GORTERIA ISSN: 0017-2294
2025 65(6)

DOI Link: https://doi.org/10.61586/CAeRo
Vol.65, Issue.6, Part.1, June 2025, PP. 2-28

The interplay between structural transformation and poverty alleviation in SADC. A value-added analysis per sector

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Received April 2025 Accepted May 2025 Published June 2025

ABSTRACT

How is structural transformation related to poverty reduction using a value-added analysis per Southern African Development Community (SADC) sector? SADC endures premature deindustrialisation and high poverty levels. The study investigated the gross domestic product value-added proportion in the manufacturing, service, agricultural, and industrial sectors. This study used a panel autoregressive and distributed lag to examine the relationship between structural transformation and poverty. The study's results indicated that the agricultural and manufacturing sectors were useful for poverty reduction in the short run. In the long run, however, the service and industrial sectors were found to be essential for reducing poverty. These findings indicate that the SADC must prioritise the efficient functioning of the agricultural, manufacturing, service, and industrial sectors for meaningful poverty reduction. It is suggested that the SADC craft robust policies for the service and industrial sectors, harness modern technology, and invest in research and development.

Keywords: economic growth; industrial development; poverty; structural transformation; sustainable development goals.

JEL Codes: E00; E60; I3; I32; L52

1. Introduction

The study examined the relationship between structural transformation and poverty reduction in the Southern African Development Community (SADC). SADC has 16 member states and was formed in 1980 to foster economic development, peace and security, growth, and alleviate poverty (Southern African Development Community, 2024). Poverty is a multidimensional aspect that includes a lack of access to education, health, water, and sanitation, among others (Zulkifli and Abidin, 2023).

The region is failing to reduce the high poverty levels. In 2019, in the region, 51% of the population was living in extreme poverty. It is projected that poverty levels will increase from 180.5 million to 209.8 million by 2043 (Le Roux, 2023). Structural transformation comprises a change from labour-intensive to capital-intensive processes in the agricultural, manufacturing, and service sectors, which eventually increases productivity, reduces poverty, and improves the socio-economic growth of any country (Habiyaremye, 2020; Tasneem and Aamir Khan, 2024).

The high poverty levels among SADC member states are caused by several factors, such as historical challenges, for example in South Africa the lack of access to land and productive resources, economic exploitation of labour by settler colonists, and apartheid-era discriminatory laws (Strauss, 2019); economic factors, such as low levels of industrialisation and political factors, such as poor levels of governance and high levels of corruption (Bonga, 2021).

SADC member states are experiencing sluggish structural transformation levels; the percentage of industry employment is less than 15%, falling far short of the targeted 30% by 2030 (SADC, 2024a). Structural transformation contributes to the reduction of poverty through a non-deterministic mechanism. As businesses expand and jobs are created; it is assumed that these jobs benefit the impoverished. They will earn an income and provide certain skills, goods and services (Abedmohisen, 2023). As a result, poverty decreases as individuals earn incomes and provide some remittances to support their families.
The SADC region has diverse policies and 26 protocols aligned with poverty reduction, including the SADC Regional Poverty Reduction Framework, the Protocol on Health 1999, and the Protocol on Education and Training 1997s among others (SADC, 2024b). Despite all these policies and protocols, the SADC member states still battle high poverty rates, manifesting as poor health and limited access to education (Martin, 2022). In 2023, in the Democratic Republic of Congo, 750 000 children lacked access to education owing to political instability (UNICEF, 2023). This may signal that the policies and protocols fail to address the high poverty levels in SADC. Enongene's (2023) researched structural transformation and poverty in Sub-Saharan Africa. However, the study did not include the SADC economies. To add more, Habanabakize

and Dickason-Koekemoer (2023) researched the role of industrialisation on employment and economic growth in South Africa and established that industrialisation positively impacted economic growth in South Africa. Although, the study focused on South Africa which is a member state of SADC, all other SADC economies were excluded. Therefore, despite other researchers such as Enongene's 2023; Habanabakize and Dickason-Koekemoer 2023) having researched on a similar subject matter, what remains unknown is the relationship between structural transformation and poverty in the SADC region especially from a sectorial analysis approach.

Therefore, the problem the SADC region faces is high poverty levels and low levels of structural transformation; thus, the study aimed to examine this relationship. Other objectives of the study are:

- to preview and describe the trends of the manufacturing, service, agricultural, and industrial sectors in the SADC region.
- to preview and describe structural transformation trends.

This study is crucial because SADC needs to increase its industrial capacity and reduce poverty which contributes to the vast inequality gap. The region must achieve the goal of poverty reduction by 2030. Failure by SADC to address structural transformation and high poverty levels can also affect the region's capacity to attain other Sustainable Development Goals (SDG), such as Good Health and Well-Being (Goal 3) and Decent Work and Economic Growth (Goal 8) (United Nations, 2024).

The three most used measures to examine structural changes at the sectoral level are value-added shares, employment value-added shares, and final consumption expenditure shares (Enongene, 2023; Herrendorf *et al*., 2014). To calculate the value-added share as a proportion of GDP, this study looked at value-added contributions in the manufacturing, service, industrial, and agricultural sectors for the SADC region.

The remainder of this paper is structured as follows: Section 2 presents theoretical and empirical reviews of the literature. The Lewis growth model is discussed in the theoretical section. The empirical discussion includes the effect of the agricultural sector on poverty reduction, and the role of the manufacturing sector and industrialisation on poverty. Section 3 is the research methodology. The findings and conclusions are presented in Sections 4 and 5, respectively.

2. Literature review

2.1 Theoretical literature review

This section presents the literature review. Section 2.1 presents the theoretical literature review and discusses the Lewis growth model. Section 2.2 provides a review of related literature.

Lewis growth model

In 1954 Lewis developed a model useful to explain structural transformation in developing economies (Dookeran, 2019). The model is based on a dual economy, which is a traditional/ agricultural and industrial/ modern economy. Any savings that accrue from the modern sector, if reinvested, ultimately lead to capital accumulation in the manufacturing sector of an economy (Habiyaremye, 2020). According to Habiyaremye (2020), the consequent growth in the capital-labour ratio encourages the transfer from the traditional sector to the modern manufacturing industry due to increased labour efficiency. The traditional sector's proportionate contribution to overall GDP eventually diminishes as modernisation accelerates and the service sector gains importance. The Lewis model suggests a development path in which economic growth is initially driven by the transfer of surplus labour from the agricultural to the manufacturing sector, resulting in structural transformation and modernisation of the economy (Agbenyo and Agbenyo, 2020; Schlogl and Sumner, 2020).

The Lewis model is crucial to this study as it assumes abundant or surplus labour in the agricultural sector; this is the case with several economies in the SADC region (SADC, 2024c). This surplus labour is not used since the people cannot offer their labour in the agricultural sector, resulting in them being exposed to poverty. It is worth noting that in the past, Africa’s labour shifted into the service sector rather than the industrial sector. This led to the premature deindustrialisation of African economies, such as South Africa, according to Rodrick (2016), Andréoni and Tregenna (2021), Asmal *et al*. (2023) and Heitzig and Newfarmer (2023).

2.2 Empirical literature review

The literature review is organised as follows: The first section discusses the impact of agriculture on poverty reduction, followed by a review of the literature on the impact of the manufacturing sector on poverty. The literature on the function of industrialisation in reducing poverty is presented next, followed by the importance of the service sector in alleviating poverty. The rationale for the several categories in this literature review is that it is important to arrange them around major areas that make diverse contributions to poverty alleviation. Furthermore, categorising the literature allows for a concentrated, in-depth investigation of each sector's distinctive role and a clear framework for understanding how they interact in the larger context of structural transformation.

Impact of agriculture on poverty reduction

An efficient agricultural sector is useful for providing raw materials to the manufacturing sector. Enongene (2023) agrees by having established that the agricultural sector is beneficial for poverty reduction in sub-Saharan Africa (SSA). However, Enongene's (2023) research did not include the SADC economies, thus providing the opportunity to study this unexplored aspect. The agricultural sector is essential to providing food and jobs that help lessen high poverty levels but this

ISSN: 0017-2294

depends on the level of efficiency in the sector. Bjornlund *et al*. (2020) cited climate change, soil quality and those diseases that cause agricultural inefficiency and food poverty in Africa. However, the role of agriculture in poverty reduction can be negative or positive but according to Bekun and Akadiri (2019), cannot be regarded as an efficient tool for reducing poverty.

Role of the manufacturing sector on poverty reduction

Agbonrofo and Olusegun (2023) indicated that in the past the manufacturing sector of African countries has been inefficient and declining. The African manufacturing share of GDP increased from 6.3% in 1970 to 15.3% in 1990, before falling to 12.8% in 2000 and 10.5% in 2008 (Itaman and Awopegba, 2022; United Nations Conference on Trade and Development, 2013).

The manufacturing sector can be efficient if there is good infrastructure, an enabling policy environment, and other necessary factors. Habiyaremye's (2020) study focused on the SADC integration agenda which established that poor customs systems, infrastructure, and delays in the implementation of the agenda affect the economic development of the region. These challenges impact the manufacturing sector's ability to reduce poverty. For this reason, the sector will not operate at full capacity if those challenges persist and as a result, the expansion of businesses that come with job creation will be adversely affected (Matenga and Mpofu, 2023). In Zimbabwe, the poor performance of the manufacturing sector led to job losses which exacerbated poverty levels (Agrawal, 2023; Vambe, 2023). This demonstrates that the weak performance of the manufacturing sector can increase poverty levels.

On the contrary, a study by Maduku and Zerihun (2023) indicated that exports by the manufacturing sector help reduce food poverty in South Africa. However, the study is silent on the transmission mechanism to explain how the manufacturing sector contributes to decreased food poverty in South Africa. Cazzuffi *et al*. (2017) and Erumban and De Vries (2024) agree with Maduku and Zerihun's (2023) narrative on the positive effect of the creation of employment opportunities in the manufacturing sector on poverty reduction. The above discussion reflects the positive or negative effects of the manufacturing sector on poverty.

Role of industrialisation on poverty reduction

Habanabakize and Dickason-Koekemoer (2023) researched the role of industrialisation on employment and economic growth in South Africa. Their findings indicated that industrialisation has a considerable positive impact on South African economic growth and job prospects. Similar results were obtained by Muyambiri (2023) who established that industrialisation positively impacted economic growth in Mozambique.

Industrialisation is a tool that can be used for poverty reduction in a non-deterministic way. Industries' expansion comes with employment creation and the provision of some social security benefits through corporate social responsibility (Choudhary and Singh, 2020). Policymakers need to redesign their industrial policies to ensure increased productivity, employment, and output, even though several African economies have experienced premature deindustrialisation. The proceeds from industrialisation help reduce poverty levels if channelled into social security programmes. Dinh (2023) suggests that African countries should prioritise employment creation and productivity growth in their development policies for long-term economic success. This indicates that African economies that have prematurely deindustrialised must reindustrialise to achieve economic development (Tregenna, 2013). According to Luke *et al*. (2023), reindustrialisation can be achieved by ensuring policy consensus, green industrialisation initiatives, improving supply chain security, values and resilience, transforming paradigms, and expanding policy space.

Role of the service sector in poverty alleviation

The service sector includes infrastructure services, like telecommunications, construction, business services that impact firm competitiveness and social services like healthcare and education (Verena *et al*., 2009). It is important for facilitating many operations in the primary and secondary sectors. Verena *et al*. (2009) established that in Mauritius the service sector contributed 68.5% of the GDP. Assuming that this growth is channelled to poverty reduction, the service sector plays a crucial role in a non-deterministic way. However, in Mozambique, it was established that the service sector had no significant effect on economic growth (Muyambiri, 2023). On the contrary, Mitra (2022) established that the service sector is crucial to poverty reduction. The above discussion illustrates that the effect of the service sector on poverty reduction varies and can be positive or negative.

Overall, the effect of the agricultural, manufacturing, industrialisation, and service sectors on poverty reduction can be positive or negative. The impact of these depends on other factors, such as the type of policies implemented and the pace of technological progress. This makes the process of poverty reduction complex. These dynamics are, therefore, captured in the research methodology.

3. Methodology

This section illustrates how structural transformation and poverty reduction are linked, drawing on arguments from the Lewis model. This is further linked to the aim of the study which was to investigate the relationship between structural transformation and poverty in the SADC region. The research methodology is therefore presented. The variables are briefly described and an econometric model is presented.

Variables

Poverty, the dependent variable, was measured using the Human Development Index (HDI). This measure is useful for comparing poverty between countries; this Index, therefore, helped in this analysis that focused on the SADC region (Smit, 2016; United Nations Development Programme, 2019). The HDI is useful in measuring poverty because it considers aspects, such as income, education, and health (Morse, 2023). When quantifying poverty, HDI provides reliable estimates in econometric analysis (Bejar, 2021; Korankye *et al*., 2020). Furthermore, one of the most robust poverty measures is the multidimensional poverty index, which includes the HDI's health and education components (United Nations Development Programme, 2022; Vollmer and Alkire, 2022). Finally, the HDI can also be used to analyse poverty trends which is useful for informing policy formulation (Sulistiani and Najmudin, 2023).

This study employed a sectoral analysis technique and four independent variables, namely agriculture value added (AVA), manufacturing value added (MVA), industrial value added (IVA), and service value added (SVA). These factors were included in the study because Enongene (2023), Habanabakize and Dickason-Koekemoer (2023), Erumban and De Vries (2021), Karahasan (2023), Mitra (2022) and Matenga and Mpofu (2023) determined that they had an impact on poverty alleviation. Their inclusion in this study is based on the research aims to investigate the relationship between structural transformation and poverty in the SADC region.

Finally, the manufacturing sector is part of the larger industrial sector; therefore, this study employed manufacturing and industrialisation as variables for the econometric analysis (Hope and Ajibola, 2023). MVA was included to assess value-added in the production processes of these industries; IVA was included to estimate value-added in specific sectors, such as mining, construction, electricity, water, and gas (a broader measure), as determined by the International Standard Industrial Classification (ISIC) (United Nations, 2008). In addition, IVA and MVA were included in the study because there was no severe multicollinearity between these variables, which was 0.14 according to Table 3’s data. Gujarati *et al*. (2012) supported this, stating that a substantial correlation between variables can be discovered when the value exceeds 0.8. Furthermore, the authors wanted to understand larger economic phenomena in the SADC region, therefore, these two variables were used in a regression analysis to provide a fuller and more thorough explanation of the economic contributions and interactions across multiple sectors in SADC.

Econometric model

The study used the panel autoregressive distributed lag (PARDL) model to examine the relationship between structural transition and poverty, developed by Pesaran and Smith in 1995. This model was selected as it can be used to estimate both short- and long-term dynamic parameters and is regarded as useful in econometric analysis (Kripfganz and Schneider, 2016; Mamvura and Sibanda, 2020; Nkoro and Uko, 2016; Shin *et al*., 2014). The study used PARDL because it can reduce the chance of spurious regression (Gholami *et al*., 2005; Ghouse *et al*., 2018). The PARDL model is applicable when the variables have a mixed order of integration that is integrated into orders 1 and 0. PARDL is effective for research with a small sample size and, therefore, suited to this study as it covers a 32-year period, deemed as a small sample (Kripfganz and Schneider, 2018; Negara *et al*., 2021). The general model is presented below:

$$\Delta Y_{i,t} = \alpha_1 + \sum_{i=1}^{p} \beta_i \Delta Y_{i,t-i} + \sum_{i=0}^{q} \delta_i \Delta X_{i,t-i} + \varphi_1 Y_{i,t-1} + \varphi_2 X_{i,t-1} + \varepsilon_{it} \quad (1)$$

Where $\boldsymbol{\Delta Y_{it}}$ represents a vector of (kx1) representing poverty measured through HDI, Δ captures differences in operator, $\boldsymbol{X_1}$ and $\boldsymbol{y_1}$ are the independent variables, which were AVA, MVA, IVA, and SVA.
$\boldsymbol{\beta_i}$ and $\boldsymbol{\delta_i}$ represent the short-run coefficients of the model explaining the short-run relationships between the variables, $\boldsymbol{\varphi_1}$ and $\boldsymbol{\varphi_2}$ represent the long-run relationship, p and q represent the lags of the dependent variable and the independent variables, respectively, and $\boldsymbol{\varepsilon_{it}}$ is the error term.

Summary of dataset

Eviews software was used to run the data. Data were sourced from the World Bank reports from 1990 to 2021. This period was selected because, from the point of view of an econometric analysis, it allows meaningful conclusions to be drawn on the subject matter. Also, this sample was selected based on data availability, which then excluded Comoros and Malawi. The variable column shows each variable, followed by the indicator used and the description of the variable. The last column shows the data source for each variable.

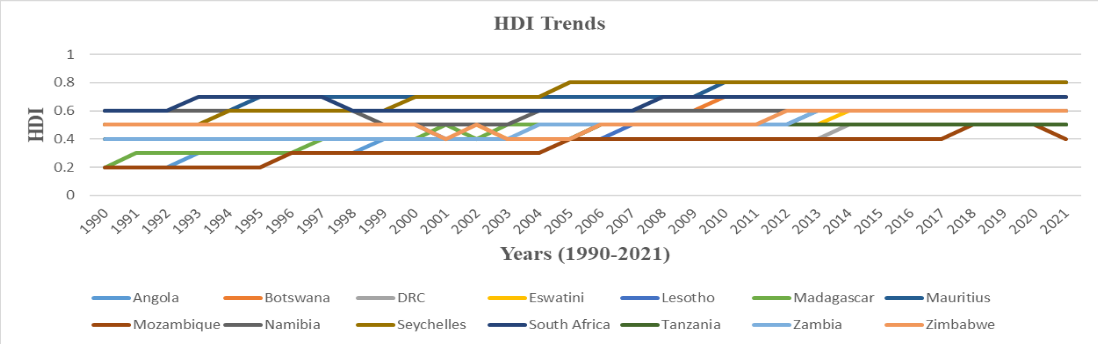
Table 1: Summary of dataset

Variable	Indicator	Variable description	Data source
Poverty (PO)	Human Development Index (HDI)	The absence of opportunities, coupled with high levels of undernourishment, hunger, illiteracy levels, lack of access to education, physical and mental diseases, and socio-economic instability.	World Bank (2024)
Agricultural value added (AVA)	Percentage of GDP	Value added is the net output of the agricultural sector after adding all outputs and subtracting intermediate inputs.	World Bank (2024)
Manufacturing value added (MVA)	Percentage of GDP	Value added is the net output of the manufacturing sector after adding all outputs and subtracting intermediate inputs.	World Bank (2024)
Industrial value added (IVA)	Percentage of GDP	Value added is the net output of the industrial sector after adding all outputs and subtracting intermediate inputs. It comprises value added in mining, manufacturing (also reported as a separate subgroup), construction, electricity, water, and gas	World Bank (2024)
Service value added (SVA)	Percentage of GDP	Value added is the net output of the service sector after adding all outputs and subtracting intermediate inputs. It includes value added in wholesale and retail trade (including hotels and restaurants), transport, and government, financial, professional, and personal services, such as education, healthcare, and real estate services. Also included are imputed bank service charges and import duties.	World Bank (2024)

3. Findings

The results presented below are for each sector; agriculture, manufacturing, industrial, and service. Period 1 refers to the years 1990 to 2000; Period 2: 2001 to 2010; and Period 3: 2011 to 2021.

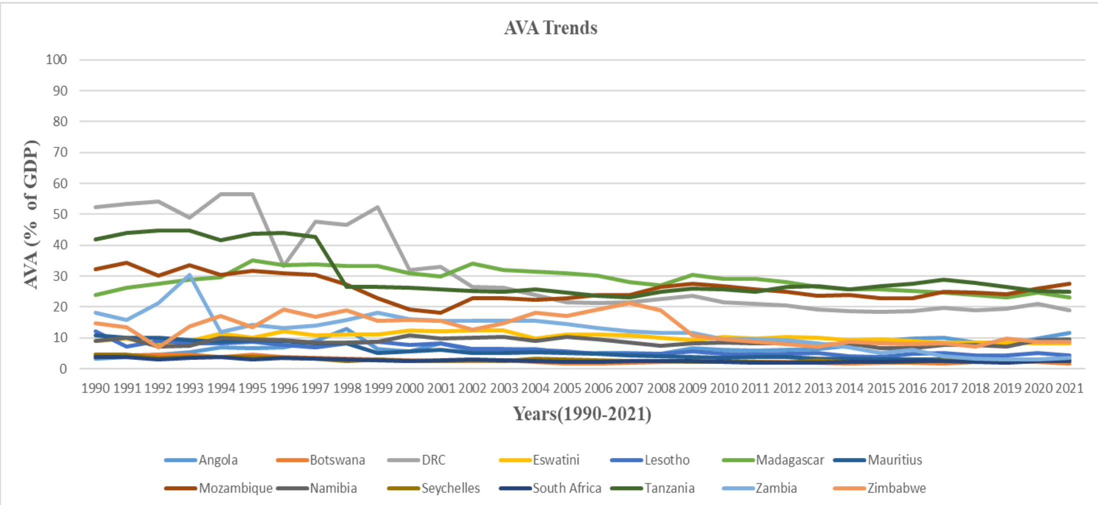
Figure 1: HDI trends



Source: Researcher's calculations based on World Bank data (2024)

In Period 1, there was a steady rise in HDI levels for most of the SADC countries. Madagascar is a country with low HDI levels below 0.4. and Zimbabwe recorded a decline in HDI levels at the end of Period 1. In Period 2, SADC recorded fluctuations in HDI levels. In Period 3, most SADC countries recorded constant levels of HDI. Overall, the HDI levels for SADC have been characterised by fluctuations. This could have been caused by natural disasters, such as Cyclone Idai, which affected livelihoods, loss of agricultural output, and the recent COVID-19 pandemic (Chingombe and Musarandega, 2021). Most of the economies have HDI levels above 0.5. Although this looks high, poverty affects people at the household level.

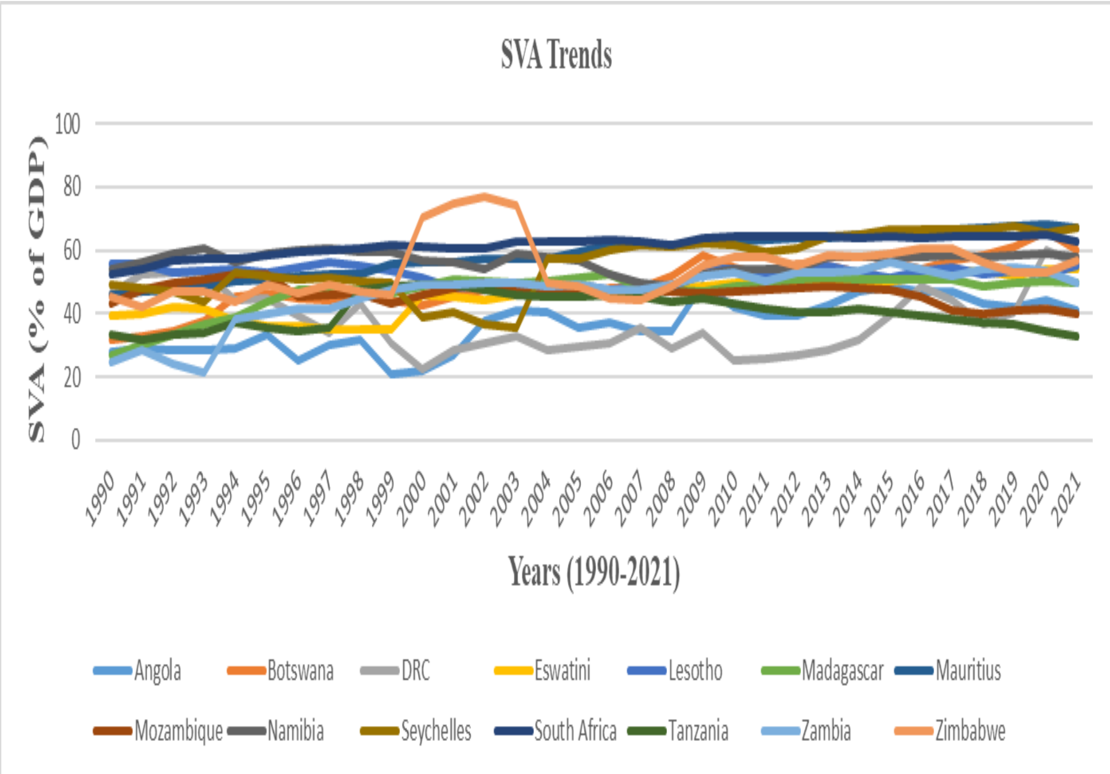
Figure 2: SADC agricultural value-added trend



Source: Researcher's calculations based on World Bank data (2024)

In Period 1, the agricultural value-added trend for SADC depicted acute fluctuations. This ranged from 50% to below 10%. In Period 2, there was a further decline in the AVA trends for most countries, although a few, such as Botswana, Madagascar, and Mozambique, recorded a slight increase in the AVA sector. The decline in the agricultural sector could have been caused by natural disasters, such as drought and floods which affect production. In Period 3, there was an almost constant trend in the AVA sector but by the end of Period 3, the region at large had AVA levels below 30%.

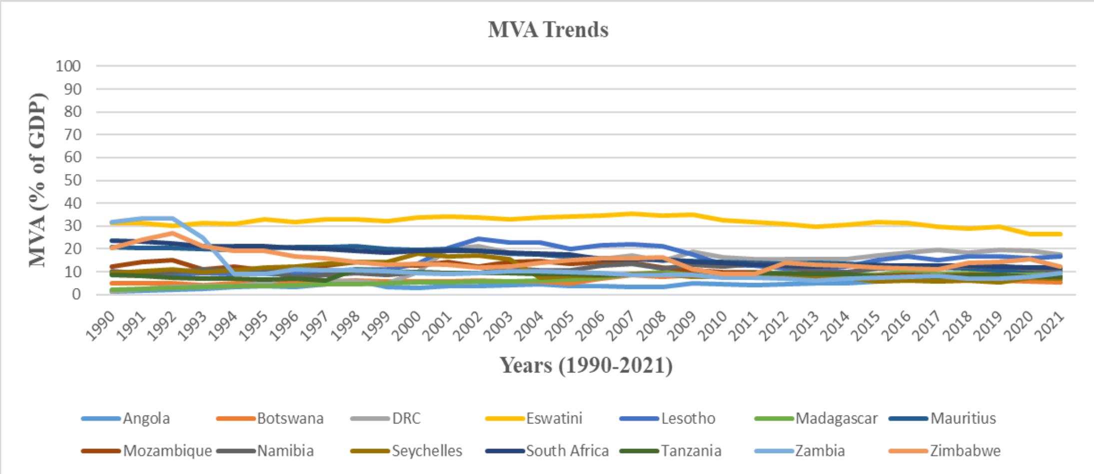
Figure 3: SADC service valued-added trend



Source: Researcher's calculations based on World Bank data (2024)

In Period 1, the SVA sector recorded an insignificant increase, except Zimbabwe which recorded a sharp increase in SVA levels towards the end of Period 1. In Periods 2 and 3, SADC recorded an almost constant increase in SVA levels. DRC and Lesotho were outliers because they depicted extreme fluctuations in the SVA trend. Overall, at the end of Period 3, the SVA trend for SADC was estimated at around 60%.

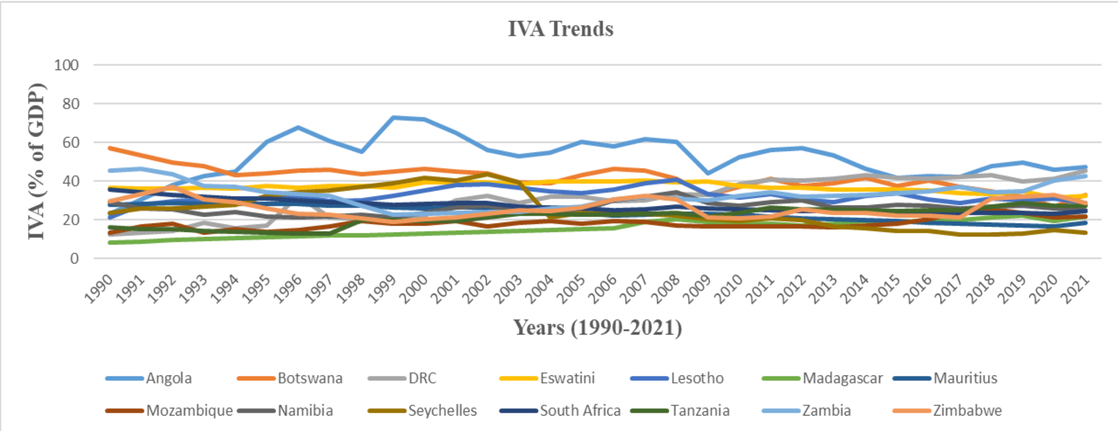
Figure 4: SADC manufacturing value-added trend



Source: Researcher's calculations based on World Bank data (2024)

Figure 4 illustrates the minor fluctuations in MVA trends for SADC in Period 1. Zambia and Zimbabwe recorded a sharp drop in MVA values. In Zimbabwe, this could have been caused by the poor performance of the economy; this led to the closure of companies and the loss of jobs (Chigora, 2018). In Periods 2 and 3, there were minor fluctuations in MVA levels in the SADC; the maximum was 30% of GDP. Overall, all the SADC countries showed a slight decrease in MVA levels from 1990 to 2021, and the trend remains almost constant.

Figure 5: SADC industrial value-added trends



Source: Researcher's calculations based on World Bank data (2024)

ISSN: 0017-2294

Figure 5 shows that the IVA trend of SADC in Period 1 was attributed to major fluctuations. Angola recorded an increase in IVA levels from an estimated 20% to 72.7% of GDP. Botswana recorded a steady decline in IVA levels. The fluctuations continued in SADC until the end of Period 3 when the highest value recorded was below 50% of the GDP. Generally, the SADC region had a low IVA value from 1990 to 2021. Madagascar and Mozambique were the least-performing countries in terms of IVA.

Descriptive statistics

This section presents the descriptive statistics.

Table 2: Descriptive statistics

Variable	HDI	AVA	SVA	MVA	IVA
Mean	0.52	13	49.1	12	29
Median	0.50	18	49.2	10	27
Maximum	0.80	56	77	35	72

Table 2 shows that the mean, median, and maximum for the HDI were 0.52, 0.5 and 0.8, respectively. This reveals that SADC has low HDI levels, which in turn means high poverty levels. AVA had a mean, median and maximum of 13%, 18% and 56%, respectively. These statistics show that SADC has low levels in its agricultural sectors. The SVA had a mean, median and maximum of 49.1%, 49.2%, and 77%, respectively. The SVA sector has moderately higher values compared to the AVA sector in the SADC from 1990 to 2021. The MVA sector had a mean, median and maximum of 12%, 10% and 35%, respectively. The SADC's MVA sector also shows low performance levels relative to the SVA sector. Finally, the IVA sector had a mean, median and maximum of 29%, 27% and 72%, respectively.

Correlation analysis

This section presents the correlation analysis.

Table 3: Correlation analysis

Variables	HDI	AVA	SVA	MVA	IVA
HDI	1.00				
AVA	-0.63	1.00			
SVA	0.64	-0.43	1.00		
MVA	0.05	-0.17	0.01	1.00	
IVA	0.01	-0.45	-0.39	0.14	1.00

Table 3 shows that HDI was negatively correlated with AVA at 63%, while the relationship between HDI, SVA, MVA, and IVA was positive at 64%, 5%, and 1%, respectively. AVA was negatively correlated with SVA, MVA, and IVA at 43%, 17%, and 45%, respectively. SVA was positively associated with MVA at 1% and negatively correlated with IVA at 39%. MVA was positively correlated with IVA at 14%. Finally, it can be concluded that there was no severe multicollinearity as all values were below 0.8 (Duda, 2022; Shrestha, 2020).

Unit root tests

The Augmented Dickey-Fuller test and Phillips-Perron test were used to test for the unit roots.

Table 4: Unit root test results

	ADF test		PP test	
Variable	**Level**	**1st Diff**	**Level**	**1st Diff**
HDI		**(152.39)** 0.00		**(301.79)** 0.00
AVA		**(222.16)** 0.00		**(356.57)** 0.00
SVA	**(47.78)** 0.00		**(106.75)** 0.00	
MVA		**(159.87)** 0.00		**(260.60)** 0.00
IVA		**(175.85)** 0.00		**(292.96)** 0.00

() represents t-statistics

These tests are useful to avoid spurious regression (Wang and Hafner, 2018). Table 4 illustrates that HDI, AVA, MVA, and IVA were stationary after the first difference. SVA was stationary at level. The order of integration was 1 and 0, and this satisfied the conditions for running a PARDL.

Lag length selection

The VAR model was used to determine the optimal lag length in this study.

Table 5: Lag length results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-4236.45	NA	63408.40	25.24	25.30	25.26
1	-2199.27	4001.59	0.39	13.26	13.61	13.40
2	-2171.14	54.43	0.39	13.25	13.87	13.49
3	-2136.67	65.64	0.36	13.19	14.10	13.55
4	-2094.96	78.21	0.33	13.09	14.28	13.57
5	-2045.57	91.12	0.28*	12.94*	14.42	13.53

The Akaike criterion was used for decision-making purposes on the appropriate lag length. Table 5 shows that Lag 5 was selected because it had the lowest AIC value of 12.94.

 ISSN: 0017-2294

Co-integration test

To test for co-integration in this research, a Johansen co-integration test was used. The results are presented below.

Table 6: Johansen co-integration test

Hypothesised No. of CE(s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
None	363.8	0.00	234.4	0.00***
At most 1	175.9	0.00	105.7	0.00***
At most 2	92.54	0.00	61.90	0.00***
At most 3	55.87	0.00	45.24	0.02**
At most 4	52.60	0.00	52.60	0.00***

***, ** and * stand for significance at the 1%, 5% and 10% levels, respectively

Table 6 indicates that at none, the p-value is less than 5%, thus the null hypothesis is rejected. Similarly, the critical value of Max-Eigen at 234.4 is less than the trace static value of 363.8. Equations 1 and 4, the p-values are also below the 5% level and are statistically significant, therefore, the null hypothesis is rejected. It can be concluded that there is a long-term relationship between the variables used in the study, which were AVA, SVA, MVA, and IVA. There are at most four co-integrating equations. Finally, because the variables employed in the study have a long-run relationship, both short-run and long-run dynamics will be estimated.

Granger causality test

The study employed the Granger causality test to determine the causal relationship between the variables.

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Table 7: Granger causality tests

Null Hypothesis	F-statistics	Probability	Equation
AVA does not Granger cause HDI HDI does not Granger cause AVA	3.7 2.4	0.02 0.09	1
SVA does not Granger cause HDI HDI does not Granger cause SVA	0.10 10.9	0.86 2.23	2
MVA does not Granger cause HDI HDI does not Granger cause MVA	0.42 0.20	0.65 0.81	3
IVA does not Granger cause HDI HDI does not Granger cause IVA	0.88 4.15	0.41 0.01	4
SVA does not Granger cause AVA AVA does not Granger cause SVA	0.57 0.02	0.56 0.00	5
MVA does not Granger cause AVA AVA does not Granger cause MVA	0.17 1.19	0.30 0.20	6
IVA does not Granger cause AVA AVA does not Granger cause IVA	0.15 5.50	0.85 0.00	7
MVA does not Granger cause SVA SVA does not Granger cause MVA	3.30 1.68	0.03 0.18	8
IVA does not Granger cause SVA SVA does not Granger cause IVA	5.85 1.09	0.03 0.33	9
IVA does not Granger cause MVA MVA does not Granger cause IVA	1.62 2.43	0.18 0.08	10

In Equation 1, the null hypothesis of no causal correlation between AVA and HDI can be rejected because the p-value of 0.02. is statistically significant. However, the null hypothesis of no causal correlation between AVA and HDI is accepted because the p-value of 0.09 is above the 5% level.

Equation 2, the null hypothesis of no causal correlation between SVA and HDI, and HDI and SVA cannot be rejected because the p-values of 0.86 and 2.23, respectively, are over the 5% level and insignificant, as shown in Table 7.

The same applies to Equation 3 on the relationship between MVA and HDI and vice versa; the p-values are above 5%, therefore, it can be concluded that there is no causal relationship between MVA and HDI. Similarly, this applies to Equation 6 on the relationship between MVA and AVA and vice versa; the p-values are above 5%, therefore, it can be concluded that there is no causal relationship between these variables.

Equation 4, the null hypothesis of no causal correlation between HDI and AVA is accepted because the p-value of 0.41 is above the 5% level. However, the null hypothesis of no causal correlation between HDI and AVA can be rejected because the p-value of 0.01 is statistically significant. This implies that there is unidirectional causality; meaning that the performance of the AVA sector leads to high HDI levels, and such high levels imply low levels of poverty.

Equation 5, the null hypothesis of no causal correlation between SVA and AVA is accepted because the p-value of 0.56 is above the 5% level. However, the null hypothesis of no causal correlation between AVA and SVA can be rejected because the p-value of 0.00 is statistically significant indicating unidirectional causality.

The null hypothesis of no causal correlation between IVA and AVA is accepted because the p-value of 0.86 is above the 5% level. However, the null hypothesis of no causal correlation between AVA and IVA can be rejected because the p-value of 0.00 is statistically significant, which reflects unidirectional causality between these variables.

Equation 7 on MVA and SVA, reflects the null hypothesis of no causal correlation between these variables can be rejected because the p-value of 0.03 is statistically significant, and there is unidirectional causality between these variables. However, for SVA and MVA, the null hypothesis of no causal correlation between these factors is accepted because the p-value of 0.18 is above the 5% level.

Equation 9, IVA and SVA, the null hypothesis of no causal correlation between these variables can be rejected because the p-value of 0.03 is statistically significant, indicating the existence of unidirectional causality between these variables. However, for SVA and IVA, the null hypothesis of no causal correlation between these factors is accepted because the p-value of 0.33 is above the 5% level.

Finally, in Equation 10 for IVA and MVA and MVA and IVA, the null hypothesis of no causal correlation between these factors is accepted because the p-values of 0.18 and 0.08 are above the 5% level.

Results of short-run auto-regressive distributed lag model

This section presents the short-run results of the auto-regressive distributed lag model.

Table 8: Short-run PARDL results

Variable	Coefficient	t-statistic	Probability
AVA	0.08	1.72	0.08*
MVA	0.09	1.94	0.05**

***, ** and * stand for significance at the 1%, 5% and 10% levels, respectively

Table 8 reports that AVA and MVA were statistically significant at 10% and 5%, respectively. A 1% increase in AVA leads to an 8% increase in HDI levels in the long-run. This means that AVA has a positive relationship with HDI and in practical terms, an increase in the performance of the AVA sector decreases poverty levels in the short-run in SADC. These research findings are on par with the results of Enongene (2023) and Bekun and Akadiri (2019), which suggest that SADC needs to keep developing its agricultural sector to ensure food security and job creation. This will help to reduce poverty in SADC.

On the other hand, a 1% increase in MVA leads to a 9% increase in HDI levels in the short-run. This implies that there is a positive relationship between MVA and HDI. Thus, efficiency in the MVA sector leads to a decrease in poverty levels in the SADC in the short-run. These research findings are on par with the views of Erumban and De Vries (2024) and Maduku and Zerihun (2023) who established a positive relationship between MVA and HDI.

Long-run PARDL results This section presents the long-run results of the auto-regressive distributed lag model.

Table 9: Auto-regressive distributed lag long-run results

Variable	Coefficient	t-statistic	Probability
AVA	-0.01	-10.05	0.00***
SVA	0.04	3.71	0.00***
MVA	-0.05	-7.91	0.00***
IVA	0.02	2.62	0.00***

***, ** and * stand for significance at the 1%, 5% and 10% levels, respectively

AVA, SVA, MVA, and IVA were statistically significant at the 1% level. A 1% increase in the AVA sector leads to a 1% decrease in HDI levels in the long-run in SADC. This depicts a negative relationship between AVA and HDI. These results are contrary to the findings of other authors, such as Bekun and Akadiri (2019) and Enongene (2023), who indicated the importance of the agricultural sector in poverty reduction. The conclusion that can be drawn from this result is that AVA increases poverty in the SADC in the long run. These findings explain that great performance in the AVA sector is possible with the use of modern equipment. Increased use of sophisticated machinery in agricultural production results in a reduction in human labour. As workers are replaced by machinery, they become unemployed and vulnerable to poverty. As a result, high productivity in agriculture may be accomplished using contemporary technology and machines but unfortunately employs limited labour (Radic *et al*., 2022).

On the other hand, a 1% increase in SVA leads to a 45% increase in HDI levels in the long-run in SADC. This reveals a positive relationship between SVA and HDI. It can, therefore, be concluded that the SVA is useful for reducing high poverty levels in SADC. These findings are in line with the views of Mitra (2022). The SADC, therefore, needs to ensure that good policies are implemented to ensure the well-functioning of the service sector, which will help with poverty reduction.

The MVA had a negative relationship with HDI. A 1% increase in MVA leads to a 5% decrease in HDI levels in the long-run (Table 7). This indicates that MVA increases poverty levels in SADC in the long term.

ISSN: 0017-2294

Finally, IVA had a positive relationship with HDI. A 1% increase in IVA leads to a 2% increase in HDI levels in SADC in the long-run. This indicates that IVA is crucial for reducing poverty levels because increased HDI levels imply reduced levels of poverty. These research findings are on par with the views of Choudhary and Singh (2020) and Habanabakize and Dickason-Koekemoer (2023). SADC should, therefore, create industrialisation opportunities and channel the proceeds to reduce poverty.

The findings show that to achieve long-term poverty reduction in the SADC area, the growth of the service and industrial sectors must be prioritised. While the agriculture and manufacturing sectors may provide short-term benefits, the service and industrial sectors are critical to long-term human development and poverty reduction. These findings underline the importance of comprehensive and forward-thinking policy frameworks that promote growth in the industrial and service sectors, ensuring that they contribute to economic diversification and improved livelihoods.

Post estimation tests

This section presents the post-estimation results.

Table 10: Post-estimation tests

Type of Test	p-value
Normality test	0.14
White test for heteroscedasticity	0.13
Breusch-Godfrey LM test	0.36

Table 10 shows that there was no heteroskedasticity or serial correlation and the data was normally distributed. This is justified by the p-value of the White test for heteroscedasticity of 0.13 above the 5% level. The Breusch-Godfrey LM test of 0.36 was above 5%, and the normality test value of 0.14 was also above 5%.

Policy recommendations

The SADC needs to address structural transformation and poverty challenges. This will help the region at large to increase its capacity to attain the SDG goals and improve the welfare of its citizens. The following recommendations are suggested:

Robust industrial policy formulation and implementation

There is a need for the SADC to craft robust industrial policies that support the efficient functioning of all sectors of the economy. These policies should be supported by sufficient financial resources and designed to ensure that the proceeds from structural transformation are channelled to poverty reduction.

Harness modern technology

Technology may improve industrial processes, making them more competitive and cost-effective. It can also help sectors migrate to more advanced and high-value products, in that way increasing their contribution to economic diversity. Similarly, the service sector, particularly finance, healthcare and education can use technology to increase access, lower prices, and improve service quality.

Research and development

Research and development are key for supporting industrialisation with product development, process improvement, resource optimisation, skills and workforce development, and policy support. This research and development should be tailor-made to address the poverty and industrialisation challenges the SADC faces.

4. Conclusion

This study investigated the association between structural transformation and poverty using a panel autoregressive and distributed lag model. The study examined the value-added share of GDP in the manufacturing, service, agricultural, and industrial sectors. According to the research findings, the agricultural and manufacturing sectors were effective in reducing poverty in the near run. In the long run, it was determined that the service and industrial sectors were beneficial in alleviating poverty in SSA. These findings from the study demonstrate that SADC must prioritise the efficient operation of the agricultural, manufacturing, service, and industrial sectors to achieve real poverty reduction. Regarding policy recommendations, it is advised that the SADC adopt strong policies for the service and industrial sectors, embrace contemporary technology, and invest in research and development.

Reference list

Abedmohisen, A. 2023. “The Role of Job Creation in Achieving Economic Growth.” https://www.researchgate.net/publication/369553323_The_Role_of_Job_Creation_in_Achieving_Economic_Growth

Agbenyo, S., and Agbenyo, J. S. 2020. “The Structural Change Theory – An Analysis of Success and Failures of Technology.” *International Journal of Research and Innovation in Social Science*. www.rsisinternational.org

Agbonrofo, H. E., and Olusegun, A. 2023. “Manufacturing Sector Development in Sub-Saharan Africa: Does Monetary Policy Matter?” *International Journal of Management, Economics and Social Sciences*, 12(2). https://doi.org/10.32327/ijmess/12.2.2023.6

Agrawal, H. 2023. “Crisis of Zimbabwe.” *International Journal of Social Science and Human Research*. https://doi.org/10.47191/ijsshr/v6-i8-25

Andreoni, A., and Tregenna, F. 2021. The Middle-Income Trap and Premature Deindustrialization in South Africa. In *Structural Transformation in South Africa* (pp. 237–260). Oxford University Press Oxford. https://doi.org/10.1093/oso/9780192894311.003.0011

Bejar, E. 2021. Human Development Index and Multidimensional Index. Retrieved from: https://ideas.repec.org/p/pra/mprapa/108501.html

Bekun, F., and Akadiri, S. 2019. Poverty and Agriculture in Southern Africa Revisited: A Panel Causality Perspective. *SAGE Open*, 9(1). https://doi.org/10.1177/2158244019828853

Bjornlund, V., Bjornlund, H., and Van Rooyen, A. F. 2020. Why agricultural production in sub-Saharan Africa remains low compared to the rest of the world–a historical perspective. *International Journal of Water Resources Development*, *sup1*, 1–34. https://doi.org/10.1080/07900627.2020.1739512

Bonga, W.G. 2021. “Corruption Prevalence in SADC Regional Bloc” (January 25, 2021). Quest Journals', *Journal of Research in Humanities and Social Science,* 9(1), pp.08-16. Available at SSRN: https://ssrn.com/abstract=3772649

Cazzuffi, C., Pereira-López, M., and Pereira-López, I. 2017. “The role of food manufacturing growth, Food Policy.” https://www.sciencedirect.com/science/article/abs/pii/S0306919216301464

Chigora, P. 2018. Zimbabwean Crises and Political, Economic and Socio-Cultural Development Impacts in Southern Africa. https://journals.co.za/doi/pdf/10.10520/EJC-107c25eea8

Chingombe, W., and Musarandega, P. 2021. From the Cyclone Idai disaster to the COVID-19. https://www.researchgate.net/publication/356611998_From_the_Cyclone_Idai_disaster_to_the_COVID-19

Choudhary, A., and Singh, V. 2020. Exploring the Impact of Corporate Social Responsibility on Poverty Reduction. In *CSR, Sustainability, Ethics and Governance* (pp. 329–338). Springer Nature. https://doi.org/10.1007/978-3-030-36970-5_18

Dinh, H. T. 2023. *Industrialization in Africa: Issues and Policies*. www.policycenter.ma

Dookeran, W. 2019. Lewis model of economic growth, linearity and convergence: does it fit today? https://www.researchgate.net/publication/336073443_Lewis_model_of_economic_growth_linearity_and_convergence_does_it_fit_today
Duda, S. 2022. Identifying and Addressing Multicollinearity in Regression Analysis. https://scottmduda.medium.com/identifying-and-addressing-multicollinearity-in-regression-analysis-ca86a21a347e#:~:text=A%20quick%20way%20to%20identify,just%20a%20rule%20of%20thumb
Enongene, B. E. 2023. Structural transformation and poverty alleviation in Sub-Saharan Africa countries: sectoral value-added analysis. *Journal of Business and Socio-Economic Development*. https://doi.org/10.1108/jbsed-12-2022-0128
Erumban, A. A., and De Vries, G. J. 2024. Structural change and poverty reduction in developing economies. *World Development*, *181*. https://doi.org/10.1016/j.worlddev.2024.106674
Gholami, R., Sang-Vong Tom, S., and Heshmati, A. 2005. The Causal Relationship between ICT and FDI. https://www.researchgate.net/publication/23566066_The_Causal_Relationship_between_ICT_and_FDI
Ghouse, G., Khan, S., and Rehman, S. 2018. ARDL model as a remedy for spurious regression: problems, performance and Prospectus. https://www.researchgate.net/publication/324808258_ARDL_model_as_a_remedy_for_spurious_regression_problems_performance_and_prospectus
Gujarati, D. N., Porter, D., and Gunasekar, S. 2012. Basic Econometrics. https://www.researchgate.net/publication/274963990_Basic_Econometrics
Habanabakize, T., and Dickason-Koekemoer, Z. 2023. The Role of Industrialization on Employment and Economic Growth in South Africa. *International Journal of Economics and Financial Issues*, 13(6), 116–123. https://doi.org/10.32479/ijefi.15094
Habiyaremye, A. 2020. Fast tracking the SADC integration agenda to unlock regional collaboration gains along growth corridors in Southern Africa. https://www.wider.unu.edu/sites/default/files/Publications/Working-paper/PDF/wp2020-95.pdf
Herrendorf, B., Rogerson, R., and Valentinyi, A. 2014. “Growth and structural transformation.” Handbook of Economic Growth, 2, pp.855-941.
https://www.nber.org/system/files/working_papers/w18996/w18996.pdf
Heitzig, C., and Newfarmer, R. 2023. Africa: Growth beyond deindustrialisation? https://www.theigc.org/africa-growth-beyond-deindustrialisation#:~:text=In%20Africa%2C%20labour%20was%20shifting,Rodrik%20termed%20%E2%80%9Cpremature%20deindustrialisation.%E2%80%9D
Hope E., and Olusegun, A. 2023. “Manufacturing sector development in Sub-Saharan Africa: Does monetary policy matter?” *International Journal of Management, Economics and Social Sciences* (IJMESS), 12(2), pp.1331–61. https://doi.org/10.32327/IJMESS/12.2.2023.6

Itaman, R. E., and Awopegba, O. E. 2022. *Manufacturing Technology Intensity, Employment, Wages and Capital Formation in Africa*. https://www.uj.ac.za/wp-content/uploads/2021/10/sarchi-wp-2022-12-itaman-september-2022.pdf

Karahasan, B. C. 2023. "To Make Growth Reduce Poverty, Industrialize: Using Manufacturing to Mediate the Effect of Growth on Poverty." *Development Policy Review, 41*(4). e12689. https://doi.org/10.1111/dpr.12689

Korankye, B., Wen, X., Nketia, E. B., and Kweitsu, G. 2020. "The Impact of Human Development on the Standard of Living in Alleviating Poverty: Evidence from Africa." *European Journal of Business and Management Research*, 5(5), 1–5. https://www.ejbmr.org/index.php/ejbmr/article/view/511

Kripfganz, S., and Schneider, D. 2022. "ARDL: Estimating autoregressive distributed lag and equilibrium correction models". TUPD Discussion Papers 18, Graduate School of Economics and Management, Tohoku University.

Le Roux, A. 2023. SADC Geographic futures. https://futures.issafrica.org/geographic/recs/sadc/

Luke, D., Macleod, J., and Ogunkola, O. 2023. The Art of Upgrading Industrial Policymaking Itself. https://www.lse.ac.uk/africa/assets/Documents/White-Paper-on-Sustainable-Industrialisation-in-Africa.pdf

Maduku, H., and Zerihun, M. F. 2023. "The impact of manufacturing exports on food poverty reduction in South Africa." *International Journal of Business & Economic Development*, *11*(01). https://doi.org/10.24052/IJBED/V011N01/ART-02

Mamvura, K., and Sibanda, M. 2020. "Modelling short-run and long-run predictors of foreign portfolio investment volatility in low-income Southern African Development Community countries." *Journal of Economic and Financial Sciences*, 13(1). https://doi.org/10.4102/jef.v13i1.559

Martin, M. 2022. The Crisis of Extreme Inequality in SADC Fighting austerity and the COVID-19 pandemic. https://oxfamilibrary.openrepository.com/bitstream/handle/10546/621370/rr-sadc-cri-100522-summ-en.pdf

Matenga, A. E., and Mpofu, K. 2023. "Africa and Industry 5.0: Challenges and Opportunities in the Future of Manufacturing." *Procedia CIRP*, 120, pp.1256–1261. https://doi.org/10.1016/j.procir.2023.09.158

Mitra, A. 2022. "Does Services Sector Encourage Migration and Reduce Poverty?" *Ind. J. Labour Econ.,* 65, pp.1–18. https://doi.org/10.1007/s41027-022-00355-z

Morse, S. 2023. "Quality of Life, Well-Being and the Human Development Index: A Media Narrative for the Developed World?" *Soc Indic Res,* 170, pp.1035–1058. https://doi.org/10.1007/s11205-023-03230-6

Muyambiri, B. 2023. "The role of agriculture, industry and the service sector in economic growth: The case of Mozambique." *African Journal of Agricultural and Resource Economics*, *18*(2), pp.190–201. https://doi.org/10.53936/AFJARE.2023.18(2).12

Negara, H. R. P., Syaharuddin, Kusuma, J. W., Saddam, Apriansyah, D., Hamidah, T. & Tamur, M. 2021. Computing the auto regressive distributed lag (ARDL) method in forecasting COVID-19 data: A case study of NTB Province until the end of 2020.

Journal of Physics: Conference Series, *1882*(1). https://doi.org/10.1088/1742-6596/1882/1/012037

Nkoro, E., and Uko, A. K. 2016. "Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation." *Journal of Statistical and Econometric Methods*, *5*(4), pp.63–91.

Pesaran, M., and Smith, R. 1995. Estimating long-run relationships from dynamic heterogeneous panels. https://www.sciencedirect.com/science/article/pii/030440769401644F

Radic, V., Radić, N., and Cogoljević, V. 2022. New technologies as a driver of change in the agricultural sector. https://www.researchgate.net/publication/359832366_New_technologies_as_a_driver_of_change_in_the_agricultural_sector

Schlogl, L., and Sumner, A. 2020. Economic Development and Structural Transformation. *Disrupted Development and the Future of Inequality in the Age of Automation* (pp. 11–20). Springer International Publishing. https://doi.org/10.1007/978-3-030-30131-6_2

Shin, Y., Yu, B., and Greenwood Nimmo, M. 2014. Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework. https://www.researchgate.net/publication/228275564_Modelling_Asymmetric_Cointegration_and_Dynamic_Multipliers_in_a_Nonlinear_ARDL_Framework

Shrestha, N. 2020. Detecting Multicollinearity in Regression Analysis. *American Journal of Applied Mathematics and Statistics*, *8*(2), 39–42. https://doi.org/10.12691/ajams-8-2-1

Smit, S. 2016. Determinants of Human Development Index: A Cross-Country Empirical Analysis. https://mpra.ub.uni-muenchen.de/73759/1/MPRA_paper_73759.pdf

Southern African Development Community (SADC). 2024. SADC Objectives. https://www.sadc.int/pages/sadc-objectives

Southern African Development Community (SADC). 2024a. Industrialisation. https://www.sadc.int/pillars/industrialisation

Southern African Development Community (SADC). 2024b. SADC protocols. https://www.sadc.int/pages/sadc-protocols

Southern African Development Community (SADC). 2024c. Employment and Labour. https://www.sadc.int/pillars/employment-labour

Strauss, M. 2019. A historical exposition of spatial injustice and segregated urban settlement in South Africa. http://www.scielo.org.za/scielo.php?script=sci_arttext&pid=S1021-545X2019000200006

Sulistiani, L. S., and Najmudin, N. 2023. Analysis of the Poverty Level and Human Development Index in Central Java For the 2016-2021 Period. *Economics and Finance*, 28–41. https://doi.org/10.51586/2754-6209.2023.11.3.28.41

Tasneem, F., and Aamir Khan, M. 2024. "Growth and structural transformation – Options for Pakistan." *Research in Globalization*, *8*. https://doi.org/10.1016/j.resglo.2023.100190

Tregenna, F. 2013. Deindustrialization and Reindustrialization. https://academic.oup.com/book/36482/chapter-abstract/321124039?redirectedFrom=fulltext

United Nations. 2024. 17 Goals. https://doi.org/sdgs.un.org/goals

United Nations Conference on Trade and Development. 2013. The state of industrial development in Africa: unexploited opportunities amidst growing challenges. https://unctad.org/system/files/official-document/presspb2013d1_en.pdf

United Nations Development Programme (UNDP). 2022. 2022 Global Multidimensional Poverty Index (MPI). https://hdr.undp.org/content/2022-global-multidimensional-poverty-index-mpi#/indicies/MPI

United Nations Development Programme. 2019. How to Build a National Multidimensional Poverty Index (MPI): Using the MPI to inform the SDGs. https://www.mppn.org/wp-content/uploads/2019/07/How_to_Build_Handbook_2019_PDF.pdf

Vambe, M. T. 2023. "Zimbabwe: the Fall from a Jewel Status." *Third World Thematics: A TWQ Journal*, *8*(4–6), pp.181–188. https://doi.org/10.1080/23802014.2023.2287495

Verena, T.-R., Vishal, R., and Ken, P. 2009. Services Sector Development and Impact on Poverty Thematic Working Group Services Sector Development: A Key to Poverty Alleviation in Mauritius.

Vollmer, F., and Alkire, S. 2022. Consolidating and improving the assets indicator in the global Multidimensional Poverty Index. *World Development*, 158, 105997. https://www.sciencedirect.com/science/article/pii/S0305750X22001875

Wang, C. S. H., and Hafner, C. M. 2018. A simple solution of the spurious regression problem. *Studies in Nonlinear Dynamics and Econometrics*, *22*(3). https://doi.org/10.1515/snde-2015-0040

Zulkifli, F., and Abidin, R. Z. 2023. The Multi-Dimensional Nature of Poverty: A Review of Contemporary Research. *International Journal of Academic Research in Economics and Management Sciences*, *12*(2). https://doi.org/10.6007/ijarems/v12-i2/17260