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A Single-Equation ECM Model of Government's Investment in Human Capital and Income Inequality in Nigeria

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Abstract

This study investigates the impact of government investment in human capital on income inequality in Nigeria using a Single-Equation Error Correction Model (ECM) approach from 1985 to 2023. The analysis involves pre-estimation checks for stationarity and lag order selection, ensuring the methodological robustness of the model. The results indicate stationarity of the variables post-differencing, affirming the reliability of the model. The Parsimonious ECM reveals that increased education expenditure significantly reduces income inequality coefficient of -0.099 ($p < 5\%$), while higher agricultural spending coefficient of 0.078 ($p < 5\%$) leads to a slight rise in inequality. Health expenditure shows no significant impact. The Error Correction Mechanism coefficient of -0.471 ($p < 5\%$) highlights the importance of addressing deviations from long-term equilibrium to reduce income inequality. This study recommends amongst others the significance of targeted policies for education and sustainable agriculture to promote equitable income distribution and economic stability in Nigeria.

Keywords: Government investment, Human capital, Income inequality, Single-Equation Error Correction Model (ECM), Long-term economic equilibrium, Targeted policies

INTRODUCTION

The single-equation Error Correction Model (ECM) has emerged as a potent tool for analyzing dynamic relationships between economic variables, particularly in the context of non-stationary macroeconomic and financial data. Cointegration theory has substantially mitigated the issue of spurious regressions, enabling meaningful analysis of long-run relationships. By synergistically combining cointegration and error correction, ECM facilitates the capture of both short-term fluctuations and long-term equilibrium relationships, thereby providing a comprehensive understanding of economic phenomena (Pinshi, 2020, Banerjee et al. 1993, Engle & Granger 1987).

Building on this, numerous studies have investigated the relationships between investment, human capital development, and income inequality. For instance, Shahabadi et al. (2018) investigated the effect of education on income inequality in Islamic countries; Coady and Dizioli (2018) investigated the relationship between schooling inequality and income inequality; and Adekoya (2018) examined the causal relationship between human capital development and improving poverty in Nigeria.

More recent studies have further expanded this research trajectory. Sarkodie and Adams (2020) investigated the interlinkages between access to electricity, human development, and income inequality in Sub-Saharan Africa. Langnel et al. (2021) explored the heterogeneous impact of income inequality, human capital, and natural resources on the ecological footprint in ECOWAS member countries. Thye et al. (2022) scrutinized the asymmetric impact of human capital development on income inequality in Indonesia, while Ogunjobi et al. (2022) studied the relationship between human capital and income inequality in Nigeria. Yuldashev et al. (2023) examined the relationship between foreign direct investment, human capital, economic growth, and income inequality in Asian countries.

This paper aims to contribute to this ongoing discourse by examining the impact of government's human capital investment on income inequality in Nigeria, utilizing data from 1985-2023. The rest of the study is organized into sections that presents the methodology, results, conclusion and recommendations.

METHODS

Data source

The study uses time series secondary data for the analysis of the effect of human investment capital on income inequality for the period 1985 to 2023. Data on relevant variables, income inequality (GINI_disp), education expenditure (Edu_Ex), health expenditure (Health_Ex), and agriculture expenditure (Agric_Ex). Data for the study were sourced from World Income Inequality Database (WIID) and Statistical Bulletin of the Central Bank of Nigeria 2023.

Model Specification

In examining the effects human investment capital on income inequality, we specify a model that includes education expenditure (Edu_Ex), health expenditure (Health_Ex), and agriculture expenditure (Agric_Ex) as key explanatory variables. The relationship can be initially represented as:

$$GINI\_disp_{it} = f(Edu\_Ex, Health\_Ex,\ Agric\_Ex) \tag{1}$$

The basic panel econometric form of the model is therefore given by:

$$\log(GINI\_disp_{it}) = \beta_0 + \beta_1 \log(Edu\_Ex) + \beta_2 \log(Health\_Ex_{it}) + \beta_3 \log(Agric\_Ex_{it}) + \varepsilon_{it} \tag{2}$$

Where:

β_0 = Intercept term; β_1 = Coefficient of $\log(Edu\_Ex_{it})$; β_2 = Coefficient of $\log(Health\_Ex_{it})$, β_3 = Coefficient of $\log(Agric\_Ex_{it})$ and ε_{it} = Stochastic or disturbance term *i* at time *t*.

Augmented Dickey-Fuller (ADF) Test

To ensure the stationarity of the data series, we begin with the Augmented Dickey-Fuller (ADF) test. This test helps determine whether the time series data contain unit roots, indicating non-stationarity. The ADF test is based on the regression:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{3}$$

where Δ represents the first difference operator, Y_t is the time series variable, *t* is a time trend, and ε_t is the error term. The null hypothesis of the ADF test is that the series has a unit root γ.

Lag Order Selection Criteria

To determine the appropriate lag length for our models, we use several criteria including the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Criterion (HQC). These criteria help in selecting the model that best balances goodness-of-fit with complexity. The lag order selection can be represented as:

$$\text{AIC}(p) = \ln(\hat{\sigma}^2) + \frac{2p}{T} \tag{4}$$

$$\text{LogL} = \sum_{t=1}^{T} \ln L(\theta \mid Y_t) \tag{5}$$

$$\text{HQC}(p) = \ln(\hat{\sigma}^2) + \frac{2p\ln(\ln(T))}{T} \tag{6}$$

where $\hat{\sigma}^2$ is the estimated variance of the residuals, p is the number of lags, and T is the sample size, $L(\theta \mid Y_t)$ is the is the likelihood function of the model given the data Y_t and parameters θ.

Error Correction Model (ECM)

The Error Correction Model (ECM) is used to estimate the short-term dynamics while maintaining the long-term equilibrium relationship between the variables. The ECM can be expressed as:

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta X_{t-i} + \sum_{j=1}^{q} \beta_j \Delta Y_{t-j} + \lambda EC_{t-1} + \varepsilon_t \tag{7}$$

where ΔY_t is the change in the dependent variable, ΔX_{t-i} are the changes in the independent variables, λ is the error correction term, and EC_{t-1} is the lagged error correction term. To obtain a parsimonious ECM, we iteratively remove insignificant variables to achieve a more efficient model. This step ensures that the model retains only the most relevant predictors while avoiding overfitting.

Variance Inflation Factors (VIF)

To check for multicollinearity among the independent variables, we calculate the Variance Inflation Factors (VIF). High VIF values indicate high collinearity, which can distort the regression estimates. The VIF for each predictor X_i is calculated as:

$$\mathrm{VIF}(X_i) = \frac{1}{1 - R_i^2} \tag{8}$$

where R_i^2 is the coefficient of determination of the regression of X_i on all other predictors.

Normality of Residuals

To validate the assumption of normally distributed residuals, we use the Jarque-Bera test. This test assesses whether the residuals have skewness and kurtosis matching a normal distribution. The Jarque-Bera test statistic is calculated as:

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{9}$$

where n is the sample size, S is the skewness, and K is the kurtosis of the residuals.

Auto-correlation and Heteroscedasticity

We test for autocorrelation using the Durbin-Watson statistic and the Breusch-Godfrey test. The presence of heteroscedasticity is checked using the Breusch-Pagan test. The Durbin-Watson statistic is given by:

$$DW = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \tag{10}$$

where e_t are the residuals.

The Breusch-Pagan test statistic is calculated as:

$$\mathrm{BP} = \frac{n \cdot R^2}{2} \tag{11}$$

where R^2 is the coefficient of determination from a regression of squared residuals on the independent variables.

RESULTS AND DISCUSSION

Descriptive analysis

Table 1 presents summary statistics for the variables under study, which include health expenditure (HEALTH_EX), agriculture expenditure (AGRIC_EX), education expenditure (EDU_EX), and the GINI index (GINI_DISP), for the period of 39 years (1985-2023). As observed, health expenditure indicates a maximum of 442.78 and a minimum of 0.04, indicating substantial variability in healthcare spending. Agriculture expenditure, with a mean of 25.98, represents investment levels in the agricultural sector, while education expenditure, with a mean of 192.05, reflects financial allocations toward educational development. The GINI index, a measure of income inequality, displays a relatively stable distribution around its mean of 44.58, with a maximum value of 61.80.

Table 1: Summary Statistics of Variables under study

	GINI_DISP	EDU_EX	AGRIC_EX	HEALTH_EX
Mean	44.58098	192.0525	25.97731	116.9100
Median	44.40000	80.53088	16.30000	40.62142
Maximum	61.80000	711.4319	82.85139	442.7823
Minimum	35.13000	0.225005	0.020365	0.041315
Std. Dev.	7.873347	227.4092	27.42461	144.9516
Observations	39	39	39	39

Figure 1 presents a comprehensive view of the trends and variations in income inequality (GINI_disp), education expenditure (Edu_Ex), health expenditure (Health_Ex), and agriculture expenditure (Agric_Ex) over the years from 1985 to 2023. Income inequality, as measured by the GINI index, fluctuates notably, with peaks in the late 1980s and dips in the late 1990s, reflecting periods of varying income distribution. Education expenditure demonstrates a consistent upward trend, indicating a significant and increasing investment in education over time, reaching its highest value in 2023. Health expenditure also shows a steady increase, with peaks and troughs but an overall rising trajectory, highlighting a growing focus on healthcare spending. In contrast, agriculture expenditure remains relatively stable and lower throughout the years, reflecting a consistent but comparatively lower investment in this sector compared to education and health.

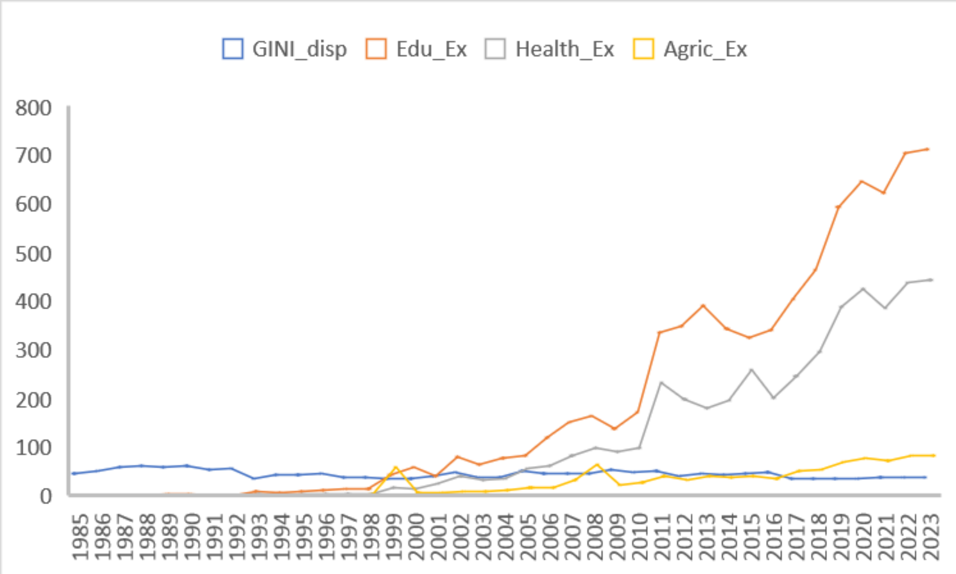

Figure 1: Trend plot of GINI_disp, Edu_Ex, Health_Ex and Agric_Ex

Pre-estimation analysis

In this subsection, a preliminary analysis is conducted, which includes tests for stationarity and lag order selection for the variables under investigation. The purpose of this analysis is to verify and ensure that the assumptions underlying the methodology adopted in this research are not violated. This is crucial to prevent the estimation of spurious relationships and ensure the reliability of the results obtained.

The Augmented Dickey-Fuller (ADF) test was adopted for examining stationarity in the variables and the as presents in Table 2 revealed that the stationarity properties of the variables GINI_DISP (representing the GINI index), AGRIC_EX (agriculture expenditure), EDU_EX (education expenditure), and HEALTH_EX (health expenditure). In their level form, all variables exhibit non-stationarity with p-values above conventional significance levels, suggesting they are integrated of order 1 (I(1)). However, after differencing once, all variables show stationary behavior with highly significant t-Statistics and p-values close to zero, indicating they become integrated of order 1 (I(1)) or stationary.

Table 2: Stationarity test

	Augmented Dickey-Fuller test statistic	t-Statistic	Prob.	Order of Integration
GINI_DISP	Level	-2.646	0.093	I(1)
	First difference	-8.771	0.000	
AGRIC_EX	Level	-0.434	0.893	I(1)
	First difference	-6.884	0.000	
EDU_EX	Level	1.727	1.000	I(1)
	First difference	-5.095	0.000	
HEALTH_EX	Level	0.965	0.995	I(1)
	First difference	-6.790	0.000	

Table 3 outlines the results for the Lag Order Selection Criteria for the model, detailing different lag orders (ranging from 0 to 3) alongside LogL, LR, FPE, AIC, SC, and HQ criterion. Notably, the LogL values for lag orders 0, 1, 2, and 3 are -89.16033, -29.11274, -8.044793, and 8.486730 respectively, corresponding to AIC values of 5.175574, 2.728485, 2.446933, and 2.417404. The log-likelihood value serves as a measure of model goodness of fit, with higher values indicating better model fit to the dataset. Additionally, smaller values of the information criterion, such as AIC, suggest superior model performance. The results clearly indicate that AIC has the smallest criterion value (2.417404) and a correspondingly large log-likelihood value (8.486730). Thus, based on these criteria, lag order 3 emerges as the preferred choice among the options due to its superior fit and smaller information criterion value.

Table 3: Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-89.16033	NA	0.002079	5.175574	5.351521	5.236984
1	-29.11274	103.4153	0.000181	2.728485	3.608218*	3.035536
2	-8.044793	31.60192*	0.000142*	2.446933	4.030452	2.999623*
3	8.486730	21.12361	0.000151	2.417404*	4.704709	3.215735

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Estimation

ECM estimate

Table 4 presents the results of an overparameterized Error Correction Model (ECM) where several coefficients exhibit high p-values, indicating no/weak statistical significance. The t-statistics for D(GINI_DISP) at lags 1, 2, and 3 are 0.089, -0.050, and 0.005, respectively, with corresponding probabilities of 0.930, 0.961, and 0.996. Similarly, the t-statistics for D(HEALTH_EX) at lags 1 and 2 are 0.246 and -0.833, with probabilities of 0.809 and 0.415. These values suggest a lack of strong explanatory power for these variables at these lagged intervals, potentially indicating overfitting or multicollinearity issues. Also, the R-squared value of 0.703 and Adjusted R-squared value of 0.468 indicate that the model displays higher discrepancy between the adjusted and unadjusted with most of the explanatory variables highly insignificant (p>5%). Further, the discrepancy between the R-squared and Adjusted R-squared values infers that the model may be overfitting or including unnecessary variables and potential autocorrelation in the model residuals, thus, underscoring a parsimonious model formulation to improve model performance and generalizability.

Table 4: Overparameterized ECM

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GINI_DISP(-1))	0.033	0.365	0.089	0.930
D(GINI_DISP(-2))	-0.011	0.228	-0.050	0.961
D(GINI_DISP(-3))	0.001	0.164	0.005	0.996
D(EDU_EX)	-0.154	0.095	-1.618	0.122
D(EDU_EX(-1))	0.026	0.095	0.272	0.789
D(EDU_EX(-2))	0.044	0.074	0.597	0.557
D(EDU_EX(-3))	0.107	0.073	1.474	0.157
D(HEALTH_EX)	0.113	0.103	1.098	0.286
D(HEALTH_EX(-1))	0.027	0.111	0.246	0.809
D(HEALTH_EX(-2))	-0.067	0.081	-0.833	0.415
D(HEALTH_EX(-3))	-0.142	0.070	-2.025	0.057
D(AGRIC_EX)	-0.065	0.038	-1.711	0.103
D(AGRIC_EX(-1))	-0.039	0.046	-0.844	0.409
D(AGRIC_EX(-2))	-0.037	0.041	-0.901	0.379
D(AGRIC_EX(-3))	0.086	0.041	2.093	0.050

ECM(-1)	-0.605	0.382	-1.581	0.130
R-squared	0.703	Mean dependent var		-0.013
Adjusted R-squared	0.468	S.D. dependent var		0.147
S.E. of regression	0.107	Akaike info criterion		-1.325
Sum squared resid	0.218	Schwarz criterion		-0.614
Log likelihood	39.182	Hannan-Quinn criter.		-1.079
Durbin-Watson stat	1.357			

Parsimonious ECM

Table 5 presents the results of a Parsimonious Error Correction Model (ECM) with coefficients, standard errors, t-statistics, and probabilities for select variables. The results shows that D(EDU_EX) has a statistically significant negative relationship with a t-statistic of -4.031 and a probability of 0.000, suggesting that changes in education expenditure have a notable impact on income inequality (GINI index). D(AGRIC_EX) at lag -3 exhibits a significant positive relationship with a t-statistic of 3.358 and a probability of 0.002, indicating the influence of agriculture expenditure changes on income inequality. Additionally, and ECM at lag -1 exhibits a significant negative relationship with a t-statistic of -3.134 and a probability of 0.004, indicating the significant influence of ECM term on income inequality. However, D(HEALTH_EX) at lag -2 show non-significant negative relationships with t-statistics of -0.812 and a p valie of 0.423, respectively. The overall goodness of fit of the model is indicated by the R-squared and Adjusted R-squared values of 0.563 and 0.521, respectively, suggesting that the model explains a significant portion of the variance in the income inequality while maintaining parsimony. The model can be expressed as follows;

$$\Delta GINI\_DISP = 0.078 \times AGRIC\_EX_{(-3)} - 0.099 \times EDU\_EX - 0.017 \times HEALTH\_EX_{(-2)} - 0.471 \times ECM_{(-1)}$$

The negative coefficient for education expenditure (-0.099, p = 0.000) suggests that an increase in education expenditure is associated with reduced income Inequality. Conversely, the positive coefficient for agricultural expenditure (0.078, p = 0.002) indicates that an increase in agricultural expenditure lagged by three periods leads to a slight rise in income inequality. The coefficient for health expenditure (-0.017, p = 0.423) suggests a minor reduction in income inequality with increased health expenditure lagged by two periods, although the result is not statistically significant.

The Error Correction Mechanism (ECM) in the model captures the short-term dynamics and long-term relationship between variables, indicating how quickly the system returns to its long-run equilibrium after a short-term shock. In this model, the negative coefficient for the ECM lagged by one period (-0.471) suggests that deviations from long-term equilibrium led to a decrease in income inequality. This implies that the system corrects itself towards a more equitable income distribution over time following short-term disturbances. Additionally, the statistically significant probability value (0.004) associated with the ECM coefficient reinforces the reliability of this relationship.

Table 5: Parsimonious ECM

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D((EDU_EX))	-0.099	0.025	-4.031	0.000
D(AGRIC_EX(-3))	0.078	0.023	3.358	0.002
D(HEALTH_EX(-2))	-0.017	0.022	-0.812	0.423
ECM(-1)	-0.471	0.150	-3.134	0.004
R-squared	0.563	Mean dependent var		-0.013
Adjusted R-squared	0.521	S.D. dependent var		0.147
S.E. of regression	0.102	Akaike info criterion		-1.625
Sum squared resid	0.321	Schwarz criterion		-1.448
Log likelihood	32.444	Hannan-Quinn criter.		-1.564
Durbin-Watson stat	1.696			

Table 6 presents the Coefficient Confidence Intervals for estimated coefficients, providing a range within which the true population values of the coefficients are likely to fall with a certain level of confidence. For D(EDU_EX), the coefficient of -0.099 has a 90% confidence interval (CI) of 0.141 to -0.057, a 95% CI of -0.149 to -0.049, and a 99% CI of -0.166 to -0.032. This indicates a high level of confidence that the true coefficient value lies within these intervals. Similarly, for D(AGRIC_EX) at lag -3, the coefficient of 0.078 has a 90% CI of 0.038 to 0.117, a 95% CI of 0.031 to 0.125, and a 99% CI of 0.014 to 0.141. The CI ranges for D(HEALTH_EX) at lag -2 and ECM at lag -1 also provide insights into the precision of the estimated coefficients.

Table 6: Coefficient Confidence Intervals for estimated coefficients

		90% CI		95% CI		99% CI	
Variable	Coefficient	Low	High	Low	High	Low	High
D((EDU_EX))	-0.099	-0.141	-0.057	-0.149	-0.049	-0.166	-0.032
D(AGRIC_EX(-3))	0.078	0.038	0.117	0.031	0.125	0.014	0.141
D(HEALTH_EX(-2))	-0.017	-0.054	0.019	-0.061	0.026	-0.077	0.041
ECM(-1)	-0.471	-0.726	-0.216	-0.778	-0.165	-0.884	-0.059

Post-estimation analysis

Following the estimation of coefficients and ECM model fitting, a post-estimation analysis of the estimated model is conducted to assess the robustness and reliability of the results. This section considers several aspects including Variance Inflation Factors (VIF), Normality of Residuals, and Auto-correlation and Heteroscedasticity. These analyses are essential for validating the assumptions and ensuring the reliability of the ECM model.

Variance Inflation Factors

Table 7 presents the results on the Variance Inflation Factors (VIF) for the variables included in the ECM model fitted. A VIF value close to 1 indicates low multicollinearity, suggesting that the variable does not significantly overlap or duplicate information from other variables in the model. In this context, all variables have VIF values relatively close to 1, with the highest VIF being 1.123 for D(AGRIC_EX(-3)), indicating that multicollinearity is not a significant concern among these variables. This suggests that the variables included in the model are relatively independent and do not pose a threat of multicollinearity.

Table 7: Variance Inflation Factors

Variable	Coefficient Variance	Uncentered VIF
D((EDU_EX))	0.000604	1.054379
D(AGRIC_EX(-3))	0.000536	1.123069
D(HEALTH_EX(-2))	0.000465	1.065157
ECM(-1)	0.022618	1.083062

Normality of Residuals

Figure 2 provides a visual representation of the distribution of errors or residuals in the ECM model. The Jarque-Bera statistic, with a value of 0.307452, and the corresponding probability of 0.857507, are measures used to assess the normality of residuals. A low Jarque-Bera statistic and a high probability indicate that the residuals follow a normal distribution, aligning well with the assumptions of linear regression. This indicates that the residuals are approximately normally distributed, validating one of the fundamental assumptions of regression analysis and enhancing the reliability of the model's results.

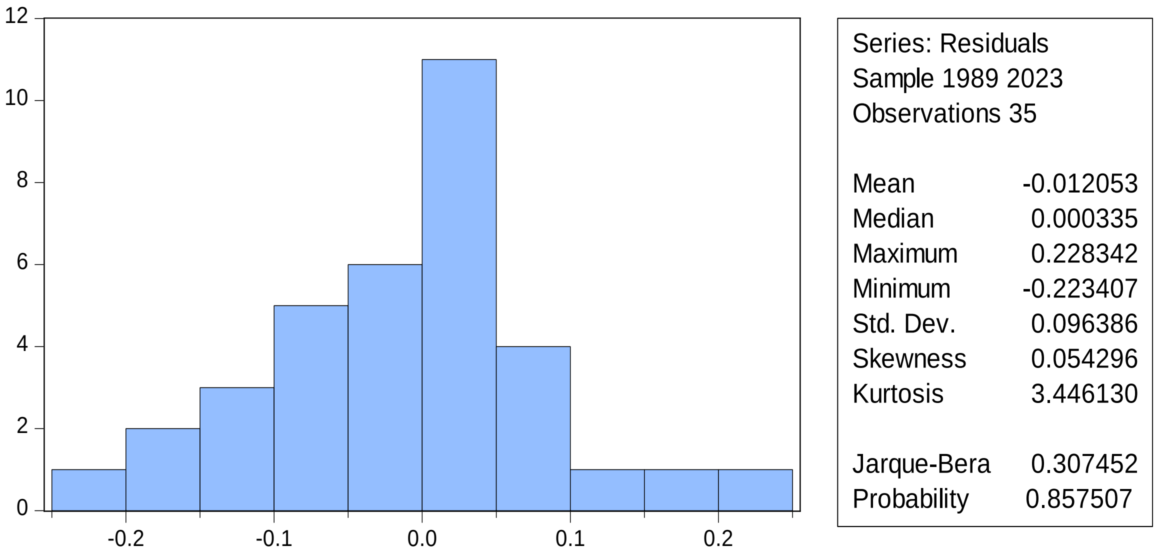

Figure 2: Histogram of Residual

Auto-correlation and Heteroscedasticity

Table 8 presents the results of the Breusch-Godfrey Serial Correlation LM Test and the Heteroskedasticity Test. For the Breusch-Godfrey Serial Correlation LM Test, the F-statistic is 0.917142 with a corresponding probability (Prob. F(3,28)) of 0.4453. Similarly, for the Heteroskedasticity Test, the F-statistic is 0.519105 with a probability (Prob. F(4,30)) of 0.7223. In this case, the probabilities associated with both the Serial Correlation and Heteroskedasticity tests are relatively high (0.4453 and 0.7223, respectively). A high probability suggests that the F-statistics are not statistically significant, indicating that there is no significant serial correlation or heteroskedasticity detected in the regression model. These results imply that the assumptions regarding the absence of serial correlation and constant variance (homoscedasticity) are not violated, enhancing the validity and reliability of the ECCM model estimated.

Table 8: Results Serial Correlation and Heteroskedasticity

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.917142	Prob. F(3,28)	0.4453
Obs*R-squared	3.131558	Prob. Chi-Square(3)	0.3718
Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	0.519105	Prob. F(4,30)	0.7223
Obs*R-squared	2.265676	Prob. Chi-Square(4)	0.6870
Scaled explained SS	2.137247	Prob. Chi-Square(4)	0.7105

CONCLUSION

The study investigated the impact of government investment in human capital on income inequality in Nigeria using a Single-Equation Error Correction Model (ECM) approach spanning the years 1985 to 2023. At the pre-estimation phase, ensuring the robustness of the methodology by conducting stationarity tests and lag order selection. The results confirm the stationarity of the variables after differencing once, validating the model's reliability.

Subsequent analysis using the Parsimonious Error Correction Model (ECM) reveals significant insights. Notably, education expenditure exhibits a substantial negative coefficient of -0.099 ($p < 5\%$), indicating that increased investment in education can effectively reduce income inequality. Conversely, agricultural expenditure lagged by three periods shows a positive coefficient of 0.078 ($p < 5\%$), suggesting a slight rise in income inequality associated with higher agricultural spending. The non-significant coefficient for health expenditure lagged by two periods (D(HEALTH_EX(-2))) at -0.017 ($p > 5\%$) indicates limited impact on income inequality.

Of significant note is the Error Correction Mechanism (ECM) with a lag of one period (ECM(-1)), exhibiting a substantial negative coefficient of -0.471 ($p = 0.004$). This finding underscores the importance of addressing deviations from long-term equilibrium to effectively reduce income inequality in Nigeria.

The study's findings highlight the critical role of targeted policies aimed at enhancing education and sustainable agricultural practices while addressing factors that disrupt long-term economic equilibrium. Implementing such policies can foster more equitable income distribution and promote economic stability in Nigeria, contributing to sustainable development and inclusive growth. The study thus recommends;

i. increasing investment in education due to its significant negative impact on income inequality. Policymakers should focus on enhancing educational infrastructure, expanding access to quality education, and improving educational outcomes at all levels.

ii. encouraging sustainable agricultural practices and providing support to farmers can positively impact income equality. Policymakers should promote agribusiness, improve agricultural productivity, and create opportunities for smallholder farmers to reduce income disparities in rural areas.

iii. while the impact of health expenditure on income inequality was minor, ensuring affordable and accessible healthcare services remains crucial. Policymakers should prioritize healthcare policies that benefit vulnerable populations and contribute to overall well-being.

iv. the study underscores the importance of long-term planning and policy stability in achieving income equality. Policymakers should focus on creating an environment conducive to investment, addressing structural barriers, and promoting economic stability to reduce income disparities.

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