Human Capital Development and Income Inequality in Sub Saharan Africa: The Post-Pandemic Era

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Abstract

Covid 19 has given rise to a number of challenges that have affected global economic conditions and social behaviour. There have been disruptions to education and healthcare services, as well as the disproportionate impact on vulnerable populations. This study explores the intricate relationship between human capital development and income inequality in sub-Saharan Africa (SSA), a region characterized by persistent human capital deficits and significant income disparities. Utilizing panel data from 31 SSA countries spanning 1996 to 2021, the study employs System Generalized Method of Moments (GMM) and Panel Corrected Standard Errors (PCSE) to investigate how human capital, represented by the Human Capital Index (HCI) and life expectancy, impacts income inequality, measured by the Gini coefficient. Our findings reveal a paradoxical positive relationship between human capital development and income inequality, suggesting that improvements in education and health do not uniformly benefit all segments of society, thereby exacerbating disparities. In contrast, factors such as access to electricity and gross fixed capital formation demonstrate an adverse effect on income inequality, showcasing their potential to foster equitable socio-economic growth. The results emphasize the importance of comprehensive policy frameworks aimed at inclusive education and healthcare access, responsive governance, and targeted economic investments, particularly in labour-intensive sectors. Our research contributes to the understanding of human capital dynamics in SSA and offers crucial insights for policymakers striving to address the complex challenge of income inequality in the region.

Keywords: Human Capital, Human Capital Development; Income Inequality, Sub Saharan Africa

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1. Introduction

The relationship between human capital development and income inequality has long been a topic of academic and policy interest, particularly in the context of developing regions like sub-Saharan Africa (SSA). Human capital is widely recognized as a crucial determinant of economic growth and productivity (Becker, 1964; Schultz, 1961). However, the distribution of human capital within a society can also have significant implications for the distribution of income and wealth. Empirical evidence from various regions has demonstrated that investments in education, training, and healthcare can contribute to more equitable income distribution (Barro, 2000; Castelló-Climent & Doménech, 2014; Mayer-Foulkes, 2001). By enhancing the abilities and opportunities of individuals from lower-income backgrounds, human capital development can help to narrow the income gap between the wealthy and the less privileged.

Despite these potential benefits, the SSA region has faced persistent challenges in fostering robust human capital development. According to the latest data from the World Bank (2023), the region's average secondary school enrolment rate stands at just 46.1%, significantly lower than the global average of 74.3%. This disparity is even more pronounced in certain countries, such as Niger, where the secondary enrolment rate is only 21.8% (World Bank, 2023). Similarly, the adult literacy rate in SSA is only 65.5%, compared to the worldwide average of 86.3% (UNESCO, 2022). Concurrent with these human capital deficits, the SSA region has also grappled with high levels of income inequality. The World Bank (2023) reports that the Gini coefficient, a widely used measure of income inequality, averages 0.43 in SSA, significantly higher than the global average of 0.38. This unequal distribution of income and wealth can have far-reaching consequences for the region's economic and social development, including reduced social mobility, political instability, and barriers to sustainable growth.

Given the critical importance of human capital development for economic and social progress, and the persistent challenges in addressing income inequality in sub-Saharan Africa, it is essential to understand the specific mechanisms through which human capital formation influences the distribution of income in the region (Goldin & Katz, 2008; Galor & Moav, 2004). While extensive research has explored the linkages between human capital and income inequality in broader samples of countries (Barro, 2000; Castelló-Climent & Doménech, 2014), there is a paucity of empirical evidence on this relationship within the unique context of sub-Saharan Africa (Bhorat et al., 2022; Anyanwu, 2014). The region's distinct socioeconomic, political, and demographic characteristics may shape the dynamics between human capital development and income distribution in ways that differ from global trends or other developing regions (Solt, 2020; Gradín, 2013).

Moreover, the COVID-19 pandemic has exacerbated the challenges in both human capital formation and income inequality in SSA, with disruptions to education and healthcare services, as well as the disproportionate impact on vulnerable populations (Ahinkorah et al., 2020; Ataguba, 2020). This underscores the urgent need to examine the relationship between human capital development and income inequality in the region, particularly in the post-pandemic era. Therefore, this study aims to fill this research gap by investigating the effects of human capital development on income inequality in sub-Saharan Africa. An important research question is, "How has the COVID-19 pandemic affected the relationship between human capital development and income inequality in sub-Saharan Africa, particularly in terms of educational attainment and health outcomes?" The goal of this paper is to examine the relationship between human capital development and income inequality in Sub-Saharan Africa. It aims to provide empirical evidence on how different aspects of human capital, such as education and life expectancy, influence income inequality. The findings are intended to inform policy decisions that prioritize investments in education and healthcare to reduce inequality.

The data employed for this study is panel data from 31 Sub Saharan African countries 1996 to 2021. The data is obtained from the World Bank's World Development Indicators (WDI, 2022), the Penn World Table, World Governance Indicator and World Income Inequality Database (WIID). The study employed the system GMM and the Panel Corrected Standard Errors procedures to estimate the relationship between human capital development and income inequality in SSA. The result showed a positive relationship between human capital index and income inequality and a negative relationship between life expectancy and income inequality. Policymakers should prioritize long-term, integrated strategies that promote education for all, create vocational training centers to develop hands-on skills, and support vulnerable populations.

2. Literature Review

One strand of the literature has focused on the role of education in shaping income inequality. Xu et al. (2023) aimed to reveal short-run and long-run asymmetries among human capital, educational inequality, and income inequality in China and they found that positive shocks to secondary education (SSE) and higher education (HE) are negatively correlated with income Gini coefficient. Flaviana et al (2021) investigated the inequality of opportunity in tertiary education: evidence from Europe. The results revealed a significant degree of heterogeneity, with Northern European countries exhibiting low levels of inequality of opportunity. Olufemi et al. (2022) examined the relationship between human capital and income inequality in Nigeria from 1981 to 2019. The results of the findings showed that one-year lagged income inequality and secondary school enrolment are both significant at the 5% level. In the long run, tertiary education enrolment, secondary school enrolment, government expenditure on health and employment rate were all statistically significant. Another author Tas (2022) investigated the effect of human capital on equality of income distribution and concluded a significant and positive effect of human capital on income equality. Hu (2021) studied the effect of income inequality on human capital inequality empirically across 31 provinces, municipalities, and autonomous regions of China during 1996 to 2018. The results were consistent with the existing theory, showing that impoverished households who have less family resources are more likely to be restrained from accessing better education opportunities under credit market imperfections.

Another line of research has investigated the influence of health outcomes on income inequality. Sengupta (2024) evaluated the impacts of income inequality on life expectancy in the African countries. The results showed that income inequality negatively affected life expectancy at birth in the African continent overall. Alexou and Trachanas (2021) revisited the relationship between health outcomes, income and income inequality and found out that evidence strongly supports the significant role that income plays in determining health outcomes. Furthermore, some studies have explored the combined effects of education and health on income inequality. Asghar and Zakar (2016) analysed panel data from developing countries and reported that investments in both education and health were instrumental in reducing income inequality. Likewise, Samir and Lutz (2017) emphasized the importance of considering the synergistic effects of education and health in addressing income disparities.

While the existing literature provides valuable insights into the linkages between human capital development and income inequality, the majority of these studies have focused on broader samples of countries or regions, with limited attention to the specific context of sub-Saharan Africa (SSA). This is a significant research gap, as the SSA region has faced persistent challenges in human capital formation and has also grappled with high levels of income inequality. Recent data from the World Bank (2023) indicates that the Gini coefficient, a widely used measure of income inequality, averages 0.43 in SSA, significantly higher than the global average of 0.38. Furthermore, the region's performance on human capital indicators, such as educational attainment and health outcomes, lags behind other developing regions (World Bank, 2023; UNESCO, 2022). Addressing this research gap by examining the specific mechanisms through which human capital development shapes income inequality in the SSA context could yield important policy implications for enhancing inclusive growth and reducing socioeconomic disparities in the region.

3. Methodology

The human capital model suggests that the level and distribution of schooling across the population determines the distribution of earnings (Becker &Chiswick 1966; Mincer 1974). Hence, the model predicts that the supply and demand of educated people influence the earnings inequality in a society. While the model predicts an unambiguously positive association between educational inequality, as measured by the variance of schooling, and income inequality, the effect of the average years of schooling on income inequality may be either positive or negative, depending on the evolution of the rates of return on education. Consider the following human capital earnings function (De Gregorio and Lee, 2002):

$$logYs_{it} = logY_0 + \sum_{j=0}^{S} \log(1+r) + \mu \dots \dots \dots . (1)$$

where *Ys* is the level of earnings with *S* level of schooling, r_j is the rate of return on the j^{th} year or level of schooling, and *u* represents other non-school-related factors that affect earnings. The following can approximate this function:

$$logYs_{it} = logY_0 + rS + \mu \dots \dots \dots . (2)$$

Taking the variance yields the following earnings distribution function:

$$Var(logYs_{it}) = \overline{r^2}Var(S) + \overline{r^2}Var(r) + 2\overline{rS}Cov(r,S) + Var(\mu) \dots \dots \dots . (3)$$

This implies that income inequality increases unambiguously with educational inequality, *Var(S)*, if controlling for other things. However, if the return on education, *r*, decreases with educational inequality, the relationship can be ambiguous. In most cases, however, educational inequality and the wage premium for higher education would move in the same direction, as an increase in the supply of higher-educated people tends to lower both the educational inequality and the wage premium. Meanwhile, educational expansion, that is, an increase in *S*, leads to a more unequal income distribution when *r* and *S* are independent. However, if the covariance between the return on education and the level of education is negative, the relationship between educational expansion and income inequality can reduce income inequality. Since the covariance term is expected to be negative, the relationship between educational expansion and income inequality should be ambiguous.

We would expect educational expansion, *S*, either to improve or to deteriorate educational distribution, *Var(S)*, depending on its initial level and distribution (De Gregorio and Lee 2002). In a society in which only a small fraction of the population has received formal education, the average educational attainment is low and the educational inequality is high. With an expansion of educational attainment, the level of educational inequality would increase if the more educated people received a higher level of education, but it would decrease if the uneducated people received some education.

Knight and Sabot (1983) suggest that educational expansion has an ambiguous effect on income distribution. They show that educational expansion has two offsetting effects on income distribution: the “composition effect,” whereby wage inequality rises initially, when the educational expansion leads to an increase in the proportion of more educated workers; and the “wage compression effect,” implying that, when the supply of educated labor exceeds the demand as a result of educational expansion, the premium for educated workers will eventually diminish and thereby wage inequality will decline. On this note, we carefully specify the following econometric model for estimation of the link between human capital development and income inequality.

$$GINI_{it} = \gamma_0 + \gamma_1 logHK_{it} + \gamma_i \chi_{it} + \mu_{it} \dots \dots \dots \dots \dots . (4)$$

Where $logGINI_{it}$ is income inequality as measured by GINI coefficient, HK_{it} is human capital development as measured by Human Capital Index representing the education aspect of human capital development and life expectancy to present the health aspect of human capital development, χ_{it} is a vector of control variables such as log of GNI gross fixed capital formation, unemployment, government effectiveness population growth, access to electricity.

Higher human capital index through better education and health tends to reduce income inequality by providing more equal opportunities for individuals to improve their skills and earning potentials. Higher unemployment tends to increase income inequality as it disproportionately affects individuals with lower income. Effective governance can lead to better public services, social safety nets, and policies that promote equitable growth, thereby reducing income inequality. Rapid population growth can strain resources and public services, potentially leading to higher poverty rates if economic growth does not keep pace. Electricity improves education outcomes by enabling students to study. Public and private investments in fixed capital, such as schools, hospitals and technology, improve education and healthcare outcomes

We carry out the estimates using a system GMM procedure. The system GMM estimator combines moment conditions for the model in first-differences with those for the models in levels. The procedure uses lagged differences of y_{it} as instruments for the equation in first-differences. Moreover, it requires a stationary restriction on the initial conditions process (Baltagi, 2008). The validity of the moment conditions imposed is usually assessed by a test of over-identifying restrictions (either Hansen's or Sargan's). The selection of this regression procedure was influenced by a number of factors. First off, there is a strong correlation between our dependent variable and its first period lag. Second, the cross-sectional dimension (countries) is larger than our time dimension. According to Roodman (2009), the cross-sectional dimension must be bigger than the time dimension for a GMM to be utilized in a regression, which is the case with our data. Thirdly, when the lagged dependent variable is included in the model, it correlates with the fixed effects in the error term. When this correlation is estimated using techniques like OLS, it results in a dynamic panel bias (Nickell, 1981). This bias is eliminated by the GMM estimation approach, which also controls cross-country dependence across panels in an equitable manner (Nchofoung et al., 2021).

The issue of having too many instruments is typically the biggest issue with GMM estimates. Although the exact number of instruments that are deemed excessive is unknown, Roodman (2009) adopted the forward orthogonal deviation as a continuation of Arellano and Bover (1995) in order to curtail the proliferation of instruments and increase sample size. Instead of removing earlier data from the subsequent ones, this method's computational methodology subtracts the average of all upcoming measurements of a variable that are currently accessible. As a result, the number of delays that may continue to be orthogonal to the error and useful as instruments in the regression is constrained. To prevent the proliferation of instruments, we use the aforementioned forward orthogonal deviation methodology in this work. We used the two-step technique to control for heteroscedasticity because the one-step procedure is consistent with homoscedasticity.

The issues of identification, simultaneity, and constraints are potential issues with the GMM estimation. According to recent literature, all of our explanatory factors are assumed to be sources of endogeneity in this regard (Asongu and Nwachukwu, 2016; Asongu and Leke, 2019; Nchofoung et al., 2021). Additionally, both the level and difference equations employ period dummies as instruments.

Given that the relationship between human capital development, as measured by the Human Capital Index (HCI) and Life Expectancy (LIFEX), and income inequality, represented by the GINI coefficient, is likely to be influenced by reverse causality, System GMM provides a reliable framework for obtaining consistent estimates. Additionally, this method combines equations in levels and differences, enhancing the efficiency of the estimates by utilizing more information from the data (Blundell & Bond, 1998).

$$INGINI_{it} = \gamma_0 + \gamma_1 INGINI_{it-1} + \gamma_2 HCD_{it} + \gamma_3 XP \sum_k^8 Z_{k,it-1} + \mu_{it} + v_t + \varepsilon_{i,t} \quad (5)$$

To eliminate country-specific effects we take the first differences of (5). HCD is further divided into its sub components education (HCI) and health (LIFEX)

$$INGINI_{it} - INGINI_{it-1} = \gamma_0 + \gamma_1(INGINI_{it-1} - INGINI_{it-2}) + \gamma_2(HCI_{it} - HCI_{it-1}) + \gamma_3 XP \sum_k^9 (Z_{k,it} - Z_{k,it-1}) + (\mu_{it} - \mu_{it-1}) + (v_t + v_{t-1}) + (\varepsilon_{it} - \varepsilon_{it-1}) \quad (6)$$

$$INGINI_{it} - INGINI_{it-1} - \gamma_0 + \gamma_1(INGINI_{it-1} - INGINI_{it-2}) + \gamma_2(LIFEX_{it} - LIFEX_{it-1}) + \gamma_3 XP \sum_k^9 (Z_{k,it} - Z_{k,it-1}) + (\mu_{it} - \mu_{it-1}) + (v_t + v_{t-1}) + (\varepsilon_{it} - \varepsilon_{it-1}) \quad (7)$$

Where; $INGINI_{it}$ is the gini coefficient for country i at time t; $INGINI_{it-1}$ is the lagged gini coefficient; HCD_{it} is human capital development for country i at time t; which is further decomposed to education component (HCI) and health component (LIFEX). HCI is the human capital index for country i at time t, $LIFEX_{it}$ is life expectancy for country i at time t. ZK_{it-1} is the vector of control variables including population growth, inflation, trade openness, unemployment, gross national income, foreign direct investment, gross fixed capital formation, and government effectiveness ;ui is the country specific effect, vt is the time specific effect; $\varepsilon i,t$ the error term.

The summary descriptive statistics table show that on the average, the level of income inequality in Sub Saharan Africa stands at 55.198 percent. Human capital development on the average in Sub Saharan Africa stands at 1.725 percent and 57.576 years for human capital development index and life expectancy respectively.

Table 1: Summary Descriptive Statistics of Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Gini Index	806	55.19866	8.128333	23.8	76.86
Access to Electricity	806	35.98594	24.60367	-.1184556	100
Gross National Income	800	23.02374	1.394256	19.95609	27.04227
Gross Fixed Capital Formation	806	20.62583	9.895979	-42.74677	81.02102
Population Growth	806	2.570909	1.083515	-.9200909	16.74996
Unemployment	806	8.16234	7.965249	.32	37.94
Government Effectiveness	806	-.6684824	.5378286	-1.849052	1.056674
Human Capital Index	806	1.725147	.4419124	1.053331	3.009325
Life Expectancy	804	57.57627	6.214338	40.64	74.51463

Source: Author(s) Computation from the data, 2025

The control variables such as electricity consumption, the log of gross national income, gross fixed capital formation, Population growth, the unemployment rate, and government effectiveness in Sub Saharan Africa stands at 35.985 percent, 23.0237 percent, 20.625 percent, 2.570 percent, 8.162 percent, and -0.668 units percent respectively. From the summary descriptive statistics, the variables present deviations from the mean values that are all less than the mean values of the variables, as such, the variables can be used for further regression estimations. Before getting to this, we conducted other tests to validate the quality of the data.

Non-stationary data constitutes a fundamental problem in econometric analysis. A non-stationary data is rendered stationary by differencing a number of times until stationarity is achieved. When a time series data is not stationary, we say that the data has unit root problems. Failure to address this problem gives rise to spurious regression results. We verify this problem by means of the Pesaran's second generation test.

Table 2: Pesaran's Second Generation Unit Root test

Variables	**Levels**		**First Difference**		**Order**
	Z[t-bar]	P Value	Z[t-bar]	P Value	
Gini Index	-0.684	0.247	-2.060	0.020	I(1)
Access to Electricity	-1.888	0.030	--	--	I(0)
Log of Gross National Income	-4.095	0.000	--	--	I(0)
Gross Fixed Capital Formation	-1.535	0.062	--	--	I(0)
Population Growth	-4.067	0.000	--	0.000	I(0)
Unemployment	2.394	0.992	-3.796	0.000	I(1)
Government Effectiveness	-0.644	0.260	-7.797	0.000	I(1)
Human Capital Index	-6.103	0.000	--	--	I(0)
Life Expectancy	2.714	0.997	-6.455	0.000	I(1)

Source: Author(s) Computation from the data, 2025

The stationarity test results show that the Gini as measure of income inequality, the unemployment rate, government effectiveness, and life expectancy at birth ae stationary after first difference while electricity consumption, the log of gross national income, gross fixed capital formation, population growth and human capital development index are stationary at levels. We reject the null hypothesis and conclude that all panels are stationary.

Table 3: Pesaran's Second-Generation Cross-Sectional Dependence Test

Variables	CD-test	P Value
Gini Index	74.16	0.000
Access to Electricity	95.29	0.000
Log Gross National Income	102.51	0.000
Gross Fixed Capital Formation	21.37	0.000
Population Growth	2.45	0.000
Unemployment	7.87	0.000
Government Effectiveness	0.78	0.434
Human Capital Index	95.12	0.000
Life Expectancy	96.43	0.000

Source: Author(s) Computation from the data, 2024

The Cross-Sectional Dependence test statistics show that the Gini index, electricity, the log of gross national income, gross fixed capital formation, population growth, the unemployment rate, human capital development index and life expectancy rejects the null hypothesis of cross-section independence while only government effectiveness index fails to reject the null hypothesis of cross-section independence. As such, most of the variables are faced with problems of cross-sectional dependence. This calls for econometric estimation approaches that takes care of the problem of cross-sectional dependence.

4. Findings and Discussion

The findings show that there is the absence of first and second order autocorrelations as the probability of AR1<10% and AR2>10% for first and second order autocorrelations, respectively. At the same time, the null hypothesis of the Sargan and Hansen over-identification restrictions tests for the validity of instruments should not be rejected (P-value >10%). Further, the null hypothesis of the Fisher statistics for the overall significance of the model should be rejected (that is P-value should be<10%). Finally, the number of instruments is kept to be less than the number of cross sections as recommended in Roodman (2009). To test the validity of our instruments, we focused on the Hansen test and the difference in Hansen test instead of the Sargan test because Sargan is not robust and the power Hansen is not weakened by instrument increases.

Table 4: Econometric Findings on the Effects of Human Capital Development on Income Inequality in Sub Saharan Africa (System GMM)

VARIABLES	(1) Gini Index	(2) Gini Index
Lag of Gini Index	1.959***	1.687***
	(0.152)	(0.232)
Human Capital Index	42.23***	
Life Expectancy		1.891***
		(0.356)
Government Effectiveness	3.899**	-5.313**
	(1.713)	(2.558)
Unemployment	-0.971**	1.440**
	(0.416)	(0.640)
Access to Electricity	-0.444***	-0.612***
	(0.0948)	(0.198)
Population Growth	2.527	7.562**
	(1.982)	(2.963)
Gross Fixed Capital Formation	-0.0774	-0.672***
	(0.0533)	(0.215)
Constant	-107.0***	-143.2***
	(13.15)	(24.80)
Observations	741	621
Number of id	31	31
F	1020	301.1
hansenp	0.297	0.306
sarganp	0.394	0.527
ar2p	0.252	0.496
ar1p	0.0202	0.101

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The regression coefficients show that the lag of income inequality has a positive effect on the level of inequality of the current year. This implies that, a unit increase in Gini of the previous year will increase inequality of the current year by 1.959 unit for human capital index model and 1.687 unit for the life expectancy model, significant at the 1 percent level of statistical significance.

We note from the findings that human capital development index and life expectancy, are paradoxically positive on income inequality in Sub Saharan Africa. This shows that a unit increase in human capital development index and life expectancy will increase income inequality by 42.23 and 1.89 unit respectively, significant at 1 percent level of significance. We therefore reject the null hypothesis and conclude that human capital development significantly affects income inequality in Sub Saharan Africa. This finding is in line with the theory put forward by Becker and Chiswick (1966), Mincer (1974), who suggested that the level and distribution of schooling across the population determines the distribution of earnings.

The model predicts that the supply and demand of educated people influence the earnings inequality in a society. Shahabadi et al. (2018), using fixed effects techniques, found mixed results where kindergarten through 12th grade education had a substantial negative effect on income disparity while university education had a positive effect on it. The authors argued that university education leads to graduates having a wider skillset and more financial capacity. Alvarado et al. (2021) use the fully modified OLS on a panel study of 75 countries from 1990 to 2016 to show that education widens the inequality gap. Conversely, other authors found a negative relationship between human capital development and income inequality. For example, Doruk et al. (2022) in a study in Brazil and Panama found that education reduces income inequality. In the same vein, Sethi et al. (2021) use the panel regression model on 27 European Union countries from 2000 to 2019 to find a significant negative relationship between education and income inequality.

The findings for the control variables indicate that gross fixed capital formation, unemployment and access to electricity are negative on income inequality in Sub Saharan Africa. The coefficients are statistically significant. The findings of this study are in line with the findings of other authors. Population growth and government effectiveness are positive on income inequality in the human capital index model while negative in the life expectancy model.

To ensure robustness of the findings, this study adopted the panel corrected standard errors (PCSE), which accounts for panel-specific heteroskedasticity and contemporaneous correlation across panels, providing more reliable standard error estimates. The results from the Panel Corrected Standard Error (PCSE) analysis provide a robust check on the findings derived from the System GMM estimates regarding the effects of human capital index and life expectancy on income inequality.

Table 5: Robustness Test on the Effect of Human Capital Development on Income Inequality in Sub Saharan Africa (Panel Corrected Standard Errors)

VARIABLES	(1) Gini Index	(2) Gini Index
Human Capital Index	0.977***	
	(0.356)	
Life Expectancy		0.124***
		(0.0421)
Government Effectiveness	0.868***	1.352***
	(0.335)	(0.322)
Unemployment	0.448***	0.437***
	(0.0356)	(0.0358)
Access to Electricity	-0.140***	-0.124***
	(0.00663)	(0.00783)
Population Growth	-1.062***	-0.954***
	(0.330)	(0.315)
Gross Fixed Capital Formation	-0.0968***	-0.0739**
	(0.0332)	(0.0365)
Constant	61.59***	69.09***
	(0.957)	(2.298)
Observations	613	641
R-squared	0.299	0.282
Number of id	31	31
chi2	1207	760.0

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The results from the panel corrected standard error analysis provide a robust check on the findings derived from the System GMM estimates regarding the effects of human capital index and life expectancy on income inequality. The human capital index with coefficient of 0.977 (statistically significant at the 1% level) imply that only certain segments of the population are benefiting from improvements in education and skills leading to a widening gap between those with high levels of human capital and those with low levels of human capital, thus increasing income inequality; these results are in line with those of the system GMM which indicated that human capital index has a positive significant effect on income inequality.

The results from the panel corrected standard error also shows that life expectancy has a negative effect on income inequality in Sub Saharan Africa. The life expectancy coefficient of 0.124, statistically significant at 1 percent level implies that improvements in life expectancy might be concentrated among wealthier individuals who have better access to healthcare, nutrition, and living conditions leading to disparities in health outcomes between different income groups, contributing to income inequality. The results are in line with those of the system GMM which indicated that life expectancy has a positive significant effect on income inequality.

5. Policy Suggestion and Conclusion

The findings of this study highlight the complex relationship between various socio-economic factors and income inequality in Sub-Saharan Africa. While some expected patterns hold, such as the positive impact of access to electricity and gross fixed capital formation on reducing inequality, the study also reveals paradoxical relationships that warrant deeper analysis. The positive association between the lag of income inequality and current-year inequality suggests that inequality is persistent over time. This underscores the need for policies that address not only current disparities but also historical patterns of inequality that continue to shape income distribution in the region.

The study finds an unexpected positive relationship between human capital index, life expectancy and income inequality. This suggests that while improvements in education, healthcare, and overall human capital are desirable for national development, they do not automatically translate into reduced income inequality. This may be attributed to structural inefficiencies, unequal access to quality education and healthcare, and disparities in labour market opportunities. It is crucial for policymakers to ensure that human capital investments are equitably distributed across different socio-economic groups to prevent worsening existing inequalities.

The study finds that government effectiveness plays a significant role in shaping income inequality. The positive relationship between government effectiveness and income inequality suggests that corruption, inefficient public spending, and misallocation of resources, particularly in education and healthcare, contribute to widening disparities. To mitigate these issues, policymakers should implement robust governance reforms, enhance public financial management, and promote transparency in public sector expenditures. Strengthening institutions that oversee education and healthcare investments will ensure that resources are directed toward the most vulnerable populations and contribute to reducing inequality.

The findings also indicate that unemployment has a negative effect on income inequality in the human capital index model, implying that lower unemployment rates contribute to more equitable income distribution. This suggests that policies aimed at job creation, skill development, and equitable economic growth are essential for narrowing income gaps. Governments should prioritize labour-intensive sectors such as agriculture, manufacturing, and digital infrastructure to generate employment opportunities, particularly for youth and marginalized groups. Additionally, vocational training programs and technology transfer initiatives should be expanded to enhance workforce skills and ensure sustainable economic mobility. In the life expectancy model and the robustness test, unemployment is positively related to income inequality. This suggest that higher unemployment is associated with greater income inequality. With higher unemployment rates in Sub Saharan Africa, a larger proportion of the population is left without stable income sources, widening the gap between those who are employed (and earning) and those who are not. This dynamic worsens income disparities, particularly in Sub Saharan Africa where social safety nets and unemployment benefits are weak.

The finding also reveals that population growth has a positive relationship with income inequality in the region. The study finds that rapid population growth, if not matched with adequate educational investments, can strain public resources and exacerbate inequality. To counteract this, governments should increase education spending, particularly at the primary and secondary levels, to ensure that expanding populations have access to quality education. Targeted policies should be implemented to reduce school dropout rates and improve technical and vocational training programs, equipping young people with the skills required for gainful employment.

The study also reveals that access to electricity plays a crucial role in income distribution, with increased access associated with reduced inequality. This finding underscores the importance of expanding electrification efforts, particularly in rural and peri-urban areas. Governments should prioritize investments in off-grid and mini-grid renewable energy solutions to extend electricity access to underserved regions. Additionally, policies that provide subsidies or incentives for private sector participation in electrification projects can enhance affordability and sustainability. Encouraging community-based solar projects and other renewable energy initiatives can further reduce dependence on expensive national grids and promote inclusive economic growth.

Another finding of the study relates to gross fixed capital formation, which is found to have a negative impact on income inequality. This suggests that capital formation contributes to equitable economic growth by enhancing productivity, creating jobs, and fostering overall development. To maximize this effect, governments should strategically allocate investments towards labour-intensive industries that have the potential to generate widespread employment. Moreover, policies that promote technology transfer and workforce upskilling should be encouraged to ensure that capital investments lead to higher wages and improved economic mobility for lower-income groups.

This study provides important insights into the complex dynamics of human capital development and income inequality in Sub-Saharan Africa. While investments in education, healthcare, and infrastructure are crucial for long-term development, they must be implemented alongside targeted policies that address structural inequalities and promote inclusive economic growth. Governments must adopt holistic approaches that integrate governance reforms, equitable resource allocation, and sustainable development strategies to ensure that human capital investments translate into tangible reductions in income inequality. By implementing evidence-based policies, policymakers can create an environment that fosters economic equity, social mobility, and long-term prosperity for all segments of society.

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