DOI: https://doi.org/10.20372/star.V15.i2.08
ISSN: 2226-7522 (Print) and 2305-3372 (Online)
Science, Technology, and Arts Research Journal
Sci. Technol. Arts Res. J., April–June 2026, 15(2), 103-130
Journal Homepage: https://journals.wgu.edu.et
Original Research

Effects of Sectoral Employment and Value-added Shares on Economic Structural Transformation in Sub-Saharan African (SSA) Countries: Using Panel Corrected Standard Error (PCSE)

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Abstract

This study investigates the effects of sectoral employment, value-added share, and growth rate on the economic structural transformation (ST) of 18 SSA countries from 1990 to 2020. Total ST was calculated using shift-share analysis. The share of employment in agriculture and the share of non-manufacturing value added positively affect ST; whereas the share of employment in non-manufacturing and services, the value added of manufacturing, agriculture, and the growth rate of services negatively affect ST. The growth rate of agriculture and manufacturing positively affects ST. The relationship of income and structural transformation appears to diverge from classical theory, exhibiting a negative linear relationship and a positive quadratic relationship between income per worker and ST. Agricultural transformation should be prioritized to ensure an increase in productivity. Results suggest that the positive employment shift and the rise of low productivity service sector absorption through re-skilling, and an absence of growth in manufacturing, should be addressed through policies to enhance value chains. Overreliance on output growth is not an adequate stimulus. The path-dependent nature of SSA's transformation, continued to focus on agriculture, poor manufacturing sector performance, and informal services proliferation, warrants country-specific and context-contingent policies to have inclusive growth, departing from historical experience.

Article Information

Article History:
Received: 14-08-2025
Revised: 15-05-2026
Accepted: 28-06-2026

Keywords:
Economic Structural Transformation, Sectoral Employment Share, Sectoral Value-Added Share, Sectoral Growth Rate, and Sub-Saharan Africa

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INTRODUCTION

As economies advance, the service sectors, including trade, transportation, finance, education, health, and personal and business services, tend to have an increasing share of employment and value-added (Duarte & Restuccia, 2020). Factors such as urbanization, the rise of the digital economy, and demand for personal and business services have contributed to the growth of the service sector (Inklaar et al., 2021). Globally, the interactions and the feedback between the employment and the value-added shares of the main sectors continue to influence the nature of structural transformation across countries. The shares of employment and value-added in industrial sectors have revealed heterogeneous patterns of growth and decline across countries (Mokri et al., 2024). In developing and developed economies, the service sector's value-added and employment shares have steadily increased (Duernecker & Herrendorf, 2022). Therefore, understanding the evolving dynamics of sectoral employment and value-added shares remains vital for policymakers in designing strategies to enable integrated and smooth structural transformations and inclusive growth, which are critical for sustained economic development. Additionally, economic structural change in Africa is an active area of inquiry, as many countries on the continent are facing the transition from largely agrarian to more industrial and service economies.

The shifting patterns and relative shares of employment and value-added across different economic sectors are critical parts of this transformation. The share of employment in the agricultural sector in Africa remains quite high and has yet to decline at a sluggish rate suggested by historical experience in other developing regions (Diao et al., 2018). Factors such as land reforms, investment in agricultural infrastructure, and the expansion of non-agricultural employment opportunities have shaped the pace of the decline of agricultural employment in Africa (Jayne et al., 2018). The employment and value-added shares of the industrial sector in Africa have exhibited mixed trends, with some countries experiencing growth and others seeing a decline (Diao et al., 2017). Manufacturing has seen its share of employment and value-added decline owing to low productivity, poor competitiveness, and the expansion of the service sector (Rodrik, 2015). In policy and investments that attempt to promote industrialization, the degree of success in different African countries fluctuates rapidly and strongly (Haraguchi et al., 2017).

The service sector, which includes trade, transportation, finance, education, healthcare, and other services, continues to grow its employment and value-added shares in African economies (Duarte & Restuccia, 2020). This sector's growth often brings about high-productivity and high-wage service industries, while also leading other sectors to outsource various activities (Mensah & Szirmai, 2018). These sectors' employment and value-added shares keep influencing the structural transformation process across different African countries.

In many African countries, agriculture accounts for a higher percentage of both employment and value-added production than in other sectors (Diao et al., 2018). The employment and value-added shares of the industrial sector have been subject to more diverse trends, as they increased for some countries but declined for others (Diao et al., 2017). In Africa, the service sector shows an increasing trend in terms of employment and value-added shares among most economies, while varying in growth pace.

The speed and patterns of structural transformation in Africa are still largely determined by natural resource endowments, trade policies, technological progress, and institutional changes (Diao et al., 2020).

A closer examination of the changing patterns in sectoral employment and value-added shares helps policymakers in Africa to craft policies that can support inclusive, sustainable structural transformations needed for economic development and poverty reduction on the continent.

Structural transformation process in Africa's economy is uneven, where manufacturing is losing its traditional role, the agricultural sector continues to exert a dominant influence, and there has been accelerated growth of services. In sub-Saharan Africa, the structural transformation has been occurring at an uneven pace, with some sectors (e.g., agriculture) still accounting for a large share of employment and others (e.g., industry) having failed to experience expansion, which would have promoted labor absorption in tune with rapid population growth rates (Diao et al, 2018). Such uneven transformation has raised questions with regard to inclusive and sustainable economic development in the region.

The manufacturing sector in Sub-Saharan Africa has frequently lost its role both as a source of employment and value-added due to low productivity, lack of competitiveness, and the spread of the service economy (Rodrik, 2015). Inability to industrialize and develop a strong manufacturing base limited the scope for job creation and productivity growth in the region (Diao et al., 2017).

The theoretical review underscores the main themes and frameworks used to analyze how sectoral employment and value-added shares affect structural transformation in the sub-Saharan African economy. Extensive theoretical and empirical work has been devoted to analyzing structural transformation in developing economies (Herrendorf et al., 2014). Structural change refers to the movement of economic activity from less productive sectors, such as agriculture (Diao et al., 2018), into more productive activities, including industry and services. The theoretical frame postulates that this is a fundamental mechanism of economic development and productivity growth.

Movements in the structure of employment by sector and the distribution of the value added by sector are seen as key indicators of the process of structural change. The importance of different sectors, as measured by their employment and value-added shares, indicates the underlying pattern of economic diversification and specialization. Theory models suggest that if labor and capital are reallocated across sectors, this can produce productivity gains and economic growth (Azenui, 2024).

The productivity gaps among sectors are thought to be significant drivers of structural transformation (Duarte & Restuccia, 2020). Theories suggest that the movement of resources from low-productivity to high-productivity sectors can enhance overall economic productivity.

This contributes to economic development (McMillan & Rodrik, 2011). Additionally, Diao et al. (2018) support these claims. The effects of technological change, institutional factors, and policy interventions on influencing sectoral productivity are also emphasized in theoretical literature. These elements shape the pace of structural transformation.

Specific country and regional contexts are the major concepts that are brought into the theoretical frameworks. It should be said that this is a must in grasping the patterns and dynamics exhibited by structural transformation. Elements (natural resource endowments, trade policies, institutional quality, and demographic changes) have an impact on the process of structural transformation in sub-Saharan African countries (Diao et al., 2020), including such contextual factors in the assessment results in a more comprehensive and detailed analysis of the structural transformation and its multifaceted nature. Providing this quality information in analysis can bind the required comprehensive understanding of the complexity and multifariousness observed in sub-Saharan African countries (Jayne et al., 2018).

The recent studies have investigated the pattern of sectors' employment and value-added share in the sub-Saharan African economy. The measures of sectoral employment and value-added shares of the sub-Saharan African countries and their implications for structural conversion are discussed (McMillan et al., 2017). It is reported that labor has been unevenly moved out of the agriculture, industry, and service sectors, and in some cases, the "premature deindustrialization" phenomenon in African economic structures has been a result of this (Mensah & Szirmai, 2018).

The heterogeneity in productivity growth and the ability to draw in investment and manufacture high-quality jobs have been identified as the main factors in the structural transformation process. This has been discussed by Martins (2019) and Diao et al. (2020).

Academic inquiries are providing information about the impact of differential productivity in different economic sectors, mainly responsible for structural transformation in sub-Saharan Africa (Mensah & Szirmai, 2018).

The research found that the undying of mega productivity differences between agriculture and non-agricultural sectors has stopped the proper reallocation of resources, but also slowed down the overall structural transformation (McMillan & Rodrik, 2011). The consequences of technology improvement, infrastructure building, and regulation on enhancing productivity are being studied (Diao et al., 2020).

Research has highlighted the importance of considering various country and region-specific environments when investigating both the process and ongoing changes of structural transformation in sub-Saharan Africa (Mensah & Szirmai, 2018). The impact of factors such as natural resource abundance, trade openness, institutional quality, and demographic changes on the rates and the course of structural transformation has been proven as well (McMillan & Harttgen, 2017). In fact, the policy interventions such as agricultural modernization, industrial development, and human capital investments, which shape structural transformation, have also been examined empirically (Diao et al., 2020).

Empirical studies underscore the critical role of structural transformation in propelling productivity growth and overall economic advancement in sub-Saharan Africa (McMillan et al., 2014). Research indicates that reallocating resources from low to high productivity sectors can yield substantial enhancements in aggregate productivity and economic expansion. Moreover, studies have explored the connections between structural transformation, job generation, and poverty alleviation that underscore the pivotal role of the structural change process in promoting inclusive development (Martins, 2019).

Empirical review synthesizes the latest research findings on the effects of sectoral employment and value-added shares on structural transformations in sub-Saharan African countries. The existing literature on the relationship between the employment share of different sectors and structural transformations in Sub-Saharan African (SSA) countries has produced conflicting results. The study conducted by Diao et al (2018) found that the shift of labor from agriculture to industry and services has played a substantial role in promoting economic growth across 39 SSA countries. However, the study also highlighted the sluggish pace of this transformation, which can be attributed to the absence of a robust manufacturing sector and the prevalence of the informal economy in SSA.

Azenui (2024) explored shifting patterns of structural change across African countries and observed that the transition of labor from low-productivity sectors did not consistently propel. They assert that the absence of a coherent industrial policy and the occurrence of falsifications in factor and product markets have impeded the structural transformation in these nations. Additionally, Diao et al. (2020) delved into the impact of public investment on catalyzing structural change in SSA countries. Their analysis suggests that increased public investment in infrastructure and capital can redistribute labor from low- to high-productivity sectors, thus escalating the process of structural transformation.

The empirical evidence regarding the impact of sectoral employment shares on structural transformations in SSA countries is varied across countries. Some studies underscore the significance of labor shifts from agriculture to industry and services, while others stress the influence of public and policy interventions in the speed and nature of structural change.

The current body of literature regarding the correlation between the value-added share of sectors and structural transformations in Sub-Saharan African (SSA) nations indicates that the distribution of value-added among various sectors can profoundly influence the rate and nature of structural transformation. Diao et al. (2018) conducted a study that analyzed the influence of structural change on economic growth in 39 countries in Sub-Saharan Africa (SSA). The study found that the growth of the industrial and services sectors' value-added share has been a significant contributor to economic growth. The authors claim that reallocating from lower-productivity to higher-productivity industries and services can expedite the process of economic transformation.

A study conducted by Azenui (2024) explored the structural changes in the SSA region. The results of the study revealed that a higher proportion of value-added in the manufacturing sector is associated with accelerated economic growth. Through the development of a strong manufacturing base, low-productivity labor can be redirected towards higher-productivity activities, therefore promoting transformation and allowing for faster growth.

The study conducted by Diao et al. (2020) investigated how public investment influences the composition of value-added among various sectors in countries located in SSA. The study concluded that more public investment in infrastructure and human capital can make it easier to move resources to sectors with higher productivity, altering the shares of value-added across sectors and facilitating the process of transformation.

Generally, the empirical evidence indicates that the distribution of value-added among various sectors, notably the growing proportion of value-added in industry and services, is a pivotal factor influencing economic transformations in Sub-Saharan African (SSA) countries. Moreover, strategic public investment in essential sectors can profoundly impact the distribution of value-added across industries, thereby influencing the speed and nature of economic structural transitions.

Statement of the Problem

Agriculture continues to be a major source of employment in Sub-Saharan Africa. The employment share of the agricultural industry in Sub-Saharan Africa is experiencing a slower decline when compared to other developing regions. Approximately 60% of all employment is agriculture-related, according to Diao et al. (2018). However, agriculture is not expected to remain the primary employment source in the future.

The service sector is growing significantly in employment and value-added shares in Sub-Saharan African economies (Duarte & Restuccia, 2020). The growth of the service sector can be a sign of economic development and the transformation of the labor force, but it is not clear if the jobs created in the service sector are all high-quality or highly productive jobs.

It is critical to recognize the importance of employment and value-added share for the establishment of sound policies that can foster inclusive and sustainable structural transformation in the region. These concerns are also key factors if sub-Saharan African countries are to achieve more balanced and equitable economic development that provides better and more productive jobs while improving overall living standards.

This study intends to understand the relationship among changes in the shares of employment and value added by the sectors and their effect on the overall process of structural transformation. With the aim of understanding these issues, this study contributes to a deeper understanding of the dynamics of structural transformation in sub-Saharan Africa and provides lessons for policymakers and development actors who are interested in how to develop more effective strategies to promote more inclusive and sustainable economic growth in the region.

Research Questions

1. What is the real effect of sectoral employment share and value-added share on economic structural transformation?
2. How do sectoral employment share and value-added share work on economic structural transformation?
3. Do they boost each other's effects?

MATERIALS AND METHODS

Description of Study Area and Data Source

This study considered SSA countries and their economic structural transformation, employment, and value-added share. Structural Transformation Database, which is entirely provided by means of GGDC (Groningen Growth and Development Center), annually releases sector-based records for 21 African countries from 1990 to 2018 for twelve industries. The last two years (2019 and 2020) data are forecasted using the moving average method. Of the 21 nations, 18 are grouped in SSA countries. Therefore, these 18 nations can be used as a sample for 46 Sub-Saharan African (SSA) countries. The sample countries are shaded in Figure 1, which covers around 47% and 63% of the sub-Saharan population and GDP, respectively (Carraro & Karfakis, 2018).

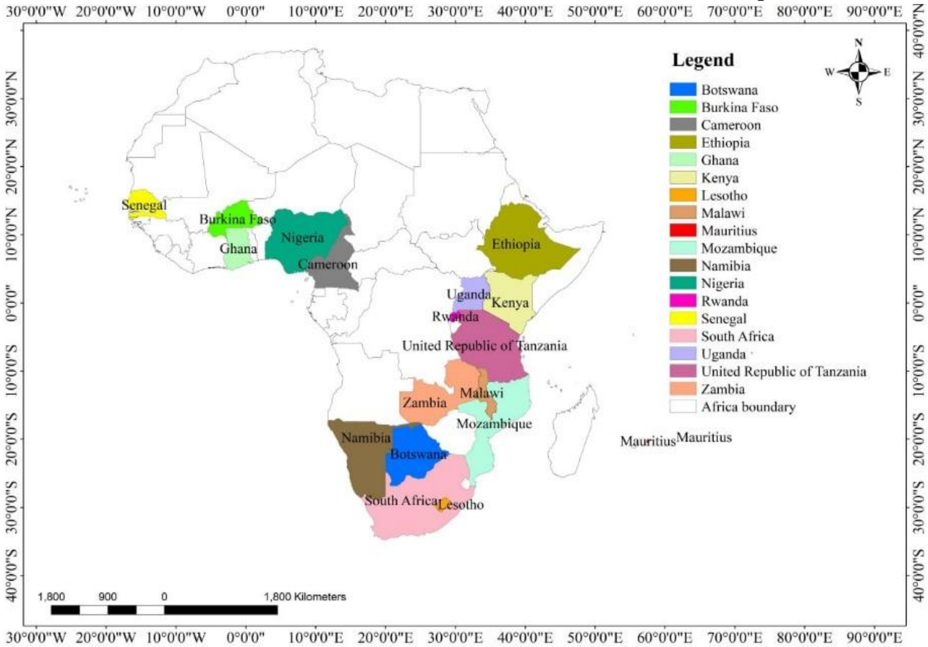

Figure 1. *Study area coverage*

This study categorizes industries into four sectors (agriculture, manufacturing, non-manufacturing, and service) and uses annual panel data ranging from 1990 to 2020. Predominant motives for choosing this period are: the period has experienced relatively continuous growth, and it has the longest uninterrupted data for the countries. Additionally, waves of globalization have reached most of the developing nations, which is the driving force of contact among the SSA and the relaxation of the arena. Other necessary data are gathered from international database centers like World Development Indicators (WDI), World Bank (WB), and Penn World Table. Countries are selected in the sample based on data availability. The conceptual framework is presented in Figure 2.

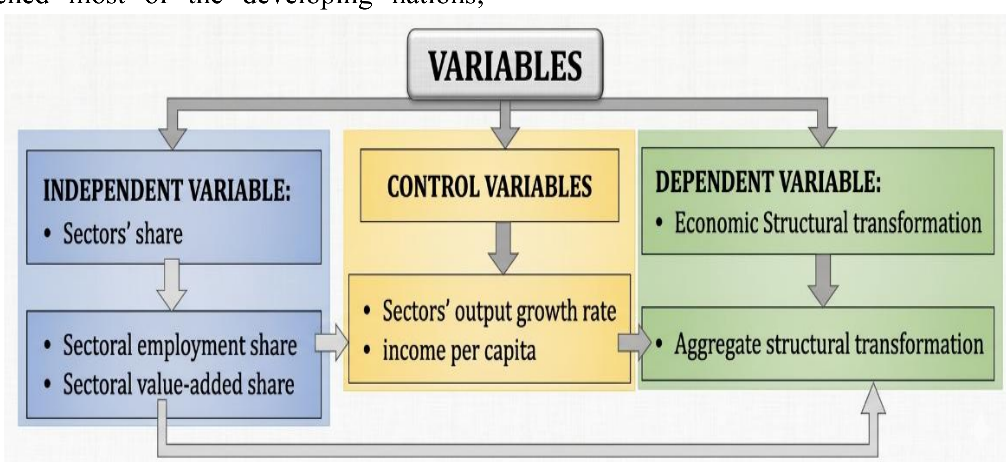

Figure 2. *Conceptual framework*

Method of Data Analysis

Econometric model specification: This research is designed to use the n-sectors disaggregation criterion for economic structural transformation appraisal. McMillan et al (2014) and De Vries et al. (2012) conducted economic transformation by using the method of shift-share analysis.

Aggregated labor productivity as well as labor share are separated into the sectors. Employment size (L) and amount of output value-added (Y) across sectors are assimilated by dividing the sectoral expressions by aggregate employment and output, respectively:

$$\sum_{i=1}^{n}\frac{L_{ict}}{L_c}=\frac{L_{1ct}}{L_c}+\frac{L_{2ct}}{L_c}\cdots\frac{L_{nct}}{L_c}=\sum_{i=1}^{n}\delta_{ict} \quad (1a)$$

$$\sum_{i=1}^{n}\frac{Y_{ict}}{Y_c}=\frac{Y_{1ct}}{Y_c}+\frac{Y_{2ct}}{Y_c}\cdots\frac{Y_{nct}}{Y_c}=\sum_{i=1}^{n}\theta_{ict} \quad (1b)$$

Total employment and output value-added shares are represented by δ_{ict} and Θ_{ict} for i sectors in country c at time t, respectively. According to a United Nations study, aggregate employment is nothing but the sum of its constituents (UN, 2016).

Within the shift-share evaluation, potential productivity growth is divided into two forces: increases in labor productivity in capital-intensive sectors due to capital accumulation and technological progress, and the labor force shift from low-productivity sectors to high-productivity sectors (Carraro & Karfakis, 2018).

Let Y_{it} and E_{it} be output value-added and employment in the sector i at year t in a country, correspondingly. Total labor productivity level at time t for the entire economy (LP_t) can be expressed as the sum of each sector's labor productivity (LP_{it}) weighted by the share of the sector i, employment δ_{it}, then total productivity at time t is expressed as:

$$LP_t=\frac{Y_t}{E_t}=\sum_{i=1}^{n}\frac{Y_{it}}{E_t}=\sum_{i=1}^{n}\frac{Y_{i,t}}{E_{i,t}}\frac{E_{i,t}}{E_t}=\sum_{i=1}^{n}LP_{i,t}\delta_{i,t} \quad (2)$$

Between t and $t-1$ the output value-added per employee growth rate to the whole economy can be expressed in first-difference form as:

$$\frac{\Delta LP_{ct}}{LP_{ct-1}}=\sum_{i=1}^{n}\frac{Y_{cit}}{Y_{ct}}\left[\frac{\Delta LP_{cit}}{LP_{cit-1}}\right]+\sum_{i=1}^{n}\left[\frac{LP_{cit}}{LP_{ct}}\right]\Delta\delta_{cit}+\sum_{i=1}^{n}\left[\frac{LP_{cit}}{LP_{ct}}\right]\left[\frac{\Delta LP_{cit}}{LP_{cit-1}}\right]\Delta\delta_{cit} \quad (3)$$

Where LP_{ct} and Y_{ct} is aggregate labor productivity and aggregate value-added at time *t* for country *c*, respectively. LP_{cit}, Y_{cit} and δ_{cit} are labor productivity, value-added, and employment share of sector *i* at time *t* for country *c,* respectively.

In this study, we exploited Panel Corrected Standard Error (PCSE) to obtain estimates that reconcile the time dimension, which is greater than the cross-sectional dimension, and minimize heteroskedasticity, cross-sectional dependence, and the endogeneity problem (Eboiyehi & Ikpesu, 2017; Chen et al., 2010).

This empirical appraisal used three stages of analysis: first, by using equation 3, we construct the total structural transformation for each sample country, which is employed as the dependent Variable. Secondly, to explore the interrelation and correlation among sectors' employment, value-added shares, and structural changes in Sub-Saharan African (SSA) countries, the subsequent econometric model is employed, which is proposed by Diao et al. (2020).

$$TST_{ct}=\beta_0+\sum_{i=1}^{4}\omega_i\,EPSH_{ct}+\sum_{i=1}^{4}\theta_i VASH_{ct}+\alpha X_{ct}+\mu_c+\lambda_t+\varepsilon_{ct} \quad (4)$$

Here, TST_{ct} signifies the indicator of total structural transformation in country *c* at time *t*. $EPSH_{ct}$ represents the array of employment share across different sectors (e.g., agriculture, manufacturing, non-manufacturing, and services) in country *c* at time *t*. $VASH_{ct}$ Signifies the array of value-added shares across different sectors in country *c* at time *t*. X_{ct} comprises a range of control variables that might impact structural transformation. μ_c is country-specific fixed effects to manage time-invariant, unobserved country characteristics influencing changes. λ_t represents time fixed effects to accommodate common shocks or trends that are affecting the structural transformations across all countries. ε_{jt} is the error term. The critical parameters are ω and θ, which assess the sectoral employment and value-added shares' effect on structural changes in countries. A positive and statistically significant coefficient for a sector's employment or value-added share would suggest that the share in that sector is linked to more pronounced structural transformations.

Thirdly, to examine the relationship of structural transformation and income per capita as non-linear and to contain what arises as income per capita increases, equation 5 is used following (Mijiyawa, 2017). More profound changes could take place among nations that compete in the lower rankings. Equation (5) is the one that captures how income per capita is related to that of structural transformation (TST).

$$\ln(\mathrm{TST})_{\mathrm{jt}} = \alpha + \beta_1 \ln(\mathrm{TST})_{\mathrm{jt-1}} + \beta_2 \ln(\mathrm{income})_{\mathrm{jt}} + \beta_3 \ln(\mathrm{income})^2_{\mathrm{jt}} + \delta_j + \tau_t + \varepsilon_{\mathrm{jt}}$$

$$\text{where; } \mathrm{E}[\delta_j] = E[\varepsilon_{\mathrm{jt}}] = E[\delta_j \varepsilon_{\mathrm{jt}}] = 0 \qquad (5)$$

δ_j,τ_t and $\varepsilon_{\mathrm{jt}}$ are unobserved country-specific effects, time-effects, and error terms, respectively. When the classical modality of structural transformation is conserved, β_2 it is positive and β_3 is negative, which indicates that the transition of labor from the traditional to the modern sector has occurred. This econometric model is computed using panel data methodologies like fixed-effects, random, or PCSE regression, depending on data assumptions, and crucial to robustness checks to address potential endogeneity concerns or consider alternative metrics of structural transformation to ensure the credibility of the results.

RESULTS AND DISCUSSION

Descriptive Result

The graphs in Figures 3 - 5 compare the mean of the sectoral value-added share, employment share, and sectoral output growth rate across sample countries, respectively.

Figure 3 demonstrates bar charts that provide sectoral value-added share and total structural transformation for sample countries. These statistics show the portion of the country's GDP added by specific industries.

AGVASH (Agricultural Value Added Share) refers to the percentage of GDP generated from agriculture. Highly AGVASH countries (e.g., Ethiopia) are more agriculturally reliant, while low AGVASH countries like Seychelles have more diversified economies. MAVASH (Manufacturing Value Added Share) refers to the percentage of GDP generated from the manufacturing sector. Countries like Senegal and Ethiopia have higher MAVASH, with more industrialized bases compared to others like Seychelles. NMAVASH (Non-Manufacturing Value Added Share) is the proportion of GDP from non-manufacturing activities, for instance, construction and mining. Botswana and Zambia have large NMAVASH, likely from mining activities. SEVASH (Service Value Added Share) captures the proportion of GDP from services, including finance, education, health, and tourism. Seychelles and Mauritius have large SEVASH values, capturing service sector-dominated economies.

TOTST (Total Structural Transformation) refers to the degree of structural transformation in an economy, a reallocation of resources from low-productivity sectors (e.g., agriculture) to higher-productivity sectors (e.g., manufacturing and services). Negative TOTST reflects limited structural transformation or reliance on traditional sectors.

Figure 4 shows the bar charts of sectoral employment shares and overall structural transformation (TOTST) in various countries. The variables are described below, and what they represent. These metrics reflect the proportion of employment in various sectors in a country.

AGEMP_SH (Agricultural Employment Share) is the share of total employment in agriculture. Large agricultural employment shares in Rwanda, Mozambique, and Ethiopia indicate subsistence agriculture dependence and minimal diversification into the other sectors. Lower AGEMP_SH values (e.g., South Africa) indicate economies that have transitioned from agriculture to industry and services.

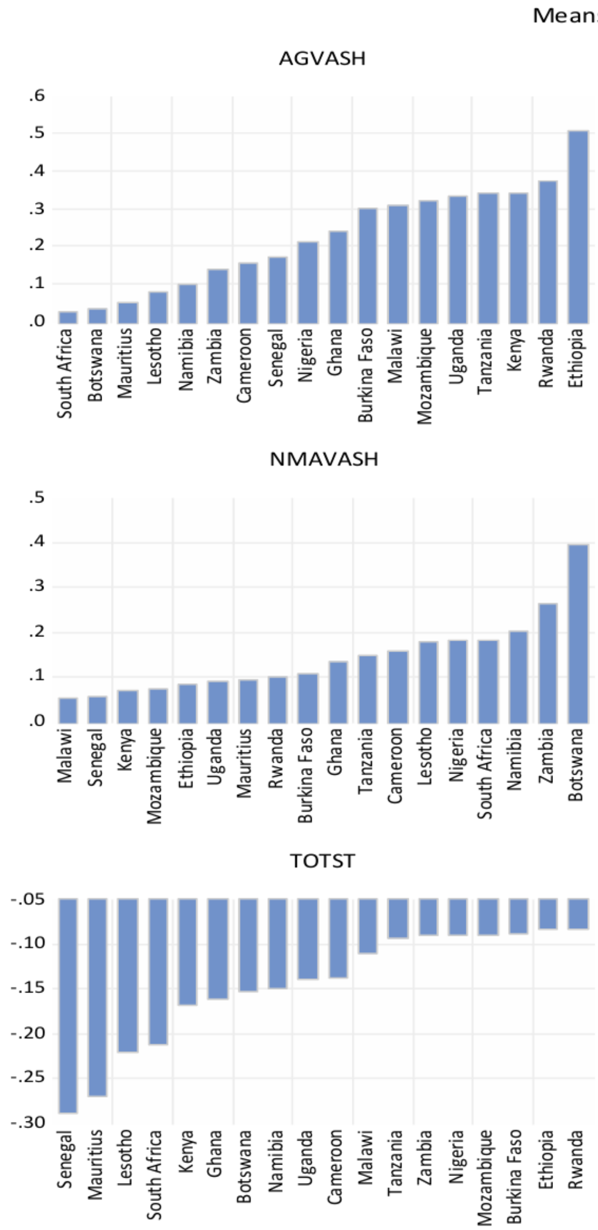

Figure 3.*The mean of sectoral value added-share from 1990 to 2020 across sample countries*

N.B: AGVASH=agricultural value added share; MAVASH=manufacturing value added share; NMAVASH= nonmanufacturing value added share; SEVASH=service value added share and TOTST= total structural transformation

MAEMP_SH (Manufacturing Employment Share) is the proportion of employment within manufacturing industries. High manufacturing employment shares in countries such as Mauritius and South Africa point toward some degree of industrialization and a more established manufacturing base. Conversely, low levels of MAEMP_SH, as seen in Rwanda, are associated with low industrialization or minimal manufacturing activity.

NNMAEMP_SH (Non-Manufacturing Employment Share) is the proportion of employment in non-manufacturing sectors, including mining, construction, and utilities. South Africa has the largest NNMAEMP_SH, likely due to its extensive mining and construction industries. In contrast, nations like Rwanda and Mozambique have lower rates of NNMAEMP_SH, indicating minimal engagement in the non-manufacturing industry.

SEVEMP_SH (Share of Service Employment) calculates the percentage of total employment in services like finance, education, health, tourism, etc. South Africa and Mauritius have high SEVEMP_SH values, showing service sector-led economies. Low SEVEMP_SH values (e.g., Ethiopia) indicate economies still rooted in agriculture or in less-developed service economies.

TOTST (Total Structural Transformation) measures the degree of structural transformation in an economy by tracking shifts in employment across industries. It calculates progress in transition from lower-productivity sectors (e.g., agriculture) to higher-productivity sectors (e.g., manufacturing and services). Negative TOTST values (e.g., Senegal) indicate no structural transformation or stagnation in diversification within the economy.

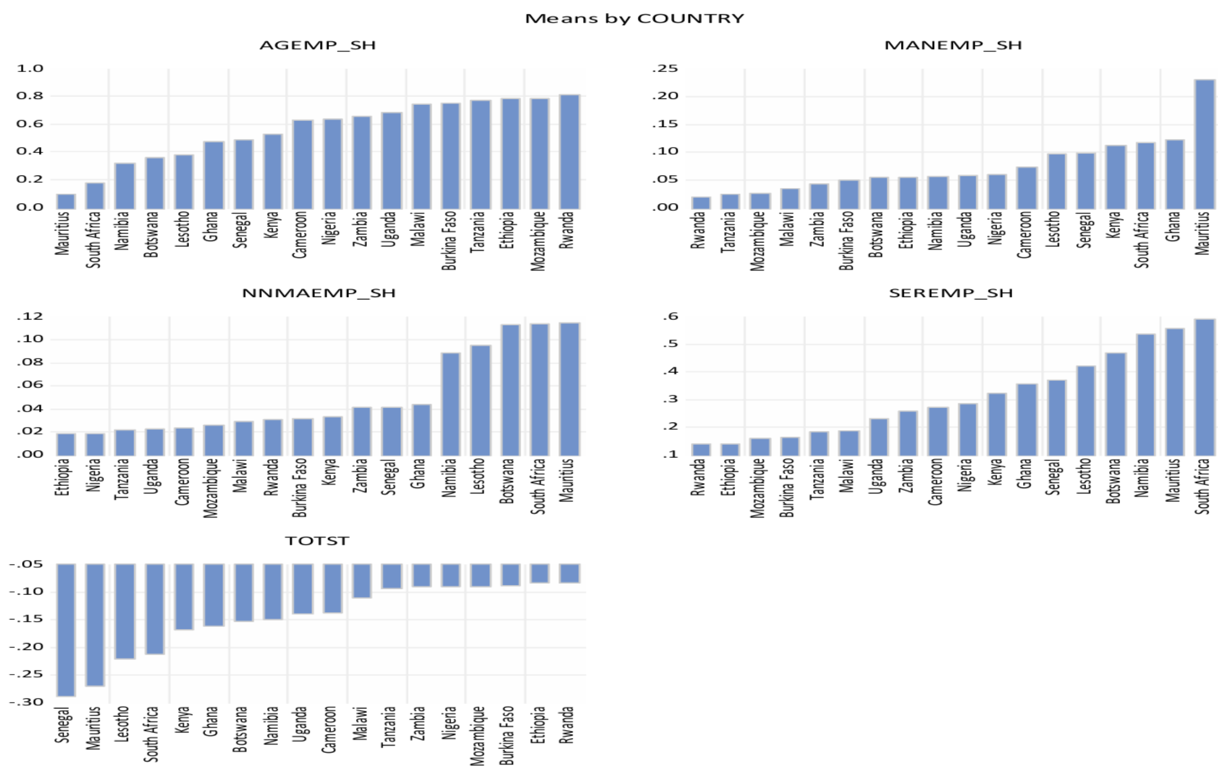

Figure 4. *The mean of sectoral employment share across sample countries from 1990 to 2020*

N.B: AGEMP_SH=agricultural employment share; MAEMP_SH=manufacturing employment share; NNMAEMP_SH=nonmanufacturing employment share; SEVEMP_SH=service employment share; and TOTST= total structural transformation.

Countries that have high AGEMP_SH are less structurally transformed as they rely on agriculture. Higher values of MAEMP_SH and SEVEMP_SH indicate economies transitioning towards industrialization and service-driven growth. TOTST is a significant measure of economic development—countries with high values of TOTST are experiencing a substantial shift towards productive sectors.

Figure 5 presents average output growth rates in agriculture, manufacturing, non-manufacturing, and services for different countries included in the sample, with the measure of overall structural transformation (TOTST) included on the chart. Higher values indicate growth gains in that sector, while TOTST likely measures the extent of a country's absence from agriculture (where a more negative TOTST value indicates more reliance on agriculture, and a positive value means less reliance on agriculture).

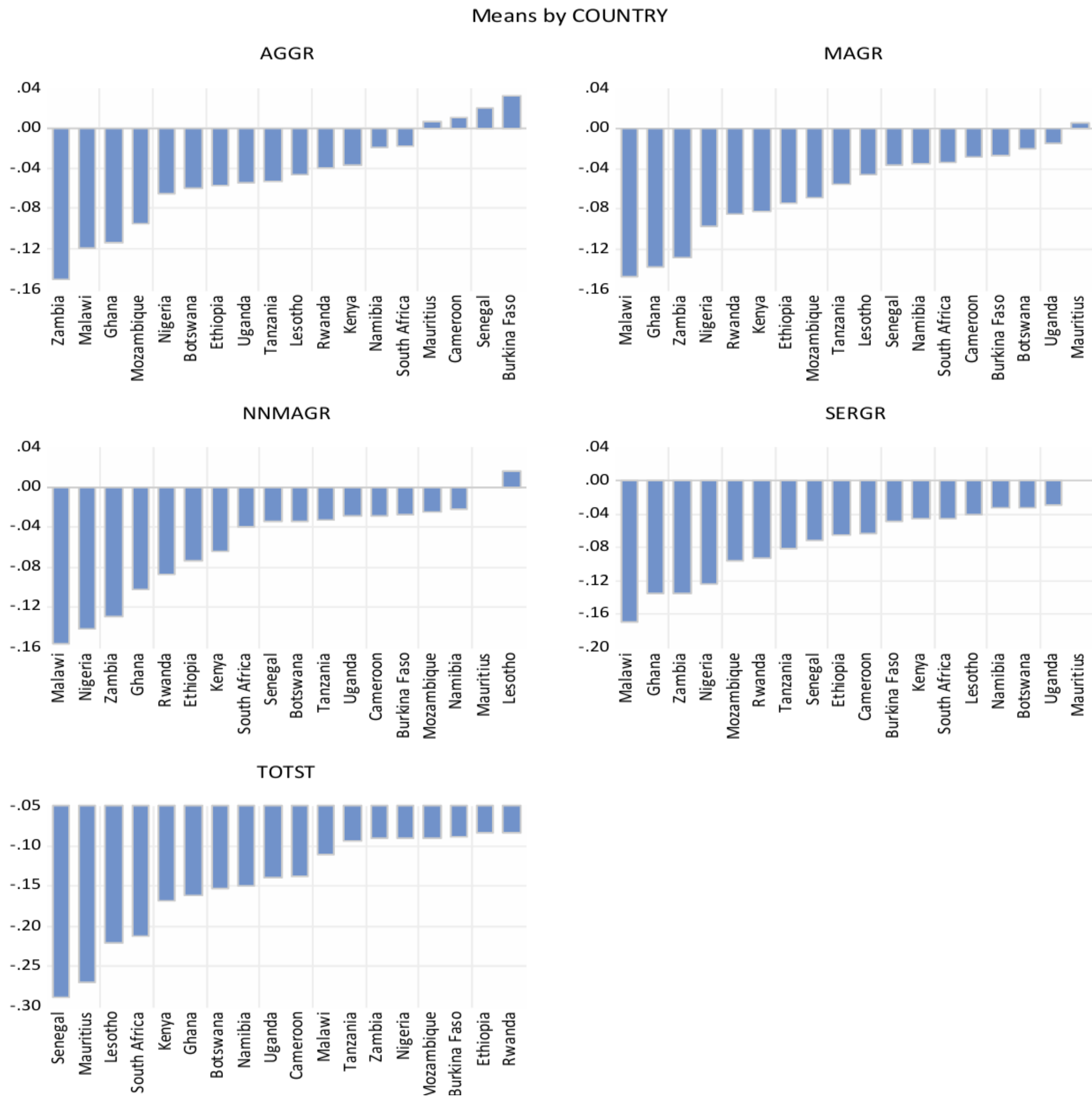

Figure 5. *The mean of the sectoral output growth rate across sample countries from 1990 to 2020*

Zambia and Malawi were seen to have the lowest values for mean in agricultural growth rates, while Burkina Faso and Mauritius had the highest. Ghana and Nigeria then have the lowest mean growth rates for manufacturing, while Mauritius exhibits the highest mean manufacturing growth rate. In contrast, Malawi and Zambia have the lowest growth rates for non-manufacturing, while Lesotho presents the highest mean rate for growth in this sector.

The average output growth rate for services was the lowest in Ghana and Malawi, whereas

Mauritius showed the highest mean growth rate for the service sector. Ethiopia and Rwanda have the highest values, with Senegal and Mauritius being the most negative TOTST values. Countries with a strongly negative TOTST that indicates persistent reliance on agriculture do not necessarily have low agricultural growth, with Senegal and Mauritius having negative TOTST scores while displaying high agricultural growth. This seems relevant for countries like Rwanda and Ethiopia, which have a much more balanced distribution of sectoral growth rates, with positive TOTST and Sectoral output growth rates.

Table 1

Descriptive of sectoral growth rate, value-added share, and employment share.

Variables	Mean	Maxi	Mini	sta.Dev	Skewness	Kurtosis	Jar-Bera	Pro	Sq.Dev
TOTST	-0.146	- 0.0245	-0.3718	0.0699	-0.7570	3.1740	52.2576	0.00	2.63
AGEMP_SH	0.5622	0.9491	0.0637	0.2292	-0.4729	2.2116	34.1074	0.00	28.31
MAEMP_SH	0.0742	0.3108	0.0088	0.0537	1.7831	7.2481	692.1922	0.00	1.555
NMAEM_SH	0.0503	0.1709	0.0023	0.0381	0.9198	2.6663	78.6421	0.00	0.784
SEREMP_SH	0.3132	0.6715	0.0397	0.1605	0.4628	2.2208	32.9389	0.00	13.879
AGGR	-0.047	0.9958	-0.6550	0.1590	0.0312	7.6809	493.0947	0.00	13.633
MAGR	-0.062	0.5190	-0.6167	0.1428	-0.3936	5.3805	141.4469	0.00	10.998
NNMAGR	-0.056	0.7276	-0.7387	0.1753	0.1692	5.3973	131.8817	0.00	16.572
SERGR	-0.073	0.6542	-0.6091	0.1498	-0.1568	5.6254	157.2938	0.00	12.087
AGVASH	0.2250	1.1990	0.0208	0.1491	0.8443	5.6704	224.5972	0.00	11.976
MAVASH	0.1184	0.9082	0.0261	0.0593	4.6952	59.7312	74398.72	0.00	1.898
NMAVASH	0.1429	0.9048	0.0205	0.0965	2.2939	12.4995	2503.995	0.00	5.015
SEVASH	0.5214	2.1701	0.2347	0.1120	5.8918	88.3786	167137.8	0.00	6.767

Studying the mean for the study period does not give critical information on the volatility of growth within a period. Various other considerations also influence structural transformation, government policies, investment, trade, and technology, among them. These graphs give a starting point for analysis; therefore, we need to add more contexts. In essence, these graphs show a bird's-eye view for comparing the performance of various sectors in different countries concerning a varied rate of economy-wide shift away from agriculture. The descriptive results are also shown in Table 1. In SSA from 1990 to 2020, the employment share in agriculture, service, manufacturing, and non-manufacturing is 56.22%, 31.32%, 7.42%, and 5.03%, respectively. All sectors' growth rates are negative. The value-added shares in the service sector, in agriculture, in non-manufacturing, and in manufacturing are 52.14%, 22.5%, 14.29% and 11.84%, respectively.

Correlation and Variance Inflation Factors (VIF) analyses

The panel correlation analyses for sectoral employment share, value added share, and growth rate are significantly correlated to each other and structural transformation. Brief results of this are demonstrated in Table 2.

Table 2 displays how the variables are related, mostly about employment shares, value-added shares, and growth rates for various sectors in Sub-Saharan Africa. It is basically a snapshot of which sectors move together and which ones do not, pulled from a typical econometric structural change. We have variables like agricultural employment share (AGEMP_SH), changes in manufacturing employment share (D.MAEMP_SH), non-manufacturing and service employment shares, plus value-added shares (AGVASH, MAVASH, NMAVASH, SEVASH) for each sector. Then there are also sectoral growth rates (AGGR, MAGR, NNMAGR, and SERGR). Table 2 just shows how much each pair of those variables moves together. If you're looking at the diagonal, it always has 1—each thing is perfectly correlated with itself. Nothing is weird there. Some relationships jump out. For instance, agricultural and service employment shares have a strong negative link (-0.9753). When jobs leave agriculture, they show up in services—a classic sign of economies shifting toward modern sectors. The value-added shares for these two also move in opposite directions, though not as sharply (-0.3717). On the flip side, services and non-manufacturing often grow together. Look at the numbers: the link between service sector employment share and service value-added share is 0.5692, and non-manufacturing employment and value-added connect at 0.4541. So, those sectors are pulling in the same direction.

Sectoral growth rates for the different sectors are also tightly tied together. Manufacturing and service growth, for example, line up at 0.7684, and agriculture and services at 0.7217; this points out a sort of synchronized rise across sectors. By contrast, manufacturing employment shares and value-added don't explain sectoral growth as much—they're only modestly connected.

Table 2

Correlation analysis among independent variables

Var	1	2	3	4	5	6	7	8	9	10	11	12
1	1											
2	0.154	1										
3	-0.8682	-0.1376	1									
4	-0.9753	-0.1363	0.8187	1								
5	0.7555	0.1833	-0.739	-0.759	1							
6	-0.3758	-0.0522	0.2602	0.3169	-0.1994	1						
7	-0.2869	-0.1053	0.4541	0.3193	-0.4358	0.078	1					
8	-0.5507	-0.1385	0.451	0.5692	-0.3717	0.6181	0.2496	1				
9	-0.1504	0.124	0.0782	0.1573	-0.0409	0.1385	-0.0119	0.1094	1			
10	-0.1736	-0.1233	0.1165	0.1862	-0.109	0.1125	0.0494	0.0916	0.7447	1		
11	-0.1508	-0.0301	0.1189	0.1513	-0.0767	0.1052	0.0854	0.0560	0.5884	0.729	1	
12	-0.2021	0.0818	0.153	0.2094	-0.0966	0.1037	0.0816	0.1017	0.7217	0.7684	0.6785	1

N.B: the variables are 1= agricultural employment share (AGEMP_SH); 2= differenced manufacturing employment share (D.MAEMP_SH); 3= non-manufacturing employment share (NNMAEM_SH): 4= service sector employment share (SEREMP_SH); 5= agricultural value added share (AGVASH); 6= manufacturing value added share (MAVASH): 7= non-manufacturing value added share (NMAVASH): 8= service sector value added share (SEVASH); 9= agricultural growth rate (AGGR); 10= manufacturing growth rate (MAGR); 11= non-manufacturing growth rate (NNMAGR) and 12= service sector growth rate (SEGR).

Mainly, we want to make sure our model doesn't get tripped up by variables moving in lockstep—multicollinearity can mess up the math in regression analysis. Generally, most values are well below the usual red-flag zone (around 0.8 or 0.9) besides those strong negatives between agriculture and the rest, which, honestly, back up the structural change story. Nothing outside the diagonal goes over 0.98. Therefore, we can safely include these variables as independent variables in the model. The differenced manufacturing employment share (D.MAEMP_SH) breaks up some connections, which gives us an extra cushion. If you want to be doubly sure, running VIF tests in Stata is our next step.

Table 3 shows VIF values for 12 variables. The VIF value for AGEMP_SH sits at 46.28, and

SEREMP_SH at 33.96—numbers so high can destroy any trust in the model. But the mean VIF comes out to 9.14, which only backs up the point: multicollinearity runs throughout the predictors.

Table 3

VIF for the multicollinearity test

Variable	VIF	1/VIF
AGEMP_SH	46.28	0.021607
SEREMP_SH	33.96	0.029446
NNMAEMP_SH	6.58	0.152076
MAGR	4.16	0.240443
SERGR	3.16	0.316672
AGVASH	2.89	0.346251
AGGR	2.8	0.35694
SEVASH	2.47	0.404054
NNMAGR	2.33	0.428596
MAVASH	2.15	0.46521
NMAVASH	1.67	0.599768
D.MANEMP_SH	1.27	0.786924
Mean of VIF	9.14	

VIF tracks how much variance inflation comes from highly correlated predictors. If VIF is above 5 or 10, we are already in trouble. In this case, the numbers mount to three to five times that limit. So the coefficients bounce around unpredictably, and the standard errors are too large. Look at the tolerances for AGEMP_SH and SEREMP_SH, which are 0.022 and 0.029, respectively. That means each explains 97–98% of the other's variance. They are basically measuring the same thing—employment share in agriculture and services—with an almost perfect linear relation.

The correlated predictors bring on the multicollinearity, with coefficients that become meaningless for inference, prediction, and/ or policymaking. That is why we use the lagged values for these variables. With a mean VIF of over nine, you can count on biased and unreliable estimates.

Panel Unit Root Test

Table 4 presents the common panel unit root test results for the total structural transformation, sectoral growth rate, sectoral employment share, and sectoral value-added share variables. Thus, this result shows that the total structural transformation (TOTST), non-manufacturing employment share (NMAEM_SH), and non-manufacturing value-added share (NMAVASH) have a unit root at the level. This is because the probability value of these variables is greater than 0.05. Therefore, one can accept the Variable has a root and reject the alternative (the Variable has no root). All other sectoral variables do not have a unit root and are stationary at the level. This is because all the probability values of these variables are less than 0.05; thus, one can have a chance to reject the null that says the variables have a unit root.

The process of individual panel unit root test for sectoral employment share, value added share, and sectoral growth rate is depicted in Table 5. The result shows total structural transformation, and all sectoral employment shares have a unit root at the level. Additionally, except for the Agricultural value added share, the other sectoral value added shares have a unit root at the level. This is because the p-value for these variables exceeds 0.05. This implies one can accept the null hypothesis, which says "the variable has a unit root".

Table 4

Common panel unit root test for employment share, value added share, and growth rate.

Methods	series	Statist	Pro.	Obser	Methods	series	Statist	Pro.	obser
	TOTST	-0.6189	0.268	504		D(NMAEMP_SH)	-11.9184	0.000	504
	D(TOTST)	-11.1471	0.00	494		SEREMP_SH	-2.3216	0.0101	506
	AGR	-16.5265	0.00	520		AGVASH	-2.22396	0.0131	504
	MANGR	-12.9373	0.00	520	Levin,	MAVASH	-2.30965	0.0105	504
Levin, Lin	MAGR	-13.4111	0.00	517	Lin	D(MAVASH)	-6.51173	0.0000	486
& Chu t	SERGR	-11.9462	0.00	519	& Chu t	NMAVASH	-0.67967	0.2484	509
	AGEMP_SH	-4.1478	0.00	505		D(NMAVASH)	-16.0775	0.0000	496
	MAEMP_SH	-2.8439	0.002	508		SEVASH	-2.25185	0.0122	518
	NMAEMP_SH	0.4075	0.658	506		D(SEVASH)	-18.8709	0.0000	501

Note: Null: assumes common unit root process, Newey-West automatic bandwidth selection, and Bartlett kernel

All sectoral growth rate variables (agricultural, manufacturing, non-manufacturing, and service sector) have no unit root that is stationary at the level. This is because, across the three methods, the p-values for these variables are all less than 0.05, even 0.01, thus one can reject the null hypothesis.

Table 5

Individual panel unit root tests for employment share, value added share, and growth rate

Method	Series	Statist	Pro.	Series	Statistic	Pro
		1.3462	0.9109		-11.7590	0.0000
	agemsh	39.9934	0.2973	magr	197.718	0.0000
		38.7878	0.3451		191.678	0.0000
		-10.7422	0.0000		-11.9892	0.0000
	d(agemsh)	183.742	0.0000	nmgr	202.566	0.0000
		195.465	0.0000		223.736	0.0000
		1.4061	0.9202		-11.9166	0.0000
	maemsh	30.1187	0.7438	segr	200.627	0.0000
		30.5670	0.7244		225.031	0.0000
		-8.1523	0.0000		-0.3880	0.3490
	d(maemsh)	140.517	0.0000	agvash	54.3613	0.0254
		162.979	0.0000		82.8616	0.0000
		1.4930	0.9323		-0.4975	0.3094
	nmaemsh	32.8113	0.6210	mavash	48.2169	0.0838
		21.3137	0.9752		51.0805	0.0492
Im,Pesar and Shin						
W.st		-12.1525	0.0000		-9.41621	0.0000
ADF - Fisher Chi-sq	d(nmaem_sh	201.983	0.0000	d(mavash)	159.215	0.0000
PP - Fisher Chi-sq		199.521	0.0000		338.544	0.0000
		2.1728	0.9851		1.0115	0.8441
	serem_sh	31.5736	0.6791	nmavash	36.7489	0.4340
		28.5538	0.8069		36.3073	0.4543
		-8.5678	0.0000		-16.8281	0.0000
	d(seem_sh)	150.207	0.0000	d(nmavash)	295.398	0.0000
		194.009	0.0000		368.345	0.0000

Table 5 continues

	-15.5903	0.0000		1.2948	0.9023
aggr	270.012	0.0000	sevash	26.6016	0.8732
	277.135	0.0000		45.9797	0.1232
				-17.7369	0.0000
			d(sevash)	323.559	0.0000
				396.760	0.0000

Null: Unit root (assumes individual unit root), Newey-West automatic bandwidth selection, and Bartlett kernel

Cross-section dependence test

Table 6 presents the results from the Pesaran cross-sectional dependence (CD) test, which we applied to panel data covering 18 countries, with an average of about 31 observations per group. The null hypothesis is cross-section independence—meaning that, once we account for the model's structure, the countries are not contemporaneously correlated. If the p-value is very small (around 0.000 or well below typical cutoffs like 0.05), you reject the null of independence and conclude that there's substantial cross-country dependence. When the p-value is greater than 0.10, we cannot reject the notion of independence, at least according to this test.

Most variables have extremely small p-values (less than 0.05), so the CD test clearly rejects cross-sectional independence for much of the data. In other words, many variables show strong evidence of cross-sectional dependence. The implication is that these countries' outcomes are not acting independently. There are likely common global shocks, regional spillovers, shared measurement practices, or other broad factors affecting the countries at the same time.

But not every Variable shows this pattern. Manufacturing employment share, manufacturing value added share, and non-manufacturing value added share have higher p-values—you don't get strong evidence of cross-sectional dependence for these variables as you do for the others.

If you look at the size of p-values, CD statistics, and the absolute values of the correlations, the most pronounced cross-sectional dependence shows up for service sector employment share, agricultural employment share, and total structural transformation. Agricultural value-added share, service sector value-added share, and non-manufacturing employment share also show moderate levels of dependence. In these cases, not only is the dependence statistically detected, but the economic significance is plausible as well.

The overall pattern in the results is consistent, but interpretation needs to be careful. For many variables, we see that the CD test and correlation measures point the same way—strong rejection of independence lines up with large absolute correlations. Yet there are exceptions: for instance, manufacturing employment share, manufacturing value added share, and non-manufacturing value added share have higher p-values, so they don't reject independence, but their absolute correlations aren't consistently small (MANEMP_SH abs(corr)=0.597; NMAVASH abs(corr)=0.616). Since the panel is unbalanced, missing data might impact both the correlation calculations and the power of the CD test. That doesn't mean the test is wrong, but it does make robust checks more important; you may need to try alternative dependence tests or model-based diagnostics.

And keep in mind, the CD test here is applied to the variables themselves—not to regression residuals. Some papers run the test on variables like Table 6; others use the residuals from an initial model. Dependence in explanatory variables doesn't automatically mean residual dependence, but it's a strong sign that pooled estimation methods, which assume independence, may not be well specified.

Given that most variables show p-values of 0.000, cross-sectional dependence is a modeling issue you shouldn't ignore. Use estimators that are robust to cross-sectional dependence, and avoid leaning on methods that assume independence across countries unless you've clearly dealt with it (for example, avoid basic pooled OLS with standard errors that rely on independence). Consider including common factors or time dummies to account for shared shocks, as long as this fits with your overall model.

Table 6
Average correlation coefficients & Pesaran cross-section dependence (CD) test

Variable	CD-test	p-value	corr	abs(corr)
TOTST	37.92	0.000	0.56	0.736
AGEMP_SH	52.32	0.000	0.772	0.793
MANEMP_SH	1.21	0.228	0.018	0.597
NNMAEMP_SH	17.75	0.000	0.262	0.574
SEREMP_SH	50.02	0.000	0.738	0.856
AGVASH	24.82	0.000	0.366	0.583
MAVASH	-1.16	0.247	-0.017	0.447
NMAVASH	1.72	0.085	0.025	0.616
SEVASH	29.45	0.000	0.435	0.541
AGGR	15.35	0.000	0.227	0.272
MAGR	17.11	0.000	0.252	0.296
NNMAGR	12.73	0.000	0.188	0.248
SERGR	15.79	0.000	0.233	0.262

Notes: Under the null hypothesis of cross-section independence, CD ~ N (0, 1), Group variable: countries id, Number of groups: 18, Average Number of observations: 31, Panel is unbalanced

In short, the Pesaran CD test provides strong evidence of cross-sectional dependence for most variables in Table 6 (with p-values close to zero for employment and value-added shares and growth rates). Country-level variables are likely to move together due to common global or regional shocks. Only a handful of variables—manufacturing employment share, manufacturing value added share, and the borderline case of non-manufacturing value added share—don't show statistically significant CD at usual significance levels. Because dependence is so widespread, methods assuming cross-sectional independence aren't suitable—they rely on CD-robust techniques.

Omitted variable test

Table 7 expresses the link test results—a standard test that researchers use to show issues like missing variables or a model that doesn't fit the data well. Here is what actually happens: we plug our model's fitted values (_hat) and their squared version (_hatsq) into a new regression. If the original model is strong, _hat should be significant, showing it explains the outcome, and _hatsq should not mean you are not missing weird nonlinearity.

Now, looking at the numbers, the F statistic is very high (948.66) with a p-value basically zero. This confirms that the fitted values generally explain the outcome very well. But the spotlight's on _hatsq is that, its p-value comes in at 0.249, comfortably above 0.05. The test doesn't pick up any signs that our model is missing important non-linear relationships or variables.

To dive into the details, _hatsq's coefficient is 0.4424, standard error 0.3830, t-value 1.16—not remotely significant, as the squared fitted value is not adding anything to the model. Meanwhile, _hat itself is clearly significant, which is exactly what we want—our predictions connect directly to the dependent Variable.

The link test presents that our model is in good shape—_hat is significant, _hatsq isn't. That is the pattern of our aim for, and it signals our specification works, at least by this test's standards. No warning signs about missing non-linear effects or key variables.

Don't get too comfortable, though. The link test tells us if there's a general issue, not what or where the problem is. It doesn't catch everything. Case in point: Table 6 showed cross-sectional dependence, something the link test simply cannot diagnose. Even if our model passes here, you might need to use methods like CD-robust estimators to deal with those dependency problems.

Also, keep in mind that the t-tests rely on standard error assumptions. If our data's messy—say, clustering, uneven variances, or serial correlation—you should use robust standard errors for the link test.

Thus, Table 7 shows the model passes the link test—_hat is significant, _hatsq isn't (p = 0.249), and fitted values match the outcome well. But model checking doesn't stop here. Always support our choices with sound theory and additional diagnostic tools, especially if earlier results point to deeper trouble. The link test is a robust starting point, not the final word. Note these tests detect misspecification (e.g., omitted variables, nonlinearity) but cannot identify specific omitted variables; add suspects based on theory and retest.

Table 7

Link test for model specification or omitted variables test

Source	SS	df	MS	Number of obs = 522		
Model	1.9927	2	0.9964	F(2, 519) =948.66		
Residual	0.5451	519	0.0011	Prob > F =0.000		
Total	2.5378	521	0.0049	R-squared = 0.7852		
				Adj –R squ = 0.7844		
				Root MSE =0.0324		
TOTST	Coefficient	Std.err.	t	P>|t|	[95% conf. interval]	
_hat	1.1454	0.1280	8.95	0.000	0.8940	1.3968
_hatsq	0.4424	0.3830	1.16	0.249	-0.3100	1.1949
_cons	0.010128	0.0095	1.07	0.287	-0.0085	0.0288

Endogeneity test

To predict 'vhat' (error term) and to hold the endogeneity test, first, we ran a regression on manufacturing growth rate (MAGR) as the dependent Variable and all others as independent variables. After we predict 'vhat', we use it as an independent variable and TOTST as a dependent variable. It is a two-step approach. First, I ran a regression with the manufacturing growth rate (MAGR) as the dependent Variable—threw in all the predictors, grabbed the residuals, and labeled them 'vhat'. The thinking is that if there is any lingering endogeneity, those residuals will pick it up.

Next, I took those 'vhat' values and used them in a second regression—this time with TOTST as the dependent Variable. The setup is all there in Table 8. I used a Prais–Winsten regression with panel-corrected standard errors (PCSE). The rule is simple: if 'vhat' turns out significant, then we've got an endogeneity problem. If not, we're on the safe side.

Looking at Table 8, 'vhat' is not doing anything interesting—its p-value lands at 0.705, nowhere near significant. So, those residuals aren't affecting the results, and we don't see any sign of endogeneity.

The rest of the model looks good. The Wald test is highly significant (Prob > chi2 = 0.000), and we've got an R-squared of about 0.8395 that has a strong explanation of the variation in the data. The model also controls for AR (1) panel-specific autocorrelation, and with PCSEs, the estimates hold up. Other variables also check out. Since 'vhat' isn't significant, the main coefficients aren't hiding any endogeneity.

Table 8

Endogeneity test using TOTST as the dependent Variable and vhat as the independent Variable

Group variable: could			Number of obs = 522			
Time variable: year			Number of groups = 18			
Panels: Correlated (balanced)			Obs per group: Min = 29			
Autocorrelation: panel-specific AR(1)			Avg =29			
			Max = 29			
Estimated covariances = 171			R-squ = 0.8395			
Estimated autocorrelations = 18			Wald chi2(12) = 1499.72			
Estimated coefficients = 13			Prob > chi2 = 0.000			
		Panel-corrected				
totst	Coefficient	std..err	z	P>|z|	[95% comf	interval]
AGEMP_SH	0.2028	0.1032	1.97	0.049	0.0005	0.4051
L1. MANEMP_SH	0.1046	0.1118	0.94	0.349	-0.1145	0.3238
L1. NMAEMP_SH	-0.4600	0.1001	-4.6	0.000	-0.6562	-0.2639
SEREMP_SH	-0.0668	0.1078	-0.62	0.536	-0.2781	0.1445
AGVASH	-0.0533	0.0137	-3.91	0.000	-0.0801	-0.0266
MAVASH	-0.0470	0.0435	-1.08	0.28	-0.1323	0.0383
NMAVASH	0.1773	0.0176	10.09	0.000	0.1429	0.2118
SEVASH	-0.0043	0.0159	-0.27	0.787	-0.0354	0.0269
AGGR	0.0259	0.0088	2.94	0.003	0.0087	0.0432
NNMAGR	0.0067	0.0059	1.16	0.246	-0.0047	0.0184
SERGR	-0.0285	0.0095	-2.99	0.003	-0.0472	-0.0099
vhat	-0.0099	0.0260	-0.38	0.705	-0.0609	0.0411
_cons	-0.2296	0.1014	-2.26	0.024	-0.4283	-0.0309
Rhos =	0.9592	0.9184	0.8659	0.7830	0.764 ... 0.8344	

That said, this all banks on 'vhat' genuinely capturing any endogeneity. If the instruments are weak or I missed something in the first-stage regression, the residuals might miss some details. Moreover, Table 6 is used for CD tests, which still show a lot of cross-sectional dependence, and some of that might survive, even with PCSEs. But honestly, based on Table 8, endogeneity just isn't showing up in the TOTST regression. The 'Vhat's' z-score is -0.38 with a p-value of 0.705. The model explains most of the story, and we feel pretty confident about the results.

Table 9 shows another test for whether hidden links might skew results - specifically checking if 'vhat' could be tied to errors. A value appears: chi² (1) = 0.14, alongside a chance-like figure, Prob > chi² = 0.7045. When peering into such biases, one idea stands out - if 'vhat' holds the piece of randomness linked to predictors, its presence should shift outcomes when bias exists. Seeing it fall flat statistically hints that this path may not distort findings - at least how 'vhat' took shape here. It turns out, the data shows little reason to doubt that 'vhat' equals zero. With a p-value of

0.7045 for Prob > chi², things look quite stable. That number sits well beyond typical cutoff points like 5% or even 10%. So here's what stands clear - there's more than enough support for sticking with 'vhat' equal to zero. One way to look at it is that the numbers don't show hidden bias messing up the link we checked. That odd bit meant to act like what 'vhat' stands for - doesn't seem tied to changes in TOTST here. So chances are low that whatever slipped out of view, the kind "vhat" tried to catch, pushed those results around after all.

Looking at Table 8, the number tied to 'vhat' didn't matter much. Then comes Table 9, which shows a similar result. Once you adjust using the fixed term, any hint of skewed influence fades away.

Stability shows up in how the regressors link to economic structural change, which shows no sign of distortion from simultaneity or missing factors sneaking through the 'vhat' path. Even though earlier tests flagged cross-sectional ties across several variables, robust methods still matter when drawing conclusions. While Table 9 tackles endogeneity using 'vhat', depending on it alone won't fix every issue tied to interdependence.

Evidence in Table 9 weakens concerns about hidden influences. Testing the idea that 'vhat' equals zero leads nowhere - results show chi² (1) is just 0.14, p sits at 0.7045. From an economic standpoint, patterns suggest 'vhat', used here as a stand-in for such biases, fails to distort the TOTST relationship consistently. So, as long as this kind of distortion matters, its mark on our model's estimates appears minimal.

Table 9

Test 'vhat' endogeneity

The null hypothesis states that Vhat = 0
chi2(1) = 0.14
Prob > chi2 = 0.7045

Sectoral employment share, value added share, and total Structural Transformation

The sectoral employment shares, sectoral output growth rates, and value added shares are applied as independent variables, and economic structural transformation is taken as the dependent Variable for the model. The model results are displayed in Table 10. In this model, we are interested in controlling for cross-panel correlation and autocorrelation using linear regression with panel corrected standard errors (PCSE). Thus, let's estimate panel-specific autocorrelation parameters and change the method of estimating the autocorrelation parameter to the one typically used to estimate autocorrelation in time-series analysis. Beck and Katz (1995) make a case against estimating panel-specific AR parameters, as opposed to one AR parameter for all panels.

Economic dynamics are influenced by sectoral employment shares, which have a significant impact on productivity, growth trajectories, and labor market efficiency. In Table 10, regression coefficients indicate that changes in employment across different sectors, such as agriculture, manufacturing, and services, influence or restrict outcomes, with indications and magnitudes of structural transformation.

Expansionary effects on economic structural transformation are indicated by the positive values for agricultural employment share, non-manufacturing value-added share, agricultural growth rate, and manufacturing growth rates. Economic structural transformation is accelerated by a 1% increase in employment share, value added share, and growth rate, which links directly to generated output and backward linkages caused by labor-intensive activities multiplied by input demands. The negative coefficients of non-manufacturing employment share, service sector employment share, and agricultural value added share, and service growth rate are indicative of contractionary pressures, which can intensify dualism in developing economies as labor absorption in low-productivity sectors overshadows high-value activities. This is exacerbated by the lack of demand for services in manufacturing industries.

Table 10

Effect of sectoral employment share, value added share, and growth rate on total Structural Transformation.

Group variable: countries id				Number of obs = 522		
Time variable: year				Number of groups = 18		
Panels: Correlated (balanced)				Obs per group: min = 29		
Autocorrelation: specific AR(1) panel- specific				Avg = 29		
				Max = 29		
Estimated covariances = 171			R-squ = 0.8278			
Estimated autocorrelations = 18			Wald chi2(12) = 1349.93			
Estimated coefficients = 13			Prob > chi2 = 0.000			
		Panel-corrected				
tst	Coefficient	std..err	z	P>|z|	[95% conf interval]	
AGEMP_SH	0.1503	0.0592	2.5400	0.0110	0.0344	0.2663
L1. MANEMP_SH	0.0329	0.0659	0.5000	0.6180	-0.0963	0.1621
L1.NNMAEMP_SH	-0.5012	0.0752	-6.6600	0.0000	-0.6487	-0.3538
SEREMP_SH	-0.1122	0.0674	-1.6700	0.0960	-0.2443	0.0198
AGVASH	-0.0566	0.0149	-3.8000	0.0000	-0.0858	-0.0274
MAVASH	-0.0546	0.0453	-1.2100	0.2280	-0.1433	0.0341
NMAVASH	0.1842	0.0177	10.4000	0.0000	0.1495	0.2189
SEVASH	0.0023	0.0158	0.1400	0.8870	-0.0288	0.0333
AGGR	0.0194	0.0031	6.2400	0.0000	0.0133	0.0254
MAGR	0.0133	0.0046	2.8700	0.0040	0.0042	0.0224
NNMAGR	0.0024	0.0027	0.9100	0.3650	-0.0028	0.0076
SERGR	-0.0371	0.0036	-10.2600	0.0000	-0.0442	-0.0300
_cons	-0.1813	0.0576	-3.1500	0.0020	-0.2941	-0.0684
rhos =	0.9449	0.8956	0.8706	0.8696	0.7669 ...	0.8255

Employment multipliers enable inclusive growth in labor-surplus economies as a result of increasing agricultural shares. Manufacturing negative effects are a manifestation of Baumol's cost disease, where inactive productivity leads to an increase in shares, which then deprives labor of vital services and limits potential output. Modernization and trade integration contribute to the positives of services, but over-reliance exposes us to automation shocks. Higher per capita income after reallocation is correlated with higher positive levels, while negative levels increase inequality in the structural sense. The positive elasticity of the wholesale/retail highlights the recovery from the consumption-led deindustrialization, while the manufacturing sector faces the challenge of managing import competition.

Empirical robustness is evident in control for endogeneity, resulting in stable coefficients (t-statistic>2.5) where positive values are maintained across specifications, but negative values weaken with skill controls, suggesting that human capital plays an active role in controlling. Other critical views include the omission of reallocation frictions (such as double adjustment times and other potential problems with search costs) along with the presence of context bias and high levels of general validity (R^2 >0.75).

Policy makers can focus on incentives such as agriculture and infrastructure bonds to allocate labor across these sectors. Counter the negative effects of labor through active labor policies, such as re-skilling skilled workers through service shifts and unemployment buffers to mitigate shocks. Invest in multipliers like utilities/transport. A tax system that prioritizes long-term growth in low-productivity shares, promotes diversity and decreases inequality, and employs annual employment surveys to adjust dynamically to prevent the occurrence of Dutch disease and commodity negative income.

Income growth and structural transformation in SSA

Studying the relationship of structural transformation and income per employment growth variables is useful to express the relationship of structural transformation and income per employment non-linearly, and also important to evaluate the conventional relationship between income per employment and structural transformation in the SSA economy.

Effects of income level on total structural transformation are demonstrated in Table 11. Based on the model result, the first difference of total structural transformation (D (TST) and income per employment square (IN_SQ) has a significant positive consequence on aggregate structural transformation. The income per employment ln(INP_EM) has a significantly negative result on aggregate structural transformation. The interpretation of the coefficients implies that a unit rise in the first difference of total structural transformation (D(TST)) and income per employment square (IN_SQ) results in an increase of 0.508492 and 0.011943 units, respectively. To the contrary, a unit escalation in the income per employment (LN (INP_EM)), there is a reduction of 0.274266 units in total structural transformation. In addition, if all the independent variables in this model reduce to zero, the total structural transformation is equal to 1.4173 units.

Since income per employment square has a positive coefficient and income per employment has a negative coefficient, the expected classical relationship of structural transformation and income per employment is violated.

The theory states that as income per employee increases exponentially, structural transformation should be reduced. But this study result shows us that as income per employment increases exponentially, structural transformation should also increase. Thus, the relationship between structural transformation and income per employment in the SSA economy is different from that in developed countries. And it does not follow the classical conversional path of structural transformation in the SSA economy.

This normality test result is shown in Figure 6. The p-value of this test is 0.0783, which is higher than 0.05. Based on this result, one can accept the null and reject the alternative hypothesis. These imply that the residuals are normally distributed.

Table 11

Effect of income level on total structural transformations

Dependent Variable: total structural transformation (TST)
Methods: Panels EGLS (Cross-sections SUR)
Cross-sections weight (PCSE) standard error & covariance

Variables	Coefficients	Std. Errors	t-Statist	Pro.
D(TST)	0.508492	0.015750	32.28561	0.0000
LN(INP_EM)	-0.274266	0.002142	-128.0194	0.0000
IN_SQ	0.011943	9.61E-05	124.2581	0.0000

Table 11 continues

C	1.417329	0.011985	118.2558	0.0000
	Weighted-Statistics			
R-sq	0.977996	Mean dependent var		-31.89251
Adj R-sq	0.977863	S.D. dependent var		66.49400
S.E. of regressions	0.996910	Sum squared resid		496.9144
F-statist	7407.548	D-W stat		1.362407
Pro(F-statist)	0.0000			
	Unweighted-Statistics			
R-sq	0.043268	Mean dependent var		-0.147850
Sum sq resid	2.337708	D-W stat		0.015006

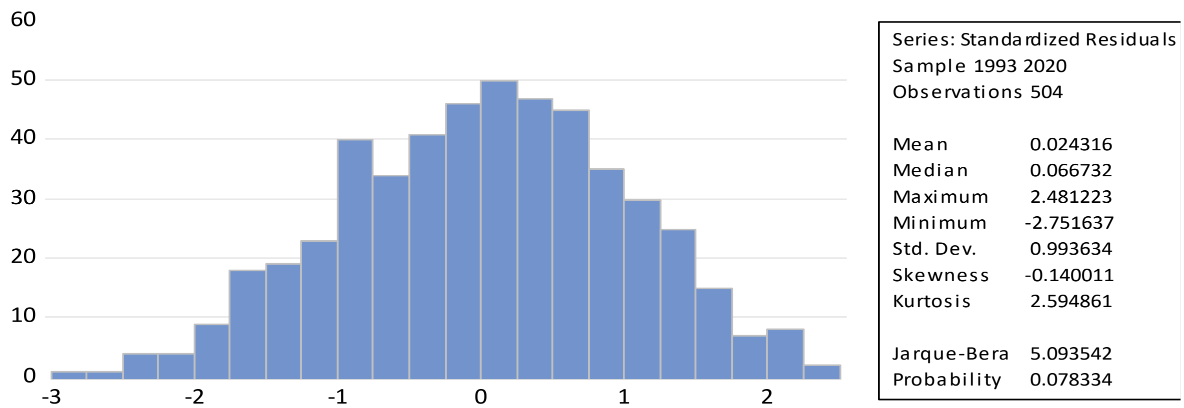

Figure 6. *Normality test for the model of income level effect*

In this model, values of Breusch-Pagan LM, Pesaran scaled LM, and Pesaran CD tests are important to test the cross-section dependence test, and their values are 25.0644, -7.3136, and 0.2854, with their corresponding p-values are 1.00, 0.00, and 0.7753, respectively. Thus, the null hypothesis (no cross-section dependence) is accepted by the Breusch-Pagan LM and the Pesaran CD test. Since these two tests accept the "no cross-section dependence" hypothesis, it implies that the residuals have no cross-section dependence at this stage.

Discussion

The results of this research indicate that, in SSA, structural transformation is complicated and does not necessarily conform to the traditional pattern of movement from agriculture to industry and then to services. While, as per conventional theory, structural transformation is usually linked with increased industrial output and a fall in agricultural employment, the findings of this research show that certain sectoral employment and value-added shares are related to structural change in ways that depart from what is expected. This supports current research from Africa (McMillan et al., 2014) indicating that change in the area is happening in conditions of low industrialization, growing informal services, and ongoing dependence on agriculture.

One key conclusion from this study is that the proportion of people working in agriculture is linked to how much the economy changes over time. This seems to go against the conventional wisdom that structural change should be followed by a smaller proportion of workers employed in agriculture. But according to more recent research, agriculture still plays a key role in job absorption, rural life, and productivity catch-up in many

African countries; hence, its link with transformation is not always negative in the short run (Jayne et al., 2018). From this perspective, the outcome might indicate that nations with bigger agricultural sectors are still in the early stages of transformation when agricultural modernization and redistribution from low-productivity agriculture remain major drivers of change (McMillan et al., 2011).

Another important conclusion is the bad influence of service-sector employment on structural transformation. While in many developed countries services are linked with modernization and high productivity, in sub-Saharan Africa, the development of services usually takes place in low-productivity, informal, and non-tradable sectors like personal services and small trade. This helps to explain why a rise in employment in the service sector might not always correspond to more profound economic change. Haraguchi et al. (2017) find evidence supporting the theory that, rather than a sign of actual productivity improvement, service-led growth in Africa may occasionally be a symptom of early deindustrialization.

The outcome for manufacturing value added is furthermore quite important for interpretation. The negative relationship between manufacturing value-added share and structural transformation indicates that in the selected nations, manufacturing has not yet evolved into the major driver of structural change predicted by conventional development theories. This supports research indicating that SSA's manufacturing sector still suffers from poor competitiveness, small size, and inadequate connections to the larger economy (Haraguchi et al., 2017). Manufacturing is theoretically expected to drive productivity growth and employment absorption, but in many SSA nations, its real impact is still limited due to infrastructural constraints, policy inconsistencies, and structural bottlenecks (Azenui, 2024).

Conversely, the positive link between agricultural value-added share and structural transformation implies that in SSA, growth in agricultural productivity may still be a major road to transformation. This supports the idea that in low-income African countries, increasing agricultural productivity can start the process of change before significant labor migration into industry is feasible (Jayne et al., 2018). Although these industries do not always provide widespread employment increases (Mensah & Szirmai, 2018), the positive impact of non-manufacturing value added may also reflect the role of construction, mining, and utilities in supporting GDP growth and sectoral upgrading.

The weight of the empirical data in this analysis tends to support the idea that in sSSA, structural transformation is erratic, path-dependent, and strongly influenced by sector-specific productivity variations. The results contradict the perfect theoretical model in which labor flows easily from agriculture to high-productivity services and industry. Rather, they favor more recent theoretical justifications stressing the need for sectoral productivity, institutional quality, public investment, and country-specific circumstances in influencing the transformation process. Policy thus ought to concentrate on raising productivity inside agriculture, boosting manufacturing competitiveness, and guaranteeing that service-sector growth generates useful and official employment rather than just on moving labor out of agriculture.

CONCLUSIONS

The structural changes in SSA are complicated and not "automatic". The research finds that in sub-Saharan Africa, economic structural change is unpredictable and path-dependent; it does not always follow the traditional development model of labor moving cleanly from agriculture → manufacturing → modern services. The discussion stressing low industrialization, informality, and ongoing agricultural reliance, as well as the study's empirical findings revealing sectoral impacts typically straying from theoretical predictions, help to support this directly.

Agriculture is still intimately related to structural transformation- A major finding is that total structural transformation (TOTST) has a strong positive correlation with the share of agricultural employment (AGEMP_SH). This implies that in SSA, a bigger agriculture labor base is still linked with observable structural change (in the short/observed panel period), which is in line with the argument that agriculture continues to have roles in job creation, rural life, and possible productivity catch-up, instead of just shrinking as modernization happens. Furthermore, supporting the more general interpretation in the debate is the study's discovery that the agricultural value-added share (AGVASH) has the opposite sign (negative in the reported model results): structural change may be occurring without agriculture always transforming into higher value-added production.

Manufacturing seems to have little importance in the transformation of the economy and can be limited. This research finds that structural change is much hampered by the manufacturing value-added share (MAVASH). The debate sees this as proof in the sampled SSA nations, manufacturing has not yet developed into the main engine of change expected by classical structural-change theories—mostly as a result of factors including competitiveness, low scale, few connections, and structural/infrastructure constraints. On the other hand, the estimated results show that the manufacturing growth rate (MAGR) is positive and significant, which means that manufacturing could grow, but this might not lead to more structural change through value-added share (or the share of manufacturing value-added might be moving in ways that don't match with the transformation).

Employment in services might show how low-productivity "informal service" is growing. According to the study, a higher share of service sector employment (SEREMP_SH) strongly slows down the process of structural transformation. This fits the argument that in SSA, service-sector expansion may sometimes occur in low-productivity, informal, and non-tradable industries (e.g., small commerce and personal services); a rise in service employment does not always signal modernization or productivity-led transformation. Simultaneously, service value-added share (SEVASH) is statistically insignificant in the reported primary regression, therefore supporting that service employment growth is insufficient for transformation unless it is linked to increased productivity and more productive/regulated value-added structures.

While the non-manufacturing employment share may impede transformation, the non-manufacturing value-added helps it. Non-manufacturing value-added share (NMAVASH) has a big positive influence on structural change, the findings reveal. The debate connects this to the economic input of non-manufacturing industries, including building, mining, utilities, and connected GDP support. However, the share of employment in the non-manufacturing (L1.NNMAEMP_SH) shows a significant negative effect, which means that when labor is pulled into non-manufacturing industries, this may reflect low-quality labor absorption or sectoral dynamics that do not match productivity-enhancing reallocation.

Although not always, sectoral growth patterns are important. Estimates from the study point to the conclusion that structural change reflects sectoral growth rates, but with the varied directionality: the agricultural growth rate has a positive and significant impact; the manufacturing growth rate has a positive and significant impact; the non-manufacturing growth rate (NNMAGR) is not significant; the service sector growth rate has a negative and significant impact. This strengthens the arguments that in SSA, "growth" in the sector can happen under circumstances when strong productivity differences, informality, and poor structural linkages persist, particularly when the high-productivity transformation is not assured.

Income per worker violates the established pattern of structural change. The research finds that the accepted traditional link between income per employment and structural change is violated. Particularly, the income-per-employment and its squared term generate indications and significance implying that, in less developed settings, transformation does not follow the traditional transformation-income curve seen in more advanced countries. The debate views this as proof that, molded by limits, informality, and inadequate industrialization, SSA's structural shift takes a different course.

Recommendation

Policy makers and leaders have to start by seeing economic transformation as something that needs active steering, not just left to happen on its own. Because of this, never take it for granted that workers will automatically shift out of farming and into factories or newer service jobs. Instead, shape rules around what data shows works in each place, responding directly to local realities like widespread informal work or weak production systems - no universal model fits every nation's journey.

Began by boosting agricultural output - not because agriculture must fade, but because it can drive change. Put resources into better tools and methods in agriculture to lift both what they produce and how efficiently people work there. The data shows that more employment in farming is linked to broader economic shifts across sub-Saharan Africa, which suggests plowing ahead in agriculture helps overall progress. Shift focus toward selling more crops and strengthening supply lines so farms add value beyond simply giving people work. Remember this: even as economies grow, countryside plans should reflect that farming stays relevant - its role evolves rather than disappears.

Not just faster growth - better results matter most in making factories competitive. Policies should lift how much value comes from each product, along with connections across industries, instead of chasing bigger production numbers alone. Evidence points to one clear fact - the portion of value created by manufacturing barely helps overall economic change, sometimes even drags it down. Yet raw factory expansion does push gains forward, proving size isn't tied directly to deeper progress built on upgraded work. So what shifts next? Stronger firms come from better tools, easier funding paths, and wider markets. Power cuts slow things down. Bad roads add cost. Border delays hurt flow. Missing supplies break the rhythm. Fixing these opens space for local networks to carry more weight - turning mere output into meaningful gain, skilled roles, lasting strength.

Focus on reshaping how service industries grow - make sure growth leads to real jobs, not just informal work. Instead of letting low-efficiency, unregulated services dominate, back those with higher output that can compete beyond local markets. Evidence shows a rising portion of workers in services (SEREMP_SH) drags down total sector performance, suggesting many roles lack structure or global reach across SSA. That points toward fixing rules, boosting worker abilities, and lifting efficiency, especially in transport, digital services, business expertise, shipping coordination, and banking tasks. Growth should link closely to factory demands - imagine repair networks, supply tracking, or export advising evolving alongside production lines.

Using non-manufacturing value-added as a partner in the economic transformation (while monitoring employment quality) - just keep an eye on job quality there too. Instead of focusing only on making things, shift toward areas like transport or energy projects if they lift output per worker. Watch closely, though, since more people working outside manufacturing does not mean better jobs appear. Sometimes those roles pay less or lack stability even as numbers grow. That means backing investments in roads, power systems, or water networks makes sense - but only if workers gain solid positions. Push rules that block dead-end hiring masked as progress. Stronger norms protect gains when work moves away from production lines.

Manage labor reallocation actively (avoid shock-driven misallocation and low-quality job transitions). Moving people between jobs works better when programs help them step through change smoothly. It turns out how much work goes where connects deeply with gains and shifts - bumps along the route can slow everything down.

Correct for the "income–transformation" mismatch observed in SSA (break the classic model expectation)- step away from standard predictions. Instead of relying on old models linking structure change to earnings per worker, skip that forecast shortcut here. Look at how sectors boost output and reorganize value, not just rising incomes alone. Shape decisions through live assessments and ongoing checks. Track job distribution across industries, changes in each sector's contribution, plus growth speeds over time - to inform real-time policy updates. Change arrives unevenly because industries move at different speeds. When jobs shift, and output evolves, so should how rules adapt - timing matters more than design alone.

CRediT Authorship Contribution Statement

Alemu Ayele: Conceptualization, Methodology. Writing, Original Draft; **Jayamohan Manchakadavath:** Investigation, Resources, Data Curation, **Arega Shumetie:** Writing - Review & Editing, Supervision, Project administration

Declaration of Competing Interest

There was no conflict of interest.

Ethical Approval

This study does not involve human participants.

Data Availability Statement

Upon reasonable request, the corresponding author will provide the data.

Acknowledgments

The authors acknowledge the Agro-economics Department, Mattu University, Bedele, Ethiopia, for its cooperation and participation in the research.

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