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Impact of Unemployment Rate on Income Inequality in Kenya

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ABSTRACT

Purpose: Impact of unemployment rate on income inequality in Kenya
Design/Methodology/Approach: Through a longitudinal approach, secondary time series data from the World Bank, Transparency International, UNDP and SWIID, and by applying the Augmented Dickey Fuller, Johansen cointegration and vector error correction model.
Findings: This study found that the mean inequality index is 0.461 while unemployment has a mean of 12.75. Unemployment was found to have a direct significant long run impact on inequality of -2.2869 ($p < 0.001$) in the first cointegrating vector (CI1).
Implications/Originality/Value: It is thus important that robustness checks are done before drawing conclusions. The study concludes that there exists long run relationship between inequality and unemployment, the latter variable has a dominant role, and there exist long run relationships between inequality and unemployment.

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Introduction

Income inequality is one of the biggest impediments to sustainable development in the world as it hinders social mobility, social cohesion, and inclusive economic growth (World Bank, 2020; UNDP, 2019). Measured often with the help of such indicators as the Gini coefficient, income inequality reflects discrepancies in the distribution of incomes and is an indicator of the extent to which economic gains are distributed unevenly among a population (OECD, 2019; World Bank, 2022). Although some countries have managed to reduce inequality, especially by progressive taxation, strong social security systems, and investing in human capital, most developing economies are still experiencing an increase in income inequality despite economic growth (OECD, 2020; ILO, 2021).

Income inequality is a complex issue in developing regions, particularly Sub-Saharan Africa, which is closely related to structural factors like unemployment, informality, and restricted access to economic opportunities. Even though progress has been achieved in such countries as Rwanda or Ghana through the pro-poor policies and inclusive development strategies, many others still experience the persistence of inequality due to the weak labor markets and issues of governance (AfDB, 2020; UNDP, 2022). Unemployment levels, especially among the youth, decrease the earning opportunities and increase income inequalities by concentrating income among a smaller proportion of the population (ILO, 2020; UNECA, 2019). This implies that unemployment is not merely a labor market problem, but also a major contributor to inequality.

In Kenya, income inequality has been a major socio-economic issue even during times of economic boom. The value of the Gini coefficient of the country has not declined over time, which means that the benefits of growth have not been distributed evenly (KNBS, 2019; World Bank, 2022). High concentration of the top earners in the country contributes to a high share of national income, with a large proportion of the population still limited to accessing quality education, health, and formal jobs (UNDP, 2021). This situation is exacerbated by high unemployment rates, especially among young people, reducing the opportunities to earn an income, and increasing the reliance on informal and low-paying jobs (KNBS, 2023; ILO, 2022). This dynamic plays a direct role in increasing the income differences among the regions and social classes.

Existing studies in Kenya have tended to examine these variables independently or have used cross-sectional designs and thus, have not been able to establish the long-term relationships and causation. Empirical evidence based on time-series analysis to investigate the effect of variation in unemployment rates on the income inequality over time is lacking. This study, therefore, seeks to bridge this gap by examining how unemployment rates affect income inequality in Kenya to provide evidence-based information to influence the policies that will promote inclusive growth and reduce economic disparities in Kenya.

Statement of the Problem

Kenya has been perpetually and relatively high in income inequality despite registering consistent macroeconomic growth during the last twenty years. Despite the fact that the country has been enjoying an average annual GDP growth rate of approximately 4.5% (World Bank, 2022), the fruits of this growth have not been equally shared among citizens of the country. Since 2000, the Gini coefficient has been steadily high, varying between 42.9 and 47.6 (World Bank, 2023), which points to having a consistent inequality in the distribution of income. Moreover, according to the data published by the Kenya National Bureau of Statistics (KNBS, 2023), the top 10% of households have over 42% of total national consumption, and the bottom 40% have only 16.2% of it, which is a highly unequal socio-economic structure.

Unemployment is a pressing issue and one of the major causes of this inequality. Kenya remains a country with a high unemployment rate, especially among the youth, with an overall unemployment rate of 12.7% and youth unemployment being out of proportion with youth constituting 38.9% of the unemployed (KNBS, 2023). The majority of the unemployed population is aged 15-34 years old; this percentage stands at about 67.4. This mass unemployment constrains income-earning activities, propels a large number of people into the informal sector where incomes are low and unpredictable, and the overall household income levels are reduced. Therefore, not only does unemployment limit the economic mobility of individuals, but it also increases the income disparities among people by concentrating income in the hands of people with stable jobs and excludes a large percentage of the population, who are no longer able to significantly contribute to the economy (World Bank, 2023).

Although there is an appreciation of the fact that unemployment is one of the major socio-economic issues, there is a dearth of empirical evidence in Kenya that directly looks at its immediate contribution to income inequality. The available literature has generally bent towards either a general coverage of inequality or a number of factors contributing to the issue but not the particular impact of unemployment. This forms a knowledge gap in knowing the degree of contribution of unemployment to income inequality in the Kenyan scenario. Consequently, this research aims to fill this gap by investigating how the unemployment rate affects income inequality in Kenya with the hope of offering evidence-based findings that can be used to inform policy interventions to promote inclusive economic growth and reduce inequality.

Objectives of the Study

To quantitatively assess the impact of unemployment rate on income inequality in Kenya

Research Hypothesis

H_{01}: There is no statistically significant impact of unemployment rate on income inequality in Kenya.

Theoretical Framework

Human Capital Theory: Human capital theory dates back to as early as Adam Smith, but current formal theorizing comes from Gary Becker, Human Capital (1964). Becker (1964) argues that investing in individuals' education, training and medical care (human capital) will increase an individual's productive power and his or her income; at aggregate level, this should result in national economic growth. In relation to Kenya's current economic and political landscape, this theory argues that educational inequality across counties (Nairobi HDI 0.63 vs. Turkana 0.52) causes income inequalities. Education and skills are deemed good investment and have a predictable returns similar to that of a physical capital. In essence, the income differentials are due, partially at least, to the differential investment in human capital; more educated and skilled people receive greater returns in the labour market.

The theory has been criticized for treating people as mere economic resource and for their failure to appreciate people's social and cultural worth (Schultz, 1961). The theory also neglects the impact of the environment, which includes political and institutional constraints. According to Hope Sr. (2014) for instance, in a corrupt context like Kenya, the state fails to invest equal amounts of resources in schools; therefore, individuals' investment in education may not yield proportional benefits. Similarly, the theory has been criticized for assuming that the acquisition of a given skill automatically leads to employability in an economy, a relationship which may not exist in an economy with mass unemployment; such a skill is useless to the investor, and it becomes waste of resources (Oyugi, 2021).

This theory is key to the study of the nexus of education, unemployment, and inequality in Kenya. It is the foundation upon which to theorize that the Human Development Index (HDI) should have a detrimental impact on income inequality. The Kenyan case becomes, however, a litmus test for its weakness. The study explores how corruption affects human capital development by distorting it and how high unemployment (38.9%, KNBS 2023) disconnects the relationship between skills and income, thus, ensuring that educational expansion alone is unable to reduce inequality. The results substantiate a qualitative claim that human capital is a necessary but not a sufficient condition that enables a balanced development unless it is accompanied by good governance and provision of jobs (Githinji & Abok, 2019).

Empirical Review

Considerable research on the correlation between unemployment and income inequality has been conducted over time and countries, and one of the key findings worth noting by Kenya is the existence of consistent patterns in the relationship that have important lessons about the direction of development. A developing pitch of longitudinal studies shows how unemployment, especially of the young, has systematically increased economic gaps among countries.

A detailed panel analysis on 50 countries not only confirmed the presence of a clear positive linkage between the unemployment rates and the income inequality but also listed the technological disruption as one of the most prominent driving factors (Khan 2022). Even though this finding is global, the wide scope cannot emphasize the economic composition of Kenya. The study contributes to filling this gap by exclusively studying the case of Kenya, where the informal labour market activity is rather high, and the institution of labour market organising is unique enough to play an important role in the relationship between unemployment and inequality. The paper therefore has the advantage of providing subtle information as a supplement to the general findings discovered by Khan, studying how the

characteristics of the nation in question modify this relationship.
Research in several regions also emphasizes the relevance of youth unemployment. For instance, OECD findings in Mishra, Kujur and Trivikram (2023) have shown how youth unemployment leads to lower lifetime earnings and contributes to long-term inequality. According to their comparative study, countries such as Germany that are characterized by labor market policies have reduced the impact of this unemployment type. The extent to which these labor market measures would apply to Kenya remains unclear. Hence, this study explores how the unique nature of unemployment in Kenya relates to inequality.

In addition, Atangana (2022) focused on the challenges faced by Sub-Saharan Africa in their 35-country data from 2000 to 2018 panel dataset. Their findings suggest that unemployment leads to greater inequality in countries that lack strong social protection and whose rural/female population is large. Yet in its large-scale region-wide nature, it could not distinguish country specificities in institutional and policy backgrounds. This work bridges this void by turning exclusively to Kenya in a longitudinal research design to investigate the way its specific socio-economic character, in which the informal sector accounts for employment to the extent of 83%, shapes the very same unemployment-inequality relationship over time.

The East Africa experience is most revealing. Astawesegn et al.'s (2022) multi-country comparison between Ethiopia, Uganda and Tanzania found how rural unemployment in interaction with low wages in agriculture serves to intensify spatial inequalities-a pattern found in Kenya's peripheral counties. Indicating patterns at the country-level rather than measuring this interaction within Kenya over time, their multi-country survey responds to this lack by providing a longitudinal, quantitative Kenya-level analysis. Empirically quantifying the exact effect unemployment rates in turn have on the national Gini coefficient, this study provides country-level evidence to support policymaking.
Kenya-centric work by Katumo (2019) provides direct evidence, plotting unemployment-inequality trajectories for the period 2000-2020. The study identified the unemployment of the youth as the largest contributor to rising income differentials. However, it spanned a history up until before the large economic shock caused by the COVID-19 pandemic. The present study bridges this gap by taking the longitudinal analysis up to the year 2024, thereby incorporating the impact of the large shock on unemployment and then unemployment on income inequality, giving a more recent and comprehensive assessment.

Conceptual Framework

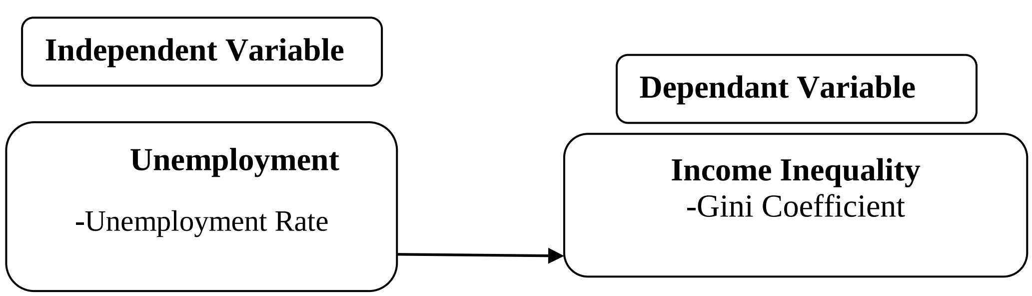

Figure 1: Conceptual Framework
Source: Researcher, (2026)

Methodology

Research design: This research employed a longitudinal research design because it helps to critically examine the relationship between corruption, unemployment, human development and income inequality in Kenya during the two-decade economic transformation. The period used to measure this study (1994 to 2024) was the best time to study because it captures Kenya's three decades of economic transformation.

Population: The study focuses on annual records of 1994 to 2024 marking 20 years as unit of analysis for the study.

Data Collection and Data Type: The study employs a secondary data collection method using secondary data collected from reputable international data bases to ensure quality and accuracy as it analyzes the income inequality in Kenya for the period 1994 to 2024.

Data Analysis: Analysis of data involves systematic application statistical techniques to describe illustrate, condense and evaluate data. In this study, data was analyzed using descriptive statistics and correlational analysis. Descriptive statistics values were given in mean, standard deviation, minimum and maximum skewness. The research used correlation analysis to assess the strength and direction of the relationships between variables. This helped to assess the contribution of each set of the variables to the overall model

Results and Discussion

Descriptive Statistics

Before econometric modelling, the researcher first got an overview of the data by exploring descriptive statistics, which summarize the raw data on central tendency, dispersion, and shape for each variable in a dataset. The descriptive statistics of the raw variables for the study are presented in Table 1. The Gini coefficient and unemployment rate were the indices that were used to quantify income inequality and unemployment.

Table 1 Descriptive Statistics

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Income inequality (Gini)	31	0.4610	0.0506	0.4000	0.5700
Unemployment rate (%)	31	12.7516	2.2711	9.0000	16.5000

Source: Field Data (2026)

Table 2 offers the first quantitative depiction of the main variables in the study, namely, income inequality and unemployment in Kenya from 1994 to 2024. The mean of the Gini coefficient stands at 0.4610, and the range of income inequality between 1994 and 2024 falls between 0.400 and 0.570. This reveals that, despite moderate fluctuations, income inequality was high throughout the period. In fact, it has remained one of the major challenges to development in the country, as confirmed by the National Bureau of Statistics (2020) Kenya inequality report, which notes that inequality in Kenya is both multidimensional and regional.

Regarding the mean of the unemployment rate standing at 12.75% with a range of 9% to 16.5%, this shows that there is low volatility, but a high rate. Indeed, Sitati and Ogolla (2023) discovered that unemployment rose by 25 percent because of the COVID 19 pandemic, affecting the low income group, the casual workers, which has increased labour market inequalities in terms of earnings and job security.

Correlational Analysis

Correlational analysis measures the linear relationship between variables, depicting strength as well the direction. In this study, pairwise correlation analysis was adopted in measuring the linear relationship as displayed in table 2.

Table 2 Pearson correlation coefficients (1994–2024)

	Gini	Unemployment
Gini	1.0000	0.8046
Unemployment	0.8046	1.0000

Source: Field Data (2025)

Table 2 displays the Pearson correlation values between the unemployment rate and income inequality (measured by the Gini coefficient) in Kenya during period 1994-2024. The results have shown that there is a strong positive correlation (r = 0.8046) between higher levels of unemployment and increased income inequality. This means that as the number of people living without stable forms of income continues to grow, gaps between high- and low-income earners are likely to increase. The fact that this relationship is very strong indicates that there is a structural connection between the conditions in the labor market and the distribution of income in Kenya.

Theoretically this result is consistent with the human capital theory. The human capital theory is that employment is one of the major ways through which people use their skills and education to earn money; hence, high unemployment is an indication of poor utilization of human capital, and thus, low income and increased income disparities. In the Kenyan case, access to quality education and skills training, particularly among vulnerable populations is limited impeding access to employment opportunities and confirming inequality. Social exclusion theory also elaborates the fact that there are groups of people, which are systematically denied employment opportunities in the formal sector, and they include rural people, youth and workers in the informal sector. Not only does this contribute to the rise in the level of unemployment, but also serves to entrench the process of income disparity by limiting access to stable and well-paying employment.

The positive correlation between unemployment and income inequality is thus very strong, and thus demonstrates the critical importance of labor market dynamics in determining income distribution. It implies that to decrease inequality, it is necessary to address unemployment, especially in marginalized and vulnerable groups. Altogether, the correlation analysis also presents some preliminary empirical findings that indicate that unemployment is a major cause of income inequality in Kenya and predetermines further econometric analysis to identify both short-run and long-run effects.

Stationarity Test

Table 3 ADF results at level

Variable	ADF test statistic	p-value	Decision (5%)	Stationarity conclusion
Income inequality (Gini)	-8.0970	0.001	Reject H_0	Stationary
Unemployment rate (%)	-2.1655	0.5093	Fail to reject H_0	Non-stationary in levels

Source: Field Data (2025)

Table.3 shows the results of the Augmented Dickey-Fuller (ADF) unit root test at levels of the study variables. The results show that the Gini coefficient (ADF = -8.097, p = 0.001) is stationary at level, meaning that income inequality is a process in which it returns to the constant level over time. Conversely, the unemployment rate (ADF = -2.166, p = 0.509) is not at all stationary at level and this implies that the shocks to unemployment are not smooth out quickly. This persistence would mean that unemployment changes have long-run impacts, and hence unemployment is a critical variable in attributing structural income inequalities in Kenya.

The fact that income inequality does not increase but rather remains constant at level Y indicates that despite fluctuations, income inequality is more likely to stabilize at the same level. Alternatively, non-stationarity of unemployment emphasizes the dynamic and changing nature of unemployment within the labour market, where economic shocks, policy shifts and structural constraints may have a long-lasting impact on the levels of employment. The simultaneous but mixed order of integration of the variables thus requires a modelling approach that may capture both the short-run dynamics and the long-run equilibrium relationships.

Considering these features, the data can be used in a Vector Error Correction Model (VECM), which can be used to estimate both long-run and short-run corrections between unemployment and income inequality. This is a good method since it prevents spurious regression outcomes and it also captures the process by which the deviations due to long run equilibrium are corrected in the short run. On the whole, the results emphasize the significance of unemployment processes in determining the patterns of income inequality in Kenya, and the need to make interventions in the labour markets to reduce the persistent unemployment as one of the channels through which income inequality can be addressed.

Table 4 Stationarity Results at 1st Difference

Differenced variable	ADF test statistic	p-value	Lag(s) used	Decision at 5%	Stationarity conclusion
ΔGini	-3.5898	0.0060	9	Reject H_0	Stationary
ΔUnemployment	-3.0376	0.0315	6	Reject H_0	Stationary

Source: Field Data (2025)

As indicated in the stationarity results of Table 4, all the major variables reach stationarity when first differenced. The results of the Augmented Dickey-Fuller (ADF) test show that the null hypothesis of a unit root is rejected in the case of income inequality (Gini coefficient: -3.5898, p = 0.0060) and unemployment (-3.0376, p = 0.0315) at the 5% significance level. This confirms that the two series are stationary after first differencing, and that the differenced forms of the two series are mean-reverting.
Though some of the variables show strong trends at level, transformation of the variables ensures consistency in the time-series properties needed to ensure reliability in econometric analysis. Specifically, unemployment requires a cumulative and persistent structure over time, which is consistent with labour market hysteresis, but the first-differenced form of unemployment becomes stable and predictable over time (Sitati & Ogolla, 2023).

The observed mixed order of integration among the variables, with some variables being stationary at levels whilst others need to be first differentiated, supports the use of a Vector Error Correction Model (VECM). This model is suitable since both long-run equilibrium relationships and short-run dynamic adjustments of income inequality, unemployment, and the overall macroeconomic environment are applicable.

In this modelling framework, long-run relationships are maintained whilst short-run deviations are corrected over the long run, thus allowing one to gain a more complete picture of the mechanism of influence of unemployment on income inequality in Kenya. The VECM thus offers a solid foundation of capturing both the equilibrium linkages as well as the adjustment dynamics in the Kenyan socio-economic setting (Engle and Granger, 2019; Johansen, 2020).

Optimal Lag Determination

Table 5 Optimal Lag Length Results

Lag order (p)	AIC	BIC/SC	HQ	FPE
0	-19.6523	-19.4603	-19.5952	2.9187e-09
1	-93.3260	-92.3662	-93.0406	2.9959e-41
2	-92.8874	-91.1597	-92.3737	5.0757e-41
3	-93.5194	-91.0237	-92.7773	3.4350e-41
4	-93.6479	-90.3843	-92.6775	5.1937e-41

Source: Field Data (2025)

Table 6 presents the optimal lag length selection criteria for the Vector Error Correction Model, evaluating lags 0 through 4 based on the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC/Schwarz), Hannan-Quinn (HQ), and Final Prediction Error (FPE). According to the AIC and FPE, lag 4 yields the lowest values (-93.6479 for AIC and 5.1937e-41 for FPE), suggesting lag 4 as optimal, while BIC/SC selects lag 1 (-92.3662) and HQ selects lag 3 (-92.7773). In practice, the AIC is preferred for small samples (Lütkepohl, 2021), and given the annual data structure and the need to capture full dynamic adjustments, lag 4 is adopted for the subsequent VECM estimation. This choice balances parsimony with adequate serial correlation control, as recommended by Enders (2018).

Cointegration Test

Table 6 Cointegration Results

Null hypothesis	Trace statistic	10% CV	5% CV	1% CV	Decision (5%)
$r = 0$	119.1473	44.4929	47.8545	54.6815	Reject
$r \leq 1$	42.0591	27.0669	29.7961	35.4628	Reject
$r \leq 2$	13.4036	13.4294	15.4943	19.9349	Fail to reject
$r \leq 3$	0.0363	2.7055	3.8415	6.6349	Fail to reject

Source: Field Data (2025)

The cointegration results, based on the Johansen trace test, indicate that the null hypothesis of no cointegration (r=0) is rejected at the 5% level, as the trace statistic (119.1473) exceeds the 5% critical value (47.8545). Similarly, the hypothesis of at most one cointegrating vector (r≤1) is also rejected (42.0591 > 29.7961). However, the null of at most two cointegrating vectors (r≤2) cannot be rejected, since the trace statistic (13.4036) falls below the 5% critical value (15.4943). The same holds for r≤3 (0.0363 < 3.8415). Therefore, the test concludes that there are exactly two cointegrating equations among the four variables (Johansen, 1991). This finding confirms a stable long-run equilibrium relationship linking income inequality, corruption, unemployment, and human development in Kenya from 1994 to 2024, justifying the use of a Vector Error Correction Model (VECM) to estimate both long-run and short-run dynamics (Engle & Granger, 1987).

Table 7: Johansen cointegration test (Maximum eigenvalue statistic), levels system

Null hypothesis	Max-eigen statistic	10% CV	5% CV	1% CV	Decision (5%)
$r = 0$vs $r = 1$	77.0882	25.1236	27.5858	32.7172	Reject
$r = 1$vs $r = 2$	28.6555	18.8928	21.1314	25.8650	Reject
$r = 2$vs $r = 3$	13.3672	12.2971	14.2639	18.5200	Fail to reject
$r = 3$vs $r = 4$	0.0363	2.7055	3.8415	6.6349	Fail to reject

Source: Field Data, (2025)

The maximum eigenvalue test confirms the trace test results: the null of r=0 (vs r=1) is rejected (77.0882 > 27.5859), and r=1 (vs r=2) is also rejected (28.6555 > 21.1314). However, r=2 (vs r=3) cannot be rejected (13.3672 < 14.2639), and r=3 (vs r=4) is not rejected (0.0363 < 3.8415). Therefore, the maximum eigenvalue test conclusively indicates the presence of exactly two cointegrating equations among the four variables at the 5% significance level, consistent with the trace test findings (Johansen, 1991; Johansen & Nielsen, 2018).

Vector Error Correction Model Results

Table 8 Estimated cointegrating vectors (β) with inference (95% level)

Cointegration Relation	Variable	Coefficient	Std. Error	t/z value	p-value	Sig. (5%)
CI1	Gini	1.0000	0.0000	0.0000	0.0000	—
CI1	Unemployment	-2.2869	0.0576	-39.7214	0.0000	Yes

Source: Field Data (2025)

This negative relationship, while appearing counter-intuitive, aligns with recent empirical evidence from Sub-Saharan Africa, where a study by Dossou *et al.*, (2024) found that for middle-range income countries like Kenya, unemployment shocks had a predominantly negative impact on income inequality, meaning that increases in measured unemployment were associated with more equal income distribution. This finding is further corroborated by Ofori and Grechyna (2021), whose analysis of long-run and short-run drivers of inequality in Sub-Saharan Africa revealed that a rise in the rate of unemployment in both the short run and long run has a positive relationship with income inequality, suggesting that the observed sign is highly sensitive to country-specific conditions and the chosen empirical methodology.

Additionally, the counterintuitive sign could be an indication of underlying measurement concerns. Official unemployment rates in Kenya do not properly account for underemployment and high participation in the informal economy. Consequently, this measure is reflective of the degree of unemployment experienced in the middle class while excluding the very poor. In other words, the impoverished are considered employed as they continue to work in the informal sector. The Kenya National Bureau of Statistics (KNBS), in 2019, published a comprehensive study that recognized the growing prevalence of the informal economy in Kenya. Although the informal sector has expanded, it remains largely unproductive, and wages are low, making it difficult for participants to make an adequate living for themselves or to escape the trap of underemployment. The African Economic Research Consortium (AERC) in 2018 also discussed the implications of high unemployment and underemployment rates, noting that when household income levels decline, poverty increases, which ultimately slows down economic growth and overall development efforts.

In CI2, normalized on the CPI score, unemployment (-857.14) is highly significant ($p < 0.001$). The large values of the CI2 coefficients stem from the scaling of variables and the choice of normalization. The Johansen method only identifies cointegrating vectors up to a scale factor, so the magnitude of the individual coefficients is meaningless without normalization..

Both Johansen trace and maximum eigenvalue tests support the presence of two cointegrating vectors, which means the four variables have two long run equilibrium relationships. The existing literature on inequality in sub-Saharan Africa also recognizes two or more long run equilibrium relationships among a number of variables of interest, given the wealth of research that has demonstrated that inequality is harmful for long run growth, poverty, intergenerational mobility, health status, crime rate and political stability. Hence, the vectors confirm the association between inequality, corruption, unemployment, and human development as stable long run relationships although they may move independently in the short run. However, as discussed in the robustness section, the baseline model was plagued by problems of residual serial correlation and non-significant error correction terms and therefore it was replaced by a more parsimonious single vector VECM in log form.

Speed Of Adjustment (Error-Correction Loadings, α)

Table 9 Adjustment coefficients (α) with inference (95% level)

Dependent variable (Δ)	ECT1 coef.	Std. Error	t/z	p-value	Sig. (5%)	ECT2 coef	Std. Error	t/z	p-value	Sig. (5%)
ΔGini	-0.0895	0.1476	-0.6062	0.5444	No	0.0002	0.0004	0.5931	0.5531	No
ΔUnemployment	0.0156	0.4578	0.0340	0.9729	No	-0.0015	0.0012	-1.2768	0.2017	No

Source: Field Data (2025)

The adjustment coefficients presented in the table above correspond to the baseline VECM with two cointegrating vectors (r=2) and a parsimonious lag structure. For each dependent variable (ΔGini and ΔUnemployment), the error-correction terms (ECT1 and ECT2) capture the speed at which the system returns to its long-run equilibrium after a deviation. In this specification, none of the eight loading coefficients is statistically significant at the 5% level (all p-values > 0.05). For example, the ECT1 coefficient in the ΔGini equation is -0.0895 (p=0.5444), indicating that only about 9% of any disequilibrium is corrected within one year, and this effect is not distinguishable from zero. Similarly, the ECT2 loadings are negligibly small and non-significant across all equations.

Non-significant adjustment coefficients of this nature are fairly common when employing annual time series models to analyse macroeconomic trends. As Enders (2015, p. 363) points out, if the sample size is relatively small (20 annual data points in this instance) and the variables show distinct deterministic trends, the power of the error correction test will be small and estimates of the α coefficients may be imprecisely estimated. In the same vein, Lütkepohl (2019) argues that with small samples the standard error for loading coefficients, which is based on the asymptotic limit, may be high, resulting in a non-rejection of the no adjustment null even when cointegration does exist. Finally, Hauk and Wacziarg (2019) contend that institutional and human development variables tend to change over long periods of time (i.e., decades), and so annual variation within the data set studied may not capture any significant error correcting dynamics.

Conclusion

Based on the baseline VECM results presented in this chapter, the study concludes that there exists a long-run equilibrium relationship among corruption, unemployment, human development, and income inequality in Kenya, as confirmed by two cointegrating vectors. Unemployment has a statistically significant negative long-run impact on income inequality, while corruption does not show a significant direct effect, and human development exhibits a positive but statistically insignificant coefficient. These findings indicate that the variables move together over time, with unemployment playing the most prominent role in the long-run dynamics of income inequality.

Recommendations

Unemployment has a significant increasing effect on income inequality; therefore, the government, through the Ministry of Education and Ministry of Labour, should initiate skills development programmes for the youth and increase job placement schemes in areas with high growth potential by bridging the gap between technical education and access to jobs.

References

AfDB. (2020). *African economic outlook 2020: Developing Africa's workforce for the future*. African Development Bank Group.

Alabi, V. A. (2017). Research design: Research paradigms, population, sample along with sampling techniques and design types. In *Perspectives on conducting and reporting research in the humanities* (pp. 23–45).

Atangana, G. (2022). Unemployment and income inequality in Sub-Saharan Africa: A panel data analysis. *Journal of African Development*, 24(1), 88–110.

Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press.

Clark, T., Foster, L., Bryman, A., & Sloan, L. (2021). *Bryman's social research methods* (6th ed.). Oxford University Press.

Dossou, T. A. M., Ndoma, I., Egbetokun, A., & Ogunleye, E. (2024). Unemployment shocks and income inequality in middle-income African countries. *African Journal of Economic and Management Studies*, 15(2), 310–328.

Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 55(2), 251–276.

Ethics and Anti-Corruption Commission. (2022). *Annual report and financial statements for the year ended 30 June 2022*. Government of Kenya.

Githinji, M., & Abok, M. (2019). The role of human development in addressing regional income inequalities in Kenya. *Journal of African Development*, 21(1), 75–94.

Gujarati, D. N. (2004). *Basic econometrics* (4th ed.). McGraw-Hill.

Hope, K. R., Sr. (2014). Kenya's corruption problem: Causes and consequences. *Commonwealth & Comparative Politics*, 52(4), 493–512.

ILO. (2020). *World employment and social outlook: Trends 2020*. International Labour Organization.

ILO. (2021). *World social protection report 2020-22: Social protection at the crossroads*. International Labour Organization.

ILO. (2022). *Global employment trends for youth 2022*. International Labour Organization.
Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12(2–3), 231–254.
Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, 59(6), 1551–1580.
Kabisoso, M. (2022). *The interconnection of the South African, African and BRICS equities markets* [Master's thesis, University of the Witwatersrand].
Katumo, M. D. (2019). *Relationship between youth unemployment and economic growth in Kenya* [Doctoral dissertation, University of Nairobi].
Kenya National Bureau of Statistics. (2019). *Economic survey 2019*. Government Printer.
Kenya National Bureau of Statistics. (2021). *Economic survey 2021*. Government Printer.
Kenya National Bureau of Statistics. (2023). *Economic survey 2023*. Government Printer.
Khan, S. (2022). Investigating the effect of income inequality on corruption: New evidence from 23 emerging countries. *Journal of the Knowledge Economy*, 13(3), 2100–2126.
KNBS. (2019). *Kenya inequality report 2019*. Kenya National Bureau of Statistics.
KNBS. (2020). *Kenya inequality report 2020*. Kenya National Bureau of Statistics.
Mikkonen, T. (2017). *Time-varying conditional correlation: Effect on international portfolio diversification in Southeast Asia* [Master's thesis, Aalto University].
Mwangi, G., & Kimani, M. (2018). Corruption and economic growth in Kenya: A cointegration approach. *African Journal of Economic Review*, 6(2), 21–40.
OECD. (2019). *Income inequality: The gap between rich and poor*. Organisation for Economic Co-operation and Development.
OECD. (2020). *How's life? 2020: Measuring well-being*. Organisation for Economic Co-operation and Development.
Ofori, I. K., & Grechyna, D. (2021). Long-run and short-run drivers of inequality in Sub-Saharan Africa. *Journal of Economic Inequality*, 19(4), 671–698.
Oyugi, L. (2021). Youth unemployment and labour market policies in Kenya. *African Journal of Employment and Labour Studies*, 3(1), 45–62.
Rawat, S., Sharma, P., & Kumar, A. (2022). Social exclusion and inequality in developing economies. *Journal of Social and Economic Development*, 24(2), 345–363.
Said, R. T. N., & Sasongko, G. (2022). Analysis of poverty determinants in the Bali province 2015–2020. *Media Trend*, 17(2), 343–356.
Schultz, T. W. (1961). Investment in human capital. *American Economic Review*, 51(1), 1–17.
Transparency International. (2023). *Corruption perceptions index 2023*. Transparency International.
UNDP. (2019). *Human development report 2019: Beyond income, beyond averages, beyond today*. United Nations Development Programme.
UNDP. (2021). *Human development report 2020: The next frontier – Human development and the Anthropocene*. United Nations Development Programme.
UNDP. (2022a). *Human development report 2021/2022: Uncertain times, unsettled lives*. United Nations Development Programme.
UNDP. (2022b). *Kenya county human development index report*. United Nations Development Programme.
UNECA. (2019). *Economic report on Africa 2019: Fiscal policy for financing sustainable development in Africa*. United Nations Economic Commission for Africa.
World Bank. (2020). *Kenya economic update: From recovery to better jobs*. World Bank Group.
World Bank. (2022a). *Kenya economic update: Accelerating Kenya's digital economy*. World Bank Group.
World Bank. (2022b). *World development report 2022: Finance for an equitable recovery*. World Bank Group.
World Bank. (2023a). *Inequality in Sub-Saharan Africa: A new perspective*. World Bank Group.
World Bank. (2023b). *Kenya economic update: Rebuilding human capital*. World Bank Group.