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ORIGINAL ARTICLE

Reverse Causal Nexus between Pro-Poor Policies and Income Inequality in Kenya

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Abstract

Different developing economies are encountering various regional challenges associated with income inequality. However, several contributing factors to inequality and access to opportunities, such as a quality education system, have been identified as the key factors. Thus, the study sought to determine the reverse causal nexus between pro-poor policies (government spending on education) and income inequality in Kenya and the spatial linking relationship with the case of Uganda's and Tanzania's economies. The autoregressive distributed lag (ARDL) model, Johansen cointegration test, and Granger Causality approach were used to model the relationship between pro-poor policies and income inequality using time-series data from 1982 to 2018. The findings indicate positive short- and long-term relationships between government spending on education and income inequality in the three economies. Furthermore, the results show a significant long-term relationship between human capital measures (average years of schooling, secondary school education attainment, and tertiary level education attainment) and income inequality in the three economies. However, the results indicate no reverse causal nexus between the study variables in Kenya and Uganda but unidirectional causal nexus exists in the case of the Tanzanian economy. The study recommends that government stakeholders implement pro-poor policy initiatives that result in the structural change of social infrastructures and enhanced quality of life.

KEYWORDS
government spending on education, Granger causality, income inequality, Kenya

1 | INTRODUCTION

Currently, there is ongoing debate concerning whether or not income inequality in a country or region is linked to an economy's level of development (Stiglitz & Greenwald, 2014). These benefits may imply revenue that the society receives in equal proportion following a successful development initiative that achieves sustainable development and impacts economic growth, hence creating higher sharable income in the society (Afonso et al., 2010). Thus, sustainable economic development can be taken as an indicator of equal distribution of national income to factors of production (profit for capital, rent for land, and wage for labor) (Todaro & Smith, 2012).

Many developing economies are faced with two key challenges: stunted economic growth and the resulting unequal distribution of national income to the key factors of production (Jerven, 2012). Moreover, these two challenges potentially generate two significant social problems in the economy. One, it results in income gaps among the citizens, and two, it results in a rise in poverty. These two problems create a development conundrum for governments: should they push for sustainable economic growth or reduce widening income inequality (Deining & Olinto, 1999)?

The notion of economic growth-enhancing policies can be traced in the works of Rostow (1959), Lewis (1955), Kaldor (1967), and Kuznets (2019), who stressed that economic pro-poor policy transformations increase economic growth through factors of production, that is, the process of moving from lower productivity to greater productivity. Specifically, increased specialization in diverse economic activities is linked with differentiated economic results. Furthermore, nations whose economic structures are directed toward producing sophisticated public goods develop faster than those specializing in simple goods (Felipe, 2012).

Dabla-Norris et al. (2015) argued that government policies that improve the education system by providing financial and apprenticeship support consequently improve the general quality of human capital and significantly impact the Organization for Economic Cooperation and Development's (OECD) income inequality vision (2012). Educational policies that increase the supply of an educated, employable workforce (measured by the graduation and transition rates from secondary to tertiary institutions) play a pivotal role in reducing income inequality. Furthermore, the OECD considers that government policies aimed at improving the quality of the education system are the main factors in containing income inequalities. This affirms the need to understand the cause–effect relationship between pro-poor policies and income distribution through growth paths (Costanza et al., 2014).

This study expands on the latest strand of the literature, which explores beyond the relationship between pro-poor economic structures that touch on human capital and economic development by arguing that income distribution is not dependent on economic growth per se but on a specific kind of growth (Hartmann et al., 2017). The literature pertaining to this topic calls for ideal economic growth measures, not just income aggregated indicators (Stiglitz, 2016). Economic development entails dynamic variations in non-tradable inputs, such as human capital and government institutional policies. These factors are key in determining a country's economic productivity (Hidalgo & Hausmann, 2009).

Various empirical reports have shown a growing accumulation of factors of production and income in few hands (Alvaredo et al., 2018). A conducive, productive environment and means to equal opportunities is one of the ways of containing inequality in an economy. Like any developing nation's economy, Kenya, Uganda, and Tanzania are encountering various challenges associated with income inequality. For a long time, the countries' Gini coefficients have averaged above 0.50 (Standardized World Income Inequality Database, 2020). Practically, income inequality has remained constant for a long time. Whereas there are many contributing factors to inequality, access to opportunities—such as education and, more specifically, the quality of the education system—has been identified as the key contributing factor.

Moreover, there is a conflict within the literature. On one hand, theoretical identification of channels through which income inequality impacts human capital, and, on the other hand, lack of harmony among economic researchers as to which of these canals has the extreme effect on the interdependencies of human capital and income inequality (Galor, 2011). Nonetheless, pertinent literature has identified several channels through which human capital and income inequality interrelate. These comprise public spending on education (Galor & Weil, 2000) and education investment incentives (Bell & Freeman, 2001).

Against this backdrop, this study sought to empirically model the reverse causal relationship between pro-poor policies that focus on human capital development, such as government spending, and income inequality using cointegration and Granger causality techniques to answer the following questions:

- Is there a short- or long-term relationship between pro-poor policies (government spending on education) and income inequality in Kenya?
- Is there a reverse causal nexus between pro-poor policies (government spending on education) and income inequality in Kenya?
- Is there a reverse causal relationship between measures of human capital—such as the average number of years of schooling, secondary and tertiary levels of educational attainment, and income inequality—in Kenya?
- Is there any spatial interactive relationship between the Kenyan case and those of its fellow East African countries, namely, Uganda and Tanzania?

The study is structured as follows: Section 1 introduces the key concepts surrounding pro-poor policies and income inequality. Section 2 reviews the theoretical and empirical literature regarding human capital components, government spending, and income inequality. Section 3 details the data collection and stylized modeling of the human capital and income quality variables using time-series data for the Kenyan economy ranging between 1982 and 2018. Additionally, this section entails time-series data from 1982 to 2018 for Uganda and Tanzania to reveal existing spatial dimensions between the study variables for East African countries. Section 4 discusses the findings in line with the theoretical and empirical foundations. Finally, Section 5 entails the conclusion and policy recommendations.

2 | THEORETICAL AND EMPIRICAL LITERATURE

Pro-poor policies refer to policy initiatives geared toward improving the capabilities of a demographic of poor people within an economy (Curran & de Renzio, 2006). These include policy interventions that directly focus on reducing poverty or enhancing income distribution among the entire population (Fosu, 2015). Income inequality manifests in income, employment opportunities, healthcare access, energy access, and general differences in standards of living in an economy's population (Brunori et al., 2019; Ramos et al., 2020).

One notable theory that anchors the relationship between pro-poor policies and income inequality is the Keynesian theory (Stack, 1978). Keynes's theory provides an in-depth explanation for the fluctuations in economic growth and employment rates, which, in turn, can be taken as indicators of income inequality (Stack, 1978). In line with Keynes's theory, a government can improve the probability of realizing the key objective of balancing consumption with saving (Soyer et al., 2020). The employment rate, a significant factor in measuring income inequality, relies on demand for goods and services (Stack, 1978).

The government designs policies in a quest to balance consumption, saving, and investment (Soyer et al., 2020). These policies comprise government expenditure, such as welfare expenditure, social security incentives, and subsidies (Stack, 1978). Additionally, the government's involvement in programs that create job opportunities boosts economic productivity and is reinvested into the economy through public institutions to ensure inclusive prosperity

(Lustig, 2016; Rauniyar & Kanbur, 2010). Therefore, Keynes's theory proposes that the government's involvement in the economy can reduce income inequality through the channel of specific types of government expenditure touching on the citizens' social welfare, and thus enhancing households' living standards (Stack, 1978).

The effect of government pro-poor policies, such as expenditure on education, create economic opportunities and contribute to an increased employment rate through increased productivity and income distribution (Stack, 1978). There is an overall assumption that expenditure on education results in reduced income inequality (Anderson et al., 2017; Ogun, 2010). Ideally, when the government directs more public funds toward education and training infrastructure, it increases general school enrolment and results in higher living standards for people with low incomes since education quality improves and becomes more affordable. Ultimately, increased access to quality education leads to greater human capital and reduces income inequality in the economy (Lokshin & Yemtsov, 2005).

To diagnose the nexus between human capital and income inequality, this study follows Becker and Chiswick's (1966) proposition. They asserted that human capital is indicated by the average years of schooling and the distribution of education incentives. Their assertions explain that the supply and demand of educated people influence inequality. Similarly, when the quality and level of education are low, the productive environment propels an increase in inequality resulting from the absence of productive capabilities (Gupta et al., 2018). This paints the picture of the nexus between human capital level and the level of income inequality (Vincens et al., 2018). Similarly, raising the human capital level leads to a fairer distribution of income within an economy that has a demand-driven agenda (Shahpari & Davoudi, 2014).

The existing empirical literature recognizes the evidence of a reverse causal nexus between human capital measures and income inequality. More specifically, methodological studies about the effect of human capital stem from the factors of human capital accumulation as the key driving forces of economic development. Most authors contend that diversification of income capabilities has a negative effect on human capital in a society, especially at greater economic development levels (Battisti et al., 2014). Additionally, income inequality is associated with the average number of school years whereby as people graduate from secondary to higher education levels, income inequality increases (Welte et al., 2015).

Paweenawat and McNown (2014) studied the relationship between income inequality and human capital in Thailand. The study utilized data from 1992 to 2011. The results demonstrated the positive effect of human capital on income inequality. Similarly, Shahpari and Davoudi (2014) assessed the association between human capital and income inequality in Iran using annual time-series data from 1969 to 2007. The findings of a vector autoregressive distributed technique cointegration indicated the presence of long-term cointegration whereby human capital has a significantly positive effect on income inequality in Iran.

Yang and Gao (2018) assessed how government policies affect the wage gap. Further, they dicomposed education expansion policies into structural effect and price effect in studying the impact of education (a measure of human capital) on income distribution. The findings pointed out the significance of education expansion in cutting down income inequality. Similarly, Lee and Lee (2018) used educational attainment to measure human capital in studying its effect on income inequality. They discovered that government policies that focus on educational expansion improve education quality, thereby resulting in a more equal distribution of income.

Madhu and Sanjay (2019) investigated the relationship between human capital and income inequality in India by using annual time-series data spanning from 1970 to 2016 and the nonlinear autoregressive distributed lag model. Their study used government expansion policies for education to model the relationship between human capital and income inequality. The study's findings dictated that the expansion of education is a major factor in reducing prevailing high-income inequality. Specifically, the study found that an increase in the average number of schooling years leads to more equal income distribution.

The theoretical and empirical literature reviewed depicts glaring evidence of the relationship between pro-poor policies and income inequality. The pro-poor policy concept is directly linked to initiatives to increase the population's income. In addition, income inequality is linked to economic growth resulting from the government's adoption of pro-poor policies. The reviewed studies provide conflicting empirical results about the nexus between pro-poor policies, human capital measures, and income inequality attributed to different sample data, sample sizes, study designs, and geographical regions where the studies were conducted. The conflicting results of the aforementioned studies allow this study to contribute to the ongoing debate about the relationship between pro-poor policies and income inequality using time-series data spanning from 1982 to 2018 to model Kenya's scenario by employing cointegration and Granger causality estimation techniques and comparing the results with those of its neighboring East African countries, Uganda and Tanzania.

3 | DATA AND METHODOLOGY

The data and methodology section presents the data's nature data, sampling period, and the method used to analyze the relationships between variables. In this study, data and methodology are divided into a description of the data and variable setting including their measurements. Moreover, it outlines the data analysis and estimation techniques, elaborates on the theoretical model that the study followed to develop the estimation strategy, and details the statistical analysis, which used software, such as Eviews, PC-Give Ox-Metrics, and STATA.

To build the appropriate model for this study, the suggestions for human capital were considered. According to the suggestions of the human capital model, the distribution and level of education across the entire population is the key determinant of the income–earnings distribution in society (Becker & Chiswick, 1966; Mincer, 1974). This implies that the model projects that the demand and supply of educated people impact societal earnings inequality. In line with the human capital model suggestions, this study considered the human capital earnings function constructed by Gregorio and Lee (2002) presented as:

$$LogY_S = LogY_0 + \sum_{J=0}^{S} Log\left(1 + r_j\right) + u, \tag{1}$$

where Y_s is earnings, S is schooling level, Y_0 is the earnings for individuals with no formal education, r_j is the return rate on *the* j^{th} level of schooling or year, and u is the presentation of other non-school factors that impact earnings.

Building on Equation 1 above, the following can be the ideal function:

$$LogY_S = LogY_0 + \mathrm{rS} + \mathrm{u}. \tag{2}$$

Taking variance on both sides of Equation 2, we developed the following more precise earnings distribution function:

$$Var(LogY_S) = \bar{\mathrm{r}}^2 Var\,(S) + \bar{\mathrm{S}}^2 Var\,(r) + 2\bar{\mathrm{r}}\bar{\mathrm{S}}\,Cov(r,S) + Var(u). \tag{3}$$

Drawing from Equation 3, this signifies that income inequality unambiguously increases with inequality of education (*Var[S]*), holding all other factors constant. Nevertheless, if returns on education (*r)* decline with education inequality, the association can be ambiguous. In several cases, the inequality of education and the wages for higher education would move in the same direction, since a rise in the supply of highly-educated individuals tends to reduce both inequality of education and wages. Temporarily, education expansion resulting from government initiatives, that is, a rise in (*S*), results in more inequality in income distribution whenever *S* and *r* are not dependent. However, provided the covariance between education level and return on education is negative, the nexus between education expansion (increase in government spending and expanded education infrastructure) and income inequality can reduce income inequality.

By building on the underlying theoretical model above, the empirical model framed to analyze the reverse cause nexus between government pro-poor policies and income inequality was built by employing time-series data spanning from 1982 to 2018. The following equation was used to model the relationship:

$$Gin_t = f\,(GSE_t, HC_t, EG_t). \tag{4}$$

Equation 4 was further subdivided into the following estimation equation:

$$Gin_t = f\,(GSE_t, ASC_t, SED_t, TED_t, EG_t), \tag{5}$$

where Gin_t is the Gini coefficient (a measure of income inequality), GSE_t is the government spending on education, ASC_t is the average number of years of schooling, SED_t is secondary school education attainment, TED_t is the tertiary level education attainment, and EG_t is the economic growth that is included as the study variable. Furthermore, the definition, measures, and data sources of various variables captured in Equation 5 above are provided in Table 1 below.

The estimation procedure for the reverse cause relationship between pro-poor policies and income inequality and human capital was carried out via the following two steps. First, descriptive analysis of the data was conducted to ascertain the data distribution in terms of mean, standard deviation, and maximum and minimum values. The normality of the data was tested using skewness, kurtosis, and Jarque–Bera statistical tests. Furthermore, to check for the data's stationarity or non-stationarity, the augmented Dickey–Fuller (ADF) unit root test proposed by Dickey and Fuller (1981) was utilized.

Second, the vector autoregressive model (VAR) was used to examine the long-term relationship between the variables. Reverse causality between the variables was estimated using Granger causality (Granger, 1988). Johansen (1988) and Johansen and Juselius (1990) introduced the cointegration concept as an improvement on Engle and Granger's (1987) cointegration concept. Johansen cointegration combines both maximum eigen and trace test statistics to verify the cointegrating equations in the VAR format. In a VAR model, all the identified variables are expressed as endogenous and function of their lags and the lags of other variables in the endogenous function, as presented in Equations 6 and 7 below.

$$\varDelta G_t = a_0 + a_1 \sum_{i=1}^{n} GSE_{t-i} + a_2 \sum_{i=1}^{n} \varDelta G_{t-1} + \pounds_{1t} \tag{6}$$

$$GSE_t = a_3 + a_4 \sum_{i=1}^{n} \varDelta G_{t-i} + a_5 \sum_{i=1}^{n} \varDelta GSE_{t-1} + \pounds_{2t}. \tag{7}$$

TABLE 1 Variable definitions and data source

Acronym	Variable	Definition	Data source
GIN	Gini coefficient	Indicator of income inequality	SWIID
GSE	Government spending on education	Indicator of education expansion	WDI
ASC	The average number of years of schooling	Indicator of human capital	WDI
SED	Secondary school education attainment	Indicator of human capital	UNESCO
TED	Tertiary level education attainment	Indicator of human capital	WDI
EG	Economic growth	GDP per capita	WDI

Note: SWIID (Standardized World Income Inequality Database), WDI (World Bank Development Indicator).
Source: Authors' construction (2021)

In addition, to further capture the long-term relationship between income inequality and human capital measures and economic growth as a plausible variable, the VAR model is presented in Equation 8.

$$\Delta Gin_t = a_0 + a_1 \sum_{i=1}^{n} ASC_{t-i} + a_2 \sum_{i=1}^{n} SED_{t-i} + a_3 \sum_{i=1}^{n} TED_{t-i} + a_4 \sum_{i=1}^{n} EGin_{t-i} a_5 \sum_{i=1}^{n} \Delta Gin_{t-1} + £_{3t} \tag{8}$$

where Gin_t is income inequality measured by the Gini coefficient, while GSE_t is the government spending on education (a proxy for pro-poor policies), ASC_t, the average number of schooling years, SED_t is secondary school education attainment, TED_t, is tertiary level education attainment, EG_t is economic growth, Δ is the operator difference, and $£_{1t}$, $£_{2t}$ and $£_{3t}$ are the stochastic terms.

Vector error correction model, which helps to reflect the short-term association between variables (Engle & Granger, 1987), and the VAR model in Equations 6 and 7 were lagged to one period and were included as an extra explanatory variable. A dummy variable was added to this model to capture the structural breaks that occurred in Kenya. When the lagged error became significant, a deduction was drawn that there is a short-term relationship between pro-poor policies (measured by government spending on education) and income inequality. The error correction model was built from Equations 6 and 7 to form Equations 9 and 10, as follows:

$$\Delta Gin_t = a_0 + a_1 \sum_{i=1}^{n} GSE_{t-i} + a_2 \sum_{i=1}^{n} \Delta Gin_{t-1} + a_3 \sum_{i=1}^{n} \Delta б_{t-1} + £_{4t}; \tag{9}$$

$$\Delta GSE_t = a_4 + a_5 \sum_{i=1}^{n} \Delta Gin_{t-1} + a_6 \sum_{i=1}^{n} \Delta GSE_{t-1} + a_7 \sum_{i=1}^{n} \Delta б_{t-1} + £_{5t}, \tag{10}$$

where б is the included dummy variable, capturing the structural breaks that occurred in Kenya in 1982, 1992, 2007, 2008, and 2009 where zero takes the absence of a structural break and one takes the structural break. In 1982, Kenya experienced a military coup. In 1992, it experienced intertribal clashes. And from 2007 to 2009, it encountered the simultaneous effects of postelection violence and the global financial crisis, whose shocks were transmitted to Kenya's neighboring countries, such as Uganda and Tanzania, due to close economic trading and commodity dependencies. This study used two kinds of likelihood test statistics, maximum eigen and trace test statistics, to verify the number of cointegrating vectors.

The study employed a lag-length selection criterion based on the information available before carrying out the Granger causality test. Akaike information criterion was used since it is a preferred information criterion for selecting lag length (Naqqar & Al-Awad, 2012). The study considered a lag length whose value for the Akaike information criterion was the smallest. To test for the presence of a reverse causal relationship between pro-poor policies (measured by government spending on education) and income inequality (measured by the Gini coefficient), a Granger causality test, proposed by Engle and Granger (1987) and Granger (1988), was used, as presented in Equations 11, 12, 13, and 14.

$$GSE_t = \alpha_1 + \beta_1 \sum_{i=1}^{n} Gin_{t-i} + \Phi_1 \sum_{i=1}^{n} GSE_{t-i} + \mu_t; \tag{11}$$

$$Gin_t = a_2 + \beta_2 \sum_{i=1}^{n} Gin_{t-i} + \Phi_2 \sum_{i=1}^{n} GSE_{t-i} + £_t. \tag{12}$$

Equation 11 tests whether pro-poor policies (measured by government spending on education) (GSE_t) is Granger-caused by the age of income inequality (Gin_{t-1}) and lag of government spending on education (GSE_{t-1}). This follows a stated null hypothesis that H_0: $\beta_1 = \beta_2 = 0$, implying that there is causal nexus between government spending on education (GSE_t) and lag of income inequality (Gin_{t-1}) against the alternative hypothesis that H_1: $\beta_1 \neq \beta_2 \neq 0$, implying the there is no Granger causal nexus between government spending on education (GSE_t) and lag of income inequality (Gin_{t-1}). Similarly, Equation 12 evaluates whether income inequality (Gin_t) is Granger-caused the by the lag of pro-poor policies (measured by government spending on education) (GSE_{t-1}) and lag of income inequality (Gin_{t-1}) with the null hypothesis stating that H_0: $\Phi_2 = 0$; implying that income inequality (Gin_t) is Granger-caused the by the lag of pro-poor policies (measured by government spending on education) (GSE_{t-1}) and lag of income inequality (Gin_{t-1}). This is tested against the alternative hypothesis stating that H_1: $\Phi_1 \neq \Phi_2 \neq 0$, implying that income inequality (Gin_t) is not Granger-caused by pro-poor policies (measured by government spending on education) (GSE_{t-1}) and lag of income inequality (Gin_{t-1}).

To further test the causal relationship between income inequality and human capital measures, the following Equations 13 and 14 are presented to capture the relationship:

$$HC_t = \alpha_1 + \theta_1 \sum_{i=1}^{n} Gin_{t-i} + \rho_1 \sum_{i=1}^{n} HC_{t-i} + \mu_t; \tag{13}$$

$$Gin_t = \alpha_1 + \theta_2 \sum_{i=1}^{n} Gin_{t-i} + \rho_2 \sum_{i=1}^{n} HC_{t-i} + \epsilon_t. \tag{14}$$

Equation 13 was used to test whether human capital (HC_t) measures (average number of years of schooling, secondary school education attainment, and tertiary level education attainment) are Granger-caused by the lag of income inequality (Gin_{t-1}) and lag of human capital measures (HC_{t-1}). Here, the stated null hypothesis is that H_0: $\theta_1 = \theta_2 = 0$, implying that there is causal nexus between human capital measures (HC_t) and lag of income inequality (Gin_{t-1}) and lag of human capital measures (HC_{t-1}) against the alternative hypothesis that H_1: $\theta_1 \neq \theta_2 \neq 0$, implying that there is no causal nexus between human capital measures (HC_t) and lag of income inequality (Gin_{t-1}) and lag of human capital measures (HC_{t-1}). Likewise, Equation 14 was used to test whether income inequality (Gin_t) is Granger-caused by the lag of human capital measures (HC_{t-1}) and lag of income inequality (Gin_{t-1}), with the null hypothesis stating that H_0 $\rho_1 = \rho_2 = 0$, implying that there is a Granger causal nexus between income inequality (Gin_t) and lag of human capital measures (HC_{t-1}) and lag of income inequality (Gin_{t-1}). The alternative hypothesis states that H_1: $\rho_1 \neq \rho_2 \neq 0$, implying that income inequality (Gin_t) does not Granger-cause lag of human capital measures (HC_{t-1}) and lag of income inequality (Gin_t).

4 | DATA ANALYSIS AND DISCUSSIONS

This section details the data analysis, statistical estimations, and the findings. The analysis and estimation comprise a summary and the descriptive statistics, normality test statistics, unit root test, cointegration analysis, lag length selection, and reverse causality test. The data were analyzed descriptively, and the findings are presented in Table 2. The results show that the mean income inequalities (DLNGIN) in Kenya, Uganda, and Tanzania are −0.00584, −0.4752, and 0.5614, respectively. The average years of schooling (DLNASC) have mean values of 0.05136, 1.3290, and 1.4858 for Kenya, Uganda, and Tanzania, respectively. The economic growth (DLNGDP) data have mean values of −0.00533, −0.8774, and −0.9221 for Kenya, Uganda, and Tanzania, respectively. The data for the pro-poor policies, measured by government spending on education (DLNGSE) in Kenya, Uganda, and Tanzania have mean values of 0.00423, 0.252, and 0.60488 correspondingly. The data ranges between −0.22996 and 0.42237. The data on secondary school education attainment (DLNSED) have mean values of 0.02248, 0.00546, and 0.00708, respectively. The tertiary level education attainment (DLNTED) have mean values of 0.10394, 0.00257, and 0.00238 in Kenya, Uganda, and Tanzania, respectively.

TABLE 2 Descriptive statistics

Statistics *Kenya*	DLNGIN	DLNASC	DLNGDP	DLNGSE	DLNSED	DLNTED
Mean	−0.00584	0.05136	−0.00533	0.00423	0.02248	0.10394
Maximum	0.06996	2.51976	0.24555	0.42237	0.10843	2.11591
Minimum	−0.09937	−2.34426	−0.37451	−0.22996	−0.04634	−1.85096
Std. dev.	0.02651	0.61714	0.11727	0.11325	0.02725	0.60173
Uganda						
Mean	−0.4752	1.329012	−0.877364	0.257201	0.00546	0.00257
Maximum	0.4308	1.824549	1.783924	0.011032	1.403013	1.864545
Minimum	0.0576	0.698135	0.036589	0.00733	1.336503	−0.453422
Std. dev.	0.0220	0.340824	0.560170	0.10673	0.329237	0.716714
Tanzania						
Mean	0.561318	1.485772	−0.922120	0.604817	0.00708	0.00238
Maximum	0.597837	1.808289	1.949702	0.194441	0.699824	4.781000
Minimum	0.494296	1.131402	1.056633	0.094700	0.962487	0.251000
Std. dev.	0.035636	0.177665	0.678192	0.324118	0.949073	1.630475

Source: Authors' Eviews estimations (2021)

To assess whether the collected data from Kenya, Uganda, and Tanzania are normally distributed or not, skewness, kurtosis, and Jarque–Bera tests were used. The findings presented in Table 3 depict that the datasets for all variables in the three economies are normally distributed. For instance, the skewness test values range between −1.56731 and 0.99185, hence falling within the threshold critical value range of ±3. The kurtosis test values range between 0.55658 and 2.40814, within the threshold of ±1 or ±2. The Jarque–Bera test values range between 0.39175 and 5.56745, signifying that the Kenyan data is normally distributed. For the Ugandan data, the skewness, kurtosis, and Jarque–Bera test values range between −0.5191 and 0.4117 < ±3; 1.6147 and 3.284 < ±1 or ±2; and 0.0043 and 3.7021 < 5.9, respectively. The p-values are less than 0.05, implying that the normality of Uganda's data is significant. Finally, for the Tanzanian data, the skewness, kurtosis, and Jarque–Bera test values range between −0.031658 and 0.554864 < ±3; 1.5155 and 2.2590 ± 1 or ±2; and 0.8527 and 5.0998 < 5.9, respectively. The p-values are less than 0.05, correspondingly.

The study used augmented Dickey–Fuller (ADF) test to check for the stationarity or non-stationarity of the data for each variable used, using the Kenyan, Ugandan and Tanzanian datasets. The findings presented in Table 4 show the results of unit root tests based on the ADF test. The findings indicate that all the ADF test values are less than the MacKinnon critical value at 5% $= -2.9500$, and all the p-values are less than 0.05 at a 95% confidence level for all three datasets. This signifies that the null hypothesis stated—that the study variables' data are not stationary—is rejected. Rather, all the study variables' data are stationary at the first difference. They are integrated into order one.

4.1 | Cointegration between Income Inequality and Pro-Poor Policies

Akaike information criterion was utilized to test for the cointegration of study variables with an optimum lag of one. Therefore, by following a lag length of one, further analyses comprising Johansen cointegration and Granger causality were carried out. The trace and maximum eigenvalue cointegration between income inequality and pro-poor policies were estimated, and the findings are presented in Table 5. Beginning with the null hypothesis of no cointegration ($R = 0^*$) among income inequality and pro-poor policies measured by government spending on

TABLE 3 Normality test findings

Kenya	LNG	LNASC	LNGDP	LNGSE	LNSED	LNTED
Skewness	−1.56731	0.11670	−0.89248	0.99185	0.02222	0.77349
Kurtosis	0.84353	1.91390	2.40814	0.55658	1.59589	1.28775
Jarque–Bera	4.3503** (0.0000)	3.7168** (0.0000)	1.9688** (0.0186)	5.5675** (0.0000)	0.3918** (0.00554)	4.6404** (0.0000)
Uganda						
Skewness	−0.0161	−0.2829	0.4117	−0.3027	0.2163	−0.5191
Kurtosis	2.9579	1.8374	1.8633	3.2848	1.6147	1.8496
Jarque–Bera	0.0043** (0.0178)	2.5773** (0.02516)	3.0372** (0.0190)	0.6900** (0.0082)	3.2473** (0.0019)	3.7021** (0.0152)
Tanzania						
Skewness	−0.352765	−0.031658	0.159937	0.184308	0.535975	0.554864
Kurtosis	1.673526	2.258987	1.515550	1.639645	1.601874	1.559008
Jarque–Bera	3.4800** (0.01755)	0.8527** (0.02885)	3.5550** (0.0169)	3.0624** (0.00216)	4.7851** (0.00140)	5.0998** (0.01780)
N	37	37	37	37	37	37

Note:
**indicates the probability values for the Jarque–Bera test showing normality of the dataset at 5%.
Source: Authors' construction (2021)

TABLE 4 Unit root test

Variable	Level Form	*Kenya_* ADF	Level Form	Uganda_ADF	Level Form	*Tanzania_* ADF
DLNG	1	−4.70636** (0.0006)	1	−3.8324** (0.0060)	1	−5.8180** (0.0000)
DLNASC	1	−6.51489** (0.0000)	1	−8.3827** (0.0000)	1	−6.2195** (0.0000)
DLNGDP	1	−7.37013** (0.0000)	1	−4.2342** (0.0021)	1	−5.3598** (0.0001)
DLNGSE	1	−6.66345** (0.0000)	1	−6.9724** (0.0000)	1	−7.0901** (0.0000)
DLNSED	1	−5.44363** (0.0001)	1	−5.5301** (0.0001)	1	−3.4311** (0.0164)
DLNTED	1	−8.40892** (0.0000)	1	−6.7869** (0.0000)	1	−5.6136** (0.0000)

Note: MacKinnon critical value at 5% = −2.95000.
**indicates the probability values of ADF values depicting that the dataset of the variables is stationary at 5%.
Source: Authors' Eviews estimations (2021)

TABLE 5 Johansen cointegration test results

Unrestricted cointegration rank test (trace)					Unrestricted cointegration rank test (maximum eigenvalue)		
*Kenya_* H_0	H_1	Trace statistic	5% critical value	Prob.*	Max. eigen stat	5% critical value	Prob.*
R = 0*	R ≥ 1*	28.7271	15.4947	0.0003	19.69034	14.26460	0.0063
R ≤ 1*	R ≥ 2*	9.03677	3.8415	0.0026	9.036771	3.841466	0.0026
*Uganda_*							
H_0	H_1						
R = 0*	R ≥ 1*	14.1918	15.4947	0.0778	11.8598	14.2646	0.1160
R ≤ 1*	R ≥ 2*	2.3320	3.8415	0.1267	2.3320	3.8415	0.1267
*Tanzania_*							
H_0	H_1						
R = 0*	R ≥ 1*	8.5435	15.4947	0.4093	8.2946	14.2646	0.3495
R ≤ 1*	R ≥ 2*	0.2490	3.8415	0.6178	0.2490	3.8415	0.6178

Source: Authors' Eviews estimations (2021)

education, the trace and maximum eigen statistics (15.4947 and 19.69034, respectively) and p-values (0.0003 and 0.0063, respectively) are less than 0.05, depicting that the null hypothesis is rejected against the alternative hypothesis *(R ≥ 1*)*. Thus, there exists at most one cointegrating vector among the variables in question for the Kenyan case. Similarly, the trace and maximum eigen statistics (3.8415 and 9.036771, respectively) and p-values (0.0026 and 0.0026, respectively) are less than 0.05, signifying that the null hypothesis of *(R ≤ 1*)* is rejected in favor of the alternative hypothesis *(R ≥ 2*)*. We can therefore conclude that there is a stable long-term relationship between income inequality and pro-poor policies (measured by government spending on education) in Kenya.

The results for the Ugandan and Tanzanian economies showed contrary outcomes compared to the Kenyan case. In the case of Uganda, regarding the null hypothesis of no cointegration (*R = 0**) between income inequality and pro-poor policies measured by government spending on education, the trace and maximum eigen statistics (15.4947 and 11. 8,598, respectively) and p-values (0.0778 and 0.1160, respectively) greater than 0.05 imply that the null hypothesis failed against the alternative hypothesis *(R ≥ 1*)*. Thus, there is no cointegrating vector among the variables in question for the Ugandan economy. Meanwhile, the Tanzanian case resulted in trace and maximum eigen statistics (15.4947 and 8.2946, respectively) and p-values (0.4093 and 0.3495, respectively) greater than 0.05, implying that the null hypothesis failed against the alternative hypothesis *(R ≥ 1*)*. Thus, there is no cointegrating vector between income inequality and pro-poor policies in Tanzania.

4.2 | Cointegration between Income Inequality and Human Capital Measures and Economic Growth as a Plausible Variable

The trace and maximum eigenvalue cointegration between income inequality and human capital measures and economic growth as a plausible variable were analyzed, and the findings are presented in Table 6. Table 6 shows the Cointegration between income inequality and human capital measures (average number of years of schooling, secondary school education attainment, and tertiary level education attainment) and economic growth as a plausible variable.

The results show that the trace and maximum eigen statistics (69.81889, 37.62427) and p-values (0.0001, 0.0170) < 0.05, pointing out that the null hypothesis is rejected against the alternative hypothesis *(R ≥ 1*)*, hence there exists at most one Cointegrating vector among the estimation variables. In the same manner, the trace and maximum eigen statistics (47.85613, 26.36297) and p-values (0.0017, 0.0157) < 0.05 signify that the null hypothesis of *(R ≤ 1*)* is rejected in favor of the alternative hypothesis *(R ≥ 2*)*, hence there is a stable long-term relationship between income inequality and human capital measures (average number of years of schooling, secondary school education attainment, and tertiary level education attainment) and economic growth in Kenya.

Regarding the Ugandan economy, the results show the trace and maximum eigen statistics (95.7537, 43.7132) and p-values (0.000, 0.0187) < 0.05, depicting that the null hypothesis is rejected against the alternative hypothesis *(R ≥ 1*)* and thus there exist at most one Cointegrating vector among the variables. Furthermore, the trace and maximum eigen statistics (92.6532, 37.0695) and p-values (0.0003, 0.0201) < 0.05, signify that the null hypothesis of *(R ≤ 1*)* is also rejected in favor of the alternative hypothesis *(R ≥ 2*)*, and the conclusion is drawn that there is a stable long-term relationship between income inequality and human capital measures (average number of years of schooling, secondary school education attainment, and tertiary level education attainment) and economic growth in Uganda.

TABLE 6 Johansen cointegration test

*Kenya_* Unrestricted Cointegration Rank Test (Trace)					Unrestricted cointegration Rank Test (Maximum eigenvalue)		
*Kenya_*H_0	H_1	Trace Statistic	5% Critical Value	Prob.*	Max. eigen stat	5% Critical value	Prob.*
R = 0*	R ≥ 1*	98.9236	69.8189	0.0001	37.62427	33.8769	0.0170
R ≤ 1*	R ≥ 2*	61.2994	47.85613	0.0017	26.36297	27.58434	0.0110
Uganda							
H_0	H_1						
R = 0*	R ≥ 1*	136.4416	95.7537	0.0000	43.7132	40.0776	0.0187
R ≤ 1*	R ≥ 2*	92.6532	69.8189	0.0003	37.0695	33.8769	0.0201
Tanzania							
H_0	H_1						
R = 0*	R ≥ 1*	115.3692	95.7537	0.0012	43.5027	40.0776	0.0198
R ≤ 1*	R ≥ 2*	71.8665	69.8189	0.0340	30.6582	33.8769	0.1155

Source: Authors' Eviews estimations (2021)

Concerning the Tanzanian economy, the trace and maximum eigen statistics results show (95.7537, 43.5027) and p-values (0.0012, 0.0189) < 0.05, implying that the null hypothesis is rejected against the alternative hypothesis *(R ≥ 1*)*, hence there exist at most one Cointegrating vector among the variables. Moreover, the trace and maximum eigen statistics (69.8189, 30.6582) and p-values (0.0340 < 0.05, 0.1155 > 0.05) depict that the null hypothesis of *(R ≤ 1*)* is not entirely rejected in favor of alternative hypothesis *(R ≥ 2*)* and conclusion is made that there is an unstable long-term relationship between income inequality and human capital measures (average number of years of schooling, secondary school education attainment, and tertiary level education attainment) and economic growth in Tanzania.

4.3 | Granger Causality

Granger causality analysis was conducted to ascertain whether there is reverse causal nexus between the study variables in Kenya, Uganda, and Tanzania. Table 7 shows the causality relationship between income inequality and pro-poor policies. The findings show the F-statistic values (1.93341, 0.67304, and 1.99067, respectively) and p-values (01623, 0.4179, and 0.1676, respectively) are greater than 0.05, which implies that the null hypothesis that pro-poor policies measured by government spending on education do not Granger-cause income inequality is accepted. Additionally, the results show that the F-statistic values (0.11954, 0.01171, and 0.54414, respectively), and p-values (0.877, 0.9145, and 0.4659, respectively) are greater than 0.05, signifying that the null hypothesis that income inequality does not Granger-cause government spending on education is accepted. Therefore, there is no reverse causal nexus between income inequality and government spending on education in Kenya, Uganda, and Tanzania.

The findings shown in Table 8 show the Granger causality test results for income inequality and human capital measures. The findings show the F-statistic values (1.2616, 0.0476, and 2.4361, respectively) and p-values (0.298, 0.829, and 0.130, respectively) are greater than 0.05, which implies that the null hypothesis that income inequality does not Granger-cause an average number of schooling years (ASC) is accepted. Furthermore, the F-statistic values (0.1215, 0.0229, and 5.0762, respectively) and p-values (0.886, 0.881 > 0.05; and 0.031 < 0.05) suggest that the null hypothesis that income inequality does not Granger-cause government spending on education is accepted. We therefore deduce that there is no reverse causal nexus between income inequality and government spending on education in Kenya, and Uganda. In contrast, there is reverse causal nexus in the Tanzanian case.

The findings of Granger causality between secondary school education attainment and income inequality, and between income inequality and tertiary level education attainment revealed F-statistic values (0.2461, 0.06276, and 0.0844), and p-values (0.783, 0.917, and 0.773) greater than 0.05, implying that the null hypothesis that income

TABLE 7 Causal nexus between income inequality and pro-poor policies

Null hypothesis:	Obs.	F-statistic	Prob.
*Kenya_*			
DLNGSE does not Granger-cause DLNG	36	1.93341	0.1623
DLNG does not Granger-cause DLNGSE		0.11954	0.8877
*Uganda_*			
DLNGSE does not Granger-cause DLNG	36	0.67304	0.4179
DLNG does not Granger-cause DLNGSE		0.01171	0.9145
*Tanzania_*			
DLNGSE does not Granger-cause DLNG	36	1.99067	0.1676
DLNG does not Granger-cause DLNGSE		0.54414	0.4659

Source: Authors' Eviews estimations (2021)

TABLE 8 Reverse causal nexus between income inequality and human capital measures and economic growth

Null hypothesis:	N	*Kenya-* F-stat	Prob.	*Uganda-* F-stat	Prob.	*Tanzania-* F-stat	Prob.
DLNASC does not Granger-cause DLNG	36	1.2616	0.298	0.0476	0.829	2.4361	0.13
DLNG does not Granger-cause DLNASC		0.1215	0.886	0.0229	0.881	5.0762	0.031
DLNSED does not Granger-cause DLNG	36	0.2461	0.783	0.0627		0.0844	0.773
DLNG does not Granger-cause DLNSED		0.1464	0.864	3.6502	0.065	17.1537	0.0002
DLNTED does not Granger-cause DLNG	36	0.2616	0.772	0.5737	0.454	1.3236	0.258
DLNG does not Granger-cause DLNTED		0.0664	0.936	0.3051	0.584	14.5526	0.001
DLNGDP does not Granger-cause DLNG	36	2.9975	0.065	0.0983	0.756	2.8360	0.1016
DLNG does not Granger-cause DLNGDP		1.9267	0.163	0.3212	0.575	2.8010	0.1037

Source: Authors' Eviews estimations (2021)

inequality does not Granger-cause secondary school education attainment, is accepted. In addition, the results show F-statistic values 0.1464, 3.6502, and 17.1537 as well as p-values 0.864 and 0.065 (greater than 0.05) and 0.0002 (less than 0.05). The findings of Granger causality between income inequality and tertiary level education attainment showed an F-statistic values (0.2616, 0.5737, and 1.3236) and p-values (0.772, 0.454, and 0.258) >0.05, implying that the null hypothesis that income inequality does not Granger-cause tertiary level education attainment is accepted. In addition, the result shows F-statistic values (0.0664, 0.3051, and 14.5526), and p-value (0.936, 0.584 > 0.05; and 0.001 < 0.05). Based on these findings, we deduce that there is no reverse causality nexus between income inequality and economic growth taken as a moderating variable in Kenya, Uganda, and Tanzania correspondingly.

4.4 | Error Correction Model Estimation for Study Variables

The error correction model estimation was employed to determine the cause–effect relationship between income inequality and the explanatory variables. The findings, presented in Table 9, show the causal effect of the explanatory variables on income inequality in Kenya, Uganda, and Tanzania. The results show the constant values of −0.002179, −0.000421, and −0.0038 and p-values less than 0.05, implying that income inequality decreases regardless of pro-poor policies, human capital, or economic growth in Kenya, Uganda and Tanzania, correspondingly.

The coefficient estimates of government spending on education are 0.017018, −0.004541, and −0.014997, and the p-values are less than 0.05, signifying that an increase in government spending on education by one unit results in an increase in income inequality by 0.017018 units in Kenya but a decrease in income inequality by 0.004541 and 0.014997 in Uganda and Tanzania, respectively. The coefficient estimates of the average number of years of schooling are −0.002773, 0.001632, and 0.000596, and the p-values are less than 0.05, indicating that an increase in the average number of years of schooling by one year leads to a decrease in income inequality by 0.002773 units in Kenya but an increase in income inequality by 0.001632 and 0.000596 units in Uganda and Tanzania, respectively.

The coefficients of secondary education school attainment are −0.035227, −0.01199, and 0.006364, and the p-values are less than 0.05. This indicates that a rise in the number of graduates attaining secondary education by one unit results in a decrease in income inequality by 0.035227 and 0.01199 units in Kenya and Uganda,

TABLE 9 Error correction model

Variable	*Kenya*_coefficient	*Uganda*_coefficient	*Tanzania*_coefficient
C	−0.002179** (0.0000)	−0.000421** (0.0031)	−0.00380** (0.00274)
DLNGSE	0.017018** (0.000)	−0.004541** (0.0112)	−0.01499** (0.02233)
DLNASC	−0.002773** (0.000)	0.001632** (0.04458)	0.000596** (0.02633)
DLNSED	−0.035227** (0.000)	−0.01199** (0.03628)	0.006364** (0.01508)
DLNTED	0.001502** (0.000)	0.015347** (0.02163)	−0.00663** (0.0071)
DLNGDP	−0.049548** (0.000)	−0.005050** (0.0112)	0.019182** (0.01755)
DUMMY	−0.01703** (0.000)	−0.81930** (0.0001)	−0.01670** (0.0000)
RESIDUALS	1.00000	8.9181E-3	0.02192
R-square	1.000	0.311806	0.175557
F-statistic	8.05E+3	1.7476	0.8213
F-prob.	(0.0000)	(0.0000)	(0.0000)

Note:
**shows the independent variable's significant effect on the dependent variable at a 5% confidence interval.
Source: Authors' Eviews estimations (2021)

respectively. In contrast, income inequality in Tanzania increases by 0.006364 units, holding all other factors constant. Concerning tertiary level education attainment, the results reveal coefficient estimates of 0.001502, 0.015347, and −0.006631 and p-values of less than 0.05, implying that an increase in the number of graduates from tertiary institutions increases income inequality by 0.001502 units in Kenya and 0.015347 units in Uganda.

The economic growth variable was included as a plausible variable to control the collinearity between human capital measures. The results reveal coefficient estimate values of −0.049548, −0.005050, and 0.019182 and p-values of less than 0.05, indicating that an increase in economic activity by one unit leads to a decline in income inequality by 0.04958 units in Kenya and 0.005050 units in Uganda; however, it leads to an increase in income inequality by 0.019182 units in Tanzania, holding all other factors constant. The coefficient estimates of dummy variables covering 1982–1983 (when Kenya experienced an attempted military coup), the hunger strike of 1998, the 1992 intertribal clashes, and 2007–2009 postelection violence and global financial crisis shocks (which were felt in Uganda and Tanzania too) are −0.01703, −0.8193, and −0.0167, and the p-values are less than 0.05. This signifies that the persistent impact of these structural breaks contributed to worsening income inequality by 0.01703, 0.8193, and 0.0167 units in Kenya and Tanzania, respectively.

4.5 | Diagnostic Analysis

Post-analysis diagnostic tests of autocorrelation checked by Durbin–Watson values (1.6474, 1.2341, and 1.0913) indicated the absence of autocorrelation. Heteroscedasticity diagnostic test was also evaluated using the Glejser test, where the F-statistic values (0.197645, 0.26196, and 0.981331) and p-values (0.9610, 0.2205, and 0.4161) were greater than 0.05, indicating the absence of heteroscedasticity. The multicollinearity test was evaluated using variance inflation factor (VIF) values (1.00, 2.13, and 4.712) less than 10.00, indicating the absence of multicollinearity. Regarding the model stability tested using the Ramsey RESET Test, the results showed F-statistics values (0.058471, 0.2136, and 0.6686) and p-values (0.8106, 0.1992, and 0.2534) greater than 0.05, signifying that the selected model is stable, and the results are sufficiently reliable (Table 10).

TABLE 10 Diagnostic test findings

Diagnostic problem	*Kenya*_stat test	Prob.	*Uganda*_stat test	Prob.	*Tanzania*_stat test	Prob.
autocorrelation (Durbin–Watson)	DW = 1.6474	0.000	1.2341	0.000	1.0913	0.000
Heteroscedasticity (Glejser test)	F-statistics = 0.197645	0.9610	0.26196	0.2205	0.981331	0.4161
Multicollinearity (VIF test)	1.00	N/A	2.13	N/A	4.712	N/A
Model specification (Ramsey RESET test)	F-statistics = 0.058471	0.8106	F-stat = 0.2136	0.1992	F-stat = 0.6686	0.2534

Source: Authors' Eviews estimations (2021)

One of the greatest challenges facing many developed and developing economies worldwide is the ballooning income gap between the well-off and the poor. Kenya, Uganda, and Tanzania are developing economies facing widening income inequality due to differences in economic activities. Using time-series data, this study investigated the reverse causal nexus between government pro-poor policies, human capital (as measured by educational attainment), and economic growth. The study employed cointegration and Granger causality approaches to explore the probable long-term relationship between pro-poor policies, income inequality, and human capital measures.

The Johansen cointegration test approach was used to ascertain the short-term and long-term relationship between the study variables. The results showed a long-term relationship between income inequality and pro-poor policies, human capital measures, and economic growth. The long-term relationship between pro-poor policies (measured by government spending on education) and income inequality suggests the importance of education expansion in achieving a fairer income distribution in Tanzania.

The Granger causality test was carried out to ascertain the reverse causal nexus between pro-poor policies (measured by government spending on education) and income inequality, and income inequality and human capital (measured by educational attainment). The results showed a neutral or no reverse causal nexus between government spending on education and income inequality in Kenya, Uganda, and Tanzania. This signifies that income inequality does not Granger-cause government spending on education, and government spending on education does not Granger-cause income inequality in the three countries under investigation. In addition, the results showed no reverse causal nexus between income inequality and human capital measures in Kenya and Uganda; however, in Tanzania, income inequality Granger-causes the average number of schooling years. Moreover, the findings of the error correction model showed the significant effect of human capital measures on income inequality. Specifically, education expansion, as a government pro-poor policy initiative, helps attain fairer income distribution, implying that governments need to expand their education systems since increased educational attainment ensures an increased supply of skilled labor force, thus increasing economic productivity, thus increasing economic productivity and fairer income distribution.

5 | CONCLUSION AND POLICY RECOMMENDATION

This study aligns with the United Nations' first 2030 sustainable development goal ("no poverty") by looking at ways to reduce income inequality within a country by evaluating the nexus between pro-poor policies and income inequality in Kenya and comparing the Kenyan experience with Uganda's and Tanzania's. The study focused on the cause–effect relationship between government spending on education and income inequality through the economic growth path. The findings contribute uniquely to the ongoing debate about the pro-poor policy-driven economic growth and income inequality nexus by modeling the contribution of government spending on quality of education by analyzing the cause–effect reliably between various measures of human capita (such as the average number of years of schooling, secondary school education attainment, and tertiary level education attainment) and income inequality.

Based on the study's findings, we conclude that the interaction of government spending and human capital measures contributes to a uniform distribution of income in society. Hence, it is paramount for governments in developing economies, such as Kenya, Uganda, and Tanzania, to review social policy interventions that will aid in enhancing unified distribution of income. Perhaps this will be effective in combining economic strategy effectively combine initiatives in fairly and dynamically developing economies like Kenya, Uganda, Tanzania, and other Sub-Saharan economies.

The empirical findings presented in this study provide significant policy implications for economic development in Kenya, Uganda, and Tanzania. Expanded human capital (as measured by educational attainment) reduces unequal income distribution. This highlights the need for proactive initiatives that can help ensure increased human capital and improve the quality of the education system for sustained economic development. Proactive development initiatives should be implemented by governments and international bodies concerned with reducing social inequalities, focusing on educational expansion and increased education quality to help drive economic growth and equalize income distribution.

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