



The Uneven Gains of Progress: Investigating Total Factor Productivity and Human Capital Effects on Inequality in the Sub-Saharan African Economies

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Abstract

In a world shaped by rapid technological advancements and evolving human capital landscapes, the issue of income inequality stands as a critical challenge with far-reaching implications in sub-Saharan Africa (SSA). This paper investigates the impact of human capital and total factor productivity on a panel of 23 SSA economies from 1980 to 2019. The dynamic common correlated effect on the mean group (DCCE-MG) estimator is deployed on heterogeneous, large N and/or T panel data. Contrary to expectations, the findings indicate that the increase in human capital, technological advancements, and their interactions has exacerbated income inequality rather than reducing it. Human capital accumulation might suggest that the level of educational attainment has reached a plateau, with no significant increase or improvement in educational outcomes. The study recommends several policy measures, such as investing in affordable and quality education with the integration of technological changes to strengthen human capital accumulation, reducing income inequality, and achieving the Sustainable Development Goals (SDGs).

Keywords: Total Factor Productivity, Human Capital Accumulation, Income Inequality, SDGs

JEL Classifications: O15, O47, J24, O55

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1. Introduction

Income inequality remains a pressing global issue with wide-reaching implications for social cohesion, political stability, and sustainable development. Across both developed and developing nations, disparities in income distribution reflect deep structural inequalities, though the patterns and drivers may differ significantly (IMF & World Bank, 2020; World Bank, 2021). In developed economies, inequality often emerges from labour market segmentation, technological shifts, and globalisation, factors that can erode middle-income job security and widen the gap between skilled and unskilled workers (Hu, 2021; Madsen & Strulik, 2020; Wang et al., 2024). In contrast, developing countries, particularly those in sub-Saharan Africa (SSA), face persistent inequality shaped by limited access to quality education, healthcare, infrastructure, and productivity (Adeleye, 2024; Asongu & Odhiambo, 2023).

In SSA, while strides have been made in poverty reduction and macroeconomic growth, income inequality remains structurally entrenched. Figure 1 depicts that the region continues to exhibit some of the highest inequality levels globally, with Gini indices often exceeding 0.5 (World Bank, 2019). The disparity is fuelled by deep-rooted differences in access to human capital resources such as education and vocational training, which constrain upward mobility and weaken the capacity of large segments of the population to benefit from economic progress (Chetty et al., 2020; Sawadogo & Semedo, 2021). Though some countries have made efforts to invest in human capital, such as improving access to schools, health services, and job training, these interventions are often unevenly distributed and insufficiently aligned with labour market needs (Ibengwe et al., 2022).

Technological change, particularly through advancements in digital infrastructure and automation, presents a dual-edged opportunity for SSA. On one hand, it offers the potential to accelerate economic transformation and bridge development gaps (Galor & Moav, 2004; Galor & Tsiddon, 1997). However, its benefits may be captured disproportionately by those already equipped with digital literacy and technical skills, exacerbating pre-existing inequalities. Limited access to electricity, internet connectivity, and technological education, particularly in rural areas, further deepens the digital divide (Ntegwa & Olan'g, 2024). These structural barriers limit inclusive participation in the digital economy and reinforce socio-economic stratification (Stiglitz, 2018; Paul et al., 2023). A key but underexamined aspect in this area is the interaction between technological change, represented by Total Factor Productivity (TFP), and human capital development. TFP indicates the overall efficiency and innovative capacity of an economy, extending beyond simple increases in physical capital and labour inputs. In theory, rising TFP can boost economic growth and productivity. However, when technological advances are not accompanied by proportional improvements in education and skills, they may generate skill-biased returns, benefit already advantaged groups, and exacerbate inequality (Autor et al., 2003; Bloom et al., 2004; Goos et al., 2014).

The limited access to quality development infrastructure disproportionately affects marginalised communities, perpetuating income disparities. Without equal opportunities to acquire skills and knowledge, individuals from disadvantaged backgrounds face barriers to socio-economic mobility. Furthermore, technological disparities exacerbate income inequality, and unequal access to technology and the digital divide create a divide between those who can leverage technological advancements for economic opportunities and those who are left behind (Stiglitz, 2018). The lack of digital skills and infrastructure in marginalised areas limits their participation in the digital

economy, leading to income disparities. Our research is positioned at the intersection of theories concerning the relationship between human capital and inequality, as well as the impact of technology on inequality. These theories suggest a range of direct and indirect pathways through which shifts in technology and the accumulation of human capital can either mitigate or worsen income inequality in developing nations. This paper aims to contribute to the lacuna of existing empirical literature by investigating the repercussions of human capital accumulation and technological changes on income disparity in large panels with heterogeneous structures. Galor & Tsiddon (1997) put forth three key rationales for the importance of investigating distribution-related aspects of human capital development, emphasising that the composition of human capital plays a vital role in shaping the trajectory of inclusive economic growth, and the distribution of human capital does not follow a linear progression.

This study is situated within the broader discourse on the inequality implications of skill-biased technological change and human capital theory (Galor & Zeira, 1993; Mincer, 1958; Acemoglu & Robinson, 2012). Our research seeks to bridge this gap by examining whether and how TFP-induced technological change and human capital accumulation interact to shape income inequality across SSA economies. Specifically, the study addresses the following research question: To what extent do technological change and human capital accumulation influence income inequality in SSA, and how does their interaction affect the distributional dynamics across heterogeneous national contexts? The study contributes to the existing literature by addressing a critical gap in understanding the joint and dynamic effects of TFP and human capital accumulation on income inequality in the SSA economies. While previous research has predominantly examined the independent effects of these variables, this paper innovatively explores their interactive influence within a large heterogeneous panel framework. By employing advanced dynamic common correlated effects estimators, the study accounts for unobserved heterogeneity and cross-sectional dependence, offering robust insights into how the synergy between technology and skills can either mitigate or intensify inequality across diverse SSA economies. The nuanced approach advances the discourse on inclusive development in contexts marked by structural constraints and rapid technological shifts. The remainder of the study is structured as follows: Section 2 presents the literature review, Section 3 outlines the data and methodology, Section 4 provides the empirical analysis and discussion, and Section 5 concludes.

2. Literature Review

2.1. Theoretical frameworks

Understanding how technological change and human capital accumulation jointly influence income inequality requires a robust conceptual grounding in the economic theories of distribution, labour markets, and development. In this subsection, the study draws upon foundational models, such as the Kuznets curve, the Mincerian income function, and the Skill-Biased Technological Change (SBTC) hypothesis. Moreover, contemporary endogenous growth and political economy perspectives provide a theoretically coherent basis for our empirical analysis. Kuznets (1955) hypothesis suggests that income inequality follows an inverted-U shape throughout economic development: initially rising as economies industrialise and shift resources from agriculture to manufacturing, and later declining as broader access to education, urbanisation, and redistribution mechanisms reduce disparities. However, the hypothesis has not held consistently in many developing economies, particularly in SSA, where inequality has remained persistently high despite growth. Among the reasons for this

divergence is the absence of inclusive institutions and unequal access to skill-enhancing opportunities, which limits the redistribution of gains from technological or structural change.

Meanwhile, technological change, particularly in the form of ICT diffusion, is theorised to influence inequality through the Skill-Biased Technological Change (SBTC) framework (Acemoglu, 1998; Autor et al., 2003; Goos et al., 2014). SBTC posits that new technologies complement skilled labour while substituting for routine, manual, or low-skilled tasks. As a result, demand for skilled workers rises, raising their relative wages and increasing income inequality, especially when the supply of skills lags behind the pace of technological change. The framework is particularly relevant in SSA, where large informal sectors, weak digital infrastructure, and limited access to education create conditions under which technology can exacerbate rather than reduce inequality (Galor & Moav, 2004). The hypothesis captures the relationship between income, K physical capital, L labour, H human capital, and T technology expressed as

$$income = f(K, L, H, T)$$

The SBTC hypothesis posits that technological progress, represented by T , tends to complement skilled labour H while substituting for routine or low-skilled tasks. Consequently, as new technologies are adopted, the productivity and earnings of skilled workers rise disproportionately compared to their less-skilled counterparts, widening income inequality (Galor & Tsiddon, 1997; Galor & Zeira, 1993). In SSA economies, the theoretical mechanism manifests sharply due to the region's uneven human capital formation and structural labour market dualities. While education and training theoretically enhance productivity and upward mobility, the benefits of human capital accumulation in SSA are often concentrated among a small, urban elite with access to quality education and digital resources. For instance, in Kenya and Nigeria, the expansion of ICT and fintech industries has generated lucrative opportunities for highly educated workers, yet the majority of low-skilled labourers in agriculture and informal services have not shared in these gains (Adeleye, 2024).

Similarly, in South Africa, technological progress in capital-intensive sectors such as manufacturing and finance has increased the wage gap between skilled and unskilled workers, reflecting skill-biased returns. Thus, although human capital investment is generally expected to reduce inequality, in SSA it often amplifies disparities when education systems produce unequal outcomes and technological adoption favours already advantaged groups. The outcome aligns with the SBTC theory and supports the empirical finding that both human capital and technological progress, in the absence of inclusive education and institutional reforms, can exacerbate rather than mitigate income inequality across the region (Surender et al., 2024).

The Mincer (1958) earnings function offers a microeconomic foundation for understanding income differences across individuals, linking wages to schooling and work experience. This framework underpins human capital theory, which posits that higher levels of education and skills enhance labour productivity and individual income, thereby potentially reducing income inequality if education is equitably accessible. However, in SSA, disparities in education quality, unequal returns to schooling, and labour market segmentation may undermine this equalising mechanism. In particular, when formal sector jobs are scarce, education may not yield sufficient returns to offset structural inequality. The Mincer function is presented as

$$income = \alpha_0 + \sum \beta_k X_k + \varepsilon$$

Where *income* denoted the income earnings, X denoted vector of human capital accumulation that is proxied by years of education and work experience, α, β , and ε are parameters to be estimated and error terms. The function suggests that higher levels of education and working experience led to higher income. Consequently, individuals with more education accumulate higher skills and knowledge and tend to have higher earnings, while those with limited education face lower earnings prospects, contributing to income inequality. De Gregorio & Lee (2002) proposed a model that predicts the supply and demand of educated individuals in a society, which depends on the evolution of return rates on education and influences inequality. A community with low educational attainment and a higher level of the technological divide is expected to have higher disparities and lower knowledge and skills accumulated due to lower adoption of technological changes.

What remains under-theorised, particularly in the African development context, is the joint influence of technological change and human capital. A dual-pathway model is useful here. Human capital serves as a complement to technology: the productivity gains from technological change are larger when workers possess the skills necessary to utilise new tools and processes. In this setting, human capital moderates the inequality-widening effect of SBTC by enabling broader participation in high-productivity sectors (Acemoglu & Autor, 2012). Moreover, technological progress can also shape the returns to education, influencing the incentive to invest in human capital. Suppose technology sharply raises the wage premium for high-skilled workers. In that case, it may increase inequality in the short run but also incentivise educational investment in the long run, provided that educational access is not restricted to elites. Furthermore, endogenous growth models (Romer, 1990; Aghion & Howitt, 1998) reinforce this interaction, suggesting that economies with greater human capital stocks are better positioned to generate and adapt to innovation. The models imply that investment in education is not only a driver of productivity growth but also a means of expanding the absorptive capacity of an economy. However, where access to education and digital infrastructure is unequally distributed, as in many SSA economies, the inequality-reducing potential of these complementarities is not realised. Leads to dual inequality traps, where both technology and education serve to concentrate rather than diffuse income gains.

2.2 Income inequality and human capital development

The accumulation and distribution of human capital play a pivotal role in shaping income inequality across societies. Foundational theoretical contributions by Galor & Moav (2004), Galor & Zeira (1993), and Sylwester (2002) emphasise that disparities in access to education and skills can influence both the demand for labour and long-term income distribution. These models suggest that when human capital is unevenly accumulated, it distorts the labour market by creating segmented access to higher-paying opportunities, thus perpetuating wage gaps and poverty traps. Galor & Moav (2004), in particular, proposed that inequality may stimulate growth in early-stage economies by incentivising human capital investments among the wealthy. However, in more advanced economies, where basic education is more widely accessible, inequality tends to hinder growth by restricting opportunities for lower-income groups to invest in skill development. In the context of achieving the United Nations Sustainable Development Goals (SDGs), especially goals related to quality education, decent work, and reducing inequality, removing structural barriers to human capital development is vital. Although the relationship between human capital and income inequality is multifaceted, it is generally acknowledged that inclusive access to education, health services, and vocational training can contribute to a more equitable income distribution (Acemoglu, 2015; Adeleye, 2024; Chetty et al., 2020; Corak, 2016; Marrero & Servén, 2022;

Surender et al., 2020; Surender et al., 2024). However, these benefits are contingent on both the quality of education and its alignment with labour market demands.

Empirical evidence on the relationship between human capital accumulation and income inequality has produced divergent outcomes, largely shaped by country or regional context and the interaction with structural factors. Sethi et al. (2021), in their investigation of India using an ARDL framework, went beyond establishing a correlation by exploring the dynamic interplay between education and inequality over time. The results suggest that the inequality-reducing effect of education becomes more pronounced in the long run, implying that the redistributive potential of human capital requires sustained policy commitment and institutional support. Underscores the notion that education reforms in low- and middle-income countries may not yield immediate equity gains, but they can be powerful over time when embedded in broader structural change. Berisha et al. (2018) applied a fixed-effects model to U.S. state-level data, finding a robust inverse relationship between educational attainment and income inequality. However, their findings also reveal that the impact of education is not uniform across the income distribution. While higher education levels compress wage gaps at the lower end, they may reinforce disparities at the top, particularly when high-skilled labour is rewarded disproportionately in innovation-intensive sectors. This calls attention to the dual nature of human capital as both a levelling and stratifying force, depending on the structure of the economy and access to complementary opportunities.

Using the Panel Study of Income Dynamics (PSID), Kim (2022) took a micro-level approach to explore how education affects wealth inequality in the U.S. context. The study finds that educational attainment contributes to asset accumulation and long-term wealth mobility, thereby dampening wealth disparities. However, the results also point to path dependency, where early-life access to quality education strongly predicts wealth accumulation decades later. Reinforces the importance of intergenerational transmission of human capital and the role of education systems in either breaking or reproducing inequality across cohorts. In contrast, Adeleye (2024) offered a regionally specific insight by examining 46 sub-Saharan African countries using the Panel Spatial Correlation Consistent (PSCC) estimator. Unlike studies from developed economies, Adeleye's findings reveal that human capital and governance indicators, when assessed independently, may exacerbate income inequality, likely due to elite capture, uneven education quality, and urban-rural disparities. Interestingly, the study also shows that the interaction between human capital and governance capacity has an equalising effect. This suggests that education alone is insufficient to reduce inequality in SSA unless accompanied by effective institutions that ensure equitable resource distribution, quality assurance, and inclusive access.

2.3 Technological change and human capital development

Empirical research on income inequality in SSA has expanded significantly in recent years, reflecting growing concern over the social and economic costs of unequal growth. However, the evidence remains mixed and often fragmented, with limited attention paid to the joint influence of total factor productivity and human capital accumulation on inequality, a gap this study seeks to address. A large body of empirical work links human capital to income inequality, often using education as a proxy. Several cross-country studies suggest that improvements in educational levels can reduce inequality by increasing earnings among lower-income groups (Kim, 2022). Berisha et al. (2018) found that educational attainment significantly reduced income disparities in the United States, while Sethi et al. (2021) reported a similar trend in India using ARDL models. In the African context, Adeleye (2024) found that while government institutions

and human capital individually exacerbated inequality, their interaction helped mitigate disparities. This finding informs the interaction-based focus of this paper.

However, such studies often fail to account for the quality and distribution of education or how human capital translates into labour market outcomes in informally structured economies like those in SSA (Corak, 2016). Moreover, much of the African literature has treated human capital as an isolated determinant, neglecting its relationship with other structural forces such as technological advancement. A growing literature has examined the role of technological change in shaping income distribution, largely through the lens of the SBTC proposition. Autor et al. (2003) and Acemoglu (1998) showed that technological progress increases wage inequality by raising demand for skilled workers, thereby increasing the returns to human capital. Empirical studies such as Goos et al. (2014) and Arendt & Grabowski (2019) demonstrated how automation and digitalisation can polarise labour markets and widen wage gaps. In Africa, studies exploring the inequality impacts of technology are relatively scarce and often adopt proxies such as ICT penetration or internet usage. Espoir & Ngepah (2021) conducted a panel cointegration analysis and found that TFP growth, often driven by technology, was associated with higher income concentration. Yet these studies tend to ignore how technological change interacts with education levels, infrastructure gaps, and labour market dynamics in African economies. Ntegwa & Olan'g (2024) recently highlighted that technological access and rural-urban divides in Tanzania exacerbate disparities in clean energy use, reflecting broader structural inequality concerns.

2.4 Role of economic policy, research gap, and novelty

A growing body of literature recognises that technological progress and human capital development are central to shaping patterns of income distribution. Studies such as Acemoglu (1998), Berman et al. (1998), and Goos et al. (2014) argue that technological change, particularly SBTC, tends to increase wage differentials by raising the returns to skills. The accumulation of human capital has been shown to reduce income disparities when education and skill acquisition are broadly accessible (Mincer, 1958; De Gregorio & Lee, 2002; Chetty et al., 2014). However, in many developing regions, especially in SSA, these dynamics are complicated by structural labour market dualities, unequal access to quality education, and institutional weaknesses. This study contributes to the literature by examining the interactive, rather than isolated, effects of technological change and human capital accumulation on income inequality. Specifically, it posits that the quality and absorptive capacity of technological change are key mediating factors in determining whether human capital development leads to more equitable income distribution. The study argues that in contexts where technological innovation outpaces the educational and skill readiness of the labour force, inequality may worsen despite aggregate growth. Conversely, when human capital aligns with technological advancements, the inequality-enhancing effects of SBTC can be mitigated or even reversed.

The study addresses two major gaps in the existing empirical literature. First, while most prior studies analyse the independent effects of either human capital or technology on inequality, few investigate how these forces interact in heterogeneous macroeconomic settings. This research explicitly explores whether human capital can moderate or amplify the inequality effects of technological change, particularly under differing levels of macroeconomic stability and institutional capacity in SSA countries. Second, the study integrates theoretical insights, providing a comprehensive conceptual framework for understanding the structural causes of inequality in developing economies. From an empirical standpoint, this study advances the methodological frontier by employing the Granger non-causality test within a heterogeneous dynamic panel

framework developed by Juodis et al. (2021). This allows for making more robust inferences about directionality and dynamic relationships, overcoming the limitations of conventional fixed effects or pooled models that dominate the literature on SSA. The novelty of this research lies in its multi-dimensional approach, which uniquely captures the conditional and interactive impacts of human capital and technology on inequality, rather than treating these variables as independent determinants. Furthermore, by focusing on SSA, a region marked by high inequality, rapid digital transitions, and education deficits. The study contributes to the ongoing discourse on inclusive development by offering evidence to support targeted policy interventions that align education systems with technological change, aiming to reduce structural income disparities and promote equitable growth. Therefore, the following hypothesis is proposed: The impact of technological advancement on income inequality is conditional on the level of human capital.

3. Data and Methodology

3.1 Data description

This study utilises a panel dataset comprising 23¹ sub-Saharan African (SSA) countries spanning the period from 1980 to 2019. The selection of countries and time frame was guided by the availability and consistency of key variables across internationally recognised databases. The data were primarily drawn from the World Bank's World Development Indicators (WDI), the Penn World Table (PWT) version 10.0 (Feenstra et al., 2015), and the World Income Inequality Database (WIID). These sources provide harmonised and cross-country comparable data suitable for empirical analysis in macro-development contexts. A central focus of the study is the impact of technological change on income inequality. Total Factor Productivity (TFP) is adopted as a proxy. TFP is a comprehensive measure of the efficiency with which capital and labour are used in production and captures improvements from innovation, management practices, infrastructure, and knowledge spillovers (Arendt & Grabowski, 2019; Espoir & Ngepah, 2021). Unlike ICT-based indicators, which only reflect technological diffusion, TFP represents a deeper structural transformation, making it more suitable for cross-country macroeconomic comparisons in long-run growth. However, TFP offers a comprehensive measure of technological efficiency and innovation; the exclusive use of this indicator may obscure distributional channels operating through specific technologies which are more directly linked to labour market and wealth outcomes.

Human capital accumulation is measured using average years of schooling for the working-age population (ages 15–64). The indicator is widely used in development economics as a summary measure of educational attainment, allowing for consistent cross-country comparison over time. The composite index incorporates both the mean years of schooling and expected years of schooling, offering a broader perspective on access and progression within the education system. The dependent variable in this study is income inequality, measured using the Gini coefficient, a widely accepted summary statistic for capturing disparities in income distribution within a country. It provides a concise representation of how evenly or unevenly income is distributed across a population. Where available, net income-based Gini estimates (post-tax and transfers) are used to better reflect redistributive outcomes. To control for broader economic factors

¹ Selection of 23 countries is primarily driven by data availability and consistency over the study horizon; nonetheless, expanding coverage in future work would allow for a more comprehensive assessment of inequality dynamics across the SSA region.

that could confound the relationship between human capital, technological change, and inequality, a set of standard macroeconomic variables was included. The inclusion of control variables is theoretically grounded in the broader inequality literature and essential for ensuring the validity of the estimated effects. According to Kuznets' hypothesis and subsequent empirical studies (Barro, 2000; Bourguignon, 2004), income inequality is systematically linked to the stage of economic development, making GDP per capita a necessary control to account for structural differences in income levels across countries. Population growth (annual %) serves as a demographic control, capturing pressures on labour markets, social services, and income distribution. Rapid population expansion may dilute economic gains and contribute to unequal access to education, employment, and infrastructure. The number of persons engaged in employment is incorporated as a labour market indicator. The variable reflects the total size of the employed workforce and helps control for structural differences in employment intensity, labour absorption capacity, and informal sector prevalence across countries. Employment levels can mediate the effects of human capital and technological change by influencing how economic gains are distributed among workers.

Table 1 presents the data description and descriptive summary of selected variables; Figure 1 panel (3) depicts the relationship matrix between the key variable and the positive relationship observed among the covariates; the data pose no serious problem from the preliminary tests.

Table 1: Data Description and Descriptive Summary

Description ²	Source	Variable	Mean	Std. Dev.	Min	Max	JB ³
Income inequality	WIID	income	8.429	.818	6.562	10.297	0.000
Human capital index	PWT	hc ⁴	1.661	.452	1.014	2.939	0.000
TFP		rtfpna	.937	.214	.345	1.635	0.000
GDP per capita		gdp	9.953	1.246	7.755	13.816	0.000
Number of persons engaged		emp	6.033	9.277	.237	73.021	0.000
Population growth	WDI	pop	16.795	27.444	.726	200.964	0.000

Source: PWT, WIID, WDI

3.2 Methodology

To examine how human capital and technological progress influence income inequality in sub-Saharan Africa, this study employs the Dynamic Common Correlated Effects Mean Group (DCCE-MG) estimator developed by Chudik & Pesaran (2015). This method extends Pesaran's (2006) Common Correlated Effects (CCE) approach, which is widely used in panel data analysis to account for cross-sectional dependence (CSD), heterogeneity across countries, and unobserved global shocks that may affect all economies simultaneously, such as changes in global technology diffusion. The DCCE-MG estimator is particularly suitable for panels that include many countries observed over a long time period. It allows each country to have its own unique relationship between income inequality, human capital, and total factor productivity, rather than

² Income per adult and GDP per capita were transformed to a logarithm term, the transformation was used to smooth the variable to offer constant variance and potentiality control of heteroskedasticity.

³ JB test for normality null hypothesis: reject if the p-value is less than the significance level.

⁴ Index measured based on years of schooling and returns to education.

assuming that all countries respond in the same way. The flexibility makes the results more realistic for the diverse economic structures within SSA.

However, the DCCE-MG estimator is well-suited to addressing CSD, slope heterogeneity, and endogeneity arising from unobserved common factors; this study focuses on mean-group estimation without applying additional small-sample or analytical bias correction techniques. Moon & Weidner (2013) developed a Gaussian quasi-maximum likelihood (QMLE) estimator with assumptions of homogeneous coefficients. Moreover, Bai (2009) introduced the interactive-effects (IFE) estimator that allows CSD errors with a homogenous slope assumption, while the estimator for lagged dependent variables is extended with heterogeneous coefficients. In practice, the method works by adding the cross-sectional averages of all variables (such as income inequality, human capital, and total factor productivity) to the model. These averages capture the influence of unobserved common factors that might bias traditional estimates. The dynamic version (DCCE-MG) further incorporates lagged values of income inequality to capture persistence over time, acknowledging that inequality tends to adjust slowly to policy or technological changes. From Pesaran (2006), the CCE function with heterogeneous coefficients

$$income_{i,t} = \sum \beta_i' X_{i,t} + \alpha_i + \gamma_i' f_t + \varepsilon_{i,t} \quad (1)$$

Where $\gamma_i', f_t, \alpha_i, \varepsilon_{i,t}$ respectively denote heterogeneous factor loading, unobserved common factor, specific fixed effect, and error term that is distributed independently and identically. $X_{i,t} = (hc, tfp)$ vector of regressor that includes human capital development index and TFP, the heterogeneous coefficients $\beta_i = \beta + v_i$ distributed randomly around a common mean where $v_i \sim N(0, \Sigma_{v_i})$ with variance-covariance matrix Σ . The estimator consistently estimates equation (1) by approximation of the unobserved common factors with cross-sectional averages under strictly exogenous covariates. In the dynamic panel of equation (2), the DCCE-MG estimator proposed with k lags given in the form of equation (3).

$$income_{i,t} = \phi_i income_{i,t-1} + \sum \beta_{i,k} X_{i,t-k} + \alpha_i + s_{i,t} \quad (2)$$

$$income_{i,t} = \phi_i income_{i,t-1} + \sum \beta_{i,k} X_{i,t-k} + \sum \gamma_{i,l}' \bar{h}_{t-l} + \alpha_i + s_{i,t} \quad (3)$$

Where the number of lags $l = \sqrt[3]{T}$ of the cross-section averages for all variables, $s_{i,t}$ denoted weakly CSD idiosyncratic error and assumed that the lagged dependent variable is no longer strictly exogenous $E(\phi_i) = \phi$. Vector of lag of dependent and strictly exogenous variables denoted as $\bar{h}_t = (\bar{y}_{t-1}, \bar{X}_t)$ with stacked parameters $\varphi_i = (\phi_i, \beta_i)$. The MG estimates are determined as $\hat{\varphi}_{MG} = \sum \frac{\hat{\varphi}_i}{N}$ having an asymptotic distribution $\sqrt{N}(\hat{\varphi}_{MG} - \varphi) \xrightarrow{d} N(0, E_{MG})$ (Chudik & Pesaran, 2015; Pesaran, 2006).

3.3. Estimation

Before estimating the model, a series of diagnostic tests was performed to ensure that the statistical assumptions were satisfied. First, panel unit root tests were used to determine whether the variables were stationary, that is, whether their statistical properties remained constant over time. Both first-generation tests (Im et al., 2003; Levin et al., 2002) and second-generation tests (the Cross-Sectionally Augmented Dickey-Fuller (CADF) and CIPS tests by Pesaran (2021)) were applied. The latter are particularly appropriate when data across countries are correlated, as is typical in SSA. The results

confirmed that the variables were stationary after taking first differences, which justified the use of a dynamic specification.

Then, panel cointegration tests (Westerlund, 2007) were conducted to check whether a long-run equilibrium relationship exists among income inequality, human capital, and technological progress. These tests allow for heterogeneity and cross-country dependence, ensuring that the estimated relationships are not spurious. The results indicated that the variables are cointegrated, implying a stable long-term association. Finally, tests for slope homogeneity (Pesaran & Yamagata, 2008) and cross-sectional dependence (Pesaran, 2015) were performed. These confirm that the effects of human capital and technology differ significantly across countries and that economies in the region are interlinked through common external shocks. Taken together, these diagnostics validate the use of the DCCE-MG estimator, which is specifically designed to handle such data features.

4. Empirical Results and Discussion

4.1 Estimation results

Global common shocks and overlooked disturbances impact the estimation of panel data, potentially leading to model misspecification or spurious results if these disturbances are not considered. The Pesaran (2015) CSD test was used to address this issue and evaluate the typical correlation of variables across selected countries with the assumption of standard normal distribution. The approach applies even to panels that are spaced out and balanced, regardless of whether they adhere to a weak or strong null hypothesis of CSD. Panel (a) column (2) of Table 2 presents the CSD statistic; the null hypothesis is rejected and, therefore, refutes CSD and correlation across a panel of selected SSA economies. LLC, IPS, and Fisher tests are based on the augmented Dickey-Fuller (ADF) as the first-generation panel stationarity test used to ascertain the stationarity of the regressors (Im et al., 2003; Levin et al., 2002). The study assesses the stationarity null hypothesis; Table 2 presents outcomes related to the stationarity tests for level and the first difference. The findings were substantial in rejecting the null hypothesis of panels containing a unit root, thus confirming the panels' stationarity.

The study revisits the panel stationarity analysis using an effective second-generational test in a heterogeneous panel with CSD across a panel. The study employs the homogeneous non-stationary null hypothesis for the Cross-Sectionally Augmented Dickey-Fuller (CADF) and CIPS panel unit root tests (Pesaran, 2021). The Pesaran CIPS panel unit root test incorporates cross-sectional and first difference means for variables, considering deterministic and dynamic lag criteria based on the F joint test, with periods truncated during the aggregation process. For the Pesaran CADF test, the cross-sectional average of variables is extracted, and extreme t-values are augmented by one lag. In Table 2 panel (b), the second-generational results are presented to validate the outcomes of the first-generational unit root tests, where the null hypothesis for the selected panel is rejected, aligning with the first-generational test results.

Furthermore, the Pesaran & Yamagata (2008) test of slope homogeneity is conducted with the null hypothesis of homogeneous slopes, requiring a large cross-sectional dimension. Imposing slope homogeneity would lead to biased and inconsistent estimations. The results in Table 3 for delta and adjusted delta indicate the rejection of

the hypothesis, suggesting that all slope coefficients are not identical across cross-sectional units. The null hypothesis of no cointegration is tested with a conditional panel error correction term set to zero, accommodating unit-specific dynamics, trends, cross-sectional dependence, and slope parameters (Westerlund, 2007). Although the study addresses CSD, the cointegration tests presented in Table 3 significantly reject the null hypothesis. The variance ratio statistics of 1.72 and -2.99 for the same and panel-specific AR, respectively, reject the null hypothesis at 5% and 1%. Additionally, the Pedroni (2001) cointegration test is employed, and the results align with those of Westerlund (2007), indicating that the variables in the model specification are cointegrated across all panels.

4.2 Baseline estimations

The study utilises panel time series models with varying slope coefficients among group members, considering the CSD issue; the Pesaran (2006) CCE-MG estimator; and the augmented mean group (AMG) estimator, as suggested by Eberhardt & Bond (2009) and Teal & Eberhardt (2010), are applied. The models incorporate country-specific slopes b_i on the observable variables, unobservable u_{it} , including standard group fixed effects a_{1i} capturing time-invariant heterogeneity across countries and an unobservable common factor f_t with diverse η_i factor loadings reflecting time-invariant heterogeneity and CSD, error term denoted as e_{it} assumed to be white noise. The estimators follow a simple model as

$$\begin{aligned} income_{it} &= \sum b_i X'_{it} + u_{it} \\ u_{it} &= \eta_i f_t + a_{1i} + e_{it} \\ X_{it} &= \eta_i f_t + \zeta_i g_t + a_{2i} + \epsilon_{it} \end{aligned}$$

Pesaran (2006) showed that CCE-MG induces CSD, a time-variant unobservable with heterogeneous effects across countries in a panel, and an identification problem if variables contain f_t then b_i is unidentified. The estimator solves the issues related to transmission bias, whereby human capital and technology change are expected to correlate with f_t that are accounted for in the estimations; the approach remains efficient even with few significant factors and a limited number of less influential factors, respectively, associated with local spillover and global shock effects (Kapetanios et al., 2011; Pesaran & Tosetti, 2011). Teal & Eberhardt (2010) developed an alternative estimator that performs as well as CCE-MG regarding bias and RMSE in panels with either non-stationary cointegrated variables or not, the AMG, with multifactor error terms.

Table 4 presents results related to the baseline model of our study, where the lag of income inequality across the models is significant and negative, suggesting an inverse nexus between shifts in income inequality and the effects of human capital accumulation and technological change. Coefficients imply that as human capital accumulation and technological advancements increase, there is a subsequent reduction in income inequality over time. The alleviation of income disparity in the region takes time to materialise and becomes evident in subsequent periods. Human capital is not significant in both estimators, which suggests no substantial changes in the level of human capital over time. The estimates imply that there is limited or no improvement in human capital levels over time, which could indicate that educational attainment, skills acquisition, or other factors contributing to human capital development are not undergoing substantial changes or improvements. CCE-MG and AMG results in panels (a) and (b) indicate a

significant positive TFP, which suggests that technological advancements in the region are occurring and positively impacting productivity. This indicates that the economy is becoming more efficient in converting inputs into outputs, beyond what can be attributed to changes in traditional inputs like labour and capital. For control variables, only GDP per capita is positive and significant, while employment and population growth indicate no impact on employment share and the growing population in the region on exacerbating income inequality.

Table 2: CSD and Stationarity Tests

Panel (a)	Pesaran (2015) CD	1st Generation					
		LLC		IPS		Fisher-based on ADF	
		Level	First difference	Level	First difference	Level	First difference
log_income	100.545***	-	-	-	-	123.702**	-
hc	100.296***	11.820***	22.651***	-3.164***	-14.619***	*	371.361***
rtfpna	98.402***	-5.805**	10.925***	3.072	-14.900***	78.253***	113.471***
log_rgdp	100.523***	-9.261**	17.2345**	0.142	-9.030***	42.026	206.304***
emp	99.908***	-9.569**	20.7479**	-0.036	-12.801***	55.184	305.997***
pop	99.954***	-8.333***	10.5773**	6.613	-4.093***	32.955	121.301***
			-			320.944**	
			18.521***	-7.891***	-20.777***	*	604.276***

Panel (b)	2nd Generation			
	PESCADF		CIPS	
	Level	First difference	Level	First difference
log_income	-2.355	-4.571***	-2.39	5.417***
hc	-1.525	-3.192***	-2.148*	-3.199***
rtfpna	-1.952	-3.614***	-1.248	-5.141***
log_rgdp	-2.367	-4.222***	-2.382***	-5.444***
emp	-2.387	-2.700**	-2.182**	-3.140***
pop	-4.507***	-5.134***	2.160**	-3.447***

Note: ***, **, * significance at $p < 0.01$, 0.05, 0.1

Source: Author(s)

Table 3: Cointegration and Slope Heterogeneity Tests

Pedroni	Autoregressive (AR) parameter				Slope heterogeneity	
	Same	Panel specific	Westerlund	Same	Panel specific	Delta
Modified variance ratio	-2.267**		Variance ratio	-1.7199**	-2.985***	38.095***
Modified Phillips-Perron t	1.337*	2.965***				41.941***
Phillips-Perron t	-3.580***	-4.501***				
Augmented Dickey-Fuller t	-4.911***	-4.004***				

Note: ***, **, * significance at $p < 0.01$, 0.05, 0.1

Source: Author(s)

Table 4: Baseline Results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel (a) Pesaran (2006) CCE-MG								
L.log_income	-	-	-	-	-	-	-	-
	0.226*** (0.0435)	0.266*** (0.0445)	0.103*** (0.0299)	0.140*** (0.0420)	0.116*** (0.0326)	0.176*** (0.0475)	0.114*** (0.0290)	0.148*** (0.0400)
D.hc	0.164 (1.111)	-0.271 (1.250)			-0.314 (0.632)	-1.453 (1.071)		
D.rtfpna			0.846*** (0.0561)	0.676*** (0.100)	0.837*** (0.0554)	0.662*** (0.112)		
D.interaction							0.544*** (0.0510)	0.448*** (0.0689)
D.log_rgdp		0.259*** (0.0488)		0.117*** (0.0415)		0.0988** (0.0464)		0.114*** (0.0386)
D.emp		-0.442 (0.509)		0.144 (0.329)		0.0685 (0.296)		0.143 (0.311)
D.pop		-0.280 (0.586)		-0.473 (0.538)		-0.522 (0.526)		-0.369 (0.531)
Panel (b) AMG								
L.log_income	-	-	-	-	-	-	-	-
	0.361*** (0.0470)	0.296*** (0.0434)	0.160*** (0.0366)	0.176*** (0.0385)	0.192*** (0.0406)	0.205*** (0.0422)	0.171*** (0.0366)	0.183*** (0.0374)
D.hc	0.548 (1.218)	-0.398 (1.097)			-0.495 (0.985)	-1.487 (1.035)		
D.rtfpna			0.793*** (0.0565)	0.683*** (0.0589)	0.743*** (0.0635)	0.671*** (0.0641)		
D.interaction							0.504*** (0.0497)	0.444*** (0.0413)

Note: Standard errors presented in parentheses; ***, **, * significance at $p < 0.01$, 0.05 , 0.1

Source: Author(s)

4.3 Estimation results

The Dynamic Common Correlated Effects Mean Group (DCCE-MG) estimator presented by Chudik & Pesaran (2015) was employed in this study. For the selected 23 SSA economies between 1980 and 2019, all variables were included with $\sqrt[3]{40} \approx 3$ number of cross-sectional averages and the half-panel jackknife (HPJ) bias-correction method. The findings speak directly to the study's central research question: To what extent do technological change and human capital influence income inequality in sub-Saharan Africa, and how does their interaction shape distributional outcomes? To capture dynamic adjustment, the lag is included in all models, acknowledging the persistence of income inequality over time. The decision to apply first differencing to the remaining variables is grounded in stationarity tests, which indicated non-stationarity in levels for most regressors. Differencing ensures that the analysis reflects short- to medium-term changes rather than long-run trends.

Table 5 presents results related to the DCCE-MG estimator with a first difference of covariates. The CSD test statistic of the model in columns (4), (6), and (8) rejects the null hypothesis of weak CSD; others reject the hypothesis. The lag of income is negative and significant across all models, while columns (1), (3), (5), and (7) present the estimates without the impact of control variables. Human capital, TFP, and intervening effect in columns (1), (3), and (7) are positive and significant, indicating that increases in the quality of human capital and technology development significantly increase income inequality. Human capital highly increases income inequality by about 2.1, while TFP increases by 0.8, with significant simultaneous impacts of 0.95 and 0.81, respectively. The positive and significant coefficient for TFP reflects the efficiency and technological

advancements within an economy, serving as an indicator of how improvements in technology and overall productivity impact income inequality.

Moreover, results suggest that an improvement in the quality of human capital in the economies, which indicates the level of knowledge, skills, and education level of individuals in a society, has a substantial impact on income inequality. The result implies that societies with higher levels of education, skill, technological development, and productivity experience greater income disparities. The interaction term of human capital and TFP is significant and positive, increasing inequality by 0.54. This implies that the joint effect of education/skills and technology on income inequality is greater than the sum of their separate effects. Furthermore, the result is consistent with De Gregorio & Lee (2002), in which educational attainment has expanded quantitatively but without commensurate improvements in quality, relevance, or alignment with labour market demands, thereby limiting its equalising potential.

The coefficient on TFP is positive and significant, indicating that technological change, when occurring in isolation, is associated with higher income inequality. Supports the Skill-Biased Technological Change (SBTC) hypothesis, suggesting that innovation disproportionately benefits higher-skilled workers in SSA, where digital infrastructure and institutional readiness remain uneven. By contrast, human capital accumulation is associated with increased inequality, as indicated by the positive and statistically significant coefficient on HC. The finding deviates from the Mincerian framework and prior empirical studies (Berisha et al., 2018; Kim, 2022), suggesting that broader access to education compresses wage differentials and improves upward mobility. The coefficient of the interaction term is positive and significant, suggesting that the inequality-increasing effect of technology is not mitigated in countries with lower human capital levels. Implies that education does not moderate the distributional consequences of technological advancement, enabling more equitable access to emerging opportunities. The result rejects this study's hypothesis, demonstrating a conditional or mediating effect in line with more flexible formulations of the SBTC theory (Acemoglu & Autor, 2012).

Selected control variables were included to assess the impacts of macroeconomic variables on the economy. Table 5 Columns (2), (4), (6), and (8) present DCCE-MG results including the control regressors. GDP per capita is positive and significant across all models, 0.56 employment share is positive and significant only with the interaction term, while population growth is insignificant and negative only with TFP. The sign of human capital in columns (2) and (6) differs significantly negatively. The result suggests that economic growth, as measured by GDP per capita, is linked to greater income disparities. In some studies, economic growth in SSA countries has been associated with reduced income inequality, particularly when accompanied by policies that advocate inclusive growth, which includes measures such as education investments, healthcare, infrastructure, and social protection programmes that ensure the benefits of growth are shared more widely among the population. Technological change often requires specialised skills and knowledge, and the demand for skilled labour creates a skill premium, where individuals with higher levels of education and technical skills command higher wages, leading to income disparities between skilled and unskilled workers. The result highlights the importance of investing in human capital development to ensure that the workforce can effectively participate in the digital economy. However, limited access to education and skills training creates barriers to economic opportunities and perpetuates income disparities in the growing population of the SSA region.

The results of the influence of human capital on inequality are in line with those of Adeleye (2024), and the negative effect is supported by control variables. The product term of human capital and technological changes aggravates income disparity in the

economies, which supports the conjecture that human capital is affected by the equalising impact of technological changes on exacerbating inequality. The significant and positive coefficient of the product term implies that the intervening impact increases income disparity by 0.54 and 0.51. The outcome is not surprising as the SSA region experiences a high technological divide, which may reduce benefits from human capital accumulations and exacerbate inequality. The positive and significant TFP implies a rejection of the SBTC hypothesis in line with that of Espoir & Ngepah (2021), undesirable outcomes will be expected if policymakers depend on the total factor productivity as a measure of technology change, economic development, and possibly reducing income disparity across economies. The outcome suggests that governments in the SSA region should increase efforts to fight inequality with a focus on increasing human capital accumulation with more adoption and use of advanced technology and reducing the dividing gap across economies by investing in developing infrastructure. Based on the outcomes, the study recommends several policies that will boost technological change in human capital and inequality. Findings suggest the need for policies that move beyond expanding enrolment towards improving education quality and ensuring closer alignment between curricula, vocational training, and evolving labour market demands, particularly in technology-intensive sectors.

Table 5: DCCE-MG Results

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.log_income	-	-	-0.0316*	-	-	-	-	-
	0.140*** (0.0247)	0.173*** (0.0278)	(0.0180)	0.0884*** (0.0270)	0.0474** (0.0205)	0.109*** (0.0296)	0.0427** (0.0181)	0.0959*** (0.0277)
D.hc	2.097** (0.839)	-0.408 (1.043)			0.945** (0.398)	-1.055 (0.876)		
D.rtfpna			0.803*** (0.0852)	0.733*** (0.0527)	0.808*** (0.0723)	0.726*** (0.0615)		
D.interaction							0.542*** (0.0603)	0.513*** (0.0461)
D.log_rgdp		0.302*** (0.0476)		0.111*** (0.0262)		0.104*** (0.0352)		0.0938*** (0.0274)
D.emp		0.0468 (0.459)		0.458 (0.285)		0.474 (0.318)		0.557* (0.332)
D.pop		0.210 (0.312)		-0.00154 (0.191)		0.0639 (0.188)		0.0185 (0.185)
CD	4.32	2.19	2.35	0.73	2.85	0.80	2.87	1.09
p-value	0.0000	0.0288	0.0186	0.4651	0.0044	0.4223	0.0041	0.2770
F-statistic	3.46	6.04	17.04	8.67	11.90	7.68	17.18	8.98
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.160	0.473	0.485	0.563	0.502	0.585	0.487	0.571
Number of groups	23	23	23	23	23	23	23	23

Note: Standard errors presented in parentheses; ***, **, * significance at $p < 0.01, 0.05, 0.1$

Source: Author(s)

Table 6: DCCE-MG with the Endogenous Assumption

VARIABLES	(1)	(2)	(3)	(4)	(5)
L.log_income	-0.416*** (0.0562)	-0.836*** (0.128)	-0.300*** (0.0606)	-0.604*** (0.142)	-0.232*** (0.0490)
D.hc	0.348 (1.922)	-4.051 (10.43)	-1.054 (2.308)	4.672 (5.735)	0.205 (1.750)
D.rtfpna			0.627*** (0.118)	0.840** (0.346)	
D.interaction					0.392*** (0.0673)
D.log_rgdp		0.148**		0.0949	

VARIABLES	(1)	(2)	(3)	(4)	(5)
		(0.0745)		(0.108)	
D.emp		-0.815		0.322	
		(0.645)		(0.545)	
D.pop		0.696		-0.436	
		(2.270)		(2.040)	
CSD	-2.54	-1.57	-1.26	-3.20	-2.05
p-value	0.0112	0.1172	0.2068	0.0014	0.0401
F statistic	5.22	2.01	9.98	2.41	10.55
Prob > F	0.000	0.000	0.000	0.000	0.000
R-squared	0.284	0.263	0.602	0.747	0.559
Number of groups	23	23	23	23	23

Note: Standard errors presented in parentheses; ***, **, * significance at $p < 0.01$, 0.05 , 0.1

Source: Author(s)

The developing countries in the region should boost structural transformation and reduce over-dependence on primary products. Implement redistributive policies such as progressive tax legislation that will ensure equitable income distribution and increase the employment share. However, the use of mean coefficients mitigates aggregation bias in heterogeneous panels; the estimated effects are interpreted as average long-run relationships, as potential finite-sample bias correction methods were not explicitly implemented in this study. The absence of a statistically robust equalising effect of population growth suggests that labour force expansion alone is insufficient to reduce income inequality in SSA. In a region characterised by limited technological absorption, high informality, and skill mismatches, population growth may instead dilute productivity gains and reinforce existing disparities rather than facilitate technology diffusion across income groups.

4.4 Robustness and sensitivity check

4.4.1 Endogeneity problem in dynamic panel data

Figure 2 panel (a) presents the plots for MG coefficients of interaction terms and control variables with a 95% confidence interval; the estimated point is depicted with a cross, and the interaction term of human capital and TFP significantly impacts the income inequality. The test on CSD was conducted to confirm the results of the models, and the residuals in the error term were predicted. Figure (2) panel (b) depicts the normality of the error term of the dependence test, and the results corroborate it. Considering endogeneity is crucial when estimating dynamic panel data models because failing to account for it can lead to biased and inconsistent parameter estimates, rendering the results unreliable. It is assumed that human capital into technology change is endogenous, whereas countries with higher per capita income distribution may have higher human capital accumulation, leading to a reversed causality of human capital into technology change and income distribution. Two lags of human capital are employed as instruments to avoid higher drops in the degree of freedom. Table 6 presents the results related to the DCCE-MG model with instrumental variable options; significant lag of income inequality and TFP are negative and positive, respectively, while human capital is insignificant across all models. The results with endogeneity are not consistent with those of Table 4, therefore rendering the employed estimation approach robust.

4.4.2 Granger non-causality approach

Conventional Granger tests assume strict exogeneity, homogeneity, and no cross-unit dependencies, assumptions that are often violated in macroeconomic panels. To assess the temporal directionality of the relationships between income inequality,

technological change, and human capital accumulation, a Granger non-causality testing framework designed specifically for dynamic panel settings was implemented. Traditional Granger causality tests are often biased or invalid when applied to panels with cross-sectional dependence, heterogeneous slopes, or endogenous regressors. To overcome these limitations, the study follows the methodology proposed by Juodis et al. (2021), which offers a consistent and powerful test in large-T, large-N panels.

Table 7 shows the Juodis et al. (2021) results for the p-value and significant Wald statistics for the null hypothesis that estimated coefficients equal zero for all cross-sectional heteroskedasticity panels, the number of lags (1) obtained using the Bayesian information criterion (BIC). The MG estimator of Granger-causation parameters was computed using the mean across cross-sectional countries in the panel; significant coefficients were estimated and reported. The null hypothesis was rejected for all variables, and this implies that human capital, technology change, and selected control variables Granger-cause income inequality. The past value of human capital and technology change includes information that helps predict income distribution above and beyond the information included in the past value of income inequality. To corroborate the results, the Granger non-causality tests based on the approach proposed by Dumitrescu & Hurlin (2012) were also employed; the results from statistics significantly support the null hypothesis of the test. Findings suggest that population growth, education expansion, and technological progress do not automatically yield inclusive outcomes; their distributional effects depend critically on education quality, labour market absorption capacity, and the sectoral channels through which technology diffuses.

Table 7: Granger Non-causality Results

Variables	MG-estimates	Z-bar
hc	-0.0826*** (0.0217)	17.7053***
rtfpna	-0.0739*** (0.0227)	14.9551***
rgdpo	0.0494*** (0.0104)	12.8685***
emp	-0.0162*** (0.0038)	14.4827***
pop	0.0084*** (0.0013)	19.6462***
Wald Chi2	84.8608	
Prob > chi2	0.0000	
BIC	-5097.682	

*Note: Standard errors presented in parentheses; ***, **, * significance at $p < 0.01$, 0.05, 0.1*

Source: Author(s)

4.4.3 Alternative measure of income inequality

In this subsection, different measures of income inequality are employed on our DCCE-MG estimator for further robustness checks. The Gini coefficient, proportional to income held by the top 1% and 10% of individuals in the society, is abstracted from the WID. The Gini coefficient and the income proportion of the top income groups are

dynamic measures that can capture changes in income inequality over time⁵ and allow this study to assess how income inequality evolves as human capital accumulation and technological change progress. The Gini coefficient is a commonly employed metric for assessing income inequality, offering a comprehensive overview of the income distribution within a society. This index takes into consideration the entire income spectrum, effectively capturing disparities across all income levels. In contrast, the pre-tax national income share held by the top 10% and top 1% focuses specifically on the concentration of income among the highest earners. These measures shed light on the income disparities at the upper echelons of the distribution, where inequality tends to be most prominent. Table 8 presents results related to alternative metrics of inequality; coefficients are positive and not significant. TFP is significant only with the top 1% group, which implies that the wealthiest segment of the population benefits more from technological changes in a country than the poor. Results indicate the robustness of the model employed in our study.

Alternative indices such as the Palma ratio and the Theil index are designed to emphasise specific distributional features. The Palma ratio focuses on income shares at the extremes, while the Theil index allows for within- and between-group decomposition. While these properties are valuable for distribution-sensitive analyses, they are less central when the research question concerns average inequality dynamics and persistence at the macroeconomic level. These indices often exhibit high empirical correlation with the Gini coefficient in cross-country settings, implying that they tend to capture similar long-run inequality trends rather than fundamentally different dynamics.

Table 8: Alternative Measures of Income Inequality

Variables	(1)	(3)	(5)	(7)
Panel (a) Gini⁶				
L.gini	0.00798 (0.0357)	0.00520 (0.0355)	0.00526 (0.0363)	0.00330 (0.0360)
D.hc	0.101 (0.168)		0.0718 (0.170)	
D.rtfpna		0.0115 (0.0111)	0.00942 (0.0114)	
D.interaction				0.00303 (0.00740)
Panel (b) p90p100⁷				
L.p90p100	0.00543 (0.0380)	0.00215 (0.0382)	0.00181 (0.0387)	-0.00115 (0.0389)
D.hc	0.116 (0.186)		0.0828 (0.187)	
D.rtfpna		0.0175 (0.0143)	0.0150 (0.0143)	
D.interaction				0.00586 (0.00932)

⁵ Pre-tax national income is referred to as the sum of all pre-tax personal income flows accruing to the owners of the production factors, labour, and capital, prior to the operation of the tax/transfer system after taking into account the operation of the pension system. The central difference between personal factor income and pre-tax income is the treatment of pensions, which are counted on a contribution basis by factor income and on a distribution basis by pre-tax income.

⁶ Pre-tax national income shares in terms of the Gini coefficient.

⁷ Pre-tax national income share held by the p90p100 group.

Variables	(1)	(3)	(5)	(7)
Panel (c) p99p100⁸				
L.p99p100	0.00210 (0.0461)	0.0216 (0.0446)	-0.000393 (0.0468)	0.0224 (0.0449)
D.hc	0.0662 (0.155)		0.0448 (0.158)	
D.rtfpna		0.0177 (0.0109)	0.0189* (0.0111)	
D.interaction				0.00758 (0.00630)

*Note: Standard errors presented in parentheses; ***, **, * significance at $p < 0.01$, 0.05 , 0.1*
Source: Author(s)

5. Conclusion

The problem of income inequality in the SSA region is a significant socio-economic challenge that has far-reaching implications. The disparity in income distribution has wide-ranging consequences for social stability, economic growth, and human development. In line with the United Nations Sustainable Development Goals (SDGs), acquiring quality education and improved healthcare outcomes can enhance productivity and overall well-being. Technological change, including advancements in information technology, automation, and innovation, has the potential to transform economies and societies. Technological progress can lead to productivity gains, increased efficiency, and the creation of new industries and job opportunities. The expectation is that human capital accumulation and technological change can work in tandem to reduce income inequality in the SSA region. By investing in education and skill development, individuals can acquire the necessary qualifications to participate in technologically advanced sectors, which tend to offer higher wages. This research investigates the heterogeneous influence of human capital and technological advancement on income inequality in a large-dimension dynamic panel of SSA economies between 1980 and 2019. The use of country-level macroeconomic data may conceal important micro-level and sector-specific dynamics through which technology and human capital affect income inequality. The distributional effects of technological change and skills accumulation often vary across industries, regions, and households, and further studies could benefit from combining macro-level analysis with household, firm-level, or sectoral data to capture these heterogeneous mechanisms more accurately.

The study empirically scrutinises the heterogeneous nexus between human capital development and technological change in the region's income distribution, which underpins the SBTC hypothesis. The Chudik & Pesaran (2015) and Ditzgen (2018) DCCE-MG estimator employed, the outcomes indicate that, contrary to expectations, the increase in human capital and technological advancements have exacerbated income inequality rather than reducing it. Human capital accumulation might suggest that the level of educational attainment has reached a plateau, with no significant increase or improvement in educational outcomes, which could be due to several factors, such as limited access to quality education or saturation in educational opportunities. Juodis et al. (2021)'s and Dumitrescu & Hurlin, (2012)'s non-causality Granger tests were

⁸ Pre-tax national income share held by the p99p100 group

employed to comprehend the MG estimates on heterogeneous panels as robustness measures, and the null hypothesis of the test was rejected; variables Granger caused income inequality.

Another notable finding was insufficient evidence pertaining to the repercussions of population growth on the equalising effect of technological change. It was expected that the expanding population in the region would help mitigate income inequality by increasing the labour force and facilitating the diffusion of technology. However, the study did not find substantial support for this argument, which suggests that while population growth is an important factor to consider in the broader context of economic development, it may not directly alleviate income disparities without complementary measures and policies. SSA policymakers should focus on expanding access to quality education in rural and underserved areas by investing in infrastructure and training to reduce disparities in human capital development. Implementing targeted vocational and technical training programmes aligned with the evolving demands of digital and technological sectors can enhance skill acquisition for marginalised populations. Policymakers should also prioritise upgrading education curricula to include digital literacy, preparing the youth for participation in the modern economy. Importantly, these measures should be complemented by social safety nets to support displaced or vulnerable workers during technological transitions, ensuring that growth inclusively benefits the broader population.

Our study is not without some notable limitations. The study focuses on the approach of mean coefficients to deal with the large T bias of the estimator; further research should include the application of the bias correction technique. Few dynamic panel studies considered bias correction with heterogeneous coefficients for both frequentist and Bayesian frameworks (Kiviet, 1995; Pesaran & Zhao, 2009). Future studies should also investigate different levels of educational attainment and health measures as proxies for human capital development in reducing inequality. Studies should include the impacts of other measures of technological changes to investigate the distributional changes in wealth, wages, and income inequality. Research⁹ should disaggregate human capital into distinct levels of educational attainment to capture heterogeneity in skill formation and returns across the income distribution. Incorporating health-related indicators would allow for a more comprehensive assessment of human capital development and its distributional consequences. Such an approach would facilitate a more nuanced understanding of how different dimensions of human capital interact with technological change to influence income inequality¹⁰. Furthermore, countries' selection in the region should be addressed by incorporating diversity to enhance the generalisability of the findings.

Another limitation of this study lies in the absence of explicit bias correction procedures within the DCCE-MG framework. While mean-group estimation reduces bias arising from parameter heterogeneity and cross-sectional dependence, several methodologies suggest that additional bias correction techniques may further improve efficiency and robustness, particularly in panels with moderate time dimensions.

⁹ While this study relies on an aggregate measure of human capital, future empirical work could benefit from employing disaggregated education and health indicators to better reflect the multidimensional nature of human capital formation.

¹⁰ While the study derives policy-relevant implications from the empirical findings, it does not explicitly examine the qualitative dimensions of policy implementation. In many SSA economies, institutional constraints may weaken the transmission of education and technology-orientated policies into inclusive income outcomes. Future research could integrate qualitative institutional assessments or governance diagnostics to better evaluate how such structural weaknesses mediate the effectiveness of inequality-reducing policies.

Notwithstanding this limitation, the study's contribution lies in its ability to uncover robust average dynamics between productivity, human capital, and inequality under conditions of CSD that are pervasive in SSA economies. Additionally, future research could extend the present analysis by incorporating bias-corrected CCE estimators or alternative dynamic panel approaches to validate the stability of the estimated relationships. While the study conceptually recognises human capital as both a potential levelling and stratifying force, it does not empirically assess how its effects vary across the income distribution. Future research could employ distribution-sensitive methods, such as quantile regressions or inequality-decomposition techniques, to identify whether the returns to education and skills are concentrated among upper-income groups or extend meaningfully to lower-income deciles.

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Data Availability

The authors will share codes under specific conditions and data available on the stated public domains.

Competing interests

The authors declare no competing interests.

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Appendix

Figure 1: Gini Index of National Income in the SSA Region and Matrix of Correlation

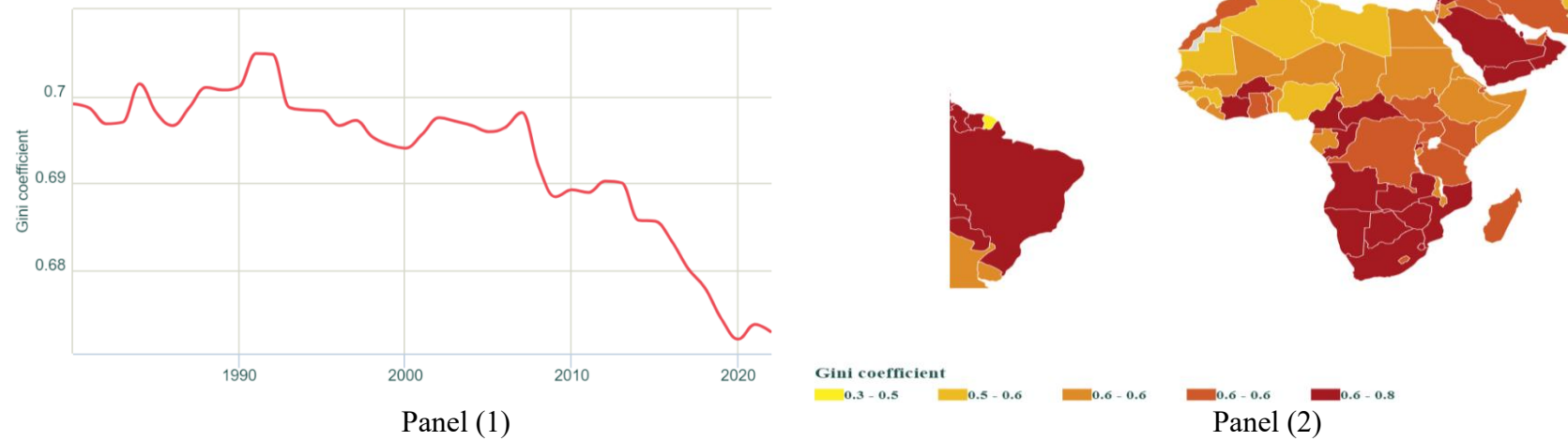
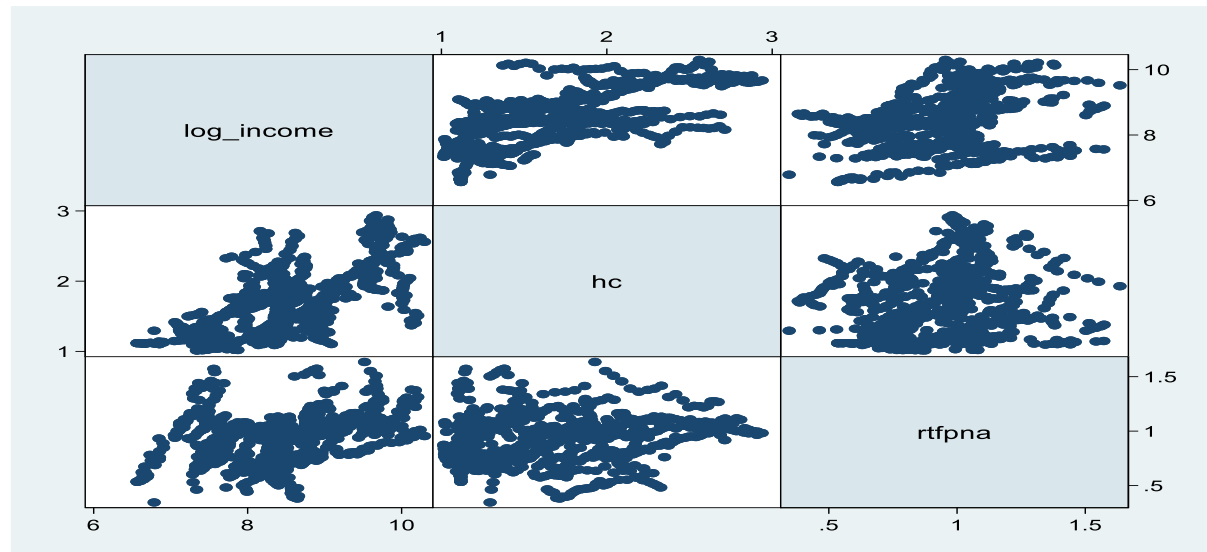


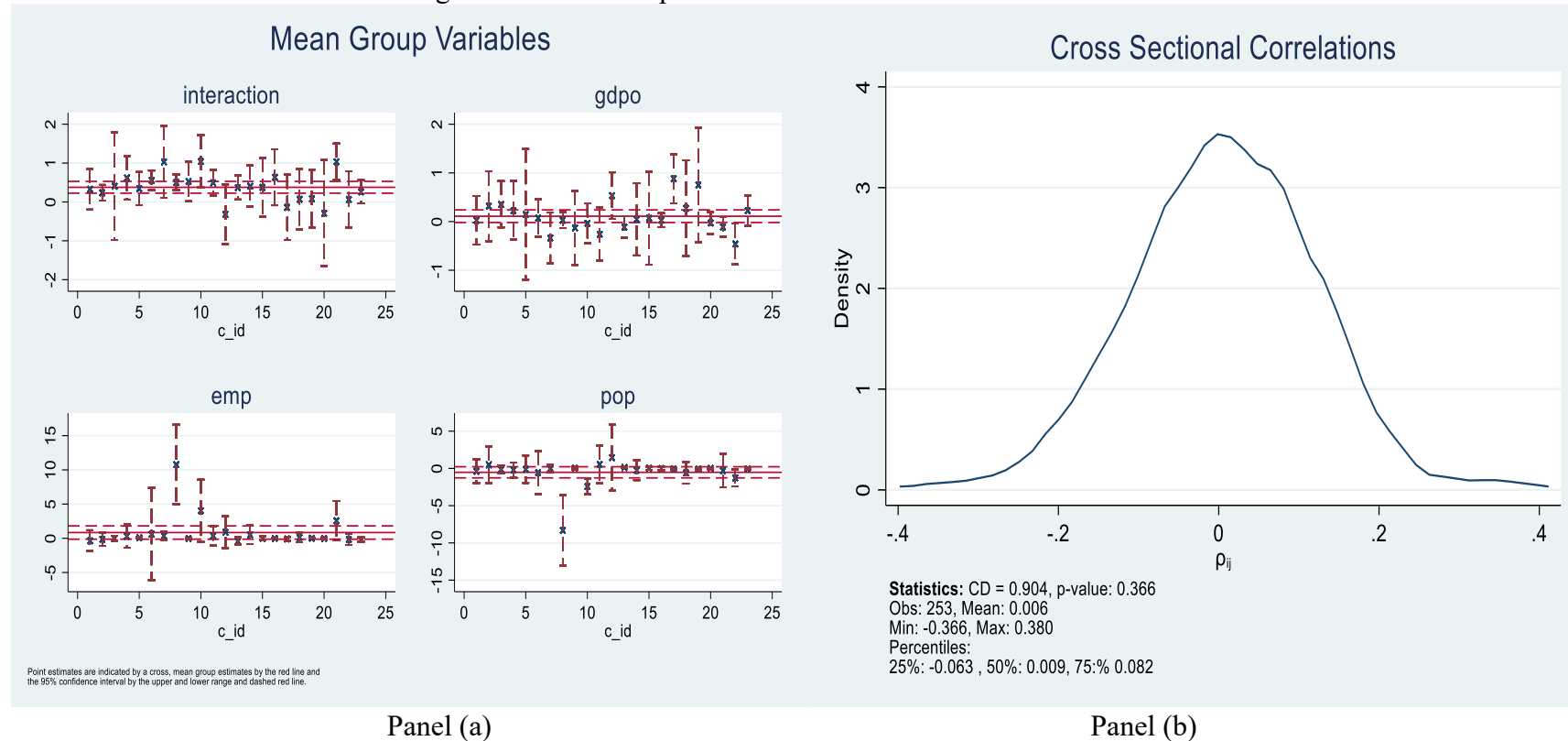
Figure 1: Gini Index of National Income in the SSA Region and Matrix of Correlation (cont.)



Panel (3)

Source: Author(s) compilation

Figure 2: Mean Group Variables and Cross-sectional Correlation



Source: Author(s) calculation

Table A1: Summary of Key Empirical Studies on Human Capital, Technology, and Income Inequality

Study	Region/Country	Methodology	Key Variables	Main findings	Contribution relative to this study
De Gregorio & Lee (2002)	Global panel of countries	Cross-country regression	Education levels, Gini index	Higher education reduces inequality	Focus on average education; lacks interaction with technology
Autor et al. (2003)	United States	SBTC model	Computer adoption, skill levels	Technology increases skill premiums and inequality	Seminal SBTC work; not applied to the SSA region
Adeleye (2024)	SSA	PSCC estimator	Human capital, institutional quality	Human capital alone increases inequality; interaction with institutions reduces it	Addresses interactions, but not with technology
Espoir & Ngepah (2021)	SSA	Panel cointegration	TFP, income concentration	TFP is associated with rising inequality	Uses TFP but omits human capital interaction
Goos et al. (2014)	Europe	Task-based analysis	Job categories, wages	Technology leads to job polarization and inequality	Limited applicability to SSA's informal labour markets
Sethi et al. (2021)	India	ARDL model	Education, inequality	Education reduces inequality over time	No technological dimension
Ntengwa & Olan'g (2024)	Tanzania	Cross-sectional	ICT access, inequality proxies	Digital divide widens inequality	Highlights rural-urban tech gaps by outside income analysis
Arendt & Grabowski (2019)	Africa and Eastern Europe	Panel regression	ICT, inequality	Technological access raises inequality in unequal education contexts	Recognizes joint effect but uses ICT rather than TFP

Source: Authors' literature review