect is substantially larger for black schools, even when considering standardized beta coefficients. In these schools, a 10 percentage point increase in the share of students in Standard IV or above is associated with a 2.5-point increase in Grade 6 math scores. The relationship is even stronger for Grade 9 test results. One possible explanation for these larger estimates in black schools is that very few of these schools had a high share of students reaching higher standards. In 1896, only 12 black schools in the Western Cape had more than 10 percent of students in Standard IV or above, all located in Cape Town or its vicinity. By contrast, 177 white schools exceeded this threshold, and they were spread across all districts. As a result, the large coefficients for black schools may reflect the influence of a few exceptional cases, rather than being representative of black schools more broadly.

Figure E.6: Unconditional Relationship of Existence of Historic and Contemporary School Quality Disaggregated by Type of School. Authors' own representation.

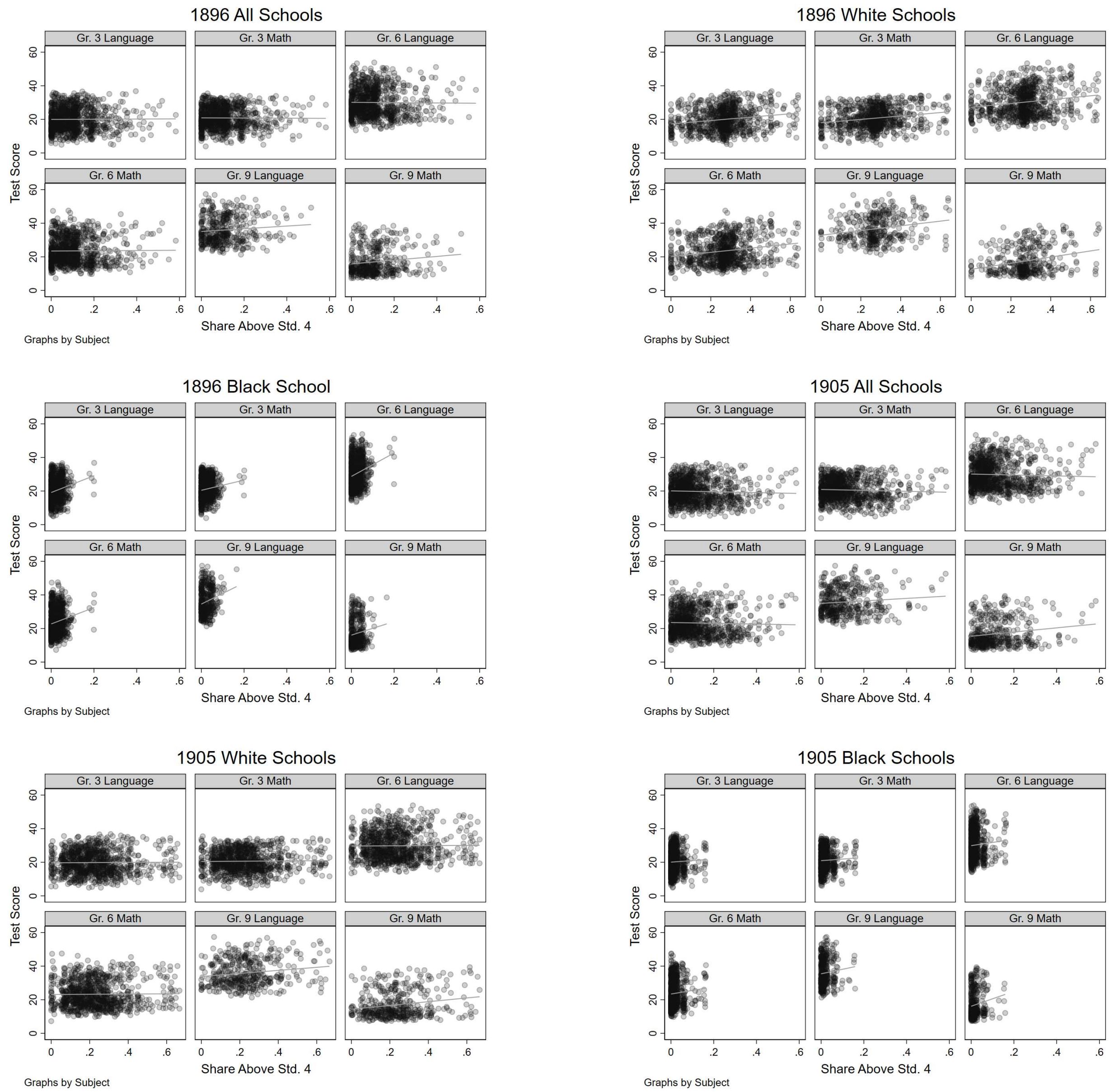


Table E.4: Quality-Quality Analysis - Baseline (IDW Interpolation)

	(1)	(2)	(3)	(4)	(5)	(6)
	Grade 3		Grade 6		Grade 9	
	Math	Language	Math	Language	Math	Language
Panel A: All Schools 1896						
Share Std. 4 or Higher	4.559*	5.889*	7.712***	5.502*	9.870***	8.898**
	(2.671)	(3.183)	(1.762)	(3.133)	(3.518)	(3.928)
Observations	1,068	1,068	1,034	1,034	454	454
R-Squared	0.197	0.203	0.197	0.203	0.187	0.227
Panel B: White Schools 1896						
Share Std. 4 or Higher	8.005***	7.770**	11.072***	10.136***	23.193***	18.250***
	(2.490)	(3.128)	(2.692)	(3.262)	(3.811)	(2.405)
Observations	1,068	1,068	1,034	1,034	454	454
R-Squared	0.208	0.210	0.209	0.214	0.243	0.260
Panel C: Black Schools 1896						
Share Std. 4 or Higher	13.818	29.402***	25.425**	44.632***	31.857**	55.581***
	(10.292)	(11.364)	(10.041)	(12.237)	(16.025)	(11.715)
Observations	1,068	1,068	1,034	1,034	454	454
R-Squared	0.195	0.206	0.195	0.213	0.185	0.239
Panel D: All Schools 1905						
Share Std. 4 or Higher	5.422	6.136***	7.370***	6.501**	12.861***	8.519***
	(.)	(2.049)	(2.809)	(2.528)	(3.453)	(1.970)
Observations	1,068	1,068	1,034	1,034	454	454
R-Squared	0.198	0.204	0.197	0.205	0.194	0.227
Panel E: White Schools 1905						
Share Std. 4 or Higher	4.144***	4.313**	5.730***	5.474**	11.536***	10.205***
	(1.332)	(2.014)	(1.241)	(2.170)	(2.526)	(1.707)
Observations	1,068	1,068	1,034	1,034	454	454
R-Squared	0.197	0.202	0.196	0.205	0.198	0.236
Panel F: Black Schools 1905						
Share Std. 4 or Higher	16.649***	17.582**	32.877***	27.038**	44.466	28.228**
	(5.360)	(6.875)	(7.166)	(11.422)	(.)	(12.963)
Observations	1,068	1,068	1,034	1,034	454	454
R-squared	0.196	0.201	0.199	0.205	0.190	0.225
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show our model for the quality-quality analysis, i.e., the relationship between historical school quality captured by the share above of students above Standard 4 and contemporary school performance captured by the mean test score achieved in the *Systemic Test*. The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905, which was interpolated using inverse distance weighting with a power parameter of four and matched to contemporary schools. The sample is limited to the Western Cape and excludes contemporary schools that are farther than 10km from the nearest historic school. Odd-numbered columns show the correlation of the respective school's quality and math test performance in Grade 3, 6, and 9, while even-numbered columns show the relationship for language test performance. GIS controls include distance to the coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km), and distance to explorer routes (km). All models include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Naturally, these results are correlational, and endogeneity remains a concern. One potential source of bias is that our findings may be driven by schools located in towns that historically, and still today, offered better education. This is particularly relevant in Cape Town, where the density of schools makes it difficult to distinguish between historically black and white institutions. We address this issue in two ways. First, we exclude all schools located in towns that had populations above 1,000 in 1891—namely, Cape Town, Beaufort West, Malmesbury, Oudtshoorn, Paarl, Stellenbosch, Worcester, and Swellendam. These towns perform better on the *Systemic Tests* in Grades 3 and 6 compared to the rest of the Western Cape, though not in Grade 9. Second, we include a control for contemporary urban status. However, this variable could act as a "bad control" in the sense of Angrist and Pischke (2009), since urbanization may itself be partly driven by past investments in education and the presence of historically high-quality schools. Table E.5 presents the results: the first six columns exclude the 1891 towns, while the final six add the urban control. Once these adjustments are made, the positive and statistically significant relationships between historical school quality and present-day outcomes persist mainly for historically white schools—particularly for Grade 9 outcomes. Including the urban control further strengthens the robustness of this relationship. In contrast, the associations between historical black school quality and present-day performance largely disappear after accounting for historical urbanity. This suggests that the persistence of quality is a pattern mainly seen among historically white schools. We discuss possible explanations for this in the next section.

These findings imply that high-quality white schools were able to sustain their institutional advantages over time, and that either these schools—or their contemporary counterparts—continue to play a central role in producing the educational elite. In contrast, we find no robust evidence that historically black schools left a lasting legacy in terms of educational quality today.

Table E.5: Quality-Quality Analysis – Excluding Urban Areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	No Towns > 1,000 (1891)						Baseline + Control for Contemporary Urbanity					
	Grade 3		Grade 6		Grade 9		Grade 3		Grade 6		Grade 9	
	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.
Panel A: All Schools 1896												
Share Std. 4 or Higher	2.215	0.078	3.642	0.311	4.875	5.439	5.101**	6.347**	8.194***	5.877**	7.501**	6.905**
	(2.351)	(2.326)	(3.183)	(3.157)	(6.033)	(5.136)	(2.475)	(2.924)	(1.635)	(2.984)	(3.400)	(3.363)
Cont. Urban Dummy							3.207	3.057	5.420***	6.405	-0.697	2.678***
							(.)	(.)	(0.248)	(.)	(.)	(0.516)
Observations	395	395	383	383	138	138	1,002	1,002	970	970	437	437
R-Squared	0.189	0.193	0.176	0.174	0.178	0.251	0.194	0.200	0.199	0.214	0.198	0.233
Panel B: White Schools 1896												
Share Std. 4 or Higher	1.012	-1.710	3.573	1.153	18.497***	16.155***	8.502***	8.190**	11.931***	10.880***	28.309***	24.069***
	(1.968)	(1.845)	(3.066)	(3.241)	(7.126)	(4.350)	(2.671)	(3.311)	(3.420)	(3.681)	(6.246)	(4.799)
Cont. Urban Dummy							4.154***	3.664	6.240***	6.856	5.738***	7.660***
							(0.414)	(.)	(0.892)	(.)	(1.893)	(1.271)
Observations	395	395	383	383	138	138	863	863	831	831	379	379
R-Squared	0.188	0.194	0.176	0.174	0.230	0.296	0.212	0.218	0.232	0.248	0.267	0.296
Panel C: Black Schools 1896												
Share Std. 4 or Higher	8.469	9.836	-6.348	8.261	-78.142**	-24.553	8.518	24.676**	17.422	34.266***	21.821	45.243***
	(16.829)	(15.119)	(34.328)	(30.719)	(35.241)	(28.389)	(9.657)	(10.547)	(11.001)	(13.028)	(13.698)	(10.839)
Cont. Urban Dummy							2.987	2.806	4.308***	5.269	-0.318	2.016
							(.)	(.)	(0.455)	(.)	(.)	(.)
Observations	395	395	383	383	138	138	905	905	873	873	408	408
R-Squared	0.188	0.193	0.174	0.174	0.189	0.248	0.182	0.193	0.183	0.216	0.204	0.250
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table E.5: cont.

	No Towns > 1,000 (1891)						Baseline + Control for Contemporary Urbanity					
	Grade 3		Grade 6		Grade 9		Grade 3		Grade 6		Grade 9	
	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.
Panel D: All Schools 1905												
Share Std. 4 or Higher	3.255***	1.574	1.278	0.596	2.570	3.838	6.169***	6.629***	8.934**	8.193**	11.565***	8.630***
	(0.614)	(1.385)	(1.860)	(1.827)	(6.887)	(6.381)	(0.482)	(2.291)	(3.843)	(3.339)	(3.434)	(2.470)
Cont. Urban Dummy							3.882	3.770	5.834***	6.998	0.831	3.740***
							(.)	(.)	(0.793)	(.)	(.)	(0.753)
Observations	395	395	383	383	138	138	1,021	1,021	985	985	441	441
R-Squared	0.191	0.194	0.174	0.174	0.176	0.249	0.202	0.203	0.203	0.219	0.189	0.227
Panel E: White Schools 1905												
Share Std. 4 or Higher	5.382***	1.731	4.703**	2.189	11.547**	12.672***	5.316***	5.390**	8.117***	9.130***	14.019***	15.679***
	(1.847)	(2.274)	(2.024)	(2.297)	(5.421)	(4.166)	(0.697)	(2.199)	(1.981)	(2.929)	(3.078)	(2.163)
Cont. Urban Dummy							4.486	4.409	6.583***	8.173***	3.613	7.563
							(.)	(.)	(0.857)	(0.154)	(.)	(.)
Observations	395	395	383	383	138	138	992	992	958	958	429	429
R-Squared	0.196	0.194	0.179	0.175	0.198	0.280	0.204	0.206	0.206	0.232	0.205	0.251
Panel F: Black Schools 1905												
Share Std. 4 or Higher	7.024	5.963	22.469	8.273	32.344	2.406	10.618	12.748**	27.404***	21.539**	43.700	30.107
	(9.952)	(11.119)	(15.366)	(15.528)	(29.095)	(24.688)	(.)	(6.442)	(4.019)	(8.761)	(.)	(.)
Cont. Urban Dummy							3.074	2.819***	5.199	5.894	-0.739	2.056*
							(.)	(0.375)	(.)	(.)	(.)	(1.196)
Observations	395	395	383	383	138	138	912	912	881	881	413	413
R-Squared	0.189	0.194	0.179	0.175	0.183	0.246	0.185	0.189	0.186	0.211	0.210	0.241
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show our model for the quality-quality analysis, i.e., the relationship between historic school quality captured by the share above of students in Standard 4 and above and contemporary school performance captured by the mean test score achieved in the *Systemic Test*, excluding historic urban areas in columns (1) to (6) and controlling for contemporary urbanity in columns (7) to (12). The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 which was interpolated using inverse distance weighting with a power parameter of four and matched to contemporary schools. The sample is limited to the Western Cape and excludes contemporary schools which are further than 10km from the next historic school. Odd numbered columns show the correlation of the respective school's quality and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

E.4.3 Robustness Checks

While we cannot fully address all endogeneity concerns, we can assess the robustness of our results across a range of alternative specifications.

First, we replicate the main regressions using the full sample of schools, rather than restricting the sample to contemporary schools located within 10 kilometers of a historic school (Table E.16). Second, we re-estimate the results using a different power parameter (2 instead of 4) in the IDW interpolation used to construct school-level historical quality (Tables E.17 and E.18). Third, we redefine our historical quality measure: instead of using the share of students in Standard IV and above, we use the average Standard per school (Tables E.19 and E.20). Fourth, we apply a spatial raster grid approach. In Table E.21, odd-numbered columns show results for grid cells that include both a historical and a contemporary school; even-numbered columns exclude those with towns above 1,000 residents in 1891. Across all these specifications, the results consistently show that the legacy of historically white schools is most pronounced in higher grades, while there is no stable evidence of lasting effects from historically black schools.

Beyond these alternative estimation strategies, we also examine whether historical school quality is associated with broader indicators of school quality today, such as the availability of sports infrastructure. According to South Africa's 1998 Government White Paper *Getting the Nation to Play* (1998), physical education and sports participation are linked to improved educational and economic outcomes. Sports infrastructure may therefore serve as a proxy for contemporary school quality, particularly for identifying schools that provide broader developmental opportunities. Moreover, large South African university such as the University of Cape Town or the University of Witwatersrand offer sports bursaries. Thus, showcasing athletic talent can also open the door to durther academic studies.

Using satellite imagery, we coded whether each school has any sports facility, artificial turf, a swimming pool, or tennis courts. While this only captures outdoor facilities, indoor options, such as pools, are likely even more resource-intensive, and their omission would bias our results downwards.[44] The results in Table E.22 show that proximity to a historically higher-quality white

[44] All types of sports infrastructure are positively correlated with test performance at conventional significance levels. The weakest correlation is between any sports facility and test scores, likely due to the widespread presence of basic sports fields, while more expensive features, especially tennis courts, show stronger associations with higher

school is associated with a greater likelihood of having such facilities. In contrast, proximity to a historically higher-quality black school is only associated with a higher likelihood of having a swimming pool.

Taken together, these findings suggest that the legacy of colonial schooling in the Cape Colony continues to shape educational quality in the present – but only for certain types of schools. The mere existence of a historic school in the vicinity does not appear to matter. Instead, it is the quality of historically white schools that persists and continues to shape educational outcomes today. This long-run persistence points to a pattern in which historically advantaged schools were able to maintain their position, while historically disadvantaged schools were not. The next section explores possible reasons for this divergence.

E.5 Mechanisms

While the histories of the black and white education systems in the Cape are closely intertwined, their long-term trajectories diverged dramatically. In this section, we explore why historically black schools show little persistence in educational quality, while historically white schools continue to exert influence over contemporary outcomes.

Even before the formal start of Apartheid, the black education system faced deep structural disadvantages. In 1921, the state revised the curriculum for black schools to emphasize manual labour over academic development, reinforcing the system's role in producing a labouring class rather than nurturing educational advancement (Molteno, 1987, p. 59). Chronic underfunding throughout the 1920s and 1930s meant that new schools could only be opened through local fundraising (Horrell, 1964, p. 31). While white students experienced improvements in grade progression, most black students dropped out before finishing the Sub-Standards, meaning without acquiring any basic literacy and numeracy skills. As a result, the accumulation of human capital remained limited: by 1946, fewer than 40 percent of Africans in the Cape Province were literate, and among the Coloured population, literacy remained under 50 percent in 1960.

These disparities intensified with the passage of the 1953 *Bantu Education Act* and the 1963 *Coloured Persons Education Act*. Control over black and Coloured schools shifted from the Cape

academic performance.

Province to the Union government. Mission schools lost access to state funding and were forced either to close or hand over operations. Only a handful of Roman Catholic schools survived independently (Horrell, 1964, p. 26). Moreover, many more of these schools had to close as a consequence of the *Group Areas Act* (Horrell, 1964, p. 28). If the schools were in an area that was declared white, they could no longer operate. In addition, black residents of these areas were removed to designated areas outside of the towns' centers (Thompson, 2014, p. 194).[45] By 1955, the state's goal was no longer to educate but to control. As Hendrik Verwoerd, leader of the Nationalist party, put it, black education was to prepare people "in accordance with their opportunities in life." For Africans, these opportunities were typically to work as an unskilled labourer on white-owned farms or in the mines (Thompson, 2014, p. 196). The majority of the Coloured population worked in low-skill blue collar jobs, as farm labourers or domestic aids (Union of South Africa, 1963). Alongside with other repressive legislation, the state ensured to keep the majority of the black population poor and uneducated. By the end of Apartheid, average years of schooling among the African population was 3.7 years and among the Coloured population 5.4 years while it was 9.3 years for the white population (Beutel and Anderson, 2008). These numbers do not yet account for the differences in quality of education.

Given these deep structural constraints, it is perhaps unsurprising that we observe no persistent effect of historically black school quality on present-day outcomes. Education under colonialism and Apartheid was not a means of empowerment for black South Africans, but a tool of control. While missionary societies may have had more progressive goals, they were undermined by state neglect and deliberate segregation policies. The early enforcement of segregation in schools at the end of the 19th century, ensured that the Apartheid state could easily implement their policies despite the strong rejection of the black population (Molteno, 1987, p. 97). While the education sector continued to expand during Apartheid, there was always a substantial gap in both quantity and quality between the black and white education system. As a result, black schools lacked the

[45] In addition, the South African government, beginning in the 1960s, removed millions of Africans to the so-called "homelands". Through the establishment of these proto-states, only recognized by South Africa as independent states, the government stripped Africans of their citizenship in an attempt to further solidify the white minority rule (Thompson, 2014, p.191). For our study, these removals only play a minor role. In 1911, less than 3 percent of the population of the contemporary Western Cape were African while almost 50 percent were Coloured. While the homeland policy had a significant impact on the demographic composition in other areas of South Africa, it did not heavily influence the composition of the Western Cape. Therefore, these removals are unlikely to play an important role in the non-persistence of black education.

institutional continuity and support needed to sustain quality or build reputational capital.

By contrast, the white education system benefited from sustained investment and policy continuity across the 20th century. The *Cape Colony Education Reports* show steady improvements in both quality and grade attainment for white students. For instance, in 1953, around 20 percent of students in white schools were enrolled in Standard 7 or above, compared to fewer than 5 percent in black schools. Nearly all white children attended school, while only about half of black children did (Cape Colony, 1953). By the end of Apartheid, white students still averaged more than nine years of schooling (Beutel and Anderson, 2008), and they remain more likely to pass the matriculation exam and attend university (Louw et al., 2007). These findings mirror our own results, which show the strongest historical persistence at the upper levels of the education system.

What explains this persistence at the local level? One possibility is that high-quality schools shape neighborhood attitudes and raise the perceived value of education. However, this would require very low residential mobility. While South African cities remain highly segregated (Parry and Van Eeden, 2015), mobility has increased significantly since the end of Apartheid, especially in cities like Cape Town (Bakker et al., 2020). Thus, individual-level persistence seems unlikely to account for the observed patterns. A more plausible explanation is that the schools themselves persist. High-quality schools develop reputations, attract capable teachers and students, and build networks that reinforce their elite status. Alumni often remain involved through donations or professional support, helping maintain the institution's prestige. Many elite schools today have active alumni associations (often called "Old Boys" or "Old Girls" Unions, for example: South African College High School Old Boys' Union (https://sacsobu.org.za/)), underscoring the strength of these institutional legacies.

Supporting this view, we find that schools with higher academic performance in 1905 were significantly more likely to still exist in 2018. We checked for each of the 1905 schools whether the school continues to exist. Surviving historically white schools, had on average 41.4 percent of students in Standard 4 or higher. For many schools, it is likely they are the same institution based on name similarities, but we could not find definitive proof.[46] In this category, the historic

[46] An example of this *Wellington High School* close to Paarl. In 1905 there is both a Girls' and Boys' high school of the same name in Wellington. However, we could not find information on the founding of Wellington High School for example on the school's webpage. We also contacted all schools without definite information via mail but only received a response from two schools.

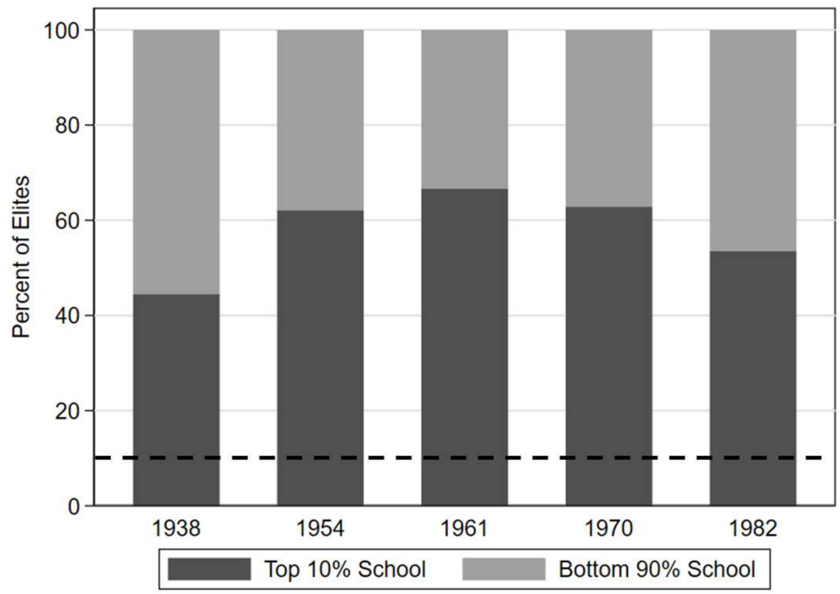
school had 25.4 percent of students in Standard 4 and above. In comparison, those schools which do not exist anymore, had on average only 15 percent of students in Standard 4 and above. This descriptive evidence suggests that the local persistence in quality is, at least to some degree, driven by these elite schools continuously operating over the last century.

In addition, we find evidence that attending these historic elite schools substantially raises the probability of someone becoming a member of the economic, social and cultural elite. We gathered data from the annual publication *Who's Who of Southern Africa* from 1938, 1954, 1961, 1970 and 1982. These publication features short biographies of prominent individuals in South Africa who are considered to be member of the elite. We digitized information of the first 500 entries in the chapter on South Africa in each edition, representing a 10 to 20 percent sample.[47] We further restricted the sample to those who received at least some portion of their secondary education in the Western Cape. It is important to note that the publication, with very few exceptions, predominantly features white South Africans. Since historically white schools generally outperform historically black schools, it is likely that these institutions also produced more elites. Nonetheless, this is an important limitation, as we are unlikely to capture any elite production at historically black schools using this source. The data shows that the schools belonging to the top 10 percent of schools in 1905 are responsible for 44 to 67 percent of the elites listed as visible in Figure E.7. If elite formation were random, this figure would be closer to 10 percent. These elite schools not only delivered strong academic outcomes but also served as gateways into political, economic, and cultural leadership.

The end of Apartheid marked a major political transition, but it did not dismantle the institutional structures that enabled white elites to retain control over the education system. Drawing on Tilly's (1998) concept of opportunity hoarding, Gruijters et al. (2024) show how white South Africans preserved access to elite schools. Despite making up just 3.8 percent of the student population, white students account for about 60 percent of those attending high-fee, high-performing

[47]The books do not provide a total number of biographical entries. The total number of entries per edition are estimated based on the total number of pages with biographical entries divided by the number of pages including the first 500 entries multiplied by 500. We assume that the average biography length is constant across all pages as well as the use of advertisement pages. For example, the 1961 edition includes 737 pages of biographical entries. The first 500 entries are on 88 pages. This leads to an estimate of $\frac{737}{88} \times 500 \approx 4188$ entries. Thus, the sample size is 11.94 percent. Following the same logic the sample sizes are 21.76 percent (1938), 14.75 percent (1954), 9.3 percent (1970) and 10.7 percent (1982). Restricting the sample to the Western Cape leaves us with 72 observations in 1938, 58 in 1954, 57 in 1961, 70 in 1970 and 71 in 1981.

Figure E.7: Share of Western Cape Educated Elite from 1905 Top 10 Percent Historic Schools. Authors' own representation.



schools. Gruijters et al. (2024) estimate that income disparities explain only around 30 percent of this overrepresentation; spatial segregation and institutional barriers account for the remainder. Retaining their economic power allowed the elite to shape institutions in ways that ensured their continued dominance, as exemplified by the education system (Acemoglu and Robinson, 2008). This phenomenon of opportunity hoarding by elites through institutional mechanisms has been documented in other historical contexts as well, such as in the Danish West Indies following the abolition of slavery (Galli et al., 2024) and in Indonesia after the fall of the Suharto regime (Martinez-Bravo et al., 2017).

In South Africa, educational institutions became vehicles of intergenerational advantage. While black education was fragmented, underfunded, and repeatedly reorganized, white schools were able to sustain high quality and elite status across a century. This institutional continuity, not individual success stories, is what likely drives the persistence we observe in the data.

E.6 Conclusion

Thirty years after the end of Apartheid, South Africa still struggles severely with the adequate provision of education for all its students. A few schools—typically those historically reserved for the white population—outperform the rest and contribute to the reproduction of an educational elite. In this article, we explore the historical roots of the unequal provision of education, focusing on South Africa's Western Cape, and examine how this has contributed to elite formation through a small number of schools.

Using novel digitized and geo-referenced data from the *Cape Colony Education Reports*, we investigate the link between historical school quality and 2018 *Systemic Test* scores—an internationally benchmarked test conducted in the Western Cape—at a fine geographic level. Compared to earlier colonial education datasets such as those used in missionary atlases, our data from the *Cape Colony Education Reports* (1881, 1896, 1905) includes a comprehensive list of schools operating in each respective year. Moreover, the 1896 and 1905 reports include detailed measures of school quality, which represent a significant contribution to the study of colonial education in Sub-Saharan Africa.

In line with previous research, we begin by examining whether proximity to historical schools, distinguishing between those for white and black children, influences contemporary educational outcomes. While our baseline results suggest a potential link, our causal identification strategy, which uses the locations of closed schools as a counterfactual, reveals no significant relationship between the mere presence of historical schools (whether for white or black students) and current educational outcomes in the Western Cape. This implies that the enduring benefits of colonial schooling do not arise solely from proximity to former school sites.

We therefore shift focus to the relationship between historical school quality and contemporary test scores, again disaggregated by school type. Across all specifications, we find a consistent association between the quality of historical white schools and contemporary educational outcomes, but not for historical black schools. Given the oppressive legislation—both in education and other spheres of life—faced by the black population throughout the 20th century, it is perhaps unsurprising that black schools offering relatively high-quality education at the time were unable to maintain their impact across generations. In contrast, white education received greater support and was allowed to persist throughout Apartheid, enabling the intergenerational transmission of high-quality education. We show that schools with higher performance in 1905 are more likely to still be operational in 2018. Furthermore, attending one of the top 10 percent of schools in 1905 is associated with a substantially higher likelihood of appearing in *Who's Who in Southern Africa* throughout the 20th century.

A limitation of our study is that it focuses solely on the Western Cape. As the first region settled by Europeans, its demographic structure is not representative of South Africa as a whole. Future research should therefore investigate whether our findings hold in other regions or are specific to the Western Cape.

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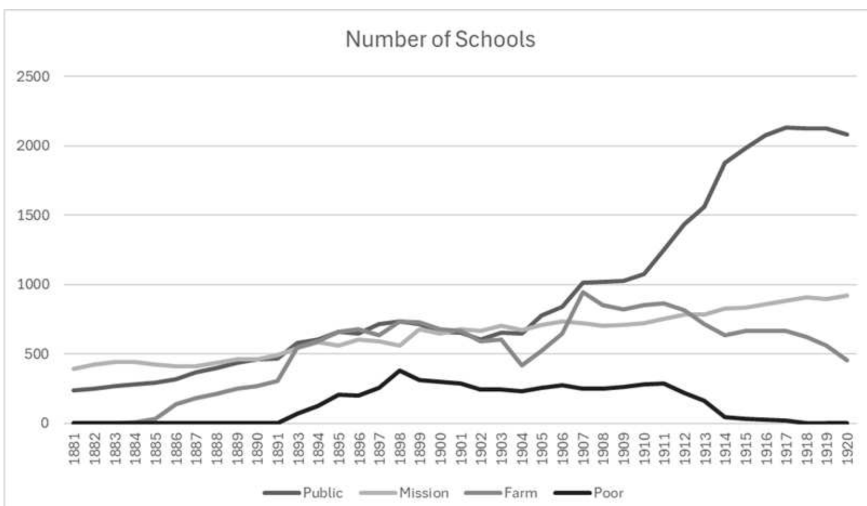
E.8 Supplementary Material

E.8.1 The Expansion of the Cape Colonial Education System (1881-1920)

The following section provides an overview of the development of the Cape Colonial education system. While for the main part of this paper, we only utilize the data until 1905 for this broader overview we cover the period until 1920 as this marks the end of the geographical expansion of the white education system in the Cape Colony. We provide this overview separately for the white and black education system.

White education. Between 1881 and 1905, the white education system in the Cape Colony experienced steady growth, as illustrated in Figures E.8 and E.9. In 1881, there were 281 public schools serving 13,246 students. By 1905, this number had increased to 735 schools with a total enrollment of 49,659 students. During this period, two new types of schools were introduced to address specific needs within the white population.

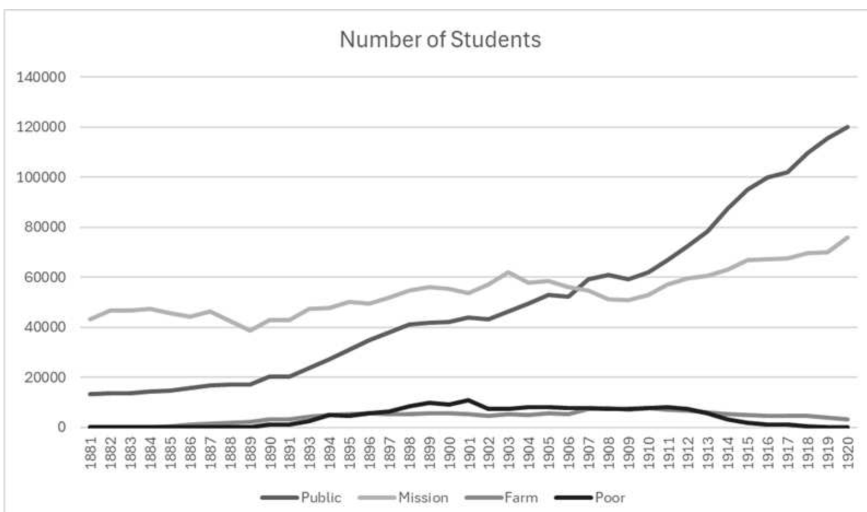
Figure E.8: Number of Schools in the Cape Colony by Type (1881-1920). Data sourced from *Cape Colony Education Reports*. Authors' own representation.



First, in 1885, under the leadership of SGE Dale, the first farm school was established. These schools required a minimum of only five students and were designed to provide basic education to the rural white population, who lived too far from public schools and in areas where population density was too low to justify establishing a conventional school (Cape Colony, 1885). Second, in 1893, one year after SGE Thomas Muir assumed office, the first poor school was inaugurated. These schools were located in more densely populated areas where segments of the white population were too impoverished to afford the pound-for-pound funding system used by regular public schools (Cape Colony, 1893). By 1905, there were 508 farm schools with 5,382 students and 239 poor schools with 6,985 students. Despite the large number of farm schools, their small size meant they educated only a small fraction of the population.

The introduction of these two new types of schools served several purposes. The primary goal was to increase the number of white children attending school. However, the pound-for-pound funding system required local demand for education. For example, SGE Dale expressed frustration over the widespread apathy towards education among many in the population (Cape Colony, 1882). To address this, the government sought to bring schools closer to the children. By the end of the 19th century, SGE Muir noted an increase in the willingness of the population to contribute to their children's education (Cape Colony, 1895).

Figure E.9: Number of Students in the Cape Colony by Type of School (1881-1920). Data sourced from *Cape Colony Education Reports*. Authors' own representation.



Another reason for introducing these school types was to segregate schools more effectively, as a significant number of white children were still attending mission schools. These mission schools were cheaper to attend, and until 1895, they outnumbered public and farm schools in the Cape. However, the government and Education Department viewed this arrangement as unsuitable (Cape Colony, 1888). In addition, with the discovery of diamonds in Kimberley and gold on the Witwatersrand, the government recognized the need to educate white children to contribute to a future industrialized society. Second, the existence of poor whites blurred the racial lines between the white and black populations, which the Education Department believed compromised the proper upbringing of white children (Duff, 2015, p. 2).

SGE Thomas Muir, who served from 1892 to 1915, played a pivotal role in the strict segregation of the education system. His tenure was marked by a focus on expanding the white education system to prepare these children for their future roles in society (Elliott, 2021, p. 24). For example, in his diary entries covering his tours to schools across the country he only reports talking to the white clergy at mission schools but never to black staff members (Elliott, 2021, p. 20). Moreover, between 1894 and 1899 he instructed the school inspectors in educationally more backward divisions to map potential new schools given there are enough children in the vicinity. These surveys, however, only focused on the white population, ignoring the educational needs of black communities.

They also allow to glimpse at the low demand for schooling in many of the Eastern divisions. In total, the inspectors suggested opening 641 schools across 20 divisions. These were mostly public and farm schools. By 1905 only 63 of these schools were in operation reflecting how the top-down approach in education provision was not very successful in the rural divisions. Nonetheless, other schools did open in these divisions, even if they were not among those initially recommended (Cape Colony, 1905).

This expansionist period continued until 1920. Following the 1905 *School Board Act*, local governance in education expanded, leading to the introduction of compulsory schooling for white children within three miles of a school by 1907 (Cape Colony, 1907). By 1913, all school boards had enforced compulsory education, spurring a rapid increase in public schools, particularly in rural areas. The number of schools more than doubled, from 735 in 1905 to 1,834 by 1920, and student enrollment nearly doubled, reflecting both growing demand and improved financial capacity. The Act also introduced the legal basis for racial segregation in education, ensuring near-universal schooling for white children, while black education remained under missionary control (Elliott, 2021, p. 128). Over the following decades, compulsory education for white children expanded in terms of age, standards, and distance criteria.

The 1910 formation of the Union of South Africa had little direct impact on education, which remained under provincial control until 1953 (Thompson, 2014, p. 153). The 1917 school reform introduced a structured classification of primary, intermediate, and secondary schools, requiring rural students to transfer to urban institutions for advanced education (Cape Colony, 1917). Finally, in 1920, free primary education was introduced in the Cape, marking the end of the expansionist period. While access improved, teacher shortages and stagnant academic standards limited quality improvements, though compulsory schooling became a lasting achievement.

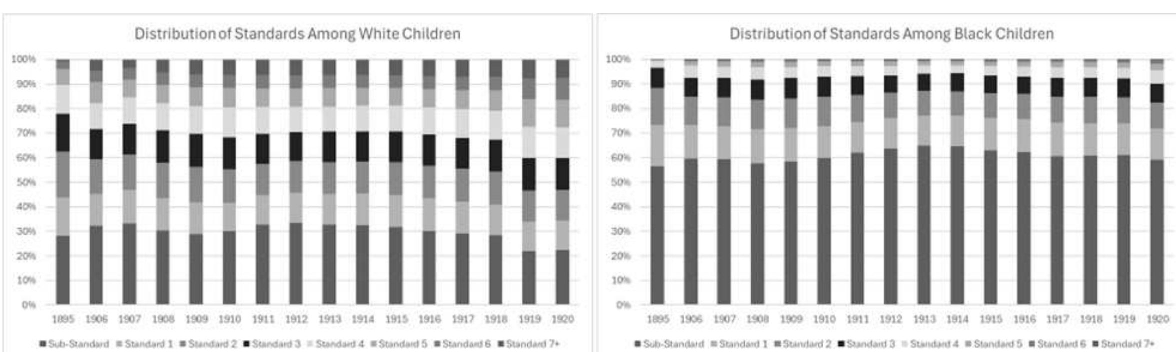
Black education. When examining the trends in black education during this period, it is essential to recognize the disparity between the official goals of education policies and their actual underlying intentions (Molteno, 1987, p. 45). The purpose of education for black people was often less about imparting knowledge and more about molding them into roles predefined by the white minority. For instance, in 1883, SGE Dale described education as "the cheapest and surest way of preserving tranquility, of encouraging the demand for clothing and other articles used by civilized people, and of assisting in the agricultural and other industrial interests of those territories" (Cape Colony, 1883, p. 6). In 1887, he further emphasized that "if the state does not by education fit the Native into the grooves of colonial society, what then will you do with him?" (Cape Colony, 1887, p. 6). Even relatively liberal educationists of the time, like Charles T. Loram, argued that it was in the moral, social, and economic interest of the white population to provide education to the black population (Loram, 1917, p. 28). Thus, while missionary societies may have had more altruistic goals, the government's primary interest lay in providing basic mass education as a form of social control (Molteno, 1987, p. 63) and ensuring a steady supply of cheap labour for mines and farms (Thompson, 2014, p. 112). Consequently, any discussion of trends in black education must keep these racist ideologies that shaped policy decisions in mind.

Between 1881 and 1905, there was a gradual but continuous increase in the number of mission schools and their students. In 1881, approximately 20 different missionary societies operated these schools, with nearly half of them run by the Wesleyan Missionary Society and the English Church (Cape Colony, 1881). As shown in Figures E.8 and E.9, there were 416 mission schools with 45,300 students in 1881, which increased to 921 schools with 76,015 students by 1920. However, this growth was slower compared to the expansion of white schools. This disparity is further evident when comparing the percentage of the total population enrolled in school in 1891 and 1921 (Cape Colony, 1891a; Union of South Africa, 1921). In 1891, about 5.4 percent of the white population and

6.8 percent of the black population were enrolled in school, reflecting the early efforts of missionary societies. By 1921, 20.7 percent of the white population was enrolled in school, compared to only 13 percent of the black population. While the Department of Education successfully increased school attendance among white children, black education remained largely dependent on local initiatives and missionary efforts.

Despite these trends, the white population harbored fears that an overly educated black population might resist labour roles or demand higher wages (Cape Colony, 1891b). However, the quality of education in black schools was significantly lower than in white schools, visible in Figure E.10. While 20 to 30 percent of white students were in the Sub-Standards between 1881 and 1920, approximately 60 percent of black students were held at this level, indicating that many were held back multiple years. A report by the Institute of Race Relations even suggested that half of the black schools could have been closed without any significant loss in knowledge dissemination (Horrell, 1964, p. 12). Black schools were severely under-resourced due to inadequate government funding, a lack of qualified teachers (Cape Colony, 1901), and rivalry between missionary societies (Cape Colony, 1892). Those teachers who did receive any training were often instructed in English, which they then used to teach, even in the lower grades, despite it not being the students' vernacular language (Cape Colony, 1897). As a result, while the quantity of education increased, its quality stagnated.

Figure E.10: Distribution of Standards in Cape Colony (1895-1920). Data sourced from *Cape Colony Education Reports*. Authors' own representation.



By the late 19th century, there was a growing demand for education among the black population, but the economic conditions made it increasingly difficult for them to afford it (Molteno, 1987). The Rinderpest epidemic of 1896–1897 devastated cattle herds, a major source of wealth for the population (Thompson, 2014, p. 123). Additionally, the shrinking availability of land, culminating in the 1913 *Native Lands Act* prohibiting the sale of land to black people, increased the dependence on wage labour as subsistence farming did not produce enough output anymore (Thompson, 2014, p. 123). These worsening socio-economic conditions limited the potential for greater expansion of schooling during this period.

In terms of governmental education policy, little was done for the black population until the introduction of free primary education in 1920. The government had no interest in expanding black schools, as it relied on a large, relatively uneducated labour force. The expansion of black education thus depended on the initiative of the local population and missionary societies. Instead, the government focused on ensuring segregation within the school system, which was largely achieved by 1909. It was only after 1920 that the Education Department and the government began to show a slightly stronger interest in black education.

E.8.2 Data Overview

Table E.6: Balance Tests - Not Found vs. Found Schools

Variable	No. Not Found	No. Found	Mean Not Found	Mean Found	Diff.	Std. Err.	t Value	p Value
1881 All Schools								
Enrolment	39	506	40.974	91.731	-50.757	15.558	-3.25	.001
Attendance	39	506	23.769	50.617	-26.848	7.442	-3.6	.001
1881 White Schools								
Enrolment	20	190	33.800	56.153	-22.352	9.619	-2.3	.021
Attendance	20	190	21.650	37.047	-15.398	6.946	-2.2	.028
1881 Black Schools								
Enrolment	19	316	48.526	113.124	-64.597	25.963	-2.5	.013
Attendance	19	316	26.000	58.776	-32.776	11.941	-2.75	.007
1896 All Schools								
Enrolment	148	1252	26.477	63.625	-37.148	5.401	-6.9	0
Attendance	148	1252	19.918	47.494	-27.576	3.998	-6.9	0
Average Standard	120	1158	1.270	1.318	-.047	.089	-.55	.595
Share Std. 4 or Higher	120	1158	0.081	.11	-.029	.015	-1.9	.06
1896 White Schools								
Enrolment	109	707	15.218	49.772	-34.554	5.798	-5.95	0
Attendance	109	707	12.664	40.554	-27.89	4.752	-5.85	0
Average Standard	82	637	1.486	1.776	-.29	.109	-2.65	.008
Share Std. 4 or Higher	82	637	0.108	.175	-.067	.021	-3.25	.002
1896 Black Schools								
Enrolment	39	545	57.943	81.595	-23.652	10.751	-2.2	.028
Attendance	39	545	40.193	56.497	-16.305	7.274	-2.25	.026
Average Standard	38	521	0.806	.758	.049	.092	.55	.595
Share Std. 4 or Higher	38	521	0.022	.03	-.008	.015	-.55	.583
1905 All Schools								
Enrolment	235	1553	24.197	65.992	-41.796	4.394	-9.5	0
Attendance	235	1553	20.283	56.073	-35.79	3.844	-9.3	0
Average Standard	184	1387	1.268	1.358	-.089	.076	-1.15	.242
Share Std. 4 or Higher	184	1387	0.104	.137	-.033	.013	-2.45	.013
1905 White Schools								
Enrolment	174	895	14.973	58.599	-43.626	5.413	-8.05	0
Attendance	174	895	13.199	52.325	-39.126	4.918	-7.95	0
Average Standard	128	770	1.524	1.832	-.308	.094	-3.25	.001
Share Std. 4 or Higher	128	770	0.139	.209	-.071	.017	-4.2	0
1905 Black Schools								
Enrolment	61	658	50.508	76.049	-25.541	7.602	-3.35	.001
Attendance	61	658	40.492	61.172	-20.681	6.25	-3.3	.001
Average Standard	56	617	0.684	.767	-.083	.079	-1.05	.293
Share Std. 4 or Higher	56	617	0.026	.046	-.021	.013	-1.5	.131

Table E.7: Summary Statistics - School-Level

Variable	Obs.	Mean	Std. Dev.	Min	Max
1881 All Schools					
Number of Students	267	112.966	121.96	10	790
Distance Coast (km)	286	35.557	37.013	0.418	226.519
Average Rainfall	286	39.66	42.488	3.8	170.7
Average Temperature	286	20.244	0.885	18.1	22.4
Average Altitude	286	273.486	217.871	3.694	1244.694
Ruggedness	286	123.351	97.443	5.636	334.081
Soil Quality	286	3.448	1.516	0.25	6.389
Dist. to Cape Town (km)	286	150.759	141.622	1.542	546.111
Dist. to Gqeberha (km)	286	539.464	146.318	199.613	737.704
Dist. to Kimberley (km)	286	736.883	95.625	367.73	853.858
Dist. to Colonial Railway (km)	286	24.468	25.464	0.246	173.774
Dist. to Explorer Route (km)	286	396.069	52.415	267.614	460.079
1881 White Schools					
Number of Students	105	57.01	41.838	10	247
Distance Coast (km)	118	46.087	39.988	0.418	226.519
Average Rainfall	118	47.572	48.902	3.8	170.7
Average Temperature	118	20.356	0.904	18.7	22.4
Average Altitude	118	294.604	230.668	10.75	1244.694
Ruggedness	118	101.178	75.637	5.636	334.081
Soil Quality	118	3.218	1.537	0.25	6.389
Dist. to Cape Town (km)	118	188.581	145.784	1.542	546.111
Dist. to Gqeberha (km)	118	502.13	152.467	208.805	717.405
Dist. to Kimberley (km)	118	708.494	95.981	367.73	853.858
Dist. to Colonial Railway (km)	118	24.002	25.167	0.254	173.774
Dist. to Explorer Route (km)	118	382.38	54.849	267.614	456.623
1881 Black Schools					
Number of Students	162	149.235	141.699	18	790
Distance Coast (km)	168	28.161	32.928	0.418	183.606
Average Rainfall	168	34.102	36.47	3.8	170.7
Average Temperature	168	20.166	0.866	18.1	22.3
Average Altitude	168	258.652	207.832	3.694	926.861
Ruggedness	168	138.925	107.726	5.636	334.081
Soil Quality	168	3.609	1.484	0.25	6.389
Dist. to Cape Town (km)	168	124.193	132.733	1.542	466.304
Dist. to Gqeberha (km)	168	565.687	136.284	199.613	737.704
Dist. to Kimberley (km)	168	756.823	90.453	451.679	853.858
Dist. to Colonial Railway (km)	168	24.794	25.741	0.246	171.748
Dist. to Explorer Route (km)	168	405.684	48.534	277.034	460.079
1896 All Schools					
Number of Students	528	32.495	37.555	0	321
Share Above Std. 4	492	0.127	0.173	0	0.88
Average Standard	492	1.4	0.997	0	5.177
Distance Coast (km)	528	40.79	39.909	0.178	228.432
Average Rainfall	528	45.156	43.509	3.8	170.7
Average Temperature	528	20.336	0.887	18.1	23
Average Altitude	528	311.69	257.442	7.056	1487.333
Ruggedness	528	117.755	96.009	4.988	471.539
Soil Quality	528	3.593	1.55	0.25	6.944
Dist. to Cape Town (km)	528	181.177	146.774	1.542	546.111
Dist. to Gqeberha (km)	528	508.195	152.309	185.749	735.569
Dist. to Kimberley (km)	528	715.844	101.501	367.73	853.858
Dist. to Colonial Railway (km)	528	24.762	25.256	0.246	173.774
Dist. to Explorer Route (km)	528	384.739	54.556	267.614	460.079

Table 7: cont.

Variable	Obs.	Mean	Std. Dev.	Min	Max
1896 White Schools					
Number of Students	331	33.091	41.98	0	321
Share Above Std. 4	303	0.192	0.191	0	0.88
Average Standard	303	1.841	1.009	0	5.177
Distance Coast (km)	331	46.767	40.967	0.178	228.432
Average Rainfall	331	50.899	45.826	3.8	170.7
Average Temperature	331	20.414	0.884	18.6	23
Average Altitude	331	346.411	274.417	10.556	1487.333
Ruggedness	331	109.15	91.722	4.988	471.539
Soil Quality	331	3.593	1.617	0.25	6.944
Dist. to Cape Town (km)	331	210.956	145.297	1.542	546.111
Dist. to Gqeberha (km)	331	478.093	152.636	185.749	720.938
Dist. to Kimberley (km)	331	694.659	100.304	367.73	853.858
Dist. to Colonial Railway (km)	331	25.284	24.656	0.254	173.774
Dist. to Explorer Route (km)	331	373.83	54.565	267.614	456.645
1896 Black Schools					
Number of Students	197	31.495	28.693	0	192
Share Above Std. 4	189	0.022	0.045	0	0.306
Average Standard	189	0.694	0.383	0	2.444
Distance Coast (km)	197	30.747	35.988	0.178	226.519
Average Rainfall	197	35.508	37.481	3.8	170.7
Average Temperature	197	20.206	0.878	18.1	22.4
Average Altitude	197	253.351	214.375	7.056	1244.694
Ruggedness	197	132.213	101.412	5.636	334.081
Soil Quality	197	3.592	1.434	0.25	6.389
Dist. to Cape Town (km)	197	131.144	135.519	1.542	546.111
Dist. to Gqeberha (km)	197	558.773	138.013	208.902	735.569
Dist. to Kimberley (km)	197	751.439	93.436	367.73	853.858
Dist. to Colonial Railway (km)	197	23.885	26.273	0.246	173.774
Dist. to Explorer Route (km)	197	403.069	49.51	267.614	460.079
1905 All Schools					
Number of Students	396	48.098	56.065	0	367
Share Above Std. 4	381	0.161	0.188	0	1
Average Standard	381	1.485	1.137	0.026	6.596
Distance Coast (km)	396	40.548	40.224	0.178	226.638
Average Rainfall	396	44.492	43.665	3.8	170.7
Average Temperature	396	20.342	0.907	18.1	23
Average Altitude	396	300.714	242.273	7.056	1368.611
Ruggedness	396	118.947	94.898	5.636	471.539
Soil Quality	396	3.515	1.562	0.25	6.778
Dist. to Cape Town (km)	396	176.849	146.293	1.542	546.111
Dist. to Gqeberha (km)	396	512.907	151.788	194.991	735.569
Dist. to Kimberley (km)	396	718.069	100.44	367.73	853.858
Dist. to Colonial Railway (km)	396	24.391	25.356	0.254	173.774
Dist. to Explorer Route (km)	396	386.417	54.403	267.614	460.079
1905 White Schools					
Number of Students	243	55.086	66.014	0	367
Share Above Std. 4	232	0.249	0.194	0	1
Average Standard	232	2.066	1.094	0.278	6.596
Distance Coast (km)	243	45.797	40.668	0.418	226.638
Average Rainfall	243	49.682	46.131	3.8	170.7
Average Temperature	243	20.404	0.901	18.628	23
Average Altitude	243	331.852	248.389	10.556	1368.611
Ruggedness	243	115.223	93.949	6.95	471.539
Soil Quality	243	3.526	1.634	0.25	6.778
Dist. to Cape Town (km)	243	200.888	147.552	1.542	546.111
Dist. to Gqeberha (km)	243	486.84	153.42	194.991	717.405
Dist. to Kimberley (km)	243	700.176	99.699	367.73	853.858
Dist. to Colonial Railway (km)	243	23.951	24.442	0.254	173.774
Dist. to Explorer Route (km)	243	377.064	54.911	267.614	456.623

Table 7: cont.

Variable	Obs.	Mean	Std. Dev.	Min	Max
1905 Black Schools					
Number of Students	153	37	32.064	0	189
Share Above Std. 4	149	0.023	0.032	0	0.163
Average Standard	149	0.581	0.315	0.026	1.587
Distance Coast (km)	153	32.211	38.178	0.178	226.519
Average Rainfall	153	36.249	38.147	3.8	170.7
Average Temperature	153	20.243	0.91	18.1	22.4
Average Altitude	153	251.258	224.258	7.056	1244.694
Ruggedness	153	124.861	96.4	5.636	334.081
Soil Quality	153	3.497	1.444	0.25	6.389
Dist. to Cape Town (km)	153	138.67	136.242	1.542	546.111
Dist. to Gqeberha (km)	153	554.307	139.953	208.902	735.569
Dist. to Kimberley (km)	153	746.488	95.215	367.73	853.858
Dist. to Colonial Railway (km)	153	25.09	26.811	0.514	173.774
Dist. to Explorer Route (km)	153	401.273	50.287	267.614	460.079
2018 Contemporary Schools					
Number of Students	1706	668.673	458.009	0	1902
Gr. 3 Language Test Score	1077	19.746	6.798	4.889	36.808
Gr. 3 Math Test Score	1077	20.57	6.244	3.889	35.462
Gr. 6 Math Test Score	1040	23.243	7.649	7.238	47.509
Gr. 6 Language Test Score	1040	29.782	8.182	11.357	53.87
Gr. 9 Language Test Score	456	35.917	7.921	21.318	57.365
Gr. 9 Math Test Score	456	16.981	7.924	7.292	39.357
Urban	1703	0.555	0.497	0	1
School Quintile (SES)	1700	3.386	1.49	1	5
Distance Coast (km)	1706	25.768	33.668	0.178	226.519
Average Rainfall	1706	28.083	33.205	3.8	170.7
Average Temperature	1706	20.287	0.773	18.1	23
Average Altitude	1706	175.12	217.676	0.472	1705.5
Ruggedness	1706	68.515	80.774	2.794	496.084
Soil Quality	1706	3.124	1.231	0.083	6.694
Dist. to Cape Town (km)	1706	94.284	120.629	1.542	546.111
Dist. to Gqeberha (km)	1706	590.805	118.286	194.991	788.05
Dist. to Kimberley (km)	1706	773.947	80.537	367.73	856.826
Dist. to Colonial Railway (km)	1706	21.333	24.756	0.179	176.904
Dist. to Explorer Route (km)	1706	414.783	42.286	267.605	460.079

Table E.8: Summary Statistics - Raster-Level (0.05×0.05 Degrees)

Variable	Obs.	Mean	Std. Dev.	Min	Max
1881 All Schools					
Number of Students	141	87.409	90.359	10	738
Distance Coast (km)	153	36.988	35.098	0.418	226.519
Average Rainfall	153	44.296	47.438	3.8	170.7
Average Temperature	153	20.316	0.963	18.1	22.4
Average Altitude	153	275.313	227.086	3.694	1244.694
Ruggedness	153	101.72	78.964	5.636	334.081
Soil Quality	153	3.324	1.55	0.25	6.389
Dist. to Cape Town (km)	153	176.577	139.13	1.542	546.111
Dist. to Gqeberha (km)	153	521.295	152.903	199.613	737.704
Dist. to Kimberley (km)	153	723.239	91.408	367.73	853.858
Dist. to Colonial Railway (km)	153	28.817	29.795	0.246	173.774
Dist. to Explorer Route (km)	153	389.301	54.007	267.614	460.079
1881 White Schools					
Number of Students	82	55.197	38.022	10	228
Distance Coast (km)	94	43.183	38.792	0.418	226.519
Average Rainfall	94	48.747	50.071	3.8	170.7
Average Temperature	94	20.373	0.95	18.7	22.4
Average Altitude	94	287.072	217.282	10.75	1244.694
Ruggedness	94	103.258	79.2	5.636	334.081
Soil Quality	94	3.231	1.555	0.25	6.389
Dist. to Cape Town (km)	94	190.929	145.388	1.542	546.111
Dist. to Gqeberha (km)	94	502.301	156.468	208.805	717.405
Dist. to Kimberley (km)	94	709.581	94.598	367.73	853.858
Dist. to Colonial Railway (km)	94	25.902	26.643	0.254	173.774
Dist. to Explorer Route (km)	94	382.523	55.704	267.614	456.623
1881 Black Schools					
Number of Students	97	118.433	117.278	18	738
Distance Coast (km)	102	33.458	32.586	0.418	183.606
Average Rainfall	102	36.371	40.665	3.8	170.7
Average Temperature	102	20.261	0.952	18.1	22.3
Average Altitude	102	258.777	232.008	3.694	926.861
Ruggedness	102	106.63	83.742	5.636	334.081
Soil Quality	102	3.42	1.505	0.25	6.389
Dist. to Cape Town (km)	102	150.141	126.613	1.542	466.304
Dist. to Gqeberha (km)	102	548.873	138.72	199.613	737.704
Dist. to Kimberley (km)	102	741.684	85.766	451.679	853.858
Dist. to Colonial Railway (km)	102	28.831	29.321	0.246	171.748
Dist. to Explorer Route (km)	102	399.28	48.815	277.034	460.079
1896 All Schools					
Number of Students	312	20.706	21.89	0	192
Share Above Std. 4	287	0.106	0.123	0	0.571
Average Standard	287	1.316	0.724	0	3.357
Distance Coast (km)	312	44.954	39.978	0.178	228.432
Average Rainfall	312	51.787	47.633	3.8	170.7
Average Temperature	312	20.405	0.943	18.1	23
Average Altitude	312	340.98	287.009	7.056	1487.333
Ruggedness	312	98.246	80.266	4.988	471.539
Soil Quality	312	3.638	1.596	0.25	6.944
Dist. to Cape Town (km)	312	217.358	140.268	1.542	546.111
Dist. to Gqeberha (km)	312	477.262	154.431	185.749	735.569
Dist. to Kimberley (km)	312	694.099	97.634	367.73	853.858
Dist. to Colonial Railway (km)	312	28.277	27.353	0.246	173.774
Dist. to Explorer Route (km)	312	373.384	54.789	267.614	460.079

Table 8: cont.

Variable	Obs.	Mean	Std. Dev.	Min	Max
1896 White Schools					
Number of Students	193	29.015	29.847	0	186
Share Above Std. 4	182	0.197	0.164	0	0.635
Average Standard	182	1.904	0.849	0.083	4.512
Distance Coast (km)	193	53.701	42.855	0.178	228.432
Average Rainfall	193	46.06	42.47	3.8	170.7
Average Temperature	193	20.52	0.873	18.628	22.9
Average Altitude	193	357.223	282.593	10.75	1487.333
Ruggedness	193	95.016	76.139	7.11	426.894
Soil Quality	193	3.499	1.649	0.25	6.778
Dist. to Cape Town (km)	193	209.155	138.551	1.542	546.111
Dist. to Gqeberha (km)	193	484.087	145.37	194.991	720.938
Dist. to Kimberley (km)	193	691.837	101.294	367.73	853.858
Dist. to Colonial Railway (km)	193	26.789	27.071	0.254	173.774
Dist. to Explorer Route (km)	193	375.476	52.349	267.614	456.645
1896 Black Schools					
Number of Students	119	25.454	26.436	0	192
Share Above Std. 4	114	0.014	0.029	0	0.2
Average Standard	114	0.638	0.313	0	1.8
Distance Coast (km)	119	35.963	37.665	0.178	226.519
Average Rainfall	119	40.223	43.149	3.8	170.7
Average Temperature	119	20.322	0.959	18.1	22.4
Average Altitude	119	261.748	244.13	7.056	1244.694
Ruggedness	119	104.528	80.513	5.636	334.081
Soil Quality	119	3.411	1.475	0.25	6.389
Dist. to Cape Town (km)	119	166.745	133.912	1.542	546.111
Dist. to Gqeberha (km)	119	533.091	145.617	208.902	735.569
Dist. to Kimberley (km)	119	730.555	92.659	367.73	853.858
Dist. to Colonial Railway (km)	119	28.73	30.547	0.246	173.774
Dist. to Explorer Route (km)	119	393.346	51.77	267.614	460.079
1905 All Schools					
Number of Students	224	32.638	30.852	0	166.5
Share Above Std. 4	216	0.144	0.122	0	0.474
Average Standard	216	1.415	0.731	0.043	3.316
Distance Coast (km)	224	44.398	39.444	0.178	226.638
Average Rainfall	224	50.249	47.581	3.8	170.7
Average Temperature	224	20.409	0.963	18.1	23
Average Altitude	224	329.591	264.753	7.056	1368.611
Ruggedness	224	103.232	81.54	5.636	471.539
Soil Quality	224	3.584	1.6	0.25	6.778
Dist. to Cape Town (km)	224	209.671	139.783	1.542	546.111
Dist. to Gqeberha (km)	224	486.032	154.901	194.991	735.569
Dist. to Kimberley (km)	224	698.65	95.712	367.73	853.858
Dist. to Colonial Railway (km)	224	27.879	27.784	0.254	173.774
Dist. to Explorer Route (km)	224	376.561	54.904	267.614	460.079
1905 White Schools					
Number of Students	137	50.884	52.195	0	295
Share Above Std. 4	131	0.269	0.147	0.032	0.667
Average Standard	131	2.167	0.806	0.548	4.434
Distance Coast (km)	137	52.916	41.783	0.418	226.638
Average Rainfall	137	46.737	42.737	3.969	170.7
Average Temperature	137	20.501	0.865	18.628	22.6
Average Altitude	137	347.735	258.035	10.75	1244.694
Ruggedness	137	102.831	77.635	8.017	426.894
Soil Quality	137	3.443	1.682	0.25	6.778
Dist. to Cape Town (km)	137	203.676	138.914	1.542	546.111
Dist. to Gqeberha (km)	137	485.764	144.055	194.991	717.405
Dist. to Kimberley (km)	137	694.463	97.415	367.73	853.858
Dist. to Colonial Railway (km)	137	24.48	25.838	0.254	173.774
Dist. to Explorer Route (km)	137	376.388	51.954	267.614	456.623

Table 8: cont.

Variable	Obs.	Mean	Std. Dev.	Min	Max
1905 Black Schools					
Number of Students	103	33.291	31.249	0	189
Share Above Std. 4	100	0.023	0.034	0	0.163
Average Standard	100	0.574	0.305	0.026	1.433
Distance Coast (km)	103	36.321	39.172	0.178	226.519
Average Rainfall	103	39.612	42.494	3.8	170.7
Average Temperature	103	20.345	0.976	18.1	22.4
Average Altitude	103	260.327	243.504	7.056	1244.694
Ruggedness	103	106.993	82.24	5.636	334.081
Soil Quality	103	3.379	1.473	0.25	6.389
Dist. to Cape Town (km)	103	166.378	133.112	1.542	546.111
Dist. to Gqeberha (km)	103	535.988	145.527	208.902	735.569
Dist. to Kimberley (km)	103	730.396	92.94	367.73	853.858
Dist. to Colonial Railway (km)	103	29.736	30.72	0.514	173.774
Dist. to Explorer Route (km)	103	394.234	51.8	267.614	460.079
2018 Contemporary Schools					
Number of Students	458	412.478	352.842	0	1520
Gr. 3 Language Test Score	365	17.677	6.136	4.889	33.556
Gr. 3 Math Test Score	365	18.414	6.059	3.889	34.235
Gr. 6 Math Test Score	357	20.883	6.536	7.238	41.329
Gr. 6 Language Test Score	357	27.705	6.983	11.357	50.471
Gr. 9 Language Test Score	166	35.478	6.397	23.667	53.857
Gr. 9 Math Test Score	166	16.529	6.34	7.292	35.675
Urban	457	0.161	0.367	0	1
School Quintile (SES)	458	2.412	1.445	1	5
Distance Coast (km)	458	45.405	40.826	0.178	226.519
Average Rainfall	458	34.695	40.336	3.8	170.7
Average Temperature	458	20.465	0.897	18.1	23
Average Altitude	458	320.298	297.428	0.472	1705.5
Ruggedness	458	96.804	84.183	2.794	496.084
Soil Quality	458	3.449	1.572	0.083	6.694
Dist. to Cape Town (km)	458	161.572	126.2	1.542	546.111
Dist. to Gqeberha (km)	458	545.847	137.626	194.991	788.05
Dist. to Kimberley (km)	458	726.122	85.839	367.73	856.826
Dist. to Colonial Railway (km)	458	29.813	33.826	0.179	176.904
Dist. to Explorer Route (km)	458	397.218	48.205	267.605	460.079

Table E.9: Geographic and Historical Control Variables

Variable	Source	Comments	Access
Rainfall	Harris et al. (2020)	Average rainfall during 1911-1920 in raster cell (mean)/at contemporary school location based on CRU TS V4.	Harris, I., Osborn, T.J., Jones, P. et al. Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. Sci Data 7, 109 (2020).
Temperature	Harris et al. (2020)	Average temperature during 1911-1920 in raster cell (mean)/at contemporary school location based on CRU TS V4	Harris, I., Osborn, T.J., Jones, P. et al. Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. Sci Data 7, 109 (2020).
Altitude	US Geological Services (2024)	Altitude in raster cell (mean)/ at contemporary school location.	https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-30-arc-second-elevation-gtopo30
Ruggedness	US Geological Services (2024)	Ruggedness (std. of altitude) in raster cell (mean)/at contemporary school location.	https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-30-arc-second-elevation-gtopo30
Distance to Coast	n.a.	Distance in km from center of raster cell/contemporary school location.	
Soil Quality (Global Agro-Ecological Zones)	Fischer et al. (2008)	Soil suitability (rain-fed, low inputs) in raster cell (mean)/ contemporary school location.	http://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/
Colonial Railways	Nunn (2011)	Distance in km from center of raster/contemporary school location.	Nunn, N. (2011), The Slave Trade and the Origins of Mistrust in Africa, American Economic Review, 101 (7), 3221-3252.
Explorer Routes	Nunn (2011)	Distance in km from center of raster/contemporary school location.	Nunn, N. (2011), The Slave Trade and the Origins of Mistrust in Africa, American Economic Review, 101 (7), 3221-3252.
Ethnic Groups	Murdock (1967), digitized by Nunn (2008)	Each raster cell/ contemporary school location assigned to an ethnic group according to Murdock.	Murdock, G. P. (1967). Ethnographic atlas: A summary. Ethnology, 6(2), 109-236. Nunn, N. (2008). The Long-Term Effects of Africa's Slave Trades, The Quarterly Journal of Economics, 123(1), 139-176.
Distance to Cape Town	n.a.	Distance in km from center of raster/contemporary school location.	
Distance to Gqeberha	n.a.	Distance in km from center of raster/contemporary school location.	
Distance to Kimberley	n.a.	Distance in km from center of raster/contemporary school location.	

E.8.3 Pontential Endogeneity of School Placement

The literature on the economics of schooling expansion in Sub-Saharan Africa suggests that schools were not randomly opened across space but that missionaries accounted for a variety of factors. Jedwab et al. (2022) demonstrate that in the former Gold Coast, missionaries initially selected areas that were less susceptible to tropical diseases like malaria, more accessible, and wealthier. Their findings also suggest that similar patterns existed across other African countries. However, the Cape's colonization process was notably different given the significant influx of Europeans. Additionally, the absence of tropical diseases in the Cape meant that neither settlers nor missionaries had to alter their behavior due to concerns about health risks or the discovery of a cure. Given these unique conditions, it is worth examining whether the expansion of education in the Cape followed the same patterns as elsewhere on the continent.

We follow a similar approach to Jedwab et al. (2022) to understand the spread of schools in the Cape. We partition the area in cells each 0.05×0.05 degrees (about 5 kilometers) and assign each school to its respective cell. As potential determinants of school locations we include the historical and geographical variables presented in the data section. We run the model as a repeated cross-section for 1881, 1896 and 1905 for all schools and for white and black schools separately. The models for 1896 and 1905 include a dummy indicating whether there was a school already present in the previous period. Moreover, we run each model once without and once with division fixed effects as the former allows us to include the information from the Cape Colony censuses.

Table E.10 presents the results of this exercise. In contrast to previous results, we do not find strong evidence that white, nor black schools were located in areas with more infrastructure or wealth, nor did they move to less advantageous locations over time. Panel A presents the results for all schools with even numbered columns adding division fixed effects. While there is some evidence for all schools that they were located in areas with slightly more rain and closer to the railway both coefficients are very small. Moreover, it appears that schools were initially located in areas with worse soil quality and moved to areas with better soil compared to 1881. In general, these climatic and historical variables cannot explain much of the variation. In Panel B focusing on white school, we overall find very similar results. The white schools in 1881 were located in slightly cooler areas and closer to the railway. Again, however, soil quality increases over time. Moreover, in both cases neither the share of literates nor the number of ploughs or engines in the division as a proxy for economic development correlate with the existence of a school. Panel C presents the results for black schools. We find limited evidence that the soil quality improves over time as the size of the negative coefficient decreases but remains significant. However, in 1905 the existence of a black school correlates negatively with the number of engines per division and positively with the share of the black population. These coefficients potentially capture the strong concentration of black schools in the eastern divisions where the majority of the population was Xhosa and hence little state-led industrialization happened. Overall, we cannot find convincing evidence, albeit only correlational, that the expansion of the education system followed the same pattern in the Cape as it did in other African countries. Schools were not located in areas with better infrastructure or economic development. This is especially noteworthy given the low population density in the Cape, especially its interior. Therefore, as discussed in the section on the longitudinal expansion, local demand probably was more important than climatic or other historical conditions for the opening of a school.

Given this low population density we further explore whether the state or missionaries followed a strategy where to open a school at the local level. Hence, we rerun the same analysis, but only compare a raster cell with a school to the empty adjacent cells instead of all other cells. Table E.11 presents the results. The results show some evidence that schools were in cooler places, however, soil quality is still worse in cells with schools compared to the adjacent cell. Moreover, there is no change over time which would indicate that schools locate to less advantageous locations over time. Again, it is rather likely that local demand was important.

It is undeniable that the black school system was neglected by the government as it received only fraction of the resources available for the white school system. However, this does not necessarily imply that black schools were located in areas with worse climatic conditions or infrastructure. For example, Fourie and Swanepoel (2015) argued that the mission schools operating in 1849 were located in areas with lower economic potential. However, in 1849 there were only 20 mission schools operating in the Cape, whereas this number had grown substantially by 1881. Therefore, we explore whether there are differences in the locations of public and mission schools. We drop all cells from our sample that include both a white and a black school which excludes most schools in towns.

Thus, we are left with a mostly rural sample for the following analysis whose results are in Table E.12. We find a negative correlation between the share of the black population and a public school which is not surprising. In 1896 and 1905, white schools are located slightly higher, less rugged terrain and closer to Cape Town. However, the effect sizes are very small. In addition, in 1905 white schools are located in hotter areas, on more nutritious soil and in less densely populated areas. However, access to infrastructure such as railways or economic development proxied by the number of engines does not differ between white and black schools. Thus, there we do not find evidence that black schools were located in overall less advantageous areas. The lower performance in these schools is thus much more likely explained by the little support they received to operate the schools efficiently.

Table E.10: Correlates of the Cape Colony's School Expansion

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	All Schools					
DV: Any School in Cell	1881		1896		1905	
School existed in previous period			0.811***	0.797***	0.654***	0.645***
			(0.022)	(0.024)	(0.026)	(0.025)
Distance Coast (km)	0.000*	0.000**	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Rainfall	0.000***	0.000*	0.000***	-0.000	0.001***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Temperature	-0.002*	-0.001	-0.003**	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average Altitude	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ruggedness	0.000***	0.000**	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soil Quality	-0.007***	-0.005***	-0.001	-0.002**	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dist. to Cape Town (km)	-0.000***	-0.000	-0.000**	-0.000	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Gqberha (km)	0.000	-0.000	0.000	0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Kimberley (km)	0.000**	0.000**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Colonial Railway (km)	-0.000*	-0.000	-0.000	-0.000	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Explorer Route (km)	-0.001**	0.000	-0.000**	-0.001**	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Literacy in Division	-0.000		0.012		-0.031	
	(0.001)		(0.055)		(0.033)	
Number of Ploughs in Division	0.000		0.000*		0.000***	
	(0.000)		(0.000)		(0.000)	
Number of Engines in Division			-0.002		-0.001***	
			(0.001)		(0.000)	
Share Black Population in Division	-0.000		-0.014		0.025	
	(0.022)		(0.031)		(0.018)	
Population Density in Division	0.000*		0.003		0.001***	
	(0.000)		(0.002)		(0.000)	
Constant	0.187**	-0.008	0.229***	0.235***	0.186***	0.128
	(0.076)	(0.134)	(0.076)	(0.077)	(0.066)	(0.087)
Observations	19,359	19,359	20,722	25,925	24,106	25,925
R-Squared	0.054	0.074	0.338	0.345	0.432	0.440
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Division FE	No	Yes	No	Yes	No	Yes

Table 10: cont.

Panel B	(1)	(2)	(3) White Schools	(4)	(5)	(6)
DV: White School in Cell	1881		1896		1905	
School existed in previous period			0.812***	0.791***	0.601***	0.596***
			(0.024)	(0.026)	(0.026)	(0.026)
Distance Coast (km)	0.000*	0.000***	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Rainfall	0.000**	0.000**	0.000***	-0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Temperature	-0.001	-0.001	-0.002*	-0.002**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average Altitude	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ruggedness	0.000***	0.000*	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soil Quality	-0.004***	-0.003***	-0.001	-0.002**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dist. to Cape Town (km)	-0.000***	-0.000*	-0.000***	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Gqberha (km)	0.000***	0.000	0.000**	0.000	0.000***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Kimberley (km)	0.000**	0.000**	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Colonial Railway (km)	-0.000**	-0.000*	-0.000	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Explorer Route (km)	-0.000***	-0.000	-0.000**	-0.000**	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Literacy in Division	-0.000		0.069		-0.018	
	(0.000)		(0.054)		(0.026)	
Number of Ploughs in Division	-0.000		-0.000		-0.000	
	(0.000)		(0.000)		(0.000)	
Number of Engines in Division			-0.001		-0.000	
			(0.001)		(0.000)	
Share Black Population in Division	-0.018		0.022		-0.006	
	(0.012)		(0.026)		(0.014)	
Population Density in Division	0.000		0.002		0.000	
	(0.000)		(0.001)		(.)	
Constant	0.139***	0.058	0.209***	0.219***	0.207***	0.141**
	(0.043)	(0.057)	(0.076)	(0.067)	(0.048)	(0.070)
Observations	19,359	19,359	20,722	25,925	24,106	25,925
R-Squared	0.025	0.039	0.229	0.238	0.337	0.344
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Division FE	No	Yes	No	Yes	No	Yes

Table 10: cont.

Panel C	(1)	(2)	(3)	(4)	(5)	(6)
	Black Schools					
DV: Black School in Cell	1881		1896		1905	
School existed in previous period			0.822***	0.820***	0.848***	0.841***
			(0.028)	(0.029)	(0.021)	(0.021)
Distance Coast (km)	0.000	0.000	0.000**	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Rainfall	0.000	0.000	0.000	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Temperature	-0.002	-0.000	-0.001**	-0.000	-0.000	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average Altitude	-0.000***	-0.000**	-0.000***	-0.000***	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ruggedness	0.000***	0.000***	0.000**	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soil Quality	-0.005***	-0.003***	-0.001**	-0.001**	-0.000	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Dist. to Cape Town (km)	-0.000**	-0.000	-0.000	0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Gqberha (km)	0.000	-0.000	-0.000	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Kimberley (km)	0.000**	0.000**	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Colonial Railway (km)	-0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Explorer Route (km)	-0.000*	0.000	-0.000	-0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Literacy in Division	-0.000		-0.032		-0.019	
	(0.000)		(0.027)		(0.014)	
Number of Ploughs in Division	0.000		0.000***		0.000***	
	(0.000)		(0.000)		(0.000)	
Number of Engines in Division			-0.001		-0.001***	
			(0.001)		(0.000)	
Share Black Population in Division	-0.000		-0.036*		0.029**	
	(0.018)		(0.020)		(0.013)	
Population Density in Division	0.000*		0.002**		0.001***	
	(0.000)		(0.001)		(0.000)	
Constant	0.123*	-0.027	0.070	0.053	0.045	0.095**
	(0.065)	(0.124)	(0.050)	(0.068)	(0.042)	(0.046)
Observations	19,359	19,359	20,722	25,925	24,106	25,925
R-Squared	0.044	0.065	0.497	0.502	0.692	0.699
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Division FE	No	Yes	No	Yes	No	Yes

Notes: The outcome variable is a dummy indicating whether a cell includes a school of the respective type. In Panel A these are all geo-referenced schools, in Panel B this is restricted to white schools and in Panel C this is restricted to black schools . The explanatory variables are all calculated at the raster cell level. The variables taken from the censuses (Average Literacy in Division, Number of Ploughs in Division, Number of Engines in Division, Share of Black Population in Division and Population Density in Division) as well as the Division FE always refer to the census taken prior to the school data year (1875 census data for 1881 school data, 1891a census data for 1896 school data, 1904 census for 1905 school data). The standard errors are adjusted for spatial autocorrelation. Stars denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table E.11: Correlates of the Cape Colony's School Expansion – Comparison with Adjacent Cells

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	All Schools					
DV: Any School in Cell	1881		1896		1905	
School existed in previous period			-0.018***	-0.025**	-0.009	-0.016*
			(0.006)	(0.011)	(0.007)	(0.009)
Distance Coast (km)	0.001***	-0.001	0.001***	0.002***	0.001***	0.001**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Average Rainfall	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Average Temperature	-0.052***	-0.072***	-0.054***	-0.062***	-0.056***	-0.071***
	(0.015)	(0.021)	(0.011)	(0.014)	(0.011)	(0.014)
Average Altitude	-0.000**	-0.001***	-0.000***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ruggedness	0.000	0.000	-0.001*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soil Quality	-0.029**	-0.044*	-0.022***	-0.031***	-0.019***	-0.022**
	(0.014)	(0.024)	(0.008)	(0.011)	(0.007)	(0.009)
Dist. to Cape Town (km)	-0.001**	-0.001***	-0.001***	-0.002***	-0.000**	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Gqberha (km)	0.000	0.002***	0.000	0.001	-0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. to Kimberley (km)	-0.001	-0.005***	-0.000	-0.001	-0.000*	-0.002***
	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)
Dist. to Colonial Railway (km)	0.001**	-0.002**	0.001**	0.000	0.000**	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Dist. to Explorer Route (km)	-0.002**	-0.007***	-0.002**	-0.005***	-0.001	-0.002
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Average Literacy in Division	-0.001		-0.140		-0.015	
	(0.002)		(0.242)		(0.116)	
Number of Ploughs in Division	0.000		-0.000		0.000**	
	(0.000)		(0.000)		(0.000)	
Number of Engines in Division			-0.001**		-0.003***	
			(0.001)		(0.001)	
Share Black Population in Division	0.089*		-0.023		0.097	
	(0.050)		(0.160)		(0.092)	
Population Density in Division	-0.000		0.001		-0.001***	
	(0.003)		(0.001)		(0.000)	
Constant	3.150***	7.356***	2.951***	4.327***	2.508***	4.194***
	(0.790)	(1.194)	(0.497)	(0.893)	(0.449)	(0.737)
Observations	652	643	1,621	1,644	2,012	1,996
R-Squared	0.031	0.050	0.029	0.042	0.031	0.044
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Division FE	No	Yes	No	Yes	No	Yes

Table 11: cont.

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
	White Schools					
DV: White School in Cell	1881		1896		1905	
School existed in previous period			-0.029***	-0.033**	-0.011	-0.021***
			(0.009)	(0.015)	(0.007)	(0.008)
Distance Coast (km)	0.002***	0.000	0.001**	0.002***	0.001***	0.001
	(0.001)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)
Average Rainfall	0.000	0.001	-0.000	-0.001	-0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Average Temperature	-0.051***	-0.077***	-0.052***	-0.053***	-0.054***	-0.068***
	(0.019)	(0.028)	(0.013)	(0.017)	(0.013)	(0.018)
Average Altitude	-0.000**	-0.001***	-0.000***	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ruggedness	0.000	0.001**	-0.001**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soil Quality	-0.044***	-0.066**	-0.026***	-0.033***	-0.019***	-0.018**
	(0.017)	(0.032)	(0.008)	(0.010)	(0.007)	(0.008)
Dist. to Cape Town (km)	-0.001*	-0.003**	-0.001**	-0.001**	-0.000**	-0.001***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Dist. to Gqberha (km)	-0.000	0.001	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Dist. to Kimberley (km)	0.000	-0.006**	-0.000	-0.000	-0.000*	-0.002***
	(0.001)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)
Dist. to Colonial Railway (km)	0.001**	0.001	0.000	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Dist. to Explorer Route (km)	-0.003	-0.008**	-0.001*	-0.003	-0.001	-0.001
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
Average Literacy in Division	-0.003*		-0.217		-0.202*	
	(0.002)		(0.245)		(0.122)	
Number of Ploughs in Division	-0.000		-0.000*		-0.000	
	(0.000)		(0.000)		(0.000)	
Number of Engines in Division			-0.001*		-0.002***	
			(0.001)		(0.001)	
Share Black Population in Division	0.099		0.054		0.025	
	(0.081)		(0.171)		(0.106)	
Population Density in Division	0.001		0.001		-0.001***	
	(0.004)		(0.001)		(0.000)	
Constant	3.081**	9.015***	2.681***	3.606***	2.666***	4.087***
	(1.439)	(2.924)	(0.564)	(0.998)	(0.535)	(0.947)
Observations	345	344	1,158	1,186	1,468	1,464
R-Squared	0.040	0.065	0.030	0.042	0.028	0.039
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Division FE	No	Yes	No	Yes	No	Yes

Table 11: cont.

Panel C	(1)	(2)	(3)	(4)	(5)	(6)
	Black Schools					
DV: Black School in Cell	1881		1896		1905	
School existed in previous period			0.002	-0.007	0.008	0.000
			(0.009)	(0.016)	(0.012)	(0.017)
Distance Coast (km)	0.001	-0.001	0.001	0.002	0.002***	0.002*
	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)
Average Rainfall	-0.001*	-0.000	-0.000	0.002**	0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Average Temperature	-0.052***	-0.078***	-0.055***	-0.068***	-0.050***	-0.054***
	(0.017)	(0.025)	(0.014)	(0.023)	(0.010)	(0.019)
Average Altitude	-0.000**	-0.001***	-0.000***	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ruggedness	0.000	0.001	0.000	0.001	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Soil Quality	-0.025	-0.039	-0.018	-0.033*	-0.026**	-0.046***
	(0.020)	(0.031)	(0.012)	(0.019)	(0.012)	(0.017)
Dist. to Cape Town (km)	-0.001***	-0.002***	-0.002***	-0.002***	-0.001***	-0.002**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Dist. to Gqberha (km)	0.000**	0.003***	0.000*	0.001**	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Dist. to Kimberley (km)	-0.002***	-0.006***	-0.001***	-0.002	-0.000	-0.003**
	(0.001)	(0.002)	(0.000)	(0.002)	(0.000)	(0.001)
Dist. to Colonial Railway (km)	0.001*	-0.002**	0.001*	-0.001	0.001**	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Dist. to Explorer Route (km)	-0.003***	-0.008***	-0.004***	-0.008***	-0.003***	-0.004*
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)
Average Literacy in Division	0.001		-0.053		0.126	
	(0.003)		(0.299)		(0.183)	
Number of Ploughs in Division	0.000		0.000		0.000**	
	(0.000)		(0.000)		(0.000)	
Number of Engines in Division			-0.002**		-0.002**	
			(0.001)		(0.001)	
Share Black Population in Division	0.120*		-0.294		0.261*	
	(0.071)		(0.202)		(0.144)	
Population Density in Division	0.000		0.002		-0.001**	
	(0.002)		(0.001)		(0.000)	
Constant	4.024***	8.267***	4.427***	5.926***	3.052***	5.140***
	(0.990)	(1.444)	(0.890)	(1.665)	(0.637)	(1.391)
Observations	469	463	742	743	861	849
R-Squared	0.031	0.049	0.034	0.058	0.042	0.078
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Division FE	No	Yes	No	Yes	No	Yes

Notes: The outcome variable is a dummy indicating whether a cell includes a school of the respective type (=1). The sample is restricted to cells with a school of the respective type and empty adjacent cells as a unit of comparison. In Panel A these are all geo-referenced schools, in Panel B this is restricted to white schools and in Panel C this is restricted to black schools. The explanatory variables are all calculated at the raster cell level. The variables taken from the censuses (Average Literacy in Division, Number of Ploughs in Division, Number of Engines in Division, Share of Black Population in Division and Population Density in Division) as well as the Division FE always refer to the census taken prior to the school data year (1875 census data for 1881 school data, 1891a census data for 1896 school data, 1904 census for 1905 school data). The standard errors are adjusted for spatial autocorrelation. Stars denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table E.12: Correlates of School Placement of White versus Black Schools

	(1)	(2)	(3)	(4)	(5)	(6)
	White vs. Black					
DV: White School in Cell	1881		1896		1905	
Distance Coast (km)	0.001	-0.001	0.000	-0.000	-0.000	-0.000
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Average Rainfall	0.002	0.002	0.001	0.000	0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Average Temperature	0.023	0.104**	0.028	0.028	0.015	0.032*
	(0.038)	(0.046)	(0.027)	(0.031)	(0.015)	(0.018)
Average Altitude	0.000	0.000	0.000***	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ruggedness	-0.000	-0.001	-0.001***	-0.001***	-0.001***	-0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Soil Quality	-0.027	-0.021	0.014	0.020	0.012	0.025**
	(0.039)	(0.036)	(0.013)	(0.012)	(0.008)	(0.012)
Dist. to Cape Town (km)	0.000	0.001	-0.001	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dist. to Gqeberha (km)	-0.001	-0.001	0.000	0.000	-0.000	0.001
	(0.001)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)
Dist. to Kimberley (km)	-0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)	(0.002)
Dist. to Colonial Railway (km)	-0.001	-0.004**	0.000	0.000	-0.000	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Dist. to Explorer Route (km)	0.004	0.006	-0.001	-0.002	0.001	-0.001
	(0.004)	(0.005)	(0.002)	(0.004)	(0.001)	(0.004)
Average Literacy in Division	0.000		-0.459		-0.604	
	(0.007)		(0.482)		(0.421)	
Number of Ploughs in Division	-0.000		-0.000		-0.000**	
	(0.000)		(0.000)		(0.000)	
Number of Engines in Division			-0.001		0.003	
			(0.003)		(0.002)	
Share Black Population in Division	-0.324*		1.520***		-1.332***	
	(0.175)		(0.330)		(0.389)	
Population Density in Division	-0.008		-0.005		-0.004***	
	(0.008)		(0.006)		(0.001)	
Constant	-0.581	-3.771	0.035	0.538	1.276	0.626
	(2.715)	(3.285)	(1.112)	(1.085)	(0.846)	(1.694)
Observations	244	244	684	706	833	848
R-Squared	0.164	0.396	0.343	0.448	0.401	0.490
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Division FE	No	Yes	No	Yes	No	Yes

Notes: The outcome variable is a dummy indicating there is a white school in a cell (=1) compared to a black school (=0). The explanatory variables are all calculated at the raster cell level. The variables taken from the censuses (Average Literacy in Division, Number of Ploughs in Division, Number of Engines in Division, Share of Black Population in Division and Population Density in Division) as well as the Division FE always refer to the census taken prior to the school data year (1875 census data for 1881 school data, 1891a census data for 1896 school data, 1904 census for 1905 school data). The standard errors are adjusted for spatial autocorrelation. Stars denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

E.8.4 Robustness Checks

Table E.13: Location-Quality Analysis – Closed School Locations as Counterfactual (Raster 0.1)

	(1)	(2)	(3)	(4)	(5)	(6)
	Grade 3		Grade 6		Grade 9	
	Math	Language	Math	Language	Math	Language
Panel A: All Schools 1905						
Open School in Raster Cell	1.401	1.719	2.125	2.311	0.008	3.107***
	(1.349)	(1.594)	(2.118)	(1.999)	(0.957)	(1.083)
Observations	143	143	141	141	87	87
R-Squared	0.509	0.442	0.486	0.482	0.455	0.481
Panel B: White Schools 1905						
Open School in Raster Cell	1.789	2.982**	1.657	2.321	-2.397	-0.142
	(1.300)	(1.487)	(1.703)	(1.549)	(1.691)	(2.089)
Observations	123	123	121	121	74	74
R-Squared	0.558	0.530	0.518	0.528	0.584	0.637
Panel C: Black Schools 1905						
Open School in Raster Cell	0.965	2.083***	3.463***	1.161**	-6.135*	-3.562**
	(1.969)	(0.709)	(1.092)	(0.526)	(3.373)	(1.680)
Observations	86	86	86	86	63	63
R-Squared	0.578	0.551	0.602	0.586	0.562	0.607
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show our counterfactual model for the location-quality analysis, i.e., the relationship between historic school locations and contemporary school performance captured by the mean test score achieved in the *Systemic Test*. The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 matched to a 0.1×0.1 degrees raster grid. The counterfactual are grid cells that included a school in 1896 but was closed by 1905. The sample is limited to the Western Cape. Odd numbered columns show the correlation of the respective school's location and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table E.14: Location-Quality Analysis – Closed School Locations as Counterfactual (Raster 0.05, Moved 0.025 Degrees Up)

	(1)	(2)	(3)	(4)	(5)	(6)
	Grade 3		Grade 6		Grade 9	
	Math	Language	Math	Language	Math	Language
Panel A: All Schools 1905						
Open School in Raster Cell	1.667	0.803	6.881**	7.181**	0.000	0.000
	(5.181)	(4.814)	(2.806)	(3.029)	(0.000)	(0.000)
Observations	162	162	157	157	95	95
R-Squared	0.356	0.344	0.389	0.386	0.342	0.347
Panel B: White Schools 1905						
Open School in Raster Cell	1.787	1.023	6.882**	6.986**	-303.364*	-228.343
	(4.383)	(3.716)	(2.818)	(3.086)	(163.204)	(177.378)
Observations	135	135	130	130	79	79
R-Squared	0.400	0.446	0.448	0.463	0.391	0.387
Panel C: Black Schools 1905						
Open School in Raster Cell	0.000	0.000	-24.221	-2.682	0.000	0.000
	(0.000)	(0.000)	(154.353)	(178.177)	(0.000)	(0.000)
Observations	99	99	98	98	69	69
R-Squared	0.481	0.439	0.414	0.436	0.454	0.458
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show our counterfactual model for the location-quality analysis, i.e., the relationship between historic school locations and contemporary school performance captured by the mean test score achieved in the *Systemic Test*. The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 matched to a 0.05×0.05 degrees raster grid. Compared to our baseline grid, we moved the grid 0.025 degrees up. The counterfactual are grid cells that included a school in 1896 but was closed by 1905. The sample is limited to the Western Cape. Odd numbered columns show the correlation of the respective school's location and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table E.15: Location-Quality Analysis – Closed School Locations as Counterfactual (Raster 0.05, Moved 0.025 Degrees Right)

	(1)	(2)	(3)	(4)	(5)	(6)
	Grade 3		Grade 6		Grade 9	
	Math	Language	Math	Language	Math	Language
Panel A: All Schools 1905						
Open School in Raster Cell	0.786	0.443	3.347*	3.666*	2.397	4.425
	(1.963)	(1.464)	(1.782)	(2.076)	(.)	(.)
Observations	176	176	172	172	93	93
R-Squared	0.419	0.407	0.424	0.442	0.328	0.359
Panel B: White Schools 1905						
Open School in Raster Cell	1.703	1.425	3.864*	4.298*	4.265***	4.809***
	(2.226)	(2.092)	(2.207)	(2.250)	(0.884)	(1.334)
Observations	151	151	147	147	81	81
R-Squared	0.435	0.441	0.454	0.459	0.339	0.399
Panel C: Black Schools 1905						
Open School in Raster Cell	1.910	1.614	0.661	0.964	0.358	5.782**
	(2.413)	(2.118)	(1.518)	(1.193)	(5.104)	(2.249)
Observations	107	107	106	106	74	74
R-Squared	0.523	0.467	0.506	0.535	0.429	0.436
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show our counterfactual model for the location-quality analysis, i.e., the relationship between historic school locations and contemporary school performance captured by the mean test score achieved in the *Systemic Test*. The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 matched to a 0.05×0.05 degrees raster grid. Compared to our baseline grid, we moved the grid 0.025 degrees to the right. The counterfactual are grid cells that included a school in 1896 but was closed by 1905. The sample is limited to the Western Cape. Odd numbered columns show the correla-tion of the respective school's location and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table E.16: Quality-Quality Analysis – Full Sample (IDW)

	(1)	(2)	(3)	(4)	(5)	(6)
	Grade 3		Grade 6		Grade 9	
	Math	Language	Math	Language	Math	Language
Panel A: All Schools 1896						
Share Std. 4 or Higher	4.559*	5.889*	7.712***	5.502*	9.870***	8.898**
	(2.671)	(3.183)	(1.762)	(3.133)	(3.518)	(3.928)
Observations	1,068	1,068	1,034	1,034	454	454
R-Squared	0.197	0.203	0.197	0.203	0.187	0.227
Panel B: White Schools 1896						
Share Std. 4 or Higher	8.005***	7.770**	11.072***	10.136***	23.193***	18.250***
	(2.490)	(3.128)	(2.692)	(3.262)	(3.811)	(2.405)
Observations	1,068	1,068	1,034	1,034	454	454
R-Squared	0.208	0.210	0.209	0.214	0.243	0.260
Panel C: Black Schools 1896						
Share Std. 4 or Higher	13.818	29.402***	25.425**	44.632***	31.857**	55.581***
	(10.292)	(11.364)	(10.041)	(12.237)	(16.025)	(11.715)
Observations	1,068	1,068	1,034	1,034	454	454
R-Squared	0.195	0.206	0.195	0.213	0.185	0.239
Panel D: All Schools 1905						
Share Std. 4 or Higher	5.422	6.136***	7.370***	6.501**	12.861***	8.519***
	(.)	(2.049)	(2.809)	(2.528)	(3.453)	(1.970)
Observations	1,068	1,068	1,034	1,034	454	454
R-Squared	0.198	0.204	0.197	0.205	0.194	0.227
Panel E: White Schools 1905						
Share Std. 4 or Higher	4.144***	4.313**	5.730***	5.474**	11.536***	10.205***
	(1.332)	(2.014)	(1.241)	(2.170)	(2.526)	(1.707)
Observations	1,068	1,068	1,034	1,034	454	454
R-Squared	0.197	0.202	0.196	0.205	0.198	0.236
Panel F: Black Schools 1905						
Share Std. 4 or Higher	16.649***	17.582**	32.877***	27.038**	44.466	28.228**
	(5.360)	(6.875)	(7.166)	(11.422)	(.)	(12.963)
Observations	1,068	1,068	1,034	1,034	454	454
R-Squared	0.196	0.201	0.199	0.205	0.190	0.225
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show a robustness check for the quality-quality analysis, i.e., the relationship between historic school quality captured by the share of students in Standard 4 and above contemporary school performance captured by the mean test score achieved in the *Systemic Test*. The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 which was interpolated using inverse distance weighting and matched to contemporary schools. The sample is limited to the Western Cape. Odd numbered columns show the correlation of the respective school's quality and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table E.17: Quality-Quality Analysis (IDW 2p 10km Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
	Grade 3		Grade 6		Grade 9	
	Math	Language	Math	Language	Math	Language
Panel A: All Schools 1896						
Share Std. 4 or Higher	6.737	6.895*	9.870***	4.528	14.830***	10.258*
	(4.163)	(3.915)	(3.665)	(4.479)	(4.512)	(5.931)
Observations	1,002	1,002	970	970	437	437
R-Squared	0.189	0.194	0.188	0.201	0.201	0.232
Panel B: White Schools 1896						
Share Std. 4 or Higher	8.880***	7.895***	12.676***	9.719***	35.782***	28.588***
	(2.831)	(2.782)	(3.242)	(2.828)	(5.547)	(3.083)
Observations	863	863	831	831	379	379
R-Squared	0.199	0.207	0.213	0.227	0.271	0.291
Panel C: Black Schools 1896						
Share Std. 4 or Higher	27.095**	43.802***	38.219**	53.656***	56.043***	81.565***
	(12.855)	(14.818)	(15.125)	(16.163)	(20.533)	(19.027)
Observations	905	905	873	873	408	408
R-Squared	0.180	0.192	0.179	0.206	0.209	0.251
Panel D: All Schools 1905						
Share Std. 4 or Higher	7.906	7.211***	9.193**	5.787***	15.382***	8.597
	(.)	(1.688)	(3.747)	(1.724)	(3.257)	(.)
Observations	1,021	1,021	985	985	441	441
R-Squared	0.196	0.196	0.191	0.202	0.189	0.223
Panel E: White Schools 1905						
Share Std. 4 or Higher	5.113**	3.663**	6.009***	4.352***	18.052***	14.243***
	(2.594)	(1.690)	(2.136)	(1.110)	(3.180)	(2.820)
Observations	992	992	958	958	429	429
R-Squared	0.194	0.197	0.190	0.209	0.209	0.238
Panel F: Black Schools 1905						
Share Std. 4 or Higher	11.969***	10.446	31.368**	19.420	51.846	32.076***
	(4.236)	(9.772)	(15.866)	(21.850)	(.)	(11.702)
Observations	912	912	881	881	413	413
R-Squared	0.179	0.184	0.175	0.198	0.207	0.237
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show robustness checks for the quality-quality analysis, i.e., the relationship between historic school quality captured by the share above of students in Standard 4 and above and contemporary school performance captured by the mean test score achieved in the *Systemic Test*. The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 which was interpolated using inverse distance weighting with a power parameter of two and matched to contemporary schools. The sample is limited to the Western Cape and excludes contemporary schools which are further than 10km from the next historic school. Odd numbered columns show the correlation of the respective school's quality and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table E.18: Quality-Quality Analysis – Excluding Urban Areas (IDW 2p)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	No Towns > 1,000 (1891)						Baseline + Control for Contemporary Urbanity					
	Grade 3		Grade 6		Grade 9		Grade 3		Grade 6		Grade 9	
	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.
Panel A: All Schools 1896												
Share Std. 4 or Higher	3.017	0.951	5.599	1.935	10.610	12.905*	7.671*	7.771*	11.502***	6.413	14.781***	11.716**
	(3.508)	(3.166)	(4.327)	(3.791)	(7.694)	(7.390)	(4.261)	(4.060)	(4.001)	(4.473)	(4.377)	(5.253)
Cont. Urban Dummy							3.319	3.114	5.558***	6.419	-0.103	3.114***
							(.)	(.)	(0.380)	(.)	(.)	(0.461)
Observations	395	395	383	383	138	138	1,002	1,002	970	970	437	437
R-squared	0.189	0.193	0.177	0.175	0.182	0.260	0.195	0.199	0.199	0.213	0.201	0.234
Panel B: White Schools 1896												
Share Std. 4 or Higher	3.582	0.203	6.964*	4.197	29.277***	26.995***	10.701***	9.469***	15.311***	12.549***	41.126***	35.633***
	(2.949)	(2.508)	(3.598)	(3.754)	(6.874)	(3.632)	(3.233)	(3.367)	(4.141)	(3.621)	(9.237)	(5.914)
Cont. Urban Dummy							4.235***	3.661	6.396***	6.868	6.208***	8.183***
							(0.456)	(.)	(0.890)	(.)	(2.141)	(0.984)
Observations	395	395	383	383	138	138	863	863	831	831	379	379
R-squared	0.190	0.193	0.180	0.177	0.270	0.343	0.209	0.214	0.228	0.242	0.280	0.309
Panel C: Black Schools 1896												
Share Std. 4 or Higher	-8.334	1.566	-9.468	12.866	-96.613**	-47.083	22.027*	39.175***	30.630**	44.198**	58.132**	78.589***
	(21.009)	(13.606)	(37.644)	(30.661)	(48.790)	(41.202)	(13.244)	(15.193)	(15.611)	(18.879)	(23.677)	(21.517)
Cont. Urban Dummy							2.704	2.468	3.998***	4.982	-0.982	1.399*
							(.)	(.)	(0.540)	(.)	(.)	(0.733)
Observations	395	395	383	383	138	138	905	905	873	873	408	408
R-squared	0.188	0.193	0.174	0.175	0.189	0.250	0.184	0.194	0.184	0.213	0.209	0.251
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 18: cont.

	No Towns > 1,000 (1891)						Baseline + Control for Contemporary Urbanity					
	Grade 3		Grade 6		Grade 9		Grade 3		Grade 6		Grade 9	
	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.
Panel D: All Schools 1905												
Share Std. 4 or Higher	5.468***	3.141	2.953	3.079	5.457	8.421	9.434***	8.656***	11.445**	8.445**	16.279***	11.551
	(1.418)	(2.542)	(4.047)	(3.916)	(8.039)	(7.630)	(1.358)	(2.518)	(5.211)	(3.509)	(3.408)	(.)
Cont. Urban Dummy							3.922	3.709	5.728***	6.761	1.196	3.935
							(.)	(.)	(0.644)	(.)	(.)	(.)
Observations	395	395	383	383	138	138	1,021	1,021	985	985	441	441
R-squared	0.193	0.195	0.175	0.175	0.177	0.253	0.204	0.202	0.203	0.216	0.190	0.227
Panel E: White Schools 1905												
Share Std. 4 or Higher	8.972***	4.514	8.543***	6.314*	23.294***	23.210***	8.377***	6.668***	10.592***	9.789***	22.963***	22.110***
	(2.577)	(3.226)	(3.036)	(3.514)	(7.581)	(6.032)	(1.491)	(1.510)	(1.857)	(1.358)	(4.124)	(2.539)
Cont. Urban Dummy							4.881	4.493	6.789***	8.054	5.296	8.484
							(.)	(.)	(0.705)	(.)	(.)	(.)
Observations	395	395	383	383	138	138	992	992	958	958	429	429
R-squared	0.202	0.197	0.184	0.180	0.237	0.320	0.206	0.205	0.205	0.227	0.215	0.254
Panel F: Black Schools 1905												
Share Std. 4 or Higher	0.017	-2.133	10.448	-4.962	30.349	-10.949	11.485***	10.000	30.793**	18.770	52.069	31.238***
	(14.369)	(14.958)	(17.964)	(14.113)	(38.052)	(31.990)	(4.355)	(9.464)	(13.785)	(19.883)	(.)	(8.694)
Cont. Urban Dummy							3.095	2.852***	5.267	5.955	-0.581	2.184*
							(.)	(0.341)	(.)	(.)	(.)	(1.176)
Observations	395	395	383	383	138	138	912	912	881	881	413	413
R-squared	0.188	0.193	0.174	0.174	0.179	0.247	0.185	0.188	0.185	0.209	0.207	0.238
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show robustness checks for the quality-quality analysis, i.e., the relationship between historic school quality captured by the share above of students in Standard 4 and above and contemporary school performance captured by the mean test score achieved in the *Systemic Test*, excluding historic urban areas in columns (1) to (6) and controlling for contemporary urbanity in columns (7) to (12). The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 which was interpolated using inverse distance weighting with a power parameter of two and matched to contemporary schools. The sample is limited to the Western Cape and excludes contemporary schools which are further than 10km from the next historic school. Odd numbered columns show the correlation of the respective school's quality and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table E.19: Quality-Quality Analysis - Alternative Independent Variable (IDW 4p 10km Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
	Grade 3		Grade 6		Grade 9	
	Math	Language	Math	Language	Math	Language
Panel A: All Schools 1896						
Mean Standard	0.968***	1.115***	1.246***	0.721*	0.629	0.356
	(0.371)	(0.422)	(0.236)	(0.430)	(0.469)	(0.540)
Observations	1,002	1,002	970	970	437	437
R-Squared	0.191	0.197	0.189	0.201	0.194	0.228
Panel B: White Schools 1896						
Mean Standard	1.264***	1.153**	1.874***	1.515**	4.346***	3.221***
	(0.434)	(0.515)	(0.558)	(0.602)	(0.813)	(0.599)
Observations	863	863	831	831	379	379
R-Squared	0.198	0.207	0.214	0.228	0.248	0.271
Panel C: Black Schools 1896						
Mean Standard	2.993***	3.302***	2.827***	2.942***	0.866	1.720***
	(0.802)	(0.650)	(0.638)	(0.543)	(.)	(0.317)
Observations	905	905	873	873	408	408
R-Squared	0.188	0.194	0.180	0.203	0.202	0.237
Panel D: All Schools 1905						
Mean Standard	1.039***	1.041**	1.532**	0.994**	1.800***	0.623
	(0.351)	(0.422)	(0.610)	(0.402)	(0.338)	(.)
Observations	1,021	1,021	985	985	441	441
R-Squared	0.197	0.198	0.196	0.205	0.189	0.220
Panel E: White Schools 1905						
Mean Standard	0.666	0.614*	1.070***	0.847**	2.180***	1.713***
	(.)	(0.370)	(0.231)	(0.332)	(0.463)	(0.379)
Observations	992	992	958	958	429	429
R-Squared	0.194	0.198	0.192	0.211	0.201	0.233
Panel F: Black Schools 1905						
Mean Standard	2.416	1.775	2.825*	0.801	2.860	-1.172
	(1.503)	(1.580)	(1.499)	(1.409)	(.)	(0.927)
Observations	912	912	881	881	413	413
R-Squared	0.184	0.186	0.176	0.197	0.203	0.235
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show robustness checks for the quality-quality analysis, i.e., the relationship between historic school quality captured by the average Standard within a school and contemporary school performance captured by the mean test score achieved in the *Systemic Test*. The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 which was interpolated using inverse distance weighting with a power parameter of four and matched to contemporary schools. The sample is limited to the Western Cape and excludes contemporary schools which are further than 10km from the next historic school. Odd numbered columns show the correlation of the respective school's quality and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table E.20: Quality-Quality Analysis – Excluding Urban Areas; Alternative Dependent Variable (IDW 2p)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	No Towns > 1,000 (1891)						Baseline + Control for Contemporary Urbanity					
	Grade 3		Grade 6		Grade 9		Grade 3		Grade 6		Grade 9	
	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.
Panel A: All Schools 1896												
Mean Standard	0.638	0.384	0.834	0.428	0.763	0.840	1.057***	1.200***	1.397***	0.897**	0.611	0.410
	(0.417)	(0.394)	(0.560)	(0.513)	(0.918)	(0.778)	(0.377)	(0.434)	(0.236)	(0.423)	(0.484)	(0.510)
Cont. Urban Dummy							3.300	3.135	5.465***	6.404	-0.821	2.526***
							(.)	(.)	(0.362)	(.)	(.)	(0.345)
Observations	395	395	383	383	138	138	1,002	1,002	970	970	437	437
R-Squared	0.191	0.194	0.178	0.175	0.177	0.250	0.197	0.202	0.200	0.214	0.194	0.230
Panel B: White Schools 1896												
Mean Standard	0.305	-0.142	0.782	0.347	3.508***	3.072***	1.640***	1.481**	2.420***	2.098***	5.597***	4.710***
	(0.473)	(0.381)	(0.611)	(0.645)	(1.093)	(0.667)	(0.526)	(0.629)	(0.742)	(0.756)	(1.580)	(1.166)
Cont. Urban Dummy							4.627***	4.033***	7.002***	7.459	7.941***	9.451***
							(0.556)	(0.134)	(1.071)	(.)	(2.970)	(1.891)
Observations	395	395	383	383	138	138	863	863	831	831	379	379
R-Squared	0.189	0.193	0.177	0.175	0.236	0.302	0.210	0.215	0.232	0.246	0.262	0.291
Panel C: Black Schools 1896												
Mean Standard	2.572**	1.978***	1.976	3.049	1.849*	3.401*	2.778***	3.084***	2.468***	2.473***	0.872	1.527***
	(1.055)	(0.195)	(2.143)	(2.352)	(1.088)	(1.772)	(0.762)	(0.607)	(0.618)	(0.576)	(.)	(0.375)
Cont. Urban Dummy							2.571	2.608	4.105***	5.362	-0.085	2.551***
							(.)	(.)	(0.595)	(.)	(.)	(0.434)
Observations	395	395	383	383	138	138	905	905	873	873	408	408
R-Squared	0.193	0.196	0.176	0.180	0.176	0.253	0.192	0.197	0.186	0.212	0.202	0.239
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 20: cont.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	No Towns > 1,000 (1891)						Baseline + Control for Contemporary Urbanity					
	Grade 3		Grade 6		Grade 9		Grade 3		Grade 6		Grade 9	
	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.	Math	Lang.
Panel D: All Schools 1905												
Mean Standard	0.453**	0.385	0.484	0.330	1.123	1.093	1.189***	1.185**	1.751**	1.251**	1.861***	0.868
	(0.224)	(0.398)	(0.451)	(0.364)	(1.473)	(1.329)	(0.400)	(0.473)	(0.712)	(0.529)	(0.321)	(.)
Cont. Urban Dummy							3.837	3.676	5.772***	6.775	0.797	3.236***
							(.)	(.)	(0.777)	(.)	(.)	(0.603)
Observations	395	395	383	383	138	138	1,021	1,021	985	985	441	441
R-Squared	0.190	0.194	0.175	0.175	0.180	0.253	0.204	0.204	0.208	0.219	0.189	0.223
Penel E: White Schools 1905												
Mean Standard	0.849***	0.422	0.909***	0.299	2.172***	2.090***	1.052	0.986**	1.625***	1.507**	2.668***	2.619***
	(0.316)	(0.436)	(0.349)	(0.309)	(0.820)	(0.549)	(.)	(0.462)	(0.449)	(0.591)	(0.568)	(0.335)
Cont. Urban Dummy							4.600	4.434	6.752***	8.026***	3.904***	7.233
							(.)	(.)	(1.104)	(0.560)	(0.551)	(.)
Observations	395	395	383	383	138	138	992	992	958	958	429	429
R-Squared	0.194	0.195	0.179	0.175	0.200	0.274	0.204	0.206	0.207	0.229	0.205	0.245
Panel F: Black Schools 1905												
Mean Standard	-0.521	-0.655	1.287	0.156	2.035	0.542	2.278	1.647	2.590**	0.526	2.859	-1.169
	(1.092)	(1.047)	(1.976)	(1.794)	(3.384)	(2.667)	(1.426)	(1.532)	(1.281)	(1.148)	(.)	(0.909)
Cont. Urban Dummy							2.933***	2.739***	5.100***	5.939***	-0.356	2.312**
							(0.060)	(0.762)	(0.504)	(0.475)	(.)	(1.033)
Observations	395	395	383	383	138	138	912	912	881	881	413	413
R-Squared	0.188	0.194	0.175	0.174	0.177	0.246	0.189	0.190	0.185	0.208	0.203	0.236
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show robustness checks for the quality-quality analysis, i.e., the relationship between historic school quality captured by the average Standard within a school and contemporary school performance captured by the mean test score achieved in the *Systemic Test*, excluding historic urban areas in columns (1) to (6) and controlling for contemporary urbanity in columns (7) to (12). The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 which was interpolated using inverse distance weighting with a power parameter of four and matched to contemporary schools. The sample is limited to the Western Cape and excludes contemporary schools which are further than 10km from the next historic school. Odd numbered columns show the correlation of the respective school's quality and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table E.21: Quality-Quality Analysis - Raster Approach (Raster 0.05)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Grade 3				Grade 6				Grade 9			
	Math		Language		Math		Language		Math		Language	
Panel A: All Schools 1896												
Share Std. 4 or Higher	9.668*	9.703**	7.951	6.822*	12.762*	13.998**	12.611**	14.285***	26.983***	29.355***	22.104***	26.152***
	(5.211)	(4.299)	(5.026)	(3.880)	(6.908)	(6.525)	(6.081)	(4.648)	(3.906)	(4.641)	(3.181)	(2.614)
Observations	142	123	142	123	138	119	138	119	79	61	79	61
R-squared	0.480	0.474	0.456	0.430	0.481	0.504	0.488	0.502	0.527	0.609	0.555	0.639
Panel B: White Schools 1896												
Share Std. 4 or Higher	12.389***	12.089**	10.699***	9.240*	15.488***	17.753***	14.859***	17.979***	29.376***	35.845***	23.332***	30.407***
	(4.363)	(5.281)	(4.081)	(5.085)	(5.164)	(6.865)	(4.927)	(5.489)	(2.762)	(5.495)	(3.071)	(4.700)
Observations	105	90	105	90	102	87	102	87	59	46	59	46
R-squared	0.557	0.558	0.574	0.545	0.575	0.573	0.604	0.604	0.712	0.798	0.747	0.832
Panel C: Black Schools 1896												
Share Std. 4 or Higher	37.268***	33.895***	28.842**	19.471*	27.151**	14.346	37.980***	26.534***	-4.761	-16.027	15.647	12.781
	(10.584)	(11.356)	(11.449)	(10.869)	(12.144)	(11.584)	(9.176)	(8.377)	(28.251)	(50.248)	(20.457)	(37.668)
Observations	89	72	89	72	88	71	88	71	61	44	61	44
R-squared	0.532	0.512	0.535	0.556	0.488	0.500	0.496	0.522	0.597	0.783	0.611	0.735
Panel D: All Schools 1905												
Share Std. 4 or Higher	10.239***	9.512**	12.169***	10.171***	10.195***	9.485**	9.812***	9.928**	18.858***	17.006***	16.172***	16.411***
	(2.753)	(3.792)	(2.931)	(3.629)	(3.485)	(4.705)	(3.489)	(4.316)	(4.447)	(5.913)	(3.641)	(4.771)
Observations	128	110	128	110	122	104	122	104	73	56	73	56
R-squared	0.580	0.578	0.589	0.579	0.551	0.557	0.555	0.575	0.490	0.567	0.534	0.600
Penel E: White Schools 1905												
Share Std. 4 or Higher	9.617***	12.368**	9.963***	11.082**	8.835*	10.993	5.598	9.712	19.639***	26.096***	17.447***	28.885***
	(3.366)	(5.348)	(3.118)	(4.996)	(4.839)	(7.880)	(4.112)	(7.238)	(2.799)	(3.993)	(2.589)	(2.695)
Observations	93	78	93	78	88	73	88	73	55	42	55	42
R-squared	0.609	0.646	0.636	0.652	0.598	0.600	0.642	0.681	0.632	0.748	0.685	0.820
Panel F: Black Schools 1905												
Share Std. 4 or Higher	14.760	3.715	17.332	1.440	27.390	11.046	17.231	1.968	44.931	-4.255	30.328**	2.277
	(22.266)	(22.858)	(23.441)	(21.999)	(21.091)	(21.991)	(31.054)	(28.409)	(.)	(25.293)	(14.705)	(23.376)
Observations	83	67	83	67	82	66	82	66	58	42	58	42
R-squared	0.519	0.490	0.545	0.558	0.510	0.513	0.504	0.520	0.613	0.770	0.630	0.754
Include 1891 Towns?	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show robustness checks for the quality-quality analysis, i.e., the relationship between historic school quality captured by the share of students in Standard 4 and above and contemporary school performance captured by the mean test score achieved in the *Systemic Test*. The underlying dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 matched to a 0.05×0.05 degree raster grid. The sample is limited to the Western Cape. Only grid cells that include both a historic and a contemporary school are included. Odd numbered columns include all observations while even numbered columns exclude grid cells that include an 1891 urban area. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table E.22: Quality-Quality Analysis - Alternative Outcome Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sports Grounds		Artificial Turf		Pool		Tennis Courts	
Panel A: All Schools 1896								
Share Std. 4 or Higher	0.008	-0.003	0.192***	0.190***	0.179**	0.182**	1.517***	1.495***
	(0.143)	(0.140)	(0.061)	(0.065)	(0.076)	(0.075)	(0.499)	(0.519)
Cont. Urban Dummy		-0.102***		-0.013		0.021		-0.192*
		(0.018)		(0.023)		(.)		(0.113)
Constant	-6.450**	-6.366**	-7.650*	-7.639*	-3.425*	-3.442*	-31.143***	-30.985***
	(2.728)	(2.752)	(4.101)	(4.115)	(2.074)	(2.040)	(11.001)	(11.037)
Observations	1,556	1,556	1,556	1,556	1,556	1,556	1,556	1,556
R-squared	0.045	0.046	0.047	0.047	0.063	0.064	0.064	0.064
Panel B: White Schools 1896								
Share Std. 4 or Higher	0.308**	0.292**	0.323***	0.325***	0.331***	0.341***	2.913***	2.929***
	(0.126)	(0.131)	(0.087)	(0.095)	(0.091)	(0.098)	(0.532)	(0.550)
Cont. Urban Dummy		-0.061		0.006		0.040*		0.063
		(0.041)		(0.032)		(0.022)		(0.130)
Constant	-6.738**	-6.682**	-7.323*	-7.329*	-1.872*	-1.909**	-27.749***	-27.808***
	(2.660)	(2.625)	(4.355)	(4.365)	(1.033)	(0.896)	(4.926)	(4.537)
Observations	1,357	1,357	1,357	1,357	1,357	1,357	1,357	1,357
R-squared	0.054	0.055	0.061	0.061	0.070	0.070	0.079	0.079
Panel C: Black Schools 1896								
Share Std. 4 or Higher	-0.146	-0.063	0.056	0.073	0.949***	0.935***	1.764	1.967
	(0.282)	(0.265)	(0.374)	(0.375)	(0.232)	(0.249)	(1.674)	(1.602)
Cont. Urban Dummy		-0.119***		-0.024		0.021		-0.292
		(0.020)		(0.023)		(.)		(.)
Constant	-6.494*	-6.469	-9.705**	-9.700**	-4.838***	-4.843***	-34.105*	-34.043*
	(3.802)	(3.973)	(4.516)	(4.550)	(1.783)	(1.737)	(18.183)	(18.668)
Observations	1,409	1,409	1,409	1,409	1,409	1,409	1,409	1,409
R-squared	0.041	0.043	0.043	0.043	0.080	0.081	0.069	0.069
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 22: cont.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sports Grounds		Artificial Turf		Pool		Tennis Courts	
Panel D: All Schools 1905								
Share Std. 4 or Higher	0.121**	0.085*	0.236**	0.238**	0.310***	0.327***	2.111***	2.108***
	(0.052)	(0.046)	(0.095)	(0.105)	(0.074)	(0.085)	(0.558)	(0.613)
Average School Urbanness in Cell		-0.106***		0.006		0.052		-0.007
		(0.017)		(0.032)		(.)		(0.153)
Constant	-6.208**	-6.164**	-6.769*	-6.772*	-2.763	-2.784	-26.787**	-26.784**
	(3.044)	(3.080)	(3.832)	(3.834)	(1.799)	(1.748)	(10.577)	(10.575)
Observations	1,588	1,588	1,588	1,588	1,588	1,588	1,588	1,588
R-squared	0.058	0.059	0.049	0.049	0.071	0.072	0.063	0.063
Panel E: White Schools 1905								
Share Std. 4 or Higher	0.393***	0.373***	0.149***	0.155**	0.238***	0.271***	1.674***	1.730***
	(0.125)	(0.132)	(0.043)	(0.064)	(0.065)	(0.091)	(0.228)	(0.299)
Average School Urbanness in Cell		-0.044***		0.013		0.071**		0.125
		(0.014)		(0.040)		(0.031)		(0.173)
Constant	-6.793**	-6.765**	-7.516*	-7.525*	-3.285	-3.331	-30.718**	-30.798**
	(2.922)	(2.922)	(4.117)	(4.132)	(2.245)	(2.239)	(14.260)	(14.246)
Observations	1,546	1,546	1,546	1,546	1,546	1,546	1,546	1,546
R-squared	0.063	0.063	0.051	0.051	0.070	0.071	0.064	0.064
Panel F: Black Schools 1905								
Share Std. 4 or Higher	-0.502	-0.452	0.432	0.443	0.304***	0.291***	5.976	6.107***
	(0.920)	(0.900)	(.)	(.)	(0.084)	(0.077)	(.)	(0.473)
Average School Urbanness in Cell		-0.122***		-0.026		0.031**		-0.323
		(0.033)		(0.025)		(0.013)		(.)
Constant	-7.219**	-7.134*	-9.635**	-9.616*	-2.676	-2.698	-31.494**	-31.268*
	(3.529)	(3.700)	(4.906)	(4.950)	(1.772)	(1.662)	(15.572)	(16.077)
Observations	1,420	1,420	1,420	1,420	1,420	1,420	1,420	1,420
R-squared	0.041	0.043	0.044	0.045	0.071	0.072	0.072	0.072
GIS Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1891 Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions show robustness checks for the quality-quality analysis, i.e., the relationship between historic school quality captured by the share of students in Standard 4 and above and contemporary school quality. In this robustness check we use alternative outcome variables capturing access to sports facilities at the school level based on satellite data. The outcome variable 'Sports' denotes whether the school has any visible sport facilities. The variable 'Artificial Turf' denotes whether the school has an artificial turf ground for sports. The variable 'Pool' denotes whether the school has a swimming pool. The variable 'Tennis Courts' is the number of tennis courts per school. The underlying historic dataset is based on the geo-referenced *Cape Colony Education Reports* from 1896 and 1905 which was interpolated using inverse distance weighting with a power parameter of four and matched to contemporary schools. The sample is limited to the Western Cape and excludes contemporary schools which are further than 10km from the next historic school. Odd numbered columns show the correlation of the respective school's quality and math test performance in Grade 3, 6 and 9 while even numbered columns show the relationship for language test performance. The GIS controls include distance to coast (km), average rainfall, average temperature, average altitude, ruggedness, soil quality, distance to Cape Town, Gqeberha, and Kimberley (km), distance to the colonial railway (km) and distance to explorer routes (km). All models also include ethnic group and 1891 division fixed effects. Standard errors are adjusted for spatial autocorrelation. Asterisks denote significance levels at *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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F Conclusion

The provision of high quality education for all is key to achieve sustainable development across Sub-Saharan Africa. Higher human capital does not only foster economic growth, it provides individuals with the agency to decide how they want to spend their lives - growing the food to feed their country as a farmer, building bridges to connect the continent as an engineer or navigating international diplomacy as a policymaker. Hopefully, one day education opens the door for every child to pursue any of these paths.

This dissertation contributes to that broader goal by deepening our understanding of the development and determinants of education in Sub-Saharan Africa. While it does not claim to offer a one-size-fits-all solution, it underscores the importance of examining education from multiple angles. The findings show that the drivers of educational outcomes are often more complex and context-dependent than they might initially appear.

Years of schooling have increased rapidly across Sub-Saharan Africa in recent decades. But why has this rise not been matched by the expected gains in economic growth? A key reason lies in the distinction between educational inputs, such as years of schooling, and outputs, like literacy and numeracy. The amount a child learns per year of schooling varies significantly across both time and place. To understand educational development in the region, we must therefore focus on outputs. While standardized tests now provide useful measures of human capital among schoolchildren in many African countries, they often exclude the sizable out-of-school population and offer little insight into long-term trends. Chapter B addresses this gap by presenting a subnational overview of numeracy, measured using the ABCC Index, for birth cohorts from 1950 to 1990. Drawing on data from household surveys and censuses on age distributions, the chapter reveals a strong contrast: while years of schooling have increased, numeracy has remained largely stagnant. There are, however, substantial regional differences. Southern Africa performs best; Western Africa, worst. Ghana stands out as a country where sustained investment in quality education has led to measurable improvements in human capital. The chapter also demonstrates the robustness of the ABCC Index as a tool for tracking educational progress across the region with limited data availability.

Why do children in some regions learn more per year of schooling than in others? Chapter C explores this question by examining educational efficiency and one of its potential determinants: children's health. Using the same dataset as in Chapter B, I estimate educational efficiency, defined as the numeracy gained per year of schooling, across regions and birth decades. The results reveal substantial spatial variation but limited change over time. The analysis then investigates the role of child health, proxied by average adult height, as a determinant of educational efficiency. While height is partly determined by genetics at the individual level, regional averages offer insight into childhood nutrition, as stunting during early life leads to reduced adult height. The findings suggest a strong and consistent relationship. This is further supported by instrumental variable estimates that use rainfall deviations during early childhood as an instrument for health. Together, the results highlight the importance of early-life health and nutrition. They lend support to interventions such as school feeding programs, which provide children with supplementary meals during their formative years.

While increases in average years of schooling across the continent do not adequately capture learning outcomes, they do reflect a significant expansion in access to education. More children than ever are attending school in Sub-Saharan Africa, driven by greater availability and reduced costs. Despite this progress, many children still never enter the classroom. One commonly named barrier to schooling is child labour. In Chapter D, I examine this relationship in greater detail using data from 17 Sub-Saharan African countries, challenging the assumption that child labour universally hinders education. Economic theory suggests that for households living at or near subsistence level, the income generated by child labour may be essential to afford schooling. Using detailed data on child labour and human capital from UNICEF's Multiple Indicator Cluster Surveys, I find that, on average, child labour outside the household is negatively associated with human capital. However, when restricting the analysis to the poorest 20 percent of households, the relationship becomes positive. Although these results do not allow for causal interpretation, they suggest that where the income effect dominates the substitution effect, child labour may support rather than hinder educational attainment. These findings do not aim to idealize child labour but instead highlight the risks of simple bans that offer no financial alternatives. Without compensation for affected families, such policies may ultimately do more harm than good.

Not all problems have their roots in the present—many run deeper, embedded in the past. In most of Sub-Saharan Africa, formal schooling was introduced by missionaries and colonial authorities, who educated children according to what they deemed "suitable" for Africans. How does this legacy continue to shape educational outcomes today? In Chapter E, I examine how South Africa's colonial education system, structured along racial lines, has contributed to persistent educational inequalities and the reproduction of elites through a small number of schools. Using school-level data from the *Cape Colony Education Reports* (1881–1905) linked to results from the 2018 *Systemic Test* in the Western Cape, I estimate the relationship between the location and quality of historic schools and present-day educational outcomes. The findings show no consistent link between proximity to a historic school and current school quality. However, there is a strong and robust association between the quality of historically white schools and the quality of their contemporary counterparts. This suggests that the benefits of colonial-era education were not broadly distributed but were concentrated in a few high-performing institutions whose influence has endured. These historically high-quality schools are more likely to still be operating today and have produced a disproportionately large share of South Africa's professional elite. Despite the formal end of Apartheid over 30 years ago, many of the same institutions continue to shape who has access to high-quality education. To ensure equal opportunity, policy efforts must extend beyond these historically advantaged schools and focus on investing in quality education across the system.

For policymakers, identifying effective strategies to improve educational outcomes can be challenging. The volume of research, from cross-country comparisons to small-scale randomized controlled trials, offers a wide array of options, making it difficult to know where to start. This dissertation highlights several key areas where progress is possible. First, it is crucial to measure educational attainment accurately. Simply increasing inputs into the education system, may have little effect if not accompanied by gains in learning outcomes. As international development funding declines - affecting major data sources like USAID's *Demographic and Health Surveys* - it becomes increasingly important to make the most of existing data to guide evidence-based policy. Second, the findings in Chapters C to E show that targeted interventions, such as improving children's nutrition, reducing financial barriers to schooling, and addressing the legacy of historical inequalities, can meaningfully enhance educational outcomes.

Still, these are only pieces of a much larger puzzle. Achieving lasting, system-wide change requires a holistic approach. While significant progress has been made in understanding education in Sub-Saharan Africa over the past two decades, the next step is to integrate these insights into coordinated, large-scale solutions that remain adaptable to local contexts. No single study can solve this puzzle, but by building on one another's work and fostering collaboration across research and policy communities, we can move closer to that goal—together.