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AFRICA INTEGRATION INTO GLOBAL VALUE CHAINS AND THE RAMIFICATIONS FOR DOMESTIC LABOUR MARKETS

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Abstract

This paper examines the implications of Africa's integration into global value chains (GVCs) and its impact on domestic labor markets. Using secondary data from 1990 to 2022 on unemployment, GVCs, secondary school enrollment, GDP growth, population growth, and foreign direct investment, the study panel quantile autoregressive distributed lag models to analyze short-term and long-term effects along with the Dumitrescu-Hurlin causality test was used to determine the aggregate level direction of causalityThe findings indicate that Africa's integration into GVCs reduces unemployment, with a more pronounced effect in the long run at the upper quantile. The causality test results show that unemployment drives GVCs in Africa, though this varies across countries. Based on these findings, the study recommends that Africa should embrace GVC integration and mitigate short-term unemployment disruptions by implementing social safety nets and unemployment benefits. Furthermore, the educational system should be strengthened to enhance school enrollment and vocational training programs, equipping the labor force with skills needed for GVC integration. Additionally, foreign direct investment should be promoted through investor-friendly policies, infrastructure improvement, political stability, and support for local industries to become competitive in GVCs, thereby maximizing the benefits of integration.

Keywords: *Labour market, unemployment, global value chains, panel quantile ARDL, Africa, Integration.*

JEL Classification: F15, F63, J2, O55.

Introduction

Globalization has profoundly transformed the world economy through advancements in communication networks, technological innovations, and reductions in transportation costs. These changes, coupled with the liberalization of trade policies, have significantly facilitated the movement of goods and services across borders. The Sustainable Development Goals (SDGs), particularly SDG 9, emphasize the importance of building resilient infrastructure, promoting inclusive and sustainable industrialization, and fostering innovation. This emphasis underscores the dramatic shift in global trade dynamics, leading to the emergence and prominence of global value chains (GVCs). Goals 7, 8, and 9 further stress the promotion of inclusive and sustainable economic growth, employment, and decent work for all. As a result, researchers are increasingly examining whether countries' integration into GVCs can provide a sustainable pathway to achieving these goals (Dwivedi et al, 2021; Ali et al, 2023).

The concept of global value chains was first introduced by Michael Porter in 1986, referring to the series of activities that businesses undertake from product design to final consumption. According to Cuervo-Cazurra & Pananond, (2023), GVCs represent a geographically dispersed production process, where different stages of production are located in various parts of the world. This concept arises from the understanding that all goods and services pass through multiple stages and actors, each contributing based on their resource endowments and logistical capacities. The goal is to efficiently manage these stages to ensure that products reach the market in a timely manner. The integration of different countries into GVCs highlights the interconnectedness of modern economies and the importance of optimizing each stage of production to maximize value.

The rise of GVCs is largely a response to the increasing competitive pressures brought about by globalization and technological advancements (Zhan, 2021). Firms around the world have responded by enhancing cross-border collaborations, integrating their production processes with companies in other countries. This strategy allows them to benefit from the economies of agglomeration, where businesses achieve efficiencies by being close to each other. Coveri and Zanfei, (2023) opine that by dispersing production stages globally, companies can tap into specialized skills, cost advantages, and innovation hubs, thereby enhancing their competitiveness.

The integration of African economies into global value chains (GVCs) signifies a major shift in the continent's economic landscape, promising increased economic growth and development (Ajide, 2023). Global value chains involve the international fragmentation of production, with different stages spread across various countries. For Africa, this integration was believed to have potential to boost foreign direct investment (FDI), bring in new technology, and provide access to larger markets (Saha et al, 2023; Takpara et al, 2023). While notable progress has been made by North African countries in integrating into GVCs, the overall success across the continent remains varied. For example, according to trade data for Africa in 2022, the total value of exports was USD 196,236 million. Despite this growth, trade practices in Africa still account for only 3% of world commerce, with Asia contributing 41.4%, Europe 14%, North America 8.1%, South America 8.1%, and Oceania 8%. This highlights that African contributions to world trade have been very poor and the least among the continents.

The issue of unemployment in African countries tends to portray the claim of the classical economist that the only people who are employed are those who are not ready to offer themselves for existing jobs at the prevailing wage rate. Thus, the true case of unemployment in Africa is voluntary one. This is evident by the recent ‘japa syndrome’ from African countries to the European and even Asian countries as people willingly take up jobs that they reject in their own domestic countries. This shows that the reasons for the prevalence of unemployment in African countries is associated with payment system (reward for labour), as professionals do not mind quitting their jobs in Africa for taking menial jobs in the United States or in any other developed countries (Okunade & Awosusi, 2023).

Over the years, there have been controversy in the literature as to whether countries benefit in integrating into global value change in terms of their labour market. While some studies have supported the integration into the global value chain that it can lead to employment opportunities (Konton & Amoule, 2020; Viegelahn et al. 2023), others argued that countries integrating into the global value chains may stand as a determent to their employment placing the issue that unskilled workers suffer and since most countries product cannot stand out in the international market, it places them at the verge of providing more employment opportunities to other countries while their labour market suffers (Guha-Khasnobis et al, 2023; Pan, 2020; Ndubuisi & Owusu, (2022),The conflicting outcome in the literature have put policy makers at cross road as to whether participating in the global value chain stand as a blessing or a curse. Consequently, this paper investigate the effect of African integration into the global value chain and its implication on the labour market.

Apart from the introduction, the rest of the paper are structured as follows: section 2 provides the literature review. Section 3 presents the methodology and data requirements. The empirical results are presented in section 4 while section 5 concludes and provide suggested recommendations.

Literature Review

Global Value Chain

A global value chain (GVC) refers to the fragmented process of global production, where different stages of making a product are spread across various countries (Jones et al. 2019). Antras (2020) defined GVC as a production process that involves value added, particularly labour services, from at least two countries. GVC is the internationalization of production processes. Internationalization of production processes has to do with the fragmentation of a product's development across multiple countries. Each stage, from initial design, through manufacturing, to final assembly, and distribution, occurs in a different country. The fragmentation in the production process is facilitated by technological advancements, reduced trade barriers, and strategic decisions by multinational corporations to optimize efficiency and cost-effectiveness (Escaith, 2017). Global value-added activities across borders enables firms to leverage the comparative advantages of various regions, and this results in enhanced productivity and cost savings (Xing, Wang, & Dollar, 2023).

Developing countries stand to gain from participation in GVCs. Participation in GVCs allows them to integrate into the global economy, enhance their industrial capabilities, and move up the value chain by upgrading their processes and products (Liao, Lo, & Pan, 2023). Integration into the global economy is essential for economic development as it provides access to larger markets, advanced technologies, and managerial expertise. However, the advantages of GVC participation are not automatic (Yan, Li, & Meng, 2023). They require supportive policies, institutional frameworks, and investments in human capital and infrastructure to maximize gains and mitigate risks (Gölgeci, Gligor, Bayraktar, & Delen, 2023).

Employment incorporates a broad array of relationships and conditions under which individuals engage in work for compensation. Traditionally, employment is defined by a formal contract between an employer and an employee, stipulating the terms of work, compensation, and benefits. However, in recent years, the nature of employment has evolved significantly due to technological advancements, globalization, and changing societal norms (Tokunova et al., 2023). These factors have given rise to various forms of employment, including part-time, temporary, freelance, and gig work, which deviate from the traditional full-time, permanent positions (Zakalyuzhnaya, 2023). Employment can be categorized into several types based on the nature and duration of the work. The categories of employment include full-time and part-time employment, temporary and permanent contracts, and self-employment (Pritvorova et al. 2020). Each type has distinct implications for job security, benefits, and worker rights. The rise of the gig economy has further diversified employment types, offering flexibility but often lacking in job security and benefits (Zhumabayeva & Nurmagambetov, 2023).

The quality of employment is important for employee wellbeing and it comprises job security, working conditions, income level, and opportunities for advancement ((Tokunova et al. 2023). High-quality employment contributes to the well-being and economic stability of individuals and their families, whereas precarious employment, characterized by insecurity and poor working conditions, can have adverse effects on mental and physical health (Bobkov & Odintsova, 2023). Employment also plays a vital role in economic development and social stability. It is a primary source of income for individuals and a driver of economic growth. Employment opportunities impact poverty levels, income distribution, and overall societal well-being. Effective employment policies and practices are essential for achieving inclusive growth and reducing economic disparities (Varsha Pramod & Ramachandran, 2023). Moreover, employment patterns are influenced by demographic changes, technological advancements, and shifts in the global economy, necessitating continuous adaptation and skill development (Węgrzyn, 2023).

Theoretical Framework

This study anchor on the modernization theory. The theory was developed in the mid-20th century by several scholars. Two of the key figures in the development of the theory was Talcott Parson an American sociologist who laid the theoretical groundwork in the 1950s and W.W. Rostow who outlined his stages of economic growth model in his 1950 book. According to this theory, societies progress through similar stages of development from traditional to modern stages. In the developing countries however, economic and social progress could be achieved by following the developmental pathways of Western industrialized nations. This can be achieved through adopting advanced technologies from developed countries as well as changes in social, economic and political institutions. Integration into the global value chain (which may be in the form of global markets) can lead to economic development that subsequently improves the domestic labour market. This is because integration has the tendency to create jobs in new industries, especially in manufacturing and high-tech sectors.

The modernization stages are of the form:

$$M = g(Y, K, L, A) \tag{1}$$

Where g represents the progression through modernization stages based on output, capital, labour, and technology. Meanwhile, the production function takes the form of Hicks-neutral:

$$Y_t = A_t f(K_t, L_t) \tag{2}$$

The production function is re-stated explicitly as Equation (3):

$$Y_t = A_t \cdot K_t^{\alpha} \cdot L_t^{\beta} \tag{3}$$

Where Y_t represents output at time *t*, K_t represents capital stock at time *t*, L_t

represents labour input at time t, A_t represents technology level at time t, αrepresents output elasticity of capital and β represents output elasticity of labour. Also, technology level is made up of domestic innovation and technology transfer such that

$$A_t = A_o e^{T_t^{\theta}} \quad (4)$$

Substituting Equation (4) into Equation (3), it yields Equation (5).

$$Y_t = A_o e^{T_t^{\theta}} \cdot K_t^{\alpha} \cdot L_t^{\beta} \quad (5)$$

Taking the natural log of both sides of Equation (5),

$$lnY_t = lnA_o + \theta lnT_t(lne) + \alpha lnK_t + \beta lnL_t \quad (6)$$

Since lne is equal to 1, Equation (6) becomes Equation (7)

$$lnY_t = lnA_o + \theta lnT_t + \alpha lnK_t + \beta lnL_t \quad (7)$$

Differentiating Equation (7) with respect to time, it yields Equation (8)

$$\frac{\dot{Y}_t}{Y_t} = \frac{\dot{A}_o}{A_o} + \theta\frac{\dot{T}_t}{T_t} + \alpha\frac{\dot{K}_t}{K_t} + \beta\frac{\dot{L}_t}{L_t} \quad (8)$$

At the balances growth path, output growth rate is the same as the capital growth rate, that is, $\frac{\dot{Y}_t}{Y_t} + \frac{\dot{K}_t}{K_t}$. Hence,

$$\frac{\dot{Y}_t}{Y_t} = \alpha\frac{\dot{Y}_t}{Y_t} + \beta\frac{\dot{L}_t}{L_t} + \frac{\dot{A}_o}{A_o} + \theta\frac{\dot{T}_t}{T_t} \quad (9)$$

Re-arranging Equation (9) by making labour growth rate the subject,

$$\beta\frac{\dot{L}_t}{L_t} = \frac{\dot{Y}_t}{Y_t} - \alpha\frac{\dot{Y}_t}{Y_t} - \frac{\dot{A}_o}{A_o} - \theta\frac{\dot{T}_t}{T_t} \quad (10)$$

$$\beta\frac{\dot{L}_t}{L_t} = (1-\alpha)\frac{\dot{Y}_t}{Y_t} - \frac{\dot{A}_o}{A_o} - \theta\frac{\dot{T}_t}{T_t} \quad (11)$$

Recall that the growth rate of initial technology $\frac{\dot{A}_o}{A_o}$ is denoted by g, meaning that the growth rate of information technology is growing at a constant rate. Therefore,

$$\beta\frac{\dot{L}_t}{L_t} = (1-\alpha)\frac{\dot{Y}_t}{Y_t} - g - \theta\frac{\dot{T}_t}{T_t} \quad (12)$$

Dividing both sides by β, Equation (12) becomes Equation (13).

$$\frac{\dot{L}_t}{L_t} = \left(\frac{1-\alpha}{\beta}\right)\frac{\dot{Y}_t}{Y_t} - \frac{g}{\beta} - \frac{\theta}{\beta}\frac{\dot{T}_t}{T_t} \quad (13)$$

Since technology transfer is a function of the country's integration into the global value chain and its absorption capacity, such that:

$$T_t = f(I_t, E_t, G_t) \quad (14)$$

Where I_t is infrastructure quality at time *t*, E_t is education level at time t, and G_t is governance quality at time t. By substituting Equation (14) into Equation (13), it becomes;

$$\frac{\dot{L}_t}{L_t} = \left(\frac{1-\alpha}{\beta}\right)\frac{\dot{Y}_t}{Y_t} - \frac{g}{\beta} - \frac{\theta}{\beta}\left(\frac{\dot{I}_t}{I_t}, \frac{\dot{E}_t}{E_t}, \frac{\dot{G}_t}{G_t}\right) \quad (15)$$

Empirical Review

Samuda (2023) examined the effect pf global value chain in both economic output and unemployment using 10 ASEAN countries for the period 1999 to 2018. Generalised Method of Moment Estimation technique was used along with panel causality test. His finding revealed that global value chain impacted positively and significantly on economic growth and also increase unemployment in the period studied. Result from causality indicated that unemployment drives global value chain in the ten countries and also economic output does not drive global value chain.

Guha-Khasnobis et al. (2023) explored how India's involvement in the global value chain affects total number of jobs created and the types of skills needed in the workforce. They applied the Generalised Methdo of Moments to annual data for the period 1990-2015. Their findings showed an inverse relationship between higher value-added and job creation. They also found that stronger backward linkages led to job losses, while stronger forward linkages created jobs, but only for unskilled workers. Additionally, their findings revealed that the downstream sectors generated more jobs in comparison to the upstream sectors, which demanded more skilled workers.

Rohit (2023) investigated the relationship between participation in global value chain and structural change. His analysed data with respect to 40 developing economies for the period 1993 to 2015. His findings showed no link between participation in global value change and structural change. However, his findings showed a likelihood that participation in global value chain may trap workers in sectors with declining productivity, which could impede progress towards healthy structural change.

Obeng et al. (2022) analysed the relationship between global value chain and inclusive growth in sub-Saharan Africa using data covering the period 1991 to 2017. They estimated the data through the Generalised Method of Moments estimators. Their findings revealed the positive effects of employment in driving inclusive growth through global value chain. They also found that the value of foreign value addition in the region is lower than domestic value addition, though foreign value addition contributed more to inclusive growth.

Ndubuisi and Owusu (2022) studied the impact of county participation in global value chain on worker's wages. Through the System Generalised Method of Moments, they analysed data of forty-five developed and developing countries, spanning 2000 to 2015. Their findings indicted that integration into global value chain increased wages in developed countries, with upstream specialisation intensifying the effect. Additionally, they found negative effects of GVC on wages for low-income workers in the developing countries.

Kouton and Amonle (2021) analysed the impact of global value chains on inclusive growth in Africa. They analysed data for thirty-five African countries for the period 1991 to 2018 through the panel autoregressive distributed lag and the cross-section augmented ARDL techniques. They used labour productivity to measure inclusive growth and found that upstream global value chain participation positively and significantly improves labour productivity, while the relationship with down stream productivity was positive but insignificant.

Yanikkaya and Altun (2020) assessed how global value chain participation by OECD countries affect sector growth and productivity using data for the period covering 1995 to 2011 as well as 2005 to 2015. Data collected were analysed using Generalised Method of Moments. The concluded that between 1995 to 2011, the sectors that participated more in global value chain enjoyed higher output in their total factor productivity growth while outcomes for the period between 2005 to 2015 indicate global value chain dampens the benefit to countries and the sectorial growth for the OECD countries.

Methodology

Data requirement and source

The study covers the period from 1990 to 2022 and consists of 40 African countries, including Algeria, Egypt, Morrocco, Sudan, Tanzania, Cameroon, Central African Republic, Chad, Congo Dem.Rep, Gabon, Sao Tome and Principe, Angola, Botswana, Lesotho, Mozambique, Namibia, South Africa, Zambia, Burundi, Djibouti, Kenya, Madagascar, Malawi, Mauritius, Rwanda, Somalia, Tunisia, Uganda, Cape Verde, Cote d'Ivoire, Gambia, Ghana, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sieria Leone and Togo. The data used were unemployment, total (% of total labour force) (modeled ILO estimate), the Global Value Chain participation index, school enrollment, secondary (% gross), foreign direct investment, net inflows (% of GDP), GDP growth (annual %), population growth (annual %). All the variables were sourced from the World Bank World Development Indicators (WDI) while data on Global Value Chain participation index was retrieved from https://worldmrio.com/unctadgvc/. Although the data for global value chains (GVC) ends in 2018, the dynamic forecast was used in computing data for the missing periods.

Model Specification and econometric methodology

Emanating from the theoretical framework, we specify out model in the form;

$$UEM_{it} = f(GVC_{it}, GDPgr_{it}, EDU_{it}, POPgr_{it}, FDI_{it}) \qquad (16)$$

Where:

UEM_{it} = Unemployment rate of country i in period t

GVC_{it} = Global value chains of individual country i in period t

$GDPgr_{it}$= Gross Domestic Product of individual country i in period t

EDU_{it} = Education measure by secondary school enrollment of individual country i in period t

$POPgr_{it}$ = Population growth of individual country i in period t

FDI_{it} = Foreign direct investment of individual country i in period t

In econometric form, equation 16 is respecified as follows

$$UEM_{it} = \beta_0 + \beta_1 GVC_{it} + \beta_2 GDPgr_{it} + \beta_3 EDU_{it} + \beta_4 POPgr_{it} + \beta_5 FDI_{it} + \varepsilon_{it} \qquad (17)$$

Where β_0 represent the constant, $\beta_1 - \beta_5$ represents the coefficient of the independent variables, i stands for individual African countries selected (1-40), t represents the time (1990 to 2022) and ε_{it} is the error term. Although, the objective of the paper is to determine the effect of global value chains on domestic labour markets in Africa, GDP growth, education, population growth and foreign direct investment are added as control variables.

Equation 17 is respecified in its logarithm form as

$$logUEM_{it} = \beta_0 + \beta_1 logGVC_{it} + \beta_2 logGDPgr_{it} + \beta_3 logEDU_{it} + \beta_4 logPOPgr_{it} + \beta_5 logFDI_{it} + \varepsilon_{it} \quad (18)$$

Estimation Techniques

Method of Moment quantile regression (MMQR)

As a robustness check, we conduct a panel quantile regression. Typically, conditional mean-based regressions like Ordinary Least Square assume that the conditional means, usually situated at the midpoint of the distribution, are sufficient to determine relationships between variables. However, this approach only offers a partial view of the entire conditional distribution, potentially leading to unreliable results, especially if the effect lies in the distribution tails (Ike et al, 2020). Therefore, we employ a quantile regression approach using the method of moments quantile regression (MMQR) with Fixed Effects model developed by Machado and Silva (2019). The MMQR model with Fixed Effects considers information across different points of the conditional distribution and identifies distributional asymmetry. It offers several advantages over the quantile regression techniques by Koenker (2004), Canay (2011), and Powel (2016). Firstly, it incorporates Fixed Effects through location parameters, which implies that their impacts are evident across the entire conditional distribution rather than just acting as location shifters. Secondly, the approach is resilient to outliers, providing robust estimates by accounting for heterogeneity and asymmetry through both location and scale parameters. The MMQR model following Machado and Silva (2019) is specified as:

$$Y_{it} = \alpha_i + K'_{it}\beta + \varphi(\pi_i + V'_{it}\delta)\mu_{it} \tag{19}$$

Where unknown parameters are $\alpha, \beta', \pi, \delta'$ and $(\alpha_i, \pi_i), i, \ldots, n$ captures the individual i fixed effects. V' shows a *x*-vector of known differentiable transformations of the components of K_{it} with element *n* defined by $V_n = V_n(K_{it})$ where $n = 1 \ldots, x$. The probability, $P(\pi_i + V'_{it}\delta > 0) = 1$, and μ_{it} is the unobservable error term which is strictly independent of K_{it}.

Following the work by Machado and Silva (2019), the density function, $F_u(\cdot)$ is bounded away from 0 and hence normalized so as to satisfy the moment conditions given as $H(U_{it}) = 0$ and $H(|U_{it}|) = 1$. Therefore, Equation (1) becomes:

$$Q_Y(\tau|K_{it}) = \big(\alpha_i + \pi_i g(\tau)\big) + K'_{it}\beta + V'_{it}\delta g(\tau) \tag{20}$$

Where $g(\tau) = F_U^{-1}(F_u(\cdot)$ and $P\big(U < g(\tau)\big) = \tau$. The scaler parameter implies that $\alpha_i(\tau) \equiv \alpha_i + \pi_i g(\tau)$ and is indicative of the quantile- τ fixed effects for individual i. Unlike the Ordinary Least Square Fixed Effects, the distributional effects of MMQR is allowed to have varying impacts across the entire quantiles of the conditional distribution of the dependent variable.

Quantile Autoregressive Distributed Lagged

Following the work by Shahbaz et al. (2018), the Quantile Autoregressive Distributed Lagged QARDL is more superior that the linear modes on several ways. First, it accommodate situations of locational asymetryin which parameters may depend on the locations of the dependent variables. Second it addresses the issues of both short-term and long-terms relationship among variables at various quantiles of the conditional distribution of the dependent variable. Third, it is able to determine the existence of quantile varying cointegration in the short term which the traditional method failed to address (Xiao, 2009). Fourth, it accommodates issues of variations in the short-term coefficient. The model also uses the data driven process that makes it more superior. Given its superiority, the study also employs the method as a further robust test. Following the work by Cho et al (2015), the basic quantile autoregressive distributed lagged (QARDL) (p, q) that accommodate variations across quantiles is given by

$$Q_{logUEM_t} = \beta(\gamma) + \sum_{i=1}^{p} \alpha_i (\gamma)\ logUEM_{t-1} + \sum_{i=0}^{q1} \partial_i(\gamma)\ logGVC_{i=1} + \sum_{i=0}^{q2} \delta_i (\gamma)\ logGDPgr_{i=1} + \sum_{i=0}^{q3} \rho_i (\gamma)\ \mathrm{logEDU}_{i=1} + \sum_{i=0}^{q4} \emptyset_i (\gamma)\ logPOPgr_{i=1} + \sum_{i=0}^{q5} \sigma_i (\gamma)\ logFDI_{i=1} + \varepsilon_t(\gamma) \quad (21)$$

Here, $\varepsilon_t(\gamma)$ equals $logUEM_t$ - $Q_{logUEM_t}[\gamma/F_{t-1}]$ and $Q_{logUEM_t}[\gamma/F_{t-1}]$ refers to the γ_{th} quantile of $logUEM_t$ conditional on the information set F_{t-1} as supported by (Kim & White, 2003). The short-run form is then specified as

$$Q_{logUEM_t} = \beta(\gamma) + \sum_{i=1}^{qi-1} \alpha_{logUEM} (\gamma)\Delta\ \mathrm{logUEM}_{t-1} + \tau_{logUEM} (\gamma) logUEM_t + \sum_{i=1}^{qi-1} \partial_{logGVC}(\gamma)\ \Delta\ logGVC_{t-1} + \tau_{logGVC} (\gamma) logGVC_t + \sum_{i=1}^{qi-1} \delta_{LREC} (\gamma)\Delta\ GDPgr_{t-1} + \tau_{logGDPgr} (\gamma) logGDPgr_t + \sum_{i=1}^{qi-1} \rho_{logEDU} (\gamma)\ \Delta logEDU_{t-1} + \tau_{logEDU} (\gamma) logEDU_t + \sum_{i=1}^{qi-1} \emptyset_{logPOPgr}\Delta (\gamma)\ logPOPgr_{t-1} + \tau_{logPOPgr} (\gamma) logPOPgr_t + \sum_{i=1}^{qi-1} \sigma_{logFDI}\Delta (\gamma)\ \mathrm{logFDI}_{t-1} + \tau_{logFDI} (\gamma) logFDI_t + \varepsilon_t(\gamma) \quad (22)$$

The long run effect is computed using the equation below

$$Q_{logUEM_t} = \mu(\gamma) + X_t'\alpha(\gamma) + M_t(\gamma) \quad (23)$$

Where X represents the vector of the independent variable along with the control variables (logGVC, logGDPgr. logEDU. logPOPgr. logFDI).

Therefore, the QARDL estimated incorporating the short-run and long run is specified as:

$$Q_{\Delta logUEM_t} = \alpha(\gamma) + \beta_1(\gamma) logUEM_{t-1} - \beta_2(\gamma) logGVC_{t-1} - \beta_{3(\gamma)} logGDPgr_{t-1} - \beta_4(\gamma) logEDU_{t-1} + \beta_5(\gamma) logPOPgr_{t-1} - \beta_6(\gamma) logFDI_{t-1} + \sum_{i=1}^{p-1} \alpha_i(\gamma)\ \Delta\mathrm{logUEM}_{t-1} + \sum_{i=0}^{qi-1} \partial_i(\gamma)\Delta\ logGVC_{t-1} + \sum_{i=0}^{qi-1} \delta_i (\gamma)\Delta\ logGDPgr_{t-1} + \sum_{i=0}^{qi-1} \rho_i (\gamma)\Delta logEDU_{t-1} + \sum_{i=0}^{qi-1} \emptyset_i (\gamma)\Delta\ logPOPgr_{t-1} + \sum_{i=0}^{qi-1} \sigma_i(\gamma)\ \Delta logFDI_{t-1} + \varepsilon_t(\gamma) \quad (24)$$

Empirical Results

Descriptive statistics

Table 1 presents the descriptive statistics of the variables used in the analysis. The average unemployment rate in the selected

African countries is 9.574%, with a standard deviation of 7.092%, indicating substantial variability in unemployment rates across these nations. The unemployment rates range from a minimum of 0.32% to a maximum of 33.2%. The mean and median values fall within this range, suggesting a relatively consistent distribution of unemployment rates. Economically, these statistics imply that while some countries experience very low unemployment, others face significantly higher rates, highlighting the diverse economic challenges within the continent. The mean value of GVC participation is 2,139,031, with a median of 209,000, indicating a significant skewness and wide disparity in GVC engagement among the countries. The maximum value is 48,116,667, and the minimum is 3,970, reflecting substantial differences in the extent of integration into global value chains. The average GDP growth rate is 3.712%, with a standard deviation of 5.123%. The values range from a significant negative growth rate of -50.248% to a high of 35.224%. This wide range suggests diverse economic performances, with some countries experiencing robust growth while others face severe economic contraction. The mean school enrollment rate is 40.098%, with a standard deviation of 27.123%. Enrollment rates vary greatly, from a minimum of 34.433% to a maximum of 186.279%. The wide range and high standard deviation reflect significant disparities in educational attainment. The mean population growth rate is 2.402%, with a standard deviation of 1.497%. The rates range from a negative growth rate of -16.881% to a high of 16.626%. This variability indicates differing demographic trends, with some countries experiencing rapid population growth while others have declining populations. The average FDI is 3.578%, with a standard deviation of 6.865%, suggesting considerable variability. FDI values range from -11.192% to 103.337%, indicating that while some countries attract substantial foreign investment, others experience significant disinvestment.

Table 1: Descriptive statistics of the variables used

	UEM	GVC	GDPgr	EDU	POPgr	FDI
Mean	9.574	2139031	3.712	40.098	2.402	3.578
Median	7.556	209000	4.033	35.171	2.565	2.054

Maximum	33.2	48116667	35.224	186.279	16.626	103.337
Minimum	0.32	3970	-50.248	34.433	-16.881	-11.192
Std. Dev.	7.092	6412810	5.123	27.123	1.497	6.865

Source: Computed using EViews from data retrieved from WDI

Correlation

The correlation matrix in Table 2 reveals several interesting relationships among the variables used in the analysis. Firstly, there is a statistically significant negative correlation ($r = -0.083, p < 0.05$) between unemployment (UEM) and participation in global value chains (GVC), suggesting that as African countries become more involved in GVCs, unemployment tends to decrease. Secondly, education (EDU) exhibits a strong positive correlation with both unemployment ($r = 0.290, p < 0.01$) and GVC participation ($r = 0.530, p < 0.01$), indicating that higher levels of education are associated with lower unemployment rates and greater integration into GVCs. Additionally, there is a significant positive correlation between population growth rate (POPgr) and unemployment ($r = 0.278, p < 0.01$), implying that as the population grows, unemployment tends to rise. Conversely, foreign direct investment (FDI) shows a weak negative correlation with unemployment ($r = -0.028$) and a slightly stronger negative correlation with GVC participation ($r = -0.108, p < 0.01$), suggesting that higher levels of FDI may be associated with lower unemployment rates and increased involvement in GVCs, although these correlations are relatively weak. Finally, the correlation between GDP growth rate (GDPgr) and the other variables appears to be non-significant.

Table 2: Correlation matrix of the variables used

		UEM	GVC	GDPgr	EDU	POPgr	FDI
UEM	Pearson Correlation	1.000					
	Sig. (2-tailed)						
GVC	Pearson Correlation	-.083**	1.000				

	Sig. (2-tailed)	(0.003)					
GDPgr	Pearson Correlation	-0.04	0.009	1.000			
	Sig. (2-tailed)	(0.150)	(0.738)				
EDU	Pearson Correlation	.290**	.530**	-0.016	1.000		
	Sig. (2-tailed)	(0.000)	(0.000)	(0.564)			
POPgr	Pearson Correlation	.278**	.110**	.102**	-.355**	1.000	
	Sig. (2-tailed)	(0.000)	(0.000)	(0.000)	(0.000)		
FDI	Pearson Correlation	-0.028	-.108**	.109**	0.04	0.015	1.000
	Sig. (2-tailed)	(0.301)	(0.000)	(0.000)	(0.151)	(0.583)	

Note: ** denotes significance at 5%

The relationship between GVC and unemployment measured as labour market dynamics is explained using the wavelet coherence technique. The cold (blue) areas on the plot indicates periods of no correlation, while the hot (red) areas show period of high correlation. The black contours denote the 5% significance level. The figure shows significant short-term coherence at a smaller scale (2 to 4 years) between UEM and GVC between 1993 to 1997, 2002 to 2005 and between 2007 to 2011. The implication of this findings is that as African economies became more integrated into the Global value Chain during this period, unemployment rate rose. This might be as a result of expansion in labour force outpacing the job creation associated with GVC participation. The correlations were however only significantly positive between 1993 and 1997 This suggests that during this period, positive movements in the GVC were closely followed by similar movements in UEM. From the figure, weak correlation exists between UEM and GVC in the medium term and long term at all scales. The evidence of weak correlation is depicted the cold blue areas across the medium- and long-term scales. Thus, over longer periods, correlations between GVC and EUM is less pronounced.

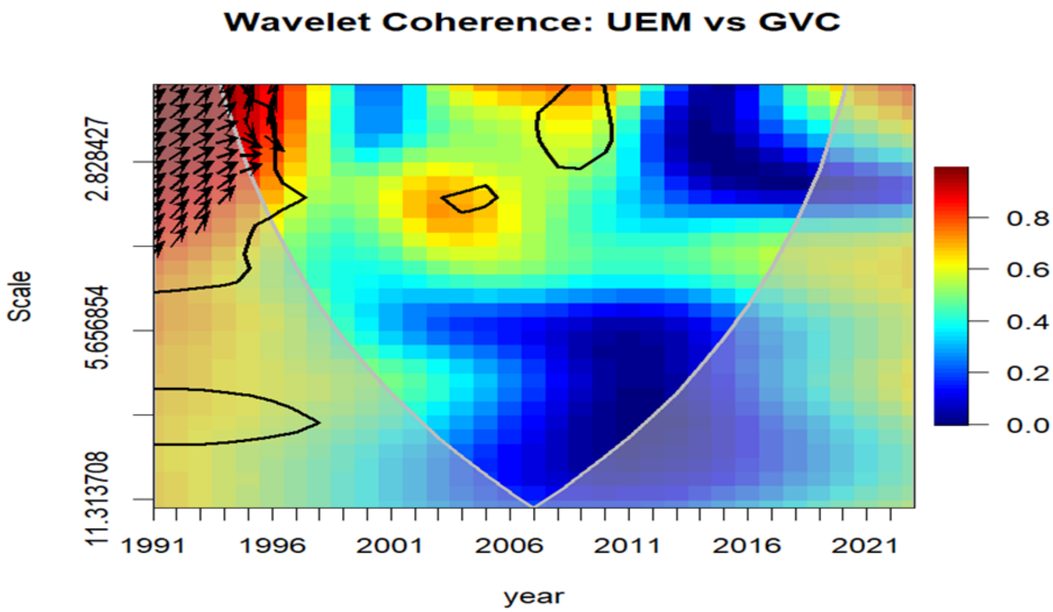

Figure 1: Correlation between unemployment and global value chain.

Cross sectional dependence tests results

The cross-section dependence test is a crucial step in panel data analysis, as it assesses the extent to which observations across different countries or entities are independent of each other. To accurately address interdependence among observations across the selected diverse African countries, we conducted the cross-sectional dependence test. This step was essential as neglecting it could lead to biased parameter estimates and erroneous conclusions, stemming from the assumption of independent observations being violated, thereby jeopardizing the reliability and validity of our findings. The results presented in Table 3 confirmed the rejection of the null hypotheses of no cross-sectional dependence across the four test statistics. Consequently, we infer that within the selected African countries, the variables indeed exhibit interdependence.

Table 3: Cross Section Dependence Test

	Test Statistics			
	Breusch-Pagan	Pesaran Scaled	Bias-Correlated Scaled	
Variables	LM	LM	LM	Pesaran CD
UEM	5485.247***	118.117***	117.492***	13.396***
	(0.000)	(0.000)	(0.000)	(0.000)
GVC	22594.41***	551.295***	550.670***	148.936***
	(0.000)	(0.000)	(0.000)	(0.000)
GDPgr	1577.902***	19.189***	18.564***	22.667***
	(0.000)	(0.000)	(0.000)	(0.000)
EDU	14197.78***	338.705***	338.080***	110.962***
	(0.000)	(0.000)	(0.000)	(0.000)
POPgr	4495.233***	93.051***	92.426***	6.379***
	(0.000)	(0.000)	(0.000)	(0.000)
FDI	2715.696***	47.996***	47.372***	31.752***
	(0.000)	(0.000)	(0.000)	(0.000)

Note: *** denotes significance at 5%. Number in parentheses are the p -values.

Slope Homogeneity

Having found the presence of cross sectional dependence among the series we proceed to determine whether the relationships between the dependent and independent variables are consistent across different cross-sectional units within the panel, as a result, we conducted a slope homogeneity test. This test is crucial as it helps to ascertain whether a single model can adequately describe the data across all units or if the relationships vary and require more complex modeling. Table 4 present the outcome of the result for the variables, the four tests were conducted, and the result ensures the robustness and accuracy of our econometric models. The delta tests for all the variables used were significant indicating the rejection of the null hypotheses of no presence of slope homogeneity among the variables.

Table 4. Test for Slope homogeneity

Delta Tests	Test Statistics and Probability					
	logUEM	logGVC	;logGDPgr	logEDU	logPOPgr	logFDI
Delta tilde	4.154***	6.682***	3.561***	3.412***	5.061***	5.024***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Delta tilde adj	3.435**	2.756***	4.341***	3.344***	3.946***	3.348***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: *** denotes significance at 5%

Unit root test results

Having established the presence of cross-sectional dependence among the variables, we proceeded to conduct the unit root test to evaluate their stationarity property. Traditional first-generation panel unit root tests are inadequate in cases of cross-sectional dependence. Therefore, we employed the CIPS unit root test by Im, Pesaran, and Shin, specifically designed for panel data with cross-sectional dependence. Table 5 displays the results of the CIPS unit root test. While the null hypothesis of a unit root cannot be rejected for logGDPgr, logPOPgr, and logFDI at the 5% significance level in level series, it is rejected for logUEM, logGVC, and logEDU at the first difference, suggesting non-stationarity. Consequently, the study concludes that all variables are stationary, indicating no evidence of spurious regression.

Table 5: Im, Pesaran, Shin Unit Root Test

Variables	Level	First Difference	Order of Integration
logUEM	-2.768	-13.929***	I(1)
	(0.997)	(0.000)	
logGVC	1.903	-17.848***	I(1)
	0.971	(0.000)	
logGDPgr	-11.835		I(0)
	(0.000)		
logEDU	3.531	-13.239***	I(1)

	(0.999)	(0.000)	
logPOPgr	-8.336		I(0)
	(0.000)		
logFDI	-4.692		I(0)
	(0.000)		

Note:*** denotes significance at 5%

Westerlund Cointegration

After confirming the presence of cross-sectional dependence and slope homogeneity, we proceeded to determine whether a long-run relationship exists among the variables. Empirical studies have shown that first-generation econometric techniques may not handle such situations effectively. Consequently, we applied the cointegration test proposed by Westerlund (2007), which can address these issues. The results, reported in Table 6, show that all test statistics confirm the presence of a long-run relationship among the variables. Based on the outcome we concluded that a long run relationship exists among the variables.

Table 6. Test for cointegration

Test Statistics	Coefficient	asymptotic ρ-value	bootstrap ρ-value
g-tau	-6.413***	0.020	0.000
g-alpha	-5.703***	0.000	0.000
p-tau	-3.012***	0.000	0.000
p-alpha	-6.453**	0.010	0.000

Note: ***,** denote significance at 1% and 5% respectively

Panel quantile autoregressive distributive lagged

For a more robust result, the panel quantile ARDL was estimated to determine the short-run and long run effect of global value chain on labour market dynamics in Africa. Table 10 displayed the outcome for both the short -run and the long run outcome at the lower quantile, middle quantile, and upper quantile denoted by 25^{th}, 50^{th}, and 75^{th} respectively. The result shows that for both the short-run and long run and at all the quantile, global value chain impacted negatively on unemployment. However, the effect is more pronounced in the long - run than in the short -run with a 1% increase in integration into the global value chain reducing unemployment by 1.558, 1.616 and 1.675 percentage points at the 25^{th},50^{th} , and 75^{th} percentile in the long run while in the short run it reduces by 0.634, 0.942 and 0.732 percentage points at the 25^{th},50^{th} , and 75^{th} percentile. The outcome was more pronounced in the upper quantile (75^{th}) in the long run. The result was not surprising in that long-term integration allows for development of necessary infrastructure, enhancement of local skills, and establishment of reliable trade relationships which collectively can foster sustainable economic growth. Moreso, over time, it is believed that countries can move up the value chain, shifting from low-value-added activities to higher-value- added ones which can creates more and better value jobs. Additionally, long term integration supports the diversification of economies and resilience against global market fluctuations, that is believed to provide a more stable environment for employment growth in Africa.

GDP growth rate in Africa also reduces unemployment both in the short-run and long – run and at all the quantiles. However, the outcome was more pronounced in the long run at the 25^{th} quantile with a reduction in unemployment by 1.248 percentage points. The short-run result was also pronounced in the 25^{th} quantile with a reduction by 0.732 percentage points. Education for both the short run and long run and at all the quantile shows inverse relationship with unemployment. The result was more pronounced in the short-run and at the 50^{th} quantile. Population growth impacted positively on unemployment both in the short-run and long run. The effect was more pronounced in the long run and at the upper (75^{th}) quantile. FDI impacted negatively on unemployment at all quantiles in the short run, however, in the long run and at the 50^{th} and 75^{th} quantile the effect was positive. The effect however was more pronounced in the short run and at the lower (25^{th}) quantile. This result was not surprising in that in the short term, FDI often leads to immediate job creation through the establishment of new enterprises infrastructure projects, and the expansion of existing businesses. This investment can swiftly absorb unemployed workers, particularly in sectors like manufacturing, construction and services. However, in the long run unemployment might stabilize as the economy adjusts to new levels of production and labour market reach equilibrium. The initial burst of job creation may taper off unless continually supported by consistent and substantial FDI inflows and complementary policies that can foster skill development and innovation

Table 7: Panel Quantile ARDL Result

	Short Run			Long Run		
	0.25	0.50	0.75	0.25	0.50	0.75
logGVC	-0.634*	-0.942	-0.743**	-1.558**	-1.616**	-1.675***
	(0.082)	(0.016)	(0.032)	(0.023)	(0.035)	(0.006)
logGDPgr	-0.732***	-0.559	-0.421**	-1.248***	-0.359***	-0.387**
	(0.000)	(0.000)	(0.036)	(0.000)	(0.000)	(0.014)
logEDU	-1.067	-2.000*	-1.561**	-0.651	-0.313**	-0.424***
	(0.479)	(0.081)	(0.012)	(0.129)	(0.038)	(0.001)
logPOPgr	0.667**	0.176**	0.062**	0.705**	0.844***	0.914***
	(0.043)	(0.017)	(0.023)	(0.045)	(0.002)	(0.000)
logFDI	-1.161*	-1.213*	-1.007***	-0.349	-0.224**	-0.806**
	(0.090)	(0.058)	(0.000)	(0.951)	(0.047)	(0.038)

Note: ***,**, and * denotes significant at 1%, 5% and 10% respectively

Causality Test

To determine the direction of causality between the labor market, represented by unemployment, and the global value chain, the Dumitrescu-Hurlin causality test was employed. Table 8 reported the outcome of the findings. As reported, a unidirectional causality between unemployment and the global value chain was found, with unemployment predicting global value chain other (W-Stat = 4.423, $p < 0.05$ and W-Stat = 2.013, $p > 0.05$). This implies that in Africa, unemployment drives the global value chain and there is no feedback effect when considered at the aggregate level. Additionally, a unidirectional causality was found from unemployment to GDP growth rate (W-Stat = 2.818, $p < 0.05$ and W-Stat =

2.322, p > 0.05), and from unemployment to foreign direct investment (W-Stat = 2.829, p < 0.05 and W-Stat = 2.311, p > 0.05), both without feedback effects. For education, measured by secondary school enrollment, a bidirectional causality was found, indicating mutual influence (W-Stat = 4.664, p < 0.05 and W-Stat = 3.891, p < 0.05). Similarly, there was bidirectional causality between unemployment and population growth rate (W-Stat = 2.996, p < 0.05 and W-Stat = 5.238, p < 0.05)

Table 8: Causality Test

Null Hypothesis:	W-Stat.	Zbar-Stat.	Prob.
LOGGVC ⟹LOGUEM	2.013	1.906	0.245
LOGUEM ⟹ LOGGVC	4.423***	3.908	0.001
LOGGDPGR ⟹LOGUEM	2.322	0.417	0.677
LOGUEM ⟹ LOGGDPGR	2.818**	1.750	0.040
LOGEDU ⟹ LOGUEM	4.664***	6.706	0.000
LOGUEM ⟹ LOGEDU	3.891***	4.631	0.000
LOGPOPGR ⟹LOGUEM	2.996***	2.227	0.026
LOGUEM ⟹ LOGPOPGR	5.238***	8.248	0.000
LOGFDI ⟹ LOGUEM	2.829*	1.777	0.076
LOGUEM⟹ LOGFDI	2.331	0.442	0.659

Note: *** ,** and * denotes significance at 1%, 5% and 10% respectively

Conclusions and Recommendations

The study investigated Africa's integration into global value chains (GVCs) and its implications for labor markets from 1990 to 2022, using advanced econometric methods. The results showed that while African countries exhibited cross-sectional dependence, there was a long-run relationship between GVC integration and unemployment, with GVC participation generally reducing unemployment, though effects varied across countries and were more significant in the long run and at higher unemployment quantiles. The analysis further revealed bidirectional causality between GVC integration and unemployment, while GDP growth, education, and foreign direct investment played positive roles in job creation. Based on these findings, the study recommended that African governments strengthen infrastructure, governance, and institutional frameworks, enhance educational reforms aligned with labor market needs, promote GDP growth and entrepreneurship, and provide targeted support for countries negatively affected by GVCs, while also developing long-term strategies in trade policy, human capital, and innovation to sustain the benefits of integration

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