

Convergence and divergence of adjusted net national income per capita and GDP per capita in Sub-Saharan Africa

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ABSTRACT

This paper uses a novel approach that combines a non-conventional indicator of income inequality (the "Adjusted Net National Income per capita" – ANNIPC) together with the traditional indicator (the "GDP per capita" – GDPPC) to test for income convergence and divergence. In addition, the paper evaluates the effects of inflation, gross fixed capital formation, unemployment, labour force, and institutional factors on ANNIPC and GDPPC using the spatial lag and OLS regression models. The results of income convergence and divergence tests for both ANNIPC and GDPPC reveal comparable patterns, with a diverging trend being apparent in the initial period (1971–1994) succeeded by a converging trend in the subsequent years (i.e., 1995 to the early 2020s). The results of the spatial regression indicated that overall, the models were statistically significant due to the inclusion of spatial components. However, the individual predictors did not significantly explain the variability in ANNIPC and GDPPC. On the other hand, the Ordinary Least Squares (OLS) results revealed that GDPPC was significantly influenced by gross capital formation, unemployment, and the total labour force. We underscore the need for policymakers and stakeholders aiming to enhance the economic prospects of Sub-Saharan Africa (SSA) to consider the complex relationships between inflation, gross capital formation, and labour dynamics. Strategies should not only address immediate economic concerns but also focus on promoting sustainable and inclusive growth for the future.

Keywords: Income Convergence and Divergence, Institutional Factors, Gross Fixed Capital Formation, Spatial Lag and OLS Regression Models, Total Labour Force

I. INTRODUCTION

There is a widespread belief that income or Gross Domestic Product per capita (GDPPC) should converge across countries such that countries with lower levels of income or GDPPC catch up to countries with higher levels (Alemu et al., 2025; Cyrek, 2025; Kant, 2019; Hartmann et al., 2017; Papava, 2016; United Nations Industrial Development Organisation [UNIDO], 2005). In this perspective, per capita income “convergence” is preferred to per capita income



“divergence” or the uneven distribution of income (i.e. the opposite of “convergence”) for economic development because the former is considered as reducing poverty.

The “convergence” school of thought maintains that in the long run, the GDP and income per capita of poor countries catch up with that of rich countries (Mensah, 2020). This viewpoint predicts more swift economic growth when the level of physical capital per capita is low (Solow, 1956; Swan, 1956), leading to all economies ultimately converging in terms of per capita income (Barro & Sala-i-Martin 1992; Barro, 1991; Baumol, 1986). It sees developing countries as having the potential to grow at faster rates than developed countries because diminishing returns, in particular to capital, are not as outstanding as in capital-rich countries. Failure to converge (i.e. divergence) occurs when the per capita income (GDPPC) for poor countries fails to catch up with that of rich countries leading to an increase in inequality gap and poverty amongst countries (Mensah, 2020). In this perspective, the increases in income inequality are associated with increases in poverty (Deaton, 2014). Excessive inequality is considered to hurt long-term growth prospects. It may jeopardize people's ability to develop new ideas (Baten, 2018) preventing equal access to assets, education, and opportunities for low-income people and marginalized ethnic groups (ibid).

However, the research on income inequality and economic growth has recently expanded further to investigate whether inequality is good or bad for economic growth (McKnight, 2019). There is already a common proposition that inequality leads to more efforts and innovations, which in turn generate higher levels of economic growth (McKnight, 2019). According to this proposition, inequality can increase the incentive for workers to move to higher paying technologically advanced sectors of the economy, and generate more innovation, entrepreneurial activity, and enterprising behaviour (Galor & Tsiddon 1997a, 1997b). In fact, much of the emerging empirical findings confirm the positive relationship between economic inequality and economic growth endorsing a polarised debate about the role of “income convergence” and “income divergence” on economic growth.

1.1 Statement of the Problem

The Sub-Saharan Africa (SSA) region is not only characterized by low levels of per capita income, but it is also one of the regions with high levels of income disparity in the globe (UNDP, 2017). Consequently, the 2030 Agenda for Sustainable Development was adopted with its famous motto or slogan of ‘leaving no one behind’ by 2030 (UNDP, 2017). However, achieving this would require a thorough understanding of the nature, trends, drivers, and outcomes of income inequality in the region (UNDP, 2017). Important is the understanding of whether the gap in income or GDPPC amongst SSA countries is narrowing (converging) or widening (diverging). Related to this is the understanding of the real drivers of per capita income “convergence” and or “divergence.” This understanding is important to inform the strategies and actions to achieve the goal of ‘leaving no one behind’ by 2030.

While the research on economic convergence is not new, studies which have investigated the question of whether the income per capita amongst SSA countries is converging or widening are scant (Aboagye, 2013). Where attempted, the studies have mostly applied a single metric of economic growth or welfare separately, mostly the GDPPC (e.g. Ebi & Nyong, 2020) or public health expenditure (e.g. Traoré, 2021) or purchasing-power-parity (Huffman & Huffman, 2021) or the Human Capital-augmented version (HC-AV) of the neoclassical growth model (Aboagye, 2013). Using a single measure alone can be misleading. For example, some studies indicated that developed countries tend to converge in terms of per capita income, but the world as a whole does not (Mensah, 2020). Many studies also indicated that countries with a low to medium-high level of development show signs of convergence, but countries with a medium-high to a very high level of development show signs of divergence (ibid). Our paper addresses the current gap regarding SSA countries using a novel approach that combines a non-conventional metric of “adjusted net national income per capita (ANNIPC)” alongside the traditional “GDP per capita (GDPPC)” to test for income convergence and divergence. Specifically, the coefficient of variation (CV) was used to assess convergence for both ANNIPC and GDPPC due to its

scale-invariance property, making it suitable for comparing income dispersion across countries with different average income levels. This ensures that the analysis is not unduly influenced by the sheer size of the economies being compared.

The effects of inflation, gross fixed capital formation, unemployment, and labour force on ANNIPC and GDPPC were evaluated in two models (models 1 and 2) respectively using the Spatial Lag and OLS models. The rationale for using both Spatial Lag and OLS models stems from the need to test for spatial dependence in the data. The next section presents the theoretical, empirical and conceptual framework of our study. This is followed by a presentation of the study approach and methodology in Section III, as well as the results (Section IV) and discussion (Sections V). The paper winds up by presenting some concluding remarks and policy implications in Section VI.

1.2 Research Objectives

This paper aims to investigate the trends of income convergence and divergence in Sub-Saharan Africa (SSA). Specifically, the research objectives are threefold:

- i) To examine the trends of convergence or divergence in both adjusted net national income per capita (ANNIPC) and GDP per capita (GDPPC) across SSA countries;
- ii) To evaluate the effects of inflation, gross fixed capital formation, unemployment, and labour force on ANNIPC and GDPPC in SSA countries; and
- iii) To assess the spatial relationships and dependencies of ANNIPC and GDPPC across SSA countries using spatial regression analysis.

The first objective allows us to compare our findings with existing studies that primarily focus on GDPPC as a measure of economic welfare. The second objective addresses the question of whether inflation, gross fixed capital formation, unemployment, and labour force constitute the key drivers of income convergence or divergence in the SSA region, measured using the metrics of on ANNIPC and GDPPC. The third objective seeks to determine the extent to which the economic performance of one country influences and is influenced by its neighbouring countries, accounting for spatial autocorrelation in the data. By employing a Spatial Autoregressive (SAR) model, we aim to capture the spatial dynamics and spillover effects that may not be evident in traditional regression models, thus providing a more comprehensive understanding of income convergence and divergence patterns in the region. This analysis involves constructing a spatial weights matrix based on geographical proximity to model the interdependencies between SSA countries and interpreting the spatial autoregressive coefficient to quantify the strength of spatial dependence.

II. LITERATURE REVIEW

2.1 Theoretical Review

The theoretical review in this paper has benefitted enormously from the “catch-up effect” or income “convergence” theory developed by the University of California, Berkeley Professor of Economics Clark Kerr in 1960 (McCoskey, 2002). The “catch-up effect” is a theory that all economies will eventually converge (catch-up) in terms of per capita income, because of the observation that underdeveloped economies tended to grow more rapidly than wealthier economies (ibid). This implies that the less wealthy economies would literally “catch-up” to the more robust economies. The theory is founded on the law of diminishing marginal returns, applied to investment at the national level, and the empirical observation that growth rates tended to slow as an economy matured (ibid). Developing nations could enhance their catch-up effect by opening up their economy to free trade and developing “social capabilities,” or the ability to absorb new technology, attract capital, and participate in global markets (ibid).

Professor Kerr believed that convergence was driven by changes in technology, communication, and transportation which would increase international trade and collaboration. The theory assumed that technology was freely traded and available to developing countries. As such, there would be no “catch-up effect” when there was no investment of



capital and if the viability of the opportunity was not noticed by international markets, leading to divergence rather than convergence. The divergence theory claims that as societies moved further from each other geographically and culturally, they became increasingly dissimilar (Ray, 2019). However, it is important to note that the “catch-up” or “convergence theory” has also been criticized for ignoring cultural and historical differences and overlooking the role of power and inequality oversimplifying the existing complexity. A country being poor doesn’t guarantee that catch-up growth would happen (Burkett & Hart-Landsberg, 2003). Social capabilities would be needed to benefit from catch-up growth (ibid). Social capabilities include the ability to attract funds, absorb new technology, and participate in global markets (ibid). Thus, before catch-up growth can occur, certain abilities must be established. Furthermore, the availability of capital can also limit this ‘catch-up’ effect, due to its costs within a country (ibid). This situation presents significant challenges for nations aiming to accelerate their economic development, as a lack of capital resources often hampers potential progress. Additionally, without the necessary capabilities, countries are initially restricted in their opportunities to close the gap with more developed economies, leaving them struggling to achieve their growth potential in a competitive global landscape (ibid).

2.2 Empirical Review

Building upon the existing literature, this paper aims to contribute to the understanding of income convergence in Sub-Saharan Africa (SSA) by employing both traditional and spatial econometric techniques. While previous studies, such as Aboagye (2013), have focused on GDP per capita (GDPPC) and found divergence in SSA, this research expands the analysis by incorporating the Annual Net National Income Per Capita (ANNIPC) as an alternative welfare measure. This approach allows for a comparison of findings with existing studies that primarily utilise GDPPC, addressing concerns raised by Aitken (2019) and the Stiglitz-Sen-Fitoussi Commission regarding the limitations of GDP as a sole indicator of well-being. Specifically, the study investigates whether inflation, gross fixed capital formation, unemployment, and labour force influence income convergence or divergence in SSA, measured by both ANNIPC and GDPPC. This analysis seeks to determine the key drivers of economic (ANNIPC or GDPPC) convergence or divergence in the SSA region.

Furthermore, this research incorporates a spatial dimension to account for the interconnectedness of SSA economies. Unlike traditional convergence studies, such as Barro and Sala-i-Martin (1992) and Sofi & Durai (2016), which primarily focus on temporal trends, this study acknowledges the potential for spatial autocorrelation, where the economic performance of one country is influenced by its neighbours. To address this, a Spatial Autoregressive (SAR) model is employed to capture spatial dynamics and spillover effects, which may not be evident in non-spatial regression models. This approach builds on the recommendations of McCoskey (2002) by accounting for spatial dependencies within the SSA region. The study constructed a spatial weights matrix based on geographical proximity to model interdependencies between SSA countries and interprets the spatial autoregressive coefficient to quantify the strength of spatial dependence. This comprehensive analysis aims to provide a more nuanced understanding of income convergence patterns in the region. It allows for a better-informed conclusion regarding whether income disparities are converging, diverging, or forming distinct clusters within SSA, accounting for both temporal trends and spatial relationships.

To further enhance the analysis and provide a more robust understanding of the factors influencing income convergence in SSA, the study also considered the role of institutional quality and governance. Several studies have highlighted the importance of these factors in promoting economic growth and convergence (Acemoglu et al., 2005; Rodrik et al., 2004). For instance, Acemoglu et al. (2005) argue that differences in institutions are a primary driver of cross-country income disparities. Similarly, Rodrik et al. (2004) demonstrate that institutions trump geography and trade in explaining income levels. Therefore, the current research incorporated measures of institutional quality and governance, such as the World Bank’s Worldwide Governance Indicators (WGI), to assess their impact on income convergence in SSA. By controlling for these factors, the study provides a more accurate assessment of the effects of inflation, gross

fixed capital formation, unemployment, and labour force on income convergence, while also accounting for the spatial dynamics within the region.

III. METHODOLOGY

3.1. The Study Area and Data Sources

This paper is based on a study that focused on the Sub-Saharan Africa (SSA) or Subsahara area of the African continent that lies south of the Sahara. The area includes Central, East, Southern, and West Africa. It should be noted that the classification of SSA countries varies based on different contexts or definitions used in political, economic, or cultural discussions. Geopolitically, the term may include African countries and territories fully situated in the region, as well as polities that have only part of their territory located in that region (United Nations [UN], 2010). SSA is therefore considered a non-standardized geographical region (ibid) with the number of countries included varying from 46 to 48 depending on the organization describing the area (e.g., UN, WHO, World Bank, etc.) (World Bank Group, 2020). The African Union (AU) adopts a distinct regional classification, recognizing 55 member states on the continent (Assèdè et al., 2023) and grouping them into five distinct and standard regions. The United Nations Geoscheme for Africa excludes Sudan, while the African Union includes Sudan but excludes Mauritania (Assèdè et al., 2023). The United Nations Development Program has 46 of the 54 countries as SSA countries, excluding Djibouti, Somalia, and Sudan (UN, 2010).

This paper utilizes the classification of 48 SSA countries adopted from Tapkigen al. (2024) (Supplementary Table 1) and secondary data obtained from the World Bank's open data source of development indicators (Table 1). The dataset dimensions are selected to encompass as many countries as possible ranging from 1971 to 2023, as the available data for many SSA countries fall within that period.

Table 1

Description of Study Variables

| Variable | Variable description | Coverage |
|-----------|--|----------------------------|
| ANNIPC | Adjusted net national income per capita (constant 2015 US\$) | Average values (1971-2021) |
| GDPPC | GDP per capita (constant 2015 US\$) | Average values (1971-2023) |
| INFLAT | Inflation, consumer prices (annual %) | Average values (1971-2023) |
| CAPITAL | Gross fixed capital formation (constant US\$) | Average values (1971-2023) |
| UNEMP | Unemployment, total (% of total labour force) | Average values (1971-2023) |
| LABOUR | Labour force, total | Average values (1971-2023) |
| INSTI | Institutional variables (scores 1= low to 6=high) | Average values (2005-2023) |
| LATITUDE | Spatially lagged latitude or latitude effects | NA |
| LONGITUDE | Spatially lagged longitude or longitude effects | NA |

Data source: <https://data.worldbank.org/country/>

ANNIPC and GDPPC: are the dependent variables for models 1 and 2 respectively. INSTI: refers to the average score of four Country Policy and Institutional Assessment (CPIA) types of data namely: the CPIA economic management cluster average; CPIA public sector management and institutions cluster average; CPIA policies for social inclusion/equity cluster average; and CPIA structural policies cluster average



3.2. Analysis of Income Convergence and Divergence

There are two concepts of convergence which are sigma and *beta* convergence. The study adopted the sigma convergence intending to observe if there was a reduction in ANNIPC and GDPPC dispersion. In particular, we used the coefficient of variation which is among the variants of sigma convergence. The coefficient of variation was calculated as in Equation 1.

$$CV = \frac{\sigma}{\mu} \tag{1}$$

Where, *CV* is the coefficient of variation (a measure of convergence or divergence), σ is the standard deviation, and μ is the mean. The decrease in the coefficient of variation would imply a declining trend in ANNIPC or GDPPC amongst SSA countries.

Where GDPPC convergence was detected, the “half-life” parameter was calculated using the first-order law of integrated rate as expressed in Equation 2. By definition, Choi et al. (2006) referred “half-life” as the time taken to move halfway to the balanced steady state, or the time required for a divergence from income per capita to dissipate by one-half.

$$\ln(Y_t) = -\beta T + \ln(Y_0) \tag{2}$$

Equation 2 could further be rearranged to get the “half-life” parameter ($T_{\frac{1}{2}}$) in Equation 3 (Jena & Barua, 2020).

$$\ln(Y_t) - \ln(Y_0) = -\beta T$$

$$\ln\left(\frac{Y_t}{Y_0}\right) = -\beta t$$

$$\ln\left(\frac{1}{2}\right) = -\beta T_{\frac{1}{2}}$$

$$T_{\frac{1}{2}} = \frac{0.693}{-\beta} \tag{3}$$

3.3 Regression Analysis

3.3.1 Model Specification

We estimated the OLS and Spatial Lag or Spatial Autoregressive (SAR) models using RStudio based on the dataset for spatial regression comprising 32 observations (i.e., 66.7% of all 48 SSA countries). The SAR model incorporated a spatially lagged dependent variable to account for spatial autocorrelation. The dependent variable at one location was influenced by its values in neighbouring locations. We specified our SAR models as shown in Equations 4 and 5.

$$ANNIPC = \beta_0 + \beta_1 INFLAT + \beta_2 CAPITAL + \beta_3 UNEMP + \beta_4 LABOUR + \beta_5 INSTI + \rho(W * ANNIPC) + \epsilon \tag{4}$$

$$GDPPC = \beta_0 + \beta_1 INFLAT + \beta_2 CAPITAL + \beta_3 UNEMP + \beta_4 LABOUR + \beta_5 INSTI + \rho(W * GDPPC) + \epsilon \tag{5}$$

Where:

ANNIPC represents the Adjusted Net National Income Per Capita (constant 2015 US\$).

GDPPC represents the GDP per capita (constant 2015 US\$).

β_0 is the intercept term.

$\beta_1, \beta_2, \beta_3, \beta_4$ and β_5 are the coefficients for the independent variables INFLAT, CAPITAL, UNEMP, LABOUR, and INSTI respectively. These coefficients represent the change in the dependent variable for a one-unit change in the corresponding independent variable, holding all other variables constant.

INFLAT is the inflation, consumer prices (annual %).

CAPITAL is the gross fixed capital formation (constant 2015 US\$).

UNEMP is the unemployment, total (% of total labour force).

LABOUR is the total labour force.

INSTI is the average score for institutional factors (CPIA).

ρ (rho) is the spatial autoregressive coefficient, which measures the strength of the spatial dependence.

W is the spatial weights matrix, which defines the spatial relationships between the locations (or countries in this case). This matrix determines which locations (countries) are considered neighbours and how much influence they have on each other. Common methods for defining W include contiguity-based weights (e.g., Queen's or Rook's contiguity) or distance-based weights. ($W * ANNIPC$) represents the spatially lagged dependent variable for Model 1, calculated by multiplying the spatial weights matrix (W) by the vector of ANNIPC values. This term represents the average of ANNIPC values in neighbouring locations, weighted by their spatial relationships.

($W * GDPPC$) represents the spatially lagged dependent variable for Model 2, calculated by multiplying the spatial weights matrix (W) by the vector of GDPPC values. This term represents the average of GDPPC values in neighbouring locations, weighted by their spatial relationships.

E is the error term, which captures the unexplained variation in the dependent variable.

The spatial weight matrix (W) was constructed based on geographical contiguity, specifically a binary contiguity matrix where countries sharing a border were assigned a value of 1, and those that do not were assigned a value of 0. This choice reflects the assumption that neighbouring countries have a direct influence on each other's economic performance. Although the analysis aimed to include all 48 SSA countries, data limitations for key economic indicators from 1971 to 2023 restricted the scope to 32 countries. As shown in Supplementary Table 2, sixteen countries were excluded from the regression analysis. These include Botswana, Cabo Verde, Equatorial Guinea, Eritrea, Eswatini, Gabon, Liberia, Malawi, Mauritius, Mozambique, Namibia, Nigeria, São Tomé & Príncipe, Seychelles, Somalia, and Sudan. As shown in Table 1, our economic indicators included the dependent variables of ANNIPC and GDPPC for models 1 and 2, respectively, along with the regressors or independent variables of INFLAT, CAPITAL, UNEMP, LABOUR, and INSTI. Additionally, the dataset included spatial coordinates, specifically latitude and longitude.

It is important to note that excluding these 16 countries could introduce bias if the missing data isn't random across Sub-Saharan Africa (SSA). If data unavailability is systematically linked to the studied variables (ANNIPC, GDPPC, INFLAT, CAPITAL, UNEMP, LABOUR, INSTI), the results from the 32-country sample may not be generalizable to the entire SSA region. For instance, the lack of INSTI data for several countries (i.e., Botswana, Equatorial Guinea, Eswatini, Gabon, Mauritius, and Namibia) could be indicative of systematic differences in governance or data reporting capacity within these nations. Similarly, the absence of INFLAT and CAPITAL data for others (e.g., Cabo Verde, Eritrea, Liberia, Malawi, Mozambique, Nigeria, Sao Tome & Principe, and Somalia) may be correlated with economic instability or underdevelopment, which are themselves linked to ANNIPC and GDPPC. To mitigate the potential for selection bias, we acknowledge this limitation in the discussion section of the paper. In addition, we used Moran's I test to assess spatial autocorrelation, and the results indicated the presence of significant spatial dependence. To determine the appropriateness of the SAR model over the OLS model, we used the Likelihood Ratio test, AIC, and BIC. These tests indicated that the SAR model better captured the spatial dynamics in our data.

IV. FINDINGS & DISCUSSION

4.1. Selected Descriptive Statistics for SSA

The key descriptive statistics for SSA are presented in Table 2 providing some important insights into the various economic indicators and their variability across the region. The mean income level of 1.71 falls within the range of low- to lower-middle-income countries. This value suggests that, on average, the countries classified in this category are leaning towards the lower middle-income spectrum. It indicates that while some low-income countries are bringing the average down, a significant presence of lower middle-income countries is pulling it upward. This numerical representation highlights the economic diversity within SSA countries, as some nations may be close to transitioning into the upper middle-income category.

Table 2

Key Descriptive Statistics for SSA Countries

| Variable | N | Minimum | Maximum | Mean | Std. Deviation |
|--|----|---------|-----------|----------|----------------|
| Income level (2023 WB Income classification) | 48 | 1 | 4 | 1.71 | 0.771 |
| Adjusted net national income per capita in 2021 (constant 2015 US\$) | 48 | 156 | 12252 | 1755 | 2226 |
| GDP per capita in 2023 (constant US\$) | 48 | 200 | 17879 | 2512 | 3248 |
| Total human population in 2023 | 48 | 119773 | 223804632 | 25872871 | 39067360 |

The mean “adjusted net national income per capita” (ANNIPC) of 1 755 constant 2015 US\$ in Table 2 reflects the average economic well-being of individuals when considering factors like depreciation and income distribution. However, the substantial standard deviation of 2 226 suggests significant variability in income levels, indicating that while some SSA countries enjoy a higher standard of living, others may be struggling, which could stem from disparities in regional economic development or access to resources. Just as important, the mean GDP per capita of 2 512 in constant 2015 US\$ demonstrates a moderate economic output per person. However, the high standard deviation of 3 248 points to considerable differences in economic productivity among individual countries, suggesting that while the economy of SSA may be growing, the benefits of this growth were not evenly distributed among countries.

The mean total human population for SSA of 25 872 871 in 2023 presents a snapshot of the demographic landscape. However, the standard deviation (39 067 360) indicates a vast range in population counts across different SSA countries. This discrepancy may reflect the presence of densely populated urban centres and sparsely populated rural regions, impacting resource allocation, governance, and social services. The high standard deviation also suggests that population growth rates in the region might be varying significantly, influencing economic planning and development strategies.

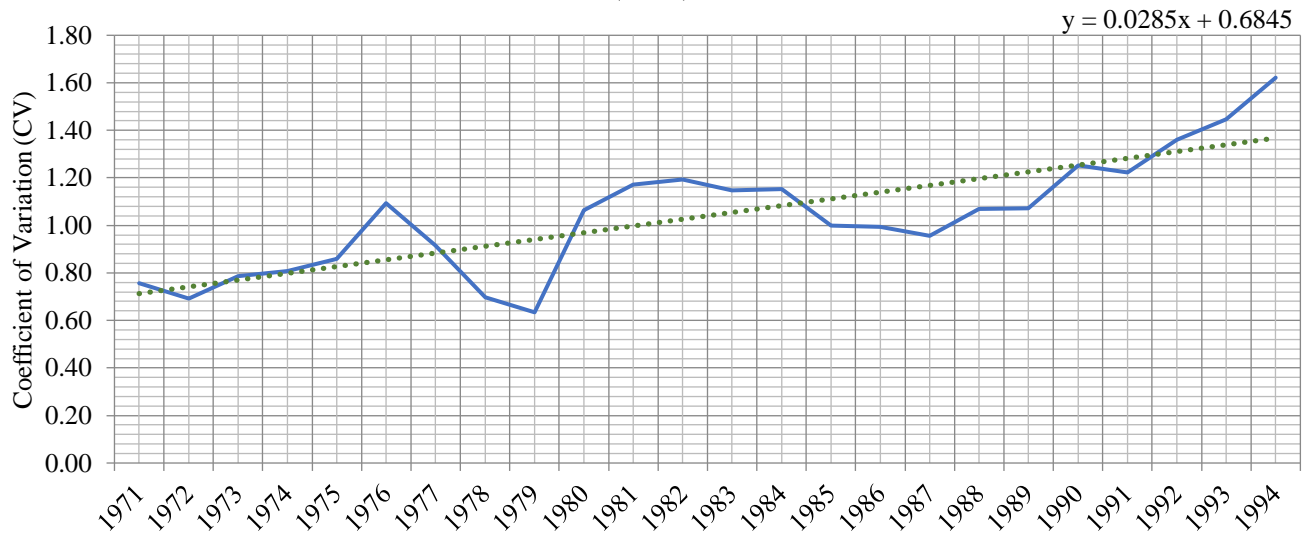
4.2. Results of Convergence and Divergence Tests

Figures 1 and 2 show similar trends in income convergence for both adjusted net national income per capita (ANNIPC) and GDP per capita (GDPPC), as also supported by the tests in Table 3. For both indicators, a divergent trend is evident during the first window (1971 – 1994), followed by a converging trend during the second window, which commenced in 1995 and continued into the early 2020s. The downward sloping trajectory in the second window suggests that the originally poorer economies in the SSA slowly started to catch up with the initially richer economies in terms of economic growth, with gradients of -0.0140 and -0.0081 for ANNIPC and GDPPC, respectively. As the gradient values in Table 3 indicate, the convergence in the second window of ANNIPC was relatively faster than that of GDP per capita. This implies that GDPPC inequality is more pronounced among the SSA economies than ANNIPC



inequality. This is also supported by the half-life values [i.e., the time taken to move halfway to the balanced steady state, or the time required for a divergence from income per capita to dissipate by one-half (Choi *et al.*, 2006)] of 86 years for GDPPC compared with only 50 years for ANNIPC.

a) CV: Adjusted Net National Income Per Capita, 1971-1994 (N=48)



b) CV: Adjusted Net National Income Per Capita, 1995-2021 (N=48)

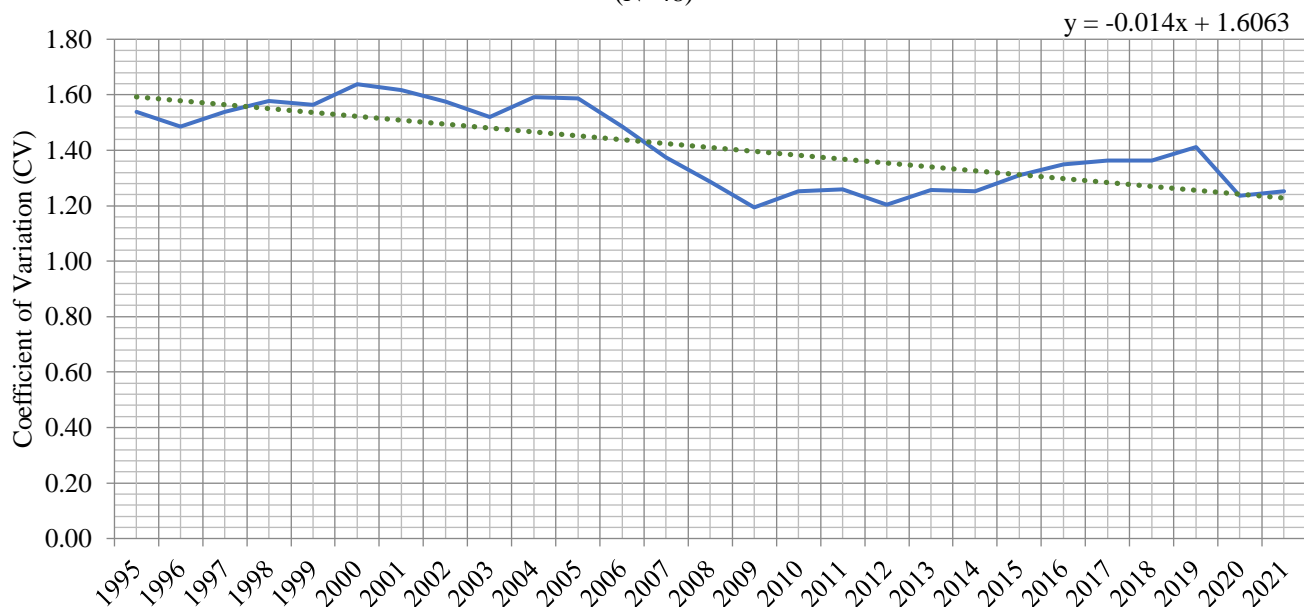


Figure 1

Trends of Income Inequality in SSA Measured Using the Coefficient of Variation of ANNIPC, 1971-1994 Versus 1995-2023

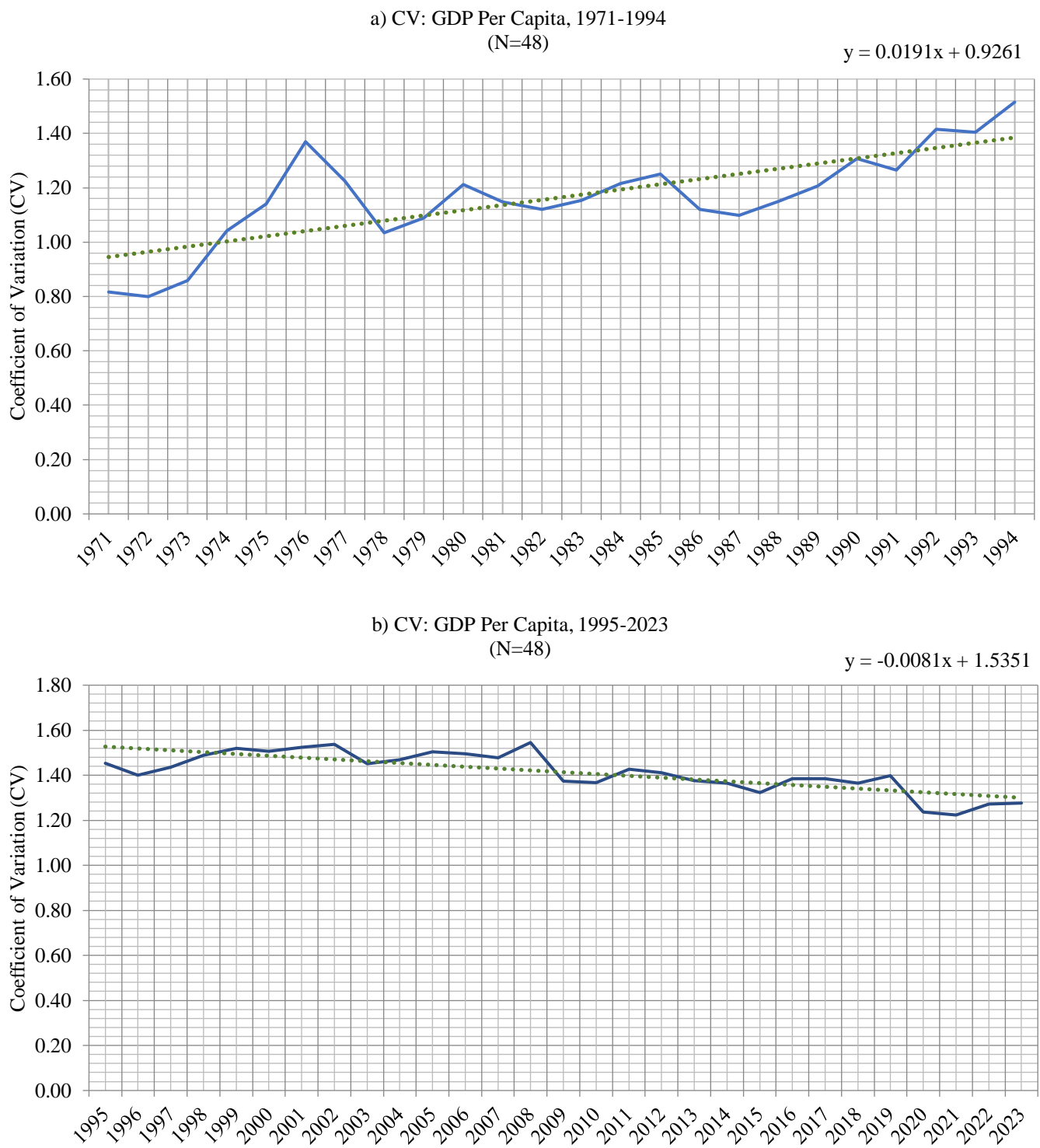


Figure 2

Trends of Income Inequality in SSA Measured Using the Coefficient of Variation of GDPPC, 1971-1994 versus 1995-2023

**Table 3***Results of Income Convergence Test, 1971-2023*

| Period | N | Gradient* | Convergence | Half-life (years) |
|---|----|-----------|-------------|-------------------|
| <i>a) Adjusted Net National Income Per Capita (ANNIPC):</i> | | | | |
| 1971–1994 Trend Equation: $Y = 0.0285x + 0.6845$ | 48 | 0.0285 | No | ∞ |
| 1995–2021 Trend Equation: $Y = -0.014x + 1.6063$ | 48 | -0.0140 | Yes | 50 |
| <i>b) GDP Per Capita (GDPPC)</i> | | | | |
| 1971–1994 Trend Equation: $Y = 0.0191x + 0.9261$ | 48 | 0.0191 | No | ∞ |
| 1995–2023 Trend Equation: $Y = -0.0081x + 1.5351$ | 48 | -0.0081 | Yes | 86 |

*The term "gradient" in Table 3 refers to the slope of a linear function plotted with the coefficients of variation (CV) (Y) against years (x). A negative slope indicates that the "catch-up" or "convergence" theory is validated, meaning there is a "convergence" in per capita income among countries, as measured by either ANNIPC or GDPPC. Conversely, a positive gradient suggests "divergence," indicating an increase in income inequality, as measured by the coefficient of variation (CV), among countries.

The observed difference in half-life values, with GDPPC converging slower than ANNIPC (86 years versus 50 years) as shown in Table 3, suggests a more persistent inequality in terms of overall economic output compared to net national income when adjusted for resource depletion and environmental degradation. Several factors might contribute to this disparity. Firstly, GDPPC, a broader measure of economic activity, is influenced by a wider array of factors, including resource rents, capital accumulation, and structural transformation, which may exhibit greater heterogeneity across Sub-Saharan African economies. These factors, particularly the exploitation of natural resources, can create disparities that are not fully captured by ANNIPC, which adjusts for the depletion of these resources. For example, countries heavily reliant on resource extraction may exhibit high GDP per capita (GDPPC) but experience slower convergence due to the "resource curse," where resource wealth hinders diversification and inclusive growth. This disparity may have resulted in slower convergence of GDPPC as compared to ANNIPC.

Secondly, differences in the composition of investment and the efficiency of capital allocation could play a role. If investments are concentrated in sectors that primarily boost GDP without necessarily translating into improved net national income (e.g., infrastructure projects with limited social returns or capital-intensive industries with high environmental costs), GDPPC convergence may lag behind ANNIPC convergence. The slower convergence of GDPPC may also be linked to the nature of investments, where higher investments do not necessarily translate to higher incomes for the citizens, thereby increasing divergence and ultimately resulting in a slower convergence for GDPPC than ANNIPC. Thirdly, the influence of external factors, such as terms of trade shocks and global financial crises, may disproportionately affect GDPPC. These shocks can induce greater volatility in GDP, leading to slower convergence, while their impact on ANNIPC may be relatively muted due to the adjustment for resource depletion and environmental costs.

From a policy perspective, these findings underscore the importance of focusing on policies that promote inclusive and sustainable growth. Given the slower convergence of GDPPC, policies aimed at diversifying economies, promoting value-added industries, and improving the efficiency of capital allocation are crucial. Moreover, addressing income inequality, strengthening institutional capacity, and promoting sustainable resource management are essential for accelerating both GDPPC and ANNIPC convergence. Specifically, policymakers should prioritise investments in human capital, infrastructure, and technology that generate broad-based benefits and reduce disparities across regions and income groups. Furthermore, promoting good governance, transparency, and accountability is critical for ensuring that the benefits of economic growth are shared equitably and that resources are managed sustainably. Addressing these



challenges will not only accelerate the convergence of both GDPPC and ANNIPC but also foster more resilient and inclusive economies in the SSA region.

4.3 Summary of Spatial Data and Statistics

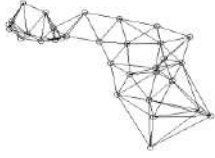
4.3.1 Number of Neighbours

Our study covered an array of coordinates indicating a range of locations, with LATITUDE spanning from -15.3101 to 46.8691 and LONGITUDE from -29.6232 to 21.0079. Spatial analysis required deciding on the number of k (the k -neighbours) to be used in the analysis. Selecting the "best" k is not straightforward. It depends on the underlying spatial relationships expected in your data and the goals of spatial analysis. It should be noted that k influences the degree of spatial autocorrelation captured by the neighbour list. A small k emphasises local spatial autocorrelation and might be suitable if the analysts believe that spatial effects are very localised. However, if k is too small, some regions might become isolated (islands), which can cause problems in spatial regression. A large k captures more global spatial autocorrelation and is suitable if spatial effects are more widespread. However, if k is too large, there is a risk of over-smoothing and masking local patterns. Also, as k approaches the number of regions, every region becomes a neighbour of every other region, and the ability to model spatial dependence is lost. A crucial consideration is to ensure that the neighbour list provides adequate connectivity. Ideally, all regions should be connected, either directly or indirectly, to all other regions. If there are "islands" (i.e., regions with no neighbours, or groups of regions only connected within themselves), spatial analysis can become problematic.

In our spatial analysis, we had 32 "regions" characterised by their relationships based on nearest neighbours, with a specified number of neighbours set to $k = 5$. The choice of $k = 5$ in our k -nearest neighbours method was guided by several considerations. First, we aimed to balance the need to capture local spatial dependencies without over-smoothing the spatial relationships. A smaller k (e.g., $k = 1$ or 2) might result in unstable outcomes, as it would only account for the immediate nearest neighbours, potentially overlooking broader spatial patterns. Conversely, a larger k (e.g., $k = 10$ or more) might smooth out local effects, reducing the spatial autocorrelation signal. Given our sample size of 32 countries (out of 48), $k = 5$ offers a reasonable compromise, incorporating a meaningful number of neighbouring countries while maintaining local specificity. Additionally, we also considered the geographical context of SSA. Countries in this region often exhibit complex interdependencies due to factors such as shared borders, trade relationships, political alliances, and historical ties. A value of $k = 5$ would enable us to capture these multifaceted relationships, recognising that a country's economic performance is likely influenced by a cluster of its closest neighbours.

Using the value of $k = 5$, we identified 160 nonzero links among the 32 regions (countries), representing 15.63% of potential connections. On average, each region (country) was linked to 5 neighbouring "regions" (countries), indicating a relatively uniform distribution among the connections. Furthermore, our findings highlighted the connectivity distribution among regions. Specifically, all 32 regions exhibited uniformity in the number of links, with the least connected regions and most connected regions both having exactly 5 links. This suggests a symmetrical connection pattern across the dataset. The plot generated from the "knn" object visually represented these neighbouring relations, wherein the coordinates corresponding to each region are displayed alongside the connections (or links) established among them. The visualization (Figure 3) aids in illustrating the spatial distribution of connectivity within our dataset, providing a clear understanding of regional relationships. It encapsulates the summary statistics and a visual representation or plot of the neighbour structure and relationship among the sample SSA countries.

| Metric | Value |
|-------------------------------|-------|
| Number of regions (countries) | 32 |
| Number of nonzero links | 160 |
| Percentage nonzero weights | 15.63 |
| Average number of links | 5 |



| Variable | Minimum | First Quartile | Median | Mean | Third Quartile | Maximum |
|----------|-----------|----------------|-----------|-----------|----------------|-----------|
| ANNIPC | 124.1 | 380.0 | 500.1 | 625.6 | 845.3 | 1460.9 |
| INFLAT | 2.82 | 3.99 | 7.13 | 65.27 | 13.49 | 1331.62 |
| CAPITAL | 2.060E+08 | 1.363E+09 | 1.820E+09 | 4.277E+09 | 5.133E+09 | 2.652E+10 |
| UNEMP | 0.890 | 3.232 | 4.360 | 6.364 | 9.037 | 20.120 |
| LABOUR | 156578 | 2102872 | 3958480 | 7026398 | 9122723 | 37971594 |
| INSTI | 1.699 | 2.799 | 3.221 | 3.137 | 3.485 | 3.485 |

Figure 3

Summary Statistics and Visual Representation of the Chosen Neighbour Structure and Relationship among “Regions”

4.3.2 Sensitivity Analysis

To assess the sensitivity of our results to the choice of k , we conducted additional analyses using alternative values of k (e.g., $k = 3$ and $k = 7$) (Supplementary Figure 1). We also compared the Moran's I statistic, likelihood ratio test, AIC, and BIC values obtained with these different k values to those obtained with $k = 5$. This allowed us to evaluate whether the spatial autocorrelation patterns and the superiority of the SAR model were robust to changes in the number of neighbours considered. Our sensitivity analysis revealed that while the magnitude of the spatial autoregressive coefficient (ρ) varied slightly with different k values, the overall conclusions regarding the presence of significant spatial dependence and the appropriateness of the SAR model remained consistent. Specifically, the Moran's I test consistently indicated significant spatial autocorrelation, and the Likelihood Ratio test, AIC, and BIC consistently favoured the SAR model over the OLS model across all tested k values. This suggests that our findings are relatively robust to the choice of k within a reasonable range.

4.4 Results of OLS and Spatial Lag Models

4.4.1 Summary of spatial lag model results

The spatial lag or Spatial Autoregressive (SAR) models were fitted with the “annual net national income per capita (ANNIPC)” and “GDP per capita (GDPPC) as the dependent variables for models 1 and 2, respectively. The model summary results are presented in Tables 4 and 5, respectively. It should be noted that the results in models 1 and 2 have leveraged spatial dependency through weight matrices (listw). The independent variables displayed varying levels of statistical significance. Specifically, the coefficients for INFLAT, CAPITAL, UNEMP, LABOUR, and INSTI in model 1 were -0.00000035 ($p = 0.8424$), 0.0000056602 ($p = 0.2480$), 0.00000309 ($p = 0.2714$), -0.0000053 ($p = 0.2802$), and -0.0000010 ($p = 0.7527$), respectively.

**Table 4***Coefficients (Asymptotic Standards Error) for the Spatial Lag Model 1*

| Variable | Estimate | Std. Error | z value | Pr(> z) |
|-------------|-------------|--------------|----------|----------|
| (Intercept) | 20018 | 0.00042864 | 46702000 | <2E-16 |
| INFLAT | -0.00000035 | 0.0000017643 | -0.1988 | 0.8424 |
| CAPITAL | 0.00000566 | 0.0000048995 | 1.1553 | 0.248 |
| UNEMP | 0.00000309 | 0.0000028134 | 1.0998 | 0.2714 |
| LABOUR | -0.0000053 | 0.0000049173 | -1.0799 | 0.2802 |
| INSTI | -0.0000010 | 0.0000032506 | -0.3151 | 0.7527 |

Dependent variable: ANNIPC

Rho: -0.81, LR test value: 53.464, p-value: 0.00000000000026334

Asymptotic standard error: 0.00000068871

z-value: -45012000, p-value: < 0.000000000000000222

Wald statistic: 2.0261e+15, p-value: < 2.22E-16 (i.e. <0.000000000000000222)

Log likelihood: -196.3135 for lag model

ML residual variance (sigma squared): 0.000000000063417, (sigma: 0.0000079635)

AIC: 408.63, (AIC for lm: 460.09)

LM test for residual autocorrelation test value: -1895.4, p-value: 1

Table 5*Coefficients (Asymptotic Standards Error) for the Spatial Lag Model 2*

| Variable | Estimate | Std. Error | z value | Pr(> z) |
|-------------|--------------|-------------|-------------|----------|
| (Intercept) | 26824.00 | 0.001 | 46688000.00 | <2E-16 |
| INFLAT | 0.00000148 | 0.000002253 | 0.657 | 0.5112 |
| CAPITAL | 0.000012393 | 0.000009432 | 1.314 | 0.1889 |
| UNEMP | 0.000004752 | 0.000003937 | 1.207 | 0.2275 |
| LABOUR | -0.000011617 | 0.000009062 | -1.282 | 0.1999 |
| INSTI | -0.000001294 | 0.000003719 | -0.348 | 0.7279 |

Dependent variable: GDPPC

Rho: -0.81, LR test value: 74.678, p-value: < 2.22E-16 (i.e. < 0.000000000000000222)

Asymptotic standard error: 6.8874E-07 (i.e. 0.00000068874)

z-value: -45010000, p-value: < 2.22E-16 (i.e. < 0.000000000000000222)

Wald statistic: 2.0259E+15 (i.e. 2025900000000000), p-value: < 2.22E-16 (i.e. < 0.000000000000000222)

Log likelihood: -189.826 for lag model

ML residual variance (sigma squared): 8.2039E-11 (i.e. 0.000000000082039), (sigma: 0.0000090576)

AIC: 395.65, (AIC for lm: 468.33)

LM test for residual autocorrelation test value: -1358.1, p-value: 1

Model 1 (Table 4) highlighted a significant parameter for the spatial autoregressive term (Rho) estimated at -0.81 and the Wald statistic was exceedingly high and significant, reinforcing the relevance of spatial effects in this analysis. The LM test for residual autocorrelation returned a test value of -1895.4 with a p-value of 1, further supporting the adequacy of the model under the spatial context. Overall, the findings indicated that the spatial lag model was statistically significant due to the spatial components. However, the individual predictors did not significantly contribute to explaining the variability in ANNIPC in our study.

The Akaike Information Criterion (AIC) was calculated to be 408.63, highlighting an improvement over a standard linear model AIC of 460.09. The LM test for residual autocorrelation yielded a test value of -1895.4, suggesting no evidence of residual spatial autocorrelation ($p = 1$), thus supporting the appropriateness of the spatial model used. In spatial econometrics, Rho (ρ) quantifies the degree to which a variable's value at one location is influenced by the values of the same variable at neighbouring locations (Nikou & Sardianous, 2025). A negative Rho (-0.81) indicates an inverse relationship, meaning that countries with higher ANNIPC tend to be surrounded by countries with lower ANNIPC, and vice versa. Its magnitude (-0.81) suggests that this effect is quite pronounced in SSA. It is also confirmed by the highly significant likelihood ratio (LR) test, Wald statistic, and associated p-values, indicating that the spatial lag model is a significant improvement over a non-spatial model (as evidenced by the AIC values), and that spatial dependence is an important feature of the ANNIPC data.

The strong negative spatial autocorrelation could arise from various factors, such as regional disparities in economic policies, resource endowments, or the diffusion of negative economic shocks across neighbouring countries. It is worth noting that, while the model captures spatial dependence, some independent variables are statistically insignificant, suggesting that other factors, not included in the model, might be influencing ANNIPC. SSA exhibits significant spatial diversity in economic structures, policies, and institutions. Thus, a single spatial lag model may not fully capture this heterogeneity, leading to a strong overall spatial effect but weak individual predictor effects.

The log-likelihood value (-189.826) in Table 5 indicates the goodness of fit of the model. A lower AIC (395.65) compared to the AIC for an ordinary least squares (OLS) model (468.33), again suggests the spatial model provides a better fit to the data. The LM Test for residual autocorrelation yielded the LM test statistic of -1358.1 with a p-value of 1 suggesting that there was no evidence of residual autocorrelation, and that the model adequately accounted for the spatial structure in the data. While our spatial lag model indicated some relationships between the independent variables and GDPPC, the majority of these relationships were not statistically significant.

In the current study, we used a contiguity-based weights matrix based on shared borders. The spatial weights matrix (W) defines the spatial relationships between countries. However, it requires that the chosen weights matrix accurately reflect the true spatial dependencies. If it doesn't, it may lead to a strong but potentially biased spatial effect. Importantly, the quality and accuracy of the data used in the regression analysis can also influence the results. For example, measurement error in the independent variables can attenuate the estimated coefficients and reduce their statistical significance. Spatial effects can also be scale-dependent. Spatial relationships observed at the country level may not hold at the regional or local levels.

4.4.2. Summary of OLS Model Results

The results of OLS for model 1 are summarised in Table 6. The F-statistic of 2.881 with a p-value of 0.03362 indicates that the model as a whole is statistically significant; suggesting that at least one of the predictors is related to the dependent variable. None of the variables have Variance Inflation Factor (VIF) values exceeding 5, but LABOUR shows a relatively higher VIF (4.703201). The R-squared value of 0.3566 indicates that approximately 35.66% of the variability in ANNIPC was explained by the independent variables in this model.

**Table 6***Summary of OLS Model 1 Results*

| Variable | Estimate | Std. Error | t value | Pr(> t) |
|-------------|---------------|--------------|---------|----------|
| (Intercept) | 619.80 | 373.80 | 1.658 | 0.1093 |
| INFLAT | -0.04751 | 0.262 | -0.181 | 0.8577 |
| CAPITAL | 0.00000003224 | 0.0000001727 | 1.868 | 0.0731 |
| UNEMP | 19.84 | 12.27 | 1.617 | 0.1179 |
| LABOUR | -0.00002155 | 0.00001396 | -1.543 | 0.1349 |
| INSTI | -33.12 | 113.60 | -0.292 | 0.7729 |

Dependent variable: ANNIPC

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 285.7 on 26 degrees of freedom

Multiple R-squared: 0.3566, Adjusted R-squared: 0.2328

F-statistic: 2.881 on 5 and 26 DF, p-value: 0.03362

The output of the LaGrange Multiplier Test (LGMT) using the studentized Breusch-Pagan (BP) method indicated the calculated BP statistic of 4.8505, corresponding to the p-value of 0.4344 which is quite high, implying that we do not have sufficient evidence to reject the null hypothesis of homoskedasticity. In simpler terms, our model did not exhibit significant heteroskedasticity at typical significance levels (such as, $\alpha = 0.05$). Thus, there was no strong evidence suggesting that the variance of the residuals from our model changed with the fitted values or with the independent variables. Therefore, the assumptions of ordinary least squares (OLS) regression regarding homoskedasticity seemed to hold in our analysis. While the model suggests some relationships between independent variables and ANNIPC, most individual predictors are not statistically significant.

Generally, the results of OLS for model 1 showed statistically insignificant relationships between the regressors and the dependent variable (ANNIPC). However, the CAPITAL variable, with a coefficient of 0.00000003224, indicates that the impact of "capital formation" on ANNIPC was small. In this model, the t-value of 1.868 denotes some degree of uncertainty regarding the impact of CAPITAL on ANNIPC. The p-value of 0.0731, while approaching the common threshold for statistical significance (0.05), does not quite meet it. This implies the absence of adequate evidence to conclude a statistically significant relationship between CAPITAL and ANNIPC at the conventional confidence level.

The output of OLS for model 2 (Table 7) yielded a multiple R-squared value of 0.5895 which suggests that our model explained a fair portion of the variability in GDPPC, and an adjusted R-squared of 0.5106 further affirms that we accounted for the number of predictors. The F-statistic of 7.467 ($p = 0.0001852$) signifies that the model was statistically significant overall. The results of the LaGrange Multiplier Test using the Breusch-Pagan method lend additional confidence to the adequacy of the OLS assumptions. With a BP statistic of 5.1439 and a p-value of 0.3986, the absence of heteroscedasticity suggests that the model provides reliable parameter estimates, which bolsters the inference drawn from the analysis (Breusch & Pagan, 1979).

The results of multicollinearity diagnostics showed that all the model variables had VIF values less than 5, suggesting that they were likely not contributing significantly to multicollinearity. Similarly, based on the results of the LaGrange Multiplier Test using the Breusch-Pagan (BP) method we could not reject the null hypothesis of homoscedasticity at any conventional significance level. Specifically, with a BP statistic of 5.1439 and a p-value of 0.3986, this suggests that the residuals from our simple OLS model did not exhibit significant heteroscedasticity. State differently, this means that the variance of the errors in our model was constant across the range of fitted values, supporting the appropriateness of the OLS assumptions. Therefore, we could proceed with confidence in the validity of our parameter



estimates, as there were no indicators from the LaGrange multiplier test that suggested the presence of spatial autocorrelation in the residuals of your model.

Table 7

Summary of OLS Model 2 Results

| Variable | Estimate | Std. Error | t value | Pr(> t) |
|-------------|---------------|---------------|---------|------------|
| (Intercept) | 791.80 | 425.20 | 1.862 | 0.07389 |
| INFLAT | 0.20 | 0.30 | 0.672 | 0.50773 |
| CAPITAL | 0.00000007059 | 0.00000001964 | 3.595 | 0.00133 ** |
| UNEMP | 30.47 | 13.95 | 2.184 | 0.03819 * |
| LABOUR | -0.00004713 | 0.00001588 | -2.968 | 0.00636 ** |
| INSTI | -41.86 | 129.20 | -0.324 | 0.74857 |

Dependent variable: GDPPC

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 325 on 26 degrees of freedom

Multiple R-squared: 0.5895, Adjusted R-squared: 0.5106

F-statistic: 7.467 on 5 and 26 DF, p-value: 0.0001852

Table 7 indicates that certain variables significantly influence GDPPC. Although the coefficient for CAPITAL is small (0.00000007059), its high significance ($p = 0.00133$) suggests that even minor increases in gross capital formation tend to increase GDPPC, emphasising the importance of capital investments for economic output. The unemployment (UNEMP) coefficient was 30.47 ($p = 0.03819$), indicating that a one-percentage-point increase in unemployment was associated with an unexpected increase of approximately 30.47 units in GDPPC. This indicated a potentially surprising relationship since one would ideally expect GDPPC to decrease with rising unemployment. The LABOUR variable yielded a coefficient of -0.00004713, which is significant ($p = 0.00636$). This indicates that an increase in the total labour force corresponded to a slight decrease in GDP per capita, also revealing an unanticipated relationship.

The positive relationship between unemployment (UNEMP) and GDP per capita (GDPPC) observed in our OLS model 2 is obviously counterintuitive. Several factors could potentially explain this unexpected relationship. Firstly, the structure of SSA economies, characterized by a significant informal sector, might play a role. In many African countries, a large proportion of the workforce is engaged in informal activities that are often not captured in official unemployment statistics, but may still contribute to GDP. Therefore, an increase in officially recorded unemployment might not necessarily reflect a decline in overall economic activity, particularly if the informal sector remains robust. Secondly, measurement issues related to both unemployment and GDP could contribute to the observed relationship. Data on unemployment in Sub-Saharan Africa are often collected through household surveys, which may suffer from recall bias or underreporting. Similarly, GDP estimates can be subject to measurement errors, particularly in countries with weak statistical capacity. A third potential explanation involves sectorial shifts within the economy. For instance, a decline in employment in traditional sectors like agriculture, coupled with growth in higher-productivity sectors such as services or manufacturing, could lead to an increase in GDPPC even if overall unemployment rises. Furthermore, it is important to note that the positive coefficient, while statistically significant, is relatively small (30.47). This suggests that while there is a positive association between unemployment and GDPPC in our model, the magnitude of the effect is not substantial. Finally, this finding may be specific to the time period under consideration. Economic shocks or policy changes during the study period could have influenced the relationship between unemployment and GDPPC in unexpected ways.



The non-significance of the institutional variable (INSTI) in our spatial models, despite its established importance in the literature (e.g., Acemoglu et al., 2005), warrants further discussion. Several factors could account for this discrepancy. First, the measurement of institutional quality is inherently challenging. Our composite INSTI variable, derived from CPIA data, may not fully capture the nuances of institutional quality in SSA countries. CPIA scores, while widely used, are subjective assessments that may not accurately reflect the actual impact of institutions on economic outcomes. Second, multicollinearity among the independent variables could be masking the effect of INSTI. While our VIF values were below 5, suggesting that multicollinearity is not a major concern, it is still possible that some degree of correlation between INSTI and other variables, such as CAPITAL or LABOUR, is attenuating its statistical significance. Third, regional heterogeneity in institutional quality could be a factor. SSA is a diverse region, with significant variations in institutional quality across countries. Our aggregate analysis may not be sensitive enough to capture these regional differences. It is also possible that the impact of institutions on economic outcomes is non-linear or contingent on other factors, such as the level of economic development or the presence of specific policies.

4.5 Discussion

4.5.1 Trends of ANNIPC and GDPPC

The divergent trend of "adjusted net national income per capita" (ANNIPC) and "GDP per capita" (GDPPC) in Sub-Saharan Africa from 1971 to 1994 could be attributed to several interrelated factors. One significant factor might be the heavy reliance on natural resource extraction during this period, which resulted in higher GDP figures driven by commodity booms, such as oil and minerals, in countries like Nigeria and Angola. While GDP grew due to these exports, the benefits were often not reflected in the ANNIPC, which accounts for the depreciation of natural capital and investments in human capital. In addition, political instability and civil conflicts ravaged numerous nations during this timeframe, resulting in underinvestment in key sectors such as education and health. For example, the civil war in Mozambique from 1977 to 1992 (Macuane, 2018) severely disrupted economic activities and human development, constraining improvements in adjusted income measures. This disparity illustrated that while GDP might have shown growth due to resource exports, the actual welfare and development of the population lagged due to conflated figures that overlooked the degradation of the environment and human capital.

Another contributing factor could be the economic policies implemented during this period, often characterized by extensive state control and mismanagement. In countries like Zimbabwe and Tanzania, socialist policies limited private enterprise and discouraged foreign investment, leading to inefficiencies. Consequently, while GDP indicators might have suggested growth, the broader impacts on personal income and adjusted metrics remained stagnant or declined. From 1994 to 2021, however, a convergence trend emerged between ANNIPC and GDPPC. This shift could be attributed, in part, to improved governance and stabilization in many Sub-Saharan countries. For instance, countries like Botswana, Rwanda, Seychelles, and Ghana implemented effective economic reforms, fostering political stability and enhancing governance structures (Isser et al., 2014; Simard & Viseth, 2022), allowing for sustainable growth in both GDP and adjusted income measures.

Moreover, an increasing awareness of the need for investment in human capital and sustainable development initiatives played a crucial role (Onatunji, 2024). Various governments acknowledged that economic growth should not come at the expense of environmental degradation and societal well-being. Countries began to invest more in education, health care, and infrastructure (as seen in Tanzania) and substantial investments in agriculture and social services (in Ethiopia) (Horvat et al., 2021) which not only boosted GDP growth but also elevated income levels. In addition, the diversification of economies beyond mere resource extraction (Ross & Werker, 2024) also contributed to this convergence. Increased participation in global trade, advancements in technology, and a growing focus on sectors such as tourism and services (Jegade, 2025), particularly in countries like Kenya and Tanzania, have contributed to more balanced economic development.



4.5.2 Spatial Lag Model Results

The results obtained from our Spatial Lag or Spatial Autoregressive (SAR) models underscore the complexities inherent in understanding the determinants of economic performance across African countries. Although the models revealed significant spatial dependency, as indicated by the parameter ρ , the individual independent variables did not demonstrate statistical significance in explaining variations in ANNIPC and GDPPC.

While the significant spatial autocorrelation suggested the presence of geographical effects affecting economic indicators, the lack of significance for independent variables like inflation (INFLAT), capital formation (CAPITAL), unemployment (UNEMP), labour force (LABOUR), and institutional factors (INSTI) would suggest an insubstantial role of these factors within the context of our analysis. Such findings are consistent with recent literature, which highlights the region's complex socio-economic dynamics, including the influence of political stability, governance quality, and informal economic activities that were not captured in our models (World Bank, 2023).

The negative relationship implied by the Rho coefficient in Model 2 further points towards a counterintuitive dynamic where high GDPPC in one region is potentially associated with lower GDPPC in neighbouring areas. This could indicate a form of economic convergence or competitive behaviour between geographically proximate nations, aligning with findings from studies focused on regional economic dynamics (LeSage & Pace, 2009).

Regarding the insignificant independent variables and the negative spatial correlation in GDPPC, it is crucial to ground our analysis in the specific realities of SSA. Firstly, the lack of significance for variables like inflation (INFLAT), capital formation (CAPITAL), unemployment (UNEMP), labour force (LABOUR), and institutional factors (INSTI) might stem from several SSA-specific issues. While these factors are generally important for economic performance, their influence can be masked or mediated by other context-specific elements. For instance, the informal sector plays a dominant role in many SSA economies. This informal activity is often poorly captured by official statistics on labour force participation or capital formation, potentially weakening the measured impact of these variables. Consider the example of street vending in cities like Dar es Salaam or Nairobi; significant economic activity occurs outside the formal channels. Similarly, traditional agricultural practices, where labour is largely unpaid, and production is primarily for subsistence, contribute substantially to the economy but may not be accurately reflected in GDP or labour force data.

Furthermore, institutional quality (INSTI), though crucial, may have a non-linear or threshold effect. A small improvement in institutional quality, from very low levels, might not immediately translate into significant economic gains. For example, simply reducing petty corruption might not unleash substantial economic activity if larger issues of political instability or macroeconomic mismanagement remain. The impact of institutional factors could also be contingent on specific policy choices, such as trade liberalisation or investment in education, which are not directly captured by the institutional variable. Consider the situation in countries like Zimbabwe, where periods of high institutional decay have had devastating impacts on formal economic activity, irrespective of labour force participation or capital availability.

Regarding the negative relationship implied by the Rho coefficient in Model 2, where high GDPPC in one region is potentially associated with lower GDPPC in neighbouring areas, this could be indicative of several dynamics. In SSA, this could reflect the “resource curse,” where resource-rich regions might exhibit high GDPPC, but neighbouring regions may suffer due to conflict, environmental degradation, or displacement linked to resource extraction. For example, the discovery of oil in one region could lead to an influx of migrants, straining resources and infrastructure in neighbouring areas, leading to lower GDPPC. This dynamic highlights the spatial spillover effects of resource wealth, where the benefits are highly localised while the costs are distributed across a wider region.

Another explanation for the negative spatial correlation in GDPPC could be the presence of competitive economic hubs within SSA. For instance, if one country (e.g., Côte d'Ivoire) is particularly successful in attracting foreign direct investment (FDI) in manufacturing or services, it might draw capital and skilled labour away from neighbouring



nations, leading to slower growth there. Similarly, the development of superior infrastructure (e.g., ports or transport networks) in one country can create a comparative advantage that undermines the economic prospects of its neighbours. This form of competitive behaviour is especially prominent given the ongoing efforts at regional integration in SSA, such as the African Continental Free Trade Area (AfCFTA), which may intensify competition among countries.

Finally, the presence of conflict and instability, a recurring challenge in SSA, could contribute to this negative spatial correlation. Regions experiencing armed conflict often suffer significant economic damage, causing displacement and hindering trade and investment. The resulting economic disruption can spill over into neighbouring regions, contributing to lower GDPPC. The effects of the Boko Haram insurgency in the Lake Chad region, for instance, have had devastating consequences for both Nigeria and its neighbours, Cameroon, Chad, and Niger, highlighting the spatial dimension of conflict-induced economic decline.

4.5.3 OLS Model Results

Our results of the OLS model using the dataset for SSA countries provide insightful perspectives on the relationships between the various economic variables used in the study and the response variable of GDP per capita (GDPPC). The small yet statistically significant coefficient for “gross capital formation (CAPITAL)”, underscored the nuanced role that capital investments play in economic output. This finding aligns with the consensus from the economic literature that views capital accumulation as a vital component of economic growth (Barro, 1991; Solow, 1956). While the effect size may seem negligible, it highlights that even small changes in capital formation can contribute to broader economic trends. Ongo and Vukenkeng (2014) examined the effect of “gross capital formation” on the economic growth of the CEMAC sub-region using the endogenous growth model and data from the World Bank Development Indicators. The results of Generalised Least Square (GLS) estimation in this study showed that private investment had a significant positive association with economic growth. Gibescu (2010) analysed the relationship between “gross fixed capital formation” and economic growth in Romania, Bulgaria, the Czech Republic, Poland, and Hungary for the period 2003-2009 using the statistical connection analysis method. The study found a direct and strong connection between economic growth and gross fixed capital formation.

Based on the understanding that “gross fixed capital formation” is the major component of domestic investment and an important process that could accelerate economic growth, Meyer and Sanusi (2019) re-examined the controversial issue of causality between domestic investment, employment, and economic growth using the case of South Africa. They used quarterly data covering the period from 1995Q1 to 2016Q4 within the framework of the Johansen cointegration and Vector Error Correction Models (VECM). Their findings suggested that a long-run relationship existed between domestic investment, employment, and economic growth, with causality running from economic growth to investment and not vice versa. They concluded that to stimulate employment, investment-enhancing policies, such as low interest rates and a favourable economic environment should be put in place to accelerate growth. As such, they recommend measures to promote economic growth, such as improved infrastructural facilities and diversification of the economy, should be further engineered to encourage increased investment.

Stupnikova and Sukhadolets (2019) investigated the interrelations between the growth of “gross fixed capital formation”, the volume of the construction industry, the supply of inter-industry balance, and the amount of fixed-asset investments in Russia between 2000 and 2016. They applied an autoregressive distributed lag (ARDL) bound testing methodology and regression analysis. In their study, Stupnikova and Sukhadolets (2019) revealed non-linear causation between construction industry volume and the growth in “gross fixed capital formation” over a long period. The correlation was stationary and cointegrated (ibid). They found the fixed investment to positively affect “gross fixed capital formation” only in periods of economic expansion with the effectiveness of fixed-asset investments having greater volatility in times of crisis (ibid). The research article by Bosworth and Collins (2003) concluded that countries with more



substantial “gross fixed capital formation” not only witnessed a rise in per capita income but also observed improvements in welfare measures due to higher investment in sustainable infrastructure.

In our study, the unexpected positive relationship between unemployment (UNEMP) and GDPPC, represented by a coefficient of 30.47 ($p = 0.03819$), challenges conventional economic wisdom. Typically, rising unemployment is associated with decreased economic activity and a reduction in GDPPC (Plosser & Schwert, 1979). This indicates not only the existing complexities but also the unique economic contexts or structural factors prevalent in the SSA countries. Several factors could contribute to this counterintuitive finding. Firstly, the informal sector, which is a significant component of many SSA economies, may not be adequately captured in official unemployment statistics. Individuals engaged in informal activities, although technically unemployed according to formal definitions, may still contribute to the GDP through unrecorded economic activities. The prevalence of informality in SSA countries means that a substantial portion of the workforce operates outside the formal regulatory framework, engaging in activities that generate income but are not captured in official employment figures. These informal activities, ranging from small-scale trading and artisanal work to subsistence agriculture, collectively contribute to the overall GDP, even as formal unemployment rates remain high. Therefore, the positive relationship between unemployment and GDP per capita could reflect the economic contribution of the informal sector, which cushions the impact of formal unemployment on overall economic output (Xaba et al., 2002).

Secondly, measurement issues related to both unemployment and GDP in SSA countries may also play a role. Data collection methodologies, statistical coverage, and the accuracy of economic indicators can vary significantly across countries in the region. Challenges in accurately measuring unemployment, particularly in rural areas or among vulnerable populations, could lead to an overestimation of unemployment rates. Similarly, GDP figures may not fully capture the economic activities in certain sectors, leading to potential biases in the analysis. Limited resources, inadequate infrastructure, and methodological challenges often constrain data quality and statistical capacity in many SSA countries. These limitations can affect the accuracy and reliability of economic indicators, potentially distorting the observed relationship between unemployment and GDP per capita. For example, underreporting of agricultural output or informal sector activities can lead to an underestimation of GDP, while incomplete labour force surveys may overstate unemployment rates (Gollin et al., 2011).

Thirdly, sectoral shifts within the economies of SSA countries could also explain the positive relationship between unemployment and GDP per capita. If economic growth is concentrated in specific sectors that are not highly labour-intensive, such as natural resource extraction or capital-intensive industries, it is possible to observe rising GDP per capita even with relatively high unemployment rates. The expansion of these sectors may generate substantial economic output, but their limited capacity to absorb labour can lead to a divergence between economic growth and employment creation. For example, countries heavily reliant on oil or mineral exports may experience significant GDP growth due to high commodity prices, while simultaneously struggling to create sufficient employment opportunities for their growing populations. This sectoral imbalance can result in a situation where overall economic output increases, but unemployment remains persistently high. Therefore, it is essential to consider the sectoral composition of economic growth and the labour intensity of different industries when interpreting the relationship between unemployment and GDP per capita in SSA countries. Furthermore, skills mismatches and structural rigidities in the labour market can also contribute to this phenomenon (Acemoglu, 2002). The education and training systems in many SSA countries may not be adequately aligned with the skills requirements of the growing sectors, leading to a situation where there is a surplus of labour with certain skills and a shortage of labour with the skills demanded by the expanding industries. This skills gap can result in higher unemployment rates, even in sectors experiencing economic growth.

The negative coefficient obtained for the “labour force (LABOUR)” variable, which suggests that an increase in total labour force corresponds with a decrease in GDPPC (-0.00004713 , $p = 0.00636$), further indicated an intriguing dynamic worthy of deeper exploration. In any case, this counterintuitive result could stem from many factors, including



underemployment or informality in the labour market, prevailing issues across many African economies that might distort traditional interpretations of labour force effects (Elvis et al., 2022). Previous studies which have examined the relationship between the “total labour force” and “income per capita” highlighted the intricate dynamics between workforce participation and economic performance. A notable study by Abid (2025) in the Gulf Cooperation Countries (GCC) provides empirical evidence on the varying impact of macroeconomic factors on labour force participation and growth within the region's economies. The study demonstrated that lagged labour force participation has a strong positive and highly significant effect, indicating persistence in workforce engagement.

Son (2010) examined how various regions are enhancing their human capital and estimated the time required for developing countries to reach the current levels of human capital seen in industrialized nations. By revisiting the role of human capital in economic growth, Son (2010) proposed a method to decompose employment growth, which is also influenced by the growth of human capital, in explaining the increase in total output per worker. Son (2010) introduced employment growth in the growth decomposition through the employment growth elasticity and found that human capital increased with a decrease in employment growth elasticity, making the economy less labour-intensive, and resulting in higher economic growth (ibid). Son (2010) also explored how different regions enhance their human capital and the time it would take for developing countries to achieve the levels of human capital currently seen in industrialized nations. By revisiting the role of human capital in economic growth, and introducing employment growth as a factor in her decomposition analysis using the employment growth elasticity concept, she found that employment growth elasticity decreased with the increase in human capital, leading to a less labour-intensive economy and ultimately resulting in higher economic growth.

The results of OLS model 2 indicate that higher unemployment is correlated with increased GDP per capita in SSA, raising important questions about the economic dynamics in the region. Standard economic theory usually suggests a negative relationship between unemployment and GDP per capita. Higher unemployment typically indicates that labour resources are not fully utilized, leading to lower economic productivity (OECD, 2020). This phenomenon merits further discussion, particularly concerning the nature of the labour market and the economic structures found in countries within Sub-Saharan Africa (SSA).

One potential explanation for this unexpected relationship could be the presence of informal labour markets prevalent in many Sub-Saharan African economies. In these markets, individuals may be engaged in low-productive informal work or underreport their income, leading to a distortion in the unemployment figures. Thus, when the official unemployment rate rises, it might not fully capture the economic activities taking place, possibly resulting in the misinterpretation that GDPPC is benefiting from higher “unemployment” (Allard, 2017).

Moreover, the relationship could also be influenced by governmental policies that prioritize certain sectors during economic downturns, effectively creating jobs that are not reflected in traditional unemployment metrics. For instance, state-led capital formation initiatives and investments in infrastructure may absorb a segment of the labour force, thereby artificially inflating GDPPC numbers while unemployment rates remain high (World Bank Group, 2024). Such dynamics might suggest that increases in unemployment could coincide with shifts in employment trends, where formal jobs are lost, yet overall economic activities, particularly in the informal sector, may still contribute positively to GDP per capita.

Another consideration could be the role of remittances in the region. Many Sub-Saharan African countries are significant recipients of remittances from abroad which contribute to local economies and may influence GDPPC positively, despite high unemployment rates (Taiwo, 2020; Ogede et al., 2023). Consequently, the apparent paradox between GDPPC and unemployment rates calls for a deeper exploration of the economic narratives framed by labour force dynamics, remittance inflows, and the overall structure of economic activities in SSA.

The relationship between governance/institutional factors and economic performance reflects mixed evidence in the literature with some scholars emphasizing the vital role of robust institutions in fostering economic growth, and



others contending that the relationship may be more complex and context-dependent. On one hand, scholars, such as Acemoglu et al. (2001), argue that there is a strong and direct link between the quality of institutions and economic outcomes. They posit that inclusive institutions tend to provide the necessary framework for investment, innovation, and entrepreneurship, which in turn leads to sustainable economic growth. Their work highlights case studies from various countries illustrating how weak institutions can stifle economic performance by perpetuating corruption and inefficiencies.

On the other hand, there are scholars, including Rodrik (2008), who present a more nuanced perspective, suggesting that while institutions matter, the relationship is not uniform across different contexts. Rodrik points to instances where countries with relatively weak institutions experienced significant economic growth due to favourable external conditions or specific economic strategies that compensated for institutional shortcomings. This school of thought encourages a deeper examination of the interplay between governance, policy choices, and economic performance within diverse socio-political contexts.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

This paper uniquely employs both Adjusted Net National Income per capita (ANNIPC) and GDP per capita (GDPPC) to investigate income convergence and divergence in Sub-Saharan Africa (SSA). Spatial Lag and OLS regression models were used to evaluate the effects of inflation, gross capital formation, unemployment, labour force, and government effectiveness on ANNIPC and GDPPC. Tests for convergence and divergence revealed similar trends using both indicators: divergence from 1971–1994, followed by convergence from 1995 to the early 2020s. Discrepancies existed in the speed of convergence between ANNIPC and GDPPC, influenced by interrelated economic and socio-political factors. Countries with significant income outflows experienced slower GDPPC convergence but maintained stable or improving ANNIPC.

Furthermore, the study found that rising unemployment does not consistently lead to a decline in GDP per capita, partly due to informal employment and entrepreneurial activities. An increase in the labour force does not guarantee enhanced economic performance without improvements in productivity and job quality. This highlights the importance of considering broader socio-economic factors and structural challenges that hinder labour productivity.

5.2 Recommendations

For policymakers and stakeholders in SSA, it is essential to consider the complex relationships among inflation, gross capital formation, and labour dynamics. Strategies should address immediate economic concerns while fostering sustainable and inclusive growth. Understanding these complexities is vital for formulating effective responses that harness the region's labour force potential and ensure equitable economic gains. To accelerate inclusive convergence in SSA, we recommend that:

- a) SSA nations should aggressively invest in education, healthcare, and skills training to enhance labour productivity and competitiveness, while diversifying economies beyond natural resources. Strengthening governance, transparency, and anti-corruption measures is crucial for attracting investment and fostering entrepreneurship.
- b) Policymakers in SSA should adopt a pragmatic approach accounting for spatial spillover effects and regional dynamics, embracing regional coordination to address income disparities, manage resources, and promote peace.
- c) Future research should explore the relationship between formal and informal economies, develop comprehensive economic activity measures, and examine institutional factors' non-linear effects. Further understanding the spatial dynamics of conflict and instability is needed for more effective sustainable and inclusive economic growth strategies.



Declaration of Interest

The authors declare that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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ANNEXES: SUPPLEMENTARY TABLES & FIGURES

**Table 1***List of Sub-Saharan Africa Countries*

| S/N | Country Name | Country Code | S/N | Country Name | Country Code |
|-----|--------------------------|--------------|-----|-----------------------|--------------|
| 1 | Angola | AGO | 25 | Liberia | LBR |
| 2 | Benin | BEN | 26 | Madagascar | MDG |
| 3 | Botswana | BWA | 27 | Malawi | MWI |
| 4 | Burkina Faso | BFA | 28 | Mali | MLI |
| 5 | Burundi | BDI | 29 | Mauritania | MRT |
| 6 | Cabo Verde | CPV | 30 | Mauritius | MUS |
| 7 | Cameroon | CMR | 31 | Mozambique | MOZ |
| 8 | Central African Republic | CAF | 32 | Namibia | NAM |
| 9 | Chad | TCD | 33 | Niger | NER |
| 10 | Comoros | COM | 34 | Nigeria | NGA |
| 11 | Congo, Rep. | COG | 35 | Rwanda | RWA |
| 12 | Cote d'Ivoire | CIV | 36 | Sao Tome and Principe | STP |
| 13 | Congo, Dem. Rep. | COD | 37 | Senegal | SEN |
| 14 | Equatorial Guinea | GNQ | 38 | Seychelles | SYC |
| 15 | Eritrea | ERI | 39 | Sierra Leone | SLE |
| 16 | Eswatini | SWZ | 40 | Somalia | SOM |
| 17 | Ethiopia | ETH | 41 | South Africa | ZAF |
| 18 | Gabon | GAB | 42 | South Sudan | SSD |
| 19 | Gambia, The | GMB | 43 | Sudan | SDN |
| 20 | Ghana | GHA | 44 | Tanzania | TZA |
| 21 | Guinea | GIN | 45 | Togo | TGO |
| 22 | Guinea-Bissau | GNB | 46 | Uganda | UGA |
| 23 | Kenya | KEN | 47 | Zambia | ZMB |
| 24 | Lesotho | LSO | 48 | Zimbabwe | ZWE |

Table 2

List of Sub-Saharan Africa Countries With Missing Data

| S/N | Country | Code | AN-NIPC ¹ | GDPPC | INFLAT | CAPI-TAL | UNEMP | LA-BOUR | INSTI |
|-----|---------------------|------|----------------------|-------|--------|----------|-------|---------|-------|
| 1 | Botswana | BWA | √ | √ | √ | √ | √ | √ | NA |
| 2 | Cabo Verde | CPV | √ | √ | NA | NA | √ | √ | √ |
| 3 | Equatorial Guinea | GNQ | √ | √ | √ | √ | √ | √ | NA |
| 4 | Eritrea | ERI | √ | √ | NA | NA | √ | √ | √ |
| 5 | Eswatini | SWZ | √ | √ | √ | √ | √ | √ | NA |
| 6 | Gabon | GAB | √ | √ | √ | √ | √ | √ | NA |
| 7 | Liberia | LBR | * | √ | NA | NA | √ | √ | √ |
| 8 | Malawi | MWI | * | √ | NA | NA | √ | √ | √ |
| 9 | Mauritius | MUS | √ | √ | √ | √ | √ | √ | NA |
| 10 | Mozambique | MOZ | √ | √ | NA | NA | √ | √ | √ |
| 11 | Namibia | NAM | √ | √ | √ | √ | √ | √ | NA |
| 12 | Nigeria | NGA | * | √ | NA | NA | √ | √ | √ |
| 13 | Sao Tome & Principe | STP | * | √ | NA | NA | √ | √ | √ |
| 14 | Seychelles | SYC | √ | √ | √ | √ | √ | NA | NA |
| 15 | Somalia | SOM | * | √ | NA | NA | √ | √ | √ |
| 16 | Sudan | SDN | * | √ | √ | √ | √ | √ | √ |

√ = Available data; NA = Data Not Available; and * = data available for one year only (2015)

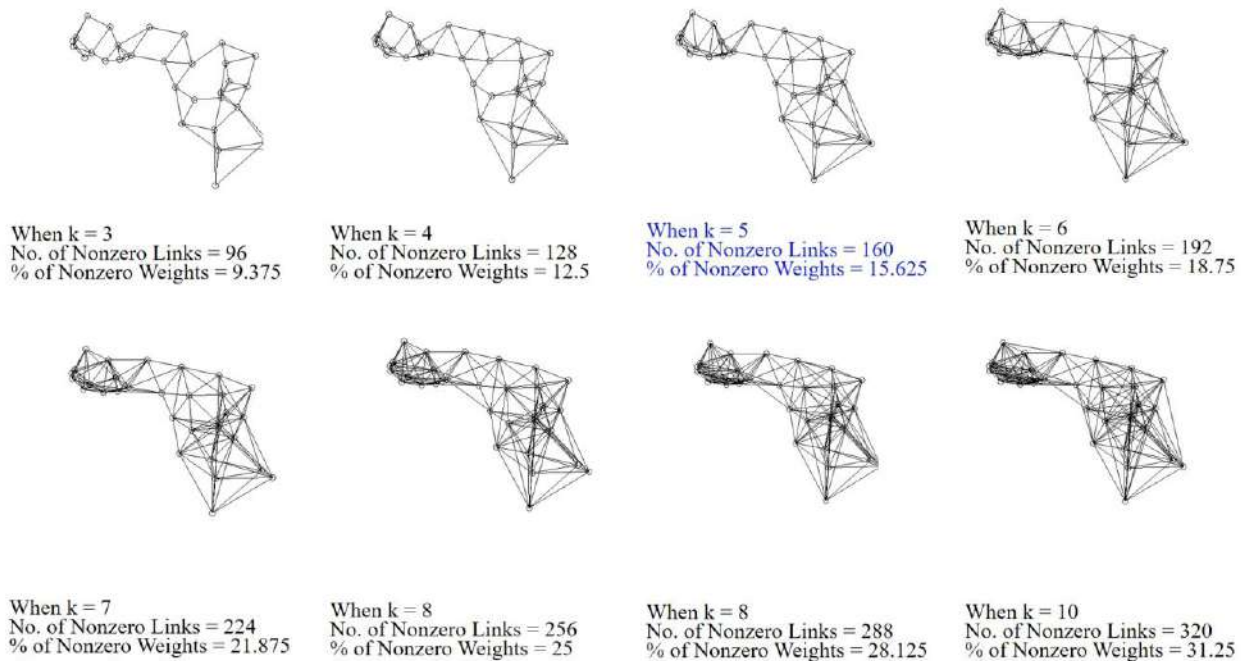


Figure 1

Summary of Sensitivity Analysis Results Using Different k-Nearest Neighbours for the SSA Sample (n=32)