Structural Economic Change and Poverty Reduction: An Analysis of Sectoral Composition in Sudan

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Abstract

This paper examines how structural economic change has influenced poverty reduction in Sudan over 1970–2022, with a particular focus on the role of sectoral composition in a fragile and conflict-affected context. The study's objective is to assess how value-added growth in agriculture, industry, and services affects poverty outcomes, measured by the headcount ratio, poverty gap, and severity index. Methodologically, the analysis constructs annual monetary poverty indices using the Foster–Greer–Thorbecke (FGT) approach, based on a lognormal distribution derived from per capita consumption and Gini coefficients, and then estimates an Autoregressive Distributed Lag (ARDL) model to capture both short- and long-run effects of sectoral value-added growth and key macroeconomic and demographic variables, including education, exports, inflation, population, credit access, and GDP growth. The results show that growth in agriculture and industry significantly reduces poverty in the long run, whereas the services sector exerts a weak, statistically insignificant effect. Education, access to credit, and higher inflation are associated with lower poverty levels, while population growth increases poverty, and export expansion is linked to higher poverty, reflecting the enclave nature of Sudan's extractive export sectors. Overall, the findings underscore that inclusive structural transformation—centered on revitalizing agriculture, fostering industrial development, and reorienting services—along with complementary policies in human capital, finance, and macroeconomic management, is essential for sustainable poverty reduction in Sudan. The study thus provides new empirical evidence to inform policymakers in Sudan and other conflict-affected low-income economies undergoing economic transition.

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1. Introduction

The sectoral structure of economic growth fundamentally shapes poverty alleviation in developing economies, with sectors differing in their capacity to foster inclusive development (Loayza & Raddatz, 2010; Ivanic & Martin, 2018; Bourguignon, 2003). Agriculture, due to its labor-intensive nature, significantly reduces poverty in rural areas by boosting employment and lowering food prices, a pattern evidenced in diverse contexts like India and Indonesia (Ravallion & Datt, 1996; Dercon, 2009; Thorbecke & Jung, 1996; Chukwu, 2025). However, industrial and service sectors may entrench inequality if growth disproportionately benefits elites (Besley & Burgess, 2003; Megbowon & Mulatu, 2025). Structural transformation, building on Lewis's (1954) insight that poverty falls when labor moves from low-productivity agriculture to higher-productivity manufacturing and services, reduces poverty only when access to these modern sectors is sufficiently broad and equitable (McMillan & Rodrik, 2011; Christiaensen et al., 2011; Pavcnik, 2017). Barriers such as skill mismatches and geographic immobility often limit the poor's participation, particularly in sub-Saharan Africa, where manufacturing's poverty-reducing impact lags behind Asia due to weak employment linkages (Erumban & de Vries, 2024; Benfica & Henderson, 2021; Maswana, 2021). Labor-intensive sectors like agriculture and construction amplify poverty reduction through wage growth and intersectoral linkages, underscoring the need for context-specific strategies (Loayza & Raddatz, 2010; Christiaensen & Kaminski, 2015).

Against this broader literature, the core question of this paper is how the pattern of structural economic change in Sudan—captured by the evolution of agriculture, industry, and services—has shaped monetary poverty over the past five decades, and which sectors offer the strongest potential for inclusive, poverty-reducing growth. This debate is particularly salient in Sudan, where persistent poverty, exacerbated by sluggish economic performance and devastating conflict, underscores profound structural challenges. Extreme poverty, defined as living below 2.15 USD a day (2017 PPP), affected 66.2% of the population in 2022 and rose to an estimated 70% in 2024, driven by a collapsing economy with a 29.4% GDP contraction in 2023 and a projected 13.5% decline in 2024. The war between the Sudanese Armed Forces and Rapid Support Forces, erupting on April 15 2023, has displaced millions of people and further intensified poverty through disrupted livelihoods and infrastructure collapse. This conflict has severely undermined Sudan's economy, with agriculture disrupted by widespread insecurity and land inaccessibility, industry—concentrated in Khartoum and Gezira states—devastated by destruction of factories and supply chains, and services crippled by urban displacement and infrastructure collapse. Sudan faces extreme undercapitalization and has failed to attract significant foreign direct investment. Its Heavily Indebted Poor Countries (HIPC) status further restricts access to international financial institutions, limiting sectoral diversification and stifling investment in productive activities. Sudan's GDP composition—with agriculture averaging 34.5% (1960–2010), services 36.8% (rising to 42.7% during the oil era, 1990–2011), and industry 16.7%—shapes its poverty dynamics, as sectoral growth differentially influences employment and income distribution. Agricultural productivity is constrained by limited irrigation (15–20% of arable land), curbing its poverty-reducing potential. Resource-driven industrial growth yields mixed outcomes; while inclusive growth can reduce poverty headcount, Sudan's oil industry has exacerbated inequality and intensified poverty severity. The service sector, despite significant GDP contributions, is dominated by informal employment, offering low wages and minimal social protection. Sudan's post-1990s oil reliance triggered a "Dutch disease" effect, undermining agriculture and non-oil industries and increasing rural poverty, while the 2011 secession of South Sudan, which sharply reduced oil output, coupled with macroeconomic instability, significantly deepened poverty. Taken together, these features depict an economy in which structural change has been substantial but not necessarily poverty reducing, making Sudan a critical case for revisiting the growth–poverty linkage through a sectoral lens.

Methodologically, the paper responds to this challenge by first constructing a long-run time series of monetary poverty—headcount, gap, and severity—using Foster–Greer–Thorbecke indices derived from per capita consumption and Gini coefficients. It then estimates an Autoregressive Distributed Lag (ARDL) model that links sectoral value-added levels and key macroeconomic variables to these poverty measures. This combination of reconstructed poverty series and ARDL modeling enables the study to distinguish clearly between short-run dynamics and long-run sector–poverty relationships in a fragile, conflict-affected setting. At the same time, the approach remains feasible and informative in a context where household survey data are sparse and irregular.

While prior studies elucidate sectoral contributions to poverty reduction, they often focus on stable or less conflict-affected settings, leaving a critical gap in understanding how sectoral composition affects poverty in fragile contexts like Sudan, characterized by informality, conflict, and macroeconomic volatility. This study addresses this gap by examining which sectors—agriculture, industry, or services—most effectively reduce poverty in Sudan and through which mechanisms: within-sector productivity growth or labor reallocation to higher-productivity sectors. Using a time-series Autoregressive Distributed Lag (ARDL) framework, we analyze the short- and long-run impacts of sectoral growth on poverty headcount (P_0), depth (P_1), and severity (P_2) from 1970 to 2022. Incorporating controls for conflict intensity, inflation, employment informality, and inequality, and utilizing Standardized World Income Inequality Database (SWIID) data for Foster-Greer-Thorbecke (FGT) poverty measures and Gini coefficients, we offer a nuanced analysis of distributional dynamics in a conflict-affected setting.

In doing so, the paper makes three interrelated contributions to the literature. First, it advances research on the sectoral pattern of growth and poverty reduction. Second, it contributes to the economics of fragility and conflict. Third, it extends methodological work on reconstructing poverty series in data-scarce environments, while providing country-specific evidence from Sudan that informs wider debates on structural transformation in low-income, conflict-affected economies. On this basis, the study addresses a central policy question—namely, which sectors most effectively reduce poverty in Sudan—and generates findings intended to inform the design of structural transformation strategies that foster inclusive growth and mitigate poverty in fragile, conflict-driven contexts.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical and empirical literature on the relationship between structural economic change and poverty reduction. Section 3 provides an overview of the socioeconomic trends and poverty dynamics in Sudan during the study period. Section 4 details the data sources and the construction of the time-series poverty metrics used in the analysis. Section 5 outlines the econometric methodology, including the ARDL model specification and estimation strategy. Section 6 presents and discusses the empirical results, examining both the long-run and short-run effects of sectoral growth on poverty. Finally, Section 7 concludes the study and offers policy implications.

2. Literature Review

The relationship between structural economic change and poverty reduction is grounded in classical economic theories, notably Arthur Lewis's dual-sector model and Walt Rostow's stages of economic growth. Lewis (1954) proposed that developing economies consist of a traditional, low-productivity agricultural sector and a modern, high-productivity industrial sector, with development driven by the reallocation of surplus labor from the former to the latter, increasing wages and reducing poverty (Lewis, 1954). This structural change enhances aggregate productivity by shifting resources to more efficient sectors (McMillan & Rodrik, 2011). However, barriers such as skill gaps or geographic immobility can limit the poor's participation in modern sectors (Pavcnik, 2017). Complementing this, Rostow's (1960) stages of economic growth outline a progression from traditional societies to industrialized economies, where early investments in agriculture and infrastructure generate surpluses for industrial expansion (Rostow, 1960). As economies mature, diversification into manufacturing and services becomes critical for sustained poverty reduction (Christiaensen et al., 2011). Taken collectively, these frameworks underscore two core mechanisms—within-sector productivity growth and inter-sectoral labor reallocation—that organize the empirical literature on sectoral growth and poverty and serve as the conceptual foundation for this study.

Empirical studies confirm that the sectoral composition of growth significantly influences poverty outcomes. Agriculture is a primary driver of poverty reduction in developing economies, particularly in rural areas where poverty is concentrated. Ravallion and Datt (1996) found that agricultural growth outperforms urban-based industrial growth in reducing poverty, a pattern observed in India and through cross-country analyses (Ravallion & Datt, 1996; Benfica & Henderson, 2021; Ligon & Sadoulet, 2018). Agricultural productivity growth raises incomes for rural households and lowers food prices, benefiting poor consumers (Dercon, 2009). For instance, Montalvo and Ravallion (2010) highlight agriculture's dominant role in poverty reduction in China, while Thorbecke and Jung (1996) show that agricultural sectors contribute more to poverty alleviation than industrial sectors in Indonesia (Montalvo & Ravallion, 2010; Thorbecke & Jung, 1996). However, as economies undergo structural transformation, non-agricultural sectors gain prominence. Christiaensen et al. (2011) and Himanshu et al. (2013) note that services and manufacturing become more effective in reducing poverty as urbanization increases (Christiaensen et al., 2011; Himanshu et al., 2013). Enongene (2024) finds that value-added growth in services positively impacts poverty alleviation in sub-Saharan Africa, though agriculture remains more effective (Enongene, 2024). These findings suggest that the poverty impact of sectoral growth is context-dependent and may evolve over time, reinforcing the need for country-specific analyses rather than assuming a universal hierarchy of sectors.

The effectiveness of structural change depends on sectoral productivity and labor reallocation. McMillan and Rodrik (2011) emphasize that moving labor to higher-productivity sectors enhances incomes, but if workers shift to lower-productivity sectors, such as informal services, poverty reduction may be limited (McMillan & Rodrik, 2011; Ravallion & Datt, 1996). Pavcnik (2017) highlights barriers like skill mismatches that restrict poor households' access to modern sectors (Pavcnik, 2017). Erumban and de Vries (2024) demonstrate that manufacturing productivity growth significantly reduces poverty in developing Asia but less so in sub-Saharan Africa due to limited industrial development (Erumban & de Vries, 2024). Similarly, Maswana (2021) finds that in Indonesia, the secondary sector's poverty-reducing impact is weaker in non-mining provinces, where services dominate (Maswana, 2021). Chukwu (2025) underscores agriculture's leading role in poverty reduction in sub-Saharan Africa, driven by its labor intensity and intersectoral linkages with services (Chukwu, 2025). For fragile African economies characterized by underdeveloped industrial bases and extensive informal sectors, these studies provoke critical inquiry into whether structural transformation has been growth-enhancing yet insufficiently poverty-reducing, a concern of direct relevance to the Sudanese context.

Labor intensity significantly influences sectoral poverty impacts, with labor-intensive sectors like agriculture and construction reducing poverty more effectively than capital-intensive industries through wage growth and intersectoral linkages (Loayza & Raddatz, 2010; Christiaensen & Kaminski, 2015). This aligns with findings that agricultural growth indirectly reduces poverty by lowering food costs (Dercon, 2009). Hasan (2013) notes that labor reallocation to higher-productivity sectors, in India, enhances poverty reduction, particularly when supported by flexible labor regulations (Hasan, 2013). However, "jobless growth" can undermine these benefits, as growth that fails to generate employment for the poor undermines poverty alleviation (Gutierrez et al., 2009). Christiaensen and Kaminski (2015) find that in Uganda, both within-sector agricultural growth and diversification into non-farm activities drive poverty reduction, with employment growth being a key channel (Christiaensen & Kaminski, 2015). This strand of work stresses the importance of examining not only which sectors expand in Sudan, but also whether their growth is sufficiently labor-absorbing to affect poverty.

Sectoral growth affects poverty through multiple channels: changes in productivity of household enterprises, prices of consumed goods, and factor returns like wages (Ravallion & Datt, 1996). Bourguignon (2003) establishes a mechanical link between income growth, poverty reduction, and income distribution, showing that equitable growth amplifies poverty reduction (Bourguignon, 2003; Fosu, 2009). Warr (2000) argues that overall economic growth is more critical than sectoral composition, though agricultural growth remains vital in rural contexts (Warr, 2000). Conversely, Ferreira et al. (2010) highlight that in Brazil, social transfers and macroeconomic stability, rather than sectoral growth, drove poverty reduction, underscoring contextual variations (Ferreira et al., 2010). Deininger and Okidi (2003) show that agricultural price liberalization in Uganda boosted incomes, confirming agriculture's role in early-stage economies (Deininger & Okidi, 2003). These studies suggest that sectoral growth cannot be evaluated in isolation from distributional regimes and macroeconomic conditions—an important consideration in Sudan's highly volatile, conflict-affected environment.

Megbowon and Mulatu (2025) find that in Lesotho, only agricultural growth significantly reduces poverty in the long run, while industrial and service sectors may increase poverty due to limited labor absorption (Megbowon & Mulatu, 2025). Similarly, Osabohien et al. (2019) and Khan et al. (2016) confirm agriculture's role in increasing earnings and reducing poverty in West Africa and Pakistan, respectively (Osabohien et al., 2019; Khan et al., 2016). The United Nations Economic and Social Commission for Asia and the Pacific (United Nations Economic and Social Commission for Asia and the Pacific [UNESCAP], 2018) emphasizes that value-added agricultural growth is critical for sustainable poverty reduction (UNESCAP, 2018). However, some studies note a diminishing role for agriculture as economies develop, with non-agricultural sectors gaining traction (Christiaensen et al., 2010; Ferreira et al., 2010). What is largely missing from this literature is evidence for countries that combine strong agricultural dependence, repeated conflict, and extreme macroeconomic instability, conditions that characterize Sudan and many other fragile states.

In conclusion, the literature highlights that structural economic change, as articulated by Lewis (1954) and Rostow (1960), influences poverty reduction through within-sector productivity growth and labor reallocation. Agriculture remains pivotal in early-stage economies due to its labor intensity and rural linkages, as evidenced in studies from India, China, and sub-Saharan Africa (Ravallion & Datt, 1996; Montalvo & Ravallion, 2010; Chukwu, 2025). As economies diversify, manufacturing and services gain prominence in reducing poverty, particularly in urbanizing contexts, though their impact varies by region (Christiaensen et al., 2011; Erumban & de Vries, 2024). Barriers such as skill mismatches, geographic immobility, and, in contexts like Sudan, conflict and undercapitalization, constrain the poverty-reducing potential of sectoral shifts (Pavcnik, 2017; Ali, 2019). Empirical evidence underscores the differential impacts of sectoral growth, with labor-intensive sectors like agriculture and construction often outperforming capital-intensive industries, mediated by channels such as wages, prices, and income distribution (Loayza & Raddatz, 2010; Bourguignon, 2003). Yet, most existing work focuses on relatively stable middle-income economies or on cross-country panels that give limited attention to fragile states. As a result, we know little about whether and how sectoral growth has translated into poverty reduction in Sudan, despite its heavy agricultural dependence, large informal sector, and repeated conflicts. This study addresses that gap by providing a country-level, time-series analysis of the links between sectoral value-added levels and monetary poverty in Sudan over 1970–2022, thereby placing Sudan within the broader comparative debate on structural transformation and poverty in fragile economies.

3. Socioeconomic Trends and Poverty Dynamics in Sudan

Understanding poverty in Sudan requires examining how changes in sectoral composition—particularly in agriculture, industry, and services—have influenced household welfare and inequality. Structural transformation not only drives economic growth but also determines the inclusivity of that growth, especially in a context of fragility and recurring shocks. This section explores how shifts in the relative performance of economic sectors have shaped poverty outcomes from 1960 to 2023. Table I provides decadal averages of socioeconomic indicators from 1960 to 2022, revealing a U-shaped trajectory in GDP per capita (constant 2015 US$), which declined from 796.27 in 1960–1969 to 765.91 in 1980–1989, rose to a peak of 1266.89 in 2010–2019, and then fell to 1013.21 in 2020–2022, reflecting initial post-independence stagnation, an oil-driven boom in the 1990s and 2000s, and a recent downturn due to the war starting April 15, 2023, which devastated production capacity and displaced millions (United Nations High Commissioner for Refugees [UNHCR], 2025). This economic volatility is mirrored in GDP per capita growth, which shifted from -0.92% in 1960–1969 to a peak of 4.43% in 1990–1999, before plunging to -4.75% in 2020–2022, underscoring the fragility of growth amid political instability. Household consumption per capita, which more directly affects poverty, mirrored this pattern. It rose from 687.44 in 1960–1969 to 1036.90 in 2010–2019, then dropping to 915.16 in 2020–2022, signaling reduced purchasing power linked to this conflict-induced decline. Population growth, peaking at 3.74% in 1970–1979 and declining to 2.24% in 2020–2022, suggests a demographic transition tempered in part by outmigration. Domestic credit to the private sector as a percentage of GDP fell to 6.55% in 2020–2022, indicating a weakened financial system that likely constrained household coping mechanisms and investment in small-scale productive activities. Human development improved, with life expectancy rising from 50.59 years in 1960–1969 to 66.58 years in 2020–2022 and infant mortality dropping from 90.55 to 38.30 per 1,000 live births, though regional disparities persist, particularly in conflict zones like Darfur, where the April 15, 2023 war's disruption threatens to reverse these gains (World Bank, 2025).

Table I: Decadal Trends in Socioeconomic Indicators in Sudan (1960–2023)

Period	GDP per capita (US$ 2015)	GDP per capita growth (%)	Household consumption per capita (US$ 2015)	Population growth (%)	Domestic credit to private sector (% of GDP)	Life expectancy (years)	Infant mortality (per 1,000)
1960–1969	796.27	-0.92	687.44	3.41	10.44	50.59	90.55
1970–1979	784.97	2.34	672.35	3.74	9.91	53.56	89.05
1980–1989	765.91	1.29	740.28	2.39	9.82	55.86	84.84
1990–1999	927.86	4.43	790.13	2.28	2.77	58.13	69.31
2000–2009	1260.92	1.55	935.16	2.49	8.91	61.59	53.25
2010–2019	1266.89	-0.83	1036.90	2.76	9.58	65.19	43.26
2020–2023	1013.21	-4.75	915.16	2.24	6.55[3]	66.58	38.30

Source: World Bank World Development Indicators (World Bank, 2025).

Table II complements this by presenting decadal averages of poverty metrics—headcount, gap index, and severity index—alongside sectoral value-added growth from 1970 to 2023. These data directly link changes in socioeconomic conditions to the evolution of poverty dynamics in Sudan. Poverty headcount declined from 72.79% in 1970–1979 to 56.93% in 2010–2019, then rose to 64.33% in 2020–2023, aligning with the GDP per capita U-shape and reflecting a period of poverty reduction during the oil boom, reversed by the 2011 secession and the 2023 war, which drove a 7.40% poverty headcount increase through displacement and economic collapse (UNHCR, 2025). The poverty gap and severity indices followed suit, dropping from 45.91% and 15.07% in 1970–1979 to 20.39% and 9.16% in 2010–2019, then rising to 30.82% and 13.36% in 2020–2023, deepening poverty amid falling consumption and credit access. Agricultural value-added growth averaged 1.62% in 1970–1979, peaked at 4.37% in 1990–1999, and then fell to –4.61% in 2020–2023, representing a sharp contraction of 4.61%. While earlier expansions supported modest poverty reduction through agriculture's labor-absorbing role, the recent conflict-induced decline—driven by land inaccessibility and outmigration—has instead contributed to the renewed surge in poverty (Food and Agriculture Organization [FAO], 2019).

Industry growth, volatile with a 13.21% peak in 2000–2009 tied to oil, contracted to -6.71% in 2020–2023, supporting poverty reduction during the boom (e.g., lowest 62.17% headcount) but contributing to the recent rise due to factory destruction (UNHCR, 2025), aligning with reduced GDP growth. Services growth, starting at 8.17% in 1970–1979, declined to -0.79% in 2010–2019 and -8.41% in 2020–2023, showing limited poverty impact despite its GDP share, likely due to

[3] For 2020–2023, the Domestic credit to private sector (% of GDP) is calculated using data for 2020–2022 due to unavailable 2023 data.

urban-biased expansion concentrating benefits in cities like Khartoum, leaving rural areas underserved and exacerbating spatial inequalities (World Bank, 2020). Furthermore, its contraction to –8.41% in 2020–2023 further reflects the vulnerability of informal and low-productivity service segments in the face of conflict and instability.

Table II: Poverty Indicators and Sectoral Growth in Sudan (1970–2023)

Period	Poverty Headcount (%)	Poverty Gap (%)	Poverty Severity (%)	Agricultural Growth (%)	Industrial Growth (%)	Services Growth (%)
1970–1979	72.79	45.91	15.07	1.62	3.93	8.17
1980–1989	68.68	34.65	13.12	2.82	5.66	2.73
1990–1999	68.03	35.26	13.10	4.37	7.99	3.48
2000–2009	62.17	26.06	10.66	1.48	13.2	5.42
2010–2019	56.93	20.39	9.16	0.27	0.35	-0.79
2020–2023	64.33	30.82	13.36	-4.61	-6.71	-8.41

Source: Standardized World Income Inequality Database (SWIID, version 9.6) and World Development Indicators (World Bank, 2025)

The interplay reveals that during 1970–1979, modest agricultural (1.62%) and services (8.17%) growth coincided with high poverty (72.79%) and low GDP per capita (784.97), reflecting structural constraints. The 1990–1999 period's balanced growth (4.37%, 7.99%, 3.48%) stabilized poverty (68.03%) with rising GDP (927.86), while 2000–2009's industrial surge (13.21%) drove the lowest poverty (62.17%) and peak GDP (1260.92). Conversely, 2020–2023's negative sectoral growth (-4.61%, -6.71%, -8.41%) mirrors the economic contraction (GDP 1013.21, growth -4.75%), highlighting vulnerability to conflict.

4. Construction of Poverty Metrics

Understanding the dynamics of poverty in Sudan requires reliable and internationally comparable measures. In this study, we adopt the Foster-Greer-Thorbecke (FGT) class of poverty indices, poverty headcount ratio (P_0), poverty gap index (P_1), and poverty severity index (P_2), to capture the incidence, depth, and intensity of poverty. These metrics are estimated using the \$2.15/day (2017 PPP) international poverty line, following World Bank standards. Given the limited availability of consistent household survey data over time, we employ a parametric estimation approach that utilizes the lognormal distribution, drawing on per capita household consumption from the World Development Indicators and Gini coefficients from the Standardized World Income Inequality Database (SWIID). This approach allows us to estimate a consistent time series of poverty measures for Sudan, forming the basis for the subsequent empirical analysis of structural change and poverty reduction.

4.1 Data Sources and Assumptions

The analysis relies on internationally recognized and methodologically consistent data sources to ensure the reliability and comparability of poverty estimates over time. Mean per capita household consumption, expressed in constant 2017 PPP USD, is obtained from the World Bank's World Development Indicators, providing a standardized measure of average living standards. Income inequality is captured through Gini coefficients sourced from the Standardized World Income

Inequality Database (SWIID, version 9.6), which offers harmonized estimates adjusted for cross-country and temporal comparability. For years where Gini coefficient data for Sudan in the SWIID (version 9.6) were missing, values were interpolated linearly using data from adjacent years to ensure a continuous time series (Datt, 1998). In line with the World Bank's global poverty thresholds, the international poverty line of $2.15 per person per day at 2017 PPP is employed as the benchmark for identifying the poor. The computation of poverty metrics is based on the assumption that household consumption follows a lognormal distribution, a common and empirically supported approach in poverty and inequality analysis (Datt, 1998; Ferreira et al., 2016).

4.2 Poverty Headcount Ratio (P_0)

The poverty headcount ratio (P_0) represents the proportion of the population living below the poverty line. Given the lognormal distribution assumption, the headcount index is calculated using the cumulative distribution function (CDF) of the lognormal distribution:

$$P_0 = \Phi\left(\frac{\ln(PL) - \mu}{s}\right) \qquad (1)$$

Where Φ is the standard normal cumulative distribution function (CDF); PL is the poverty line ($2.15/day or $784.75/year), μ is the mean of the log distribution of consumption (estimated from WDI); and s the standard deviation, derived from the Gini coefficient (G) using:

$$G = 2\Phi\left(\frac{s}{\sqrt{2}}\right) - 1 \Rightarrow s = \sqrt{2}\,\Phi^{-1}\left(\frac{G+1}{2}\right) \qquad (2)$$

This enables the estimation of the proportion of individuals with consumption levels below the poverty line for each year in the sample.

4.3 Poverty Gap Index (P_1)

The poverty gap index (P_1) measures the average shortfall of the poor from the poverty line, expressed as a proportion of the poverty line. It reflects the depth of poverty and is estimated using the following formula under lognormality:

$$P_1 = \int_0^{PL} \left(1 - \frac{x}{PL}\right) f(x)\,dx \qquad (3)$$

Using the lognormal distribution and its parameters (μ, s), this integral is computed numerically or using standard formulas found in the literature (e.g., Datt, 1998; Ferreira et al., 2016). P_1 provides an estimate of how far, on average, the poor fall below the poverty line.

4.4 Poverty Severity Index (P_2)

The poverty severity index (P_2), or squared poverty gap, accounts for inequality among the poor. It gives greater weight to those who are farthest below the poverty line. It defined as:

$$P_2 = \int_0^{PL} \left(1 - \frac{x}{PL}\right)^2 f(x)dx \qquad (4)$$

Again, assuming a lognormal distribution, this expression is evaluated based on the derived values of μ and s for each year. P_2 captures both the incidence and intensity of poverty, offering a comprehensive perspective on the distribution of deprivation among the poor.

The three poverty indices, P_0, P_1, and P_2, are computed for each year from 1970 to 2022, generating a consistent and internationally comparable time series for Sudan. These estimates form the dependent variables in the subsequent econometric analysis, where the influence of sectoral composition and other relevant control factors on poverty is examined.

5. Methodology

5.1 Model Specification

This study builds on the empirical foundations of Ravallion and Chen (2007), Suryahadi et al. (2009), and Ravallion and Datt (1996), who emphasize the role of sectoral composition and macroeconomic factors in shaping poverty outcomes. More recent contributions, such as Erumban & de Vries (2024), reinforce the relevance of structural transformation in reducing poverty. Drawing from these studies, the present model examines changes in sectoral value added and selected macroeconomic indicators influence poverty metrics in Sudan over time.

The general functional form of the model is specified as:

$$\mathrm{POV}_t = f(\mathrm{AGR}_t, \mathrm{IND}_t, \mathrm{SERV}_t, \mathrm{POP}_t, \mathrm{EDU}_t, \mathrm{CRD}_t, \mathrm{EXP}_t, \mathrm{INF}_t, \mathrm{GDPG}_t, \mathrm{PRIV}_t) \qquad (5)$$

In econometric terms, the model is estimated as:

$$\begin{aligned}\mathrm{lnPOV_t} = {} & \alpha_0 + \alpha_1 \mathrm{lnAGR_t} + \alpha_2 \mathrm{lnIND_t} + \alpha_3 \mathrm{lnSERV_t} + \alpha_4 \mathrm{lnPOP_t} + \alpha_5 \mathrm{lnEDU_t} + \alpha_6 \mathrm{lnCRD_t} \\ & + \alpha_7 \mathrm{lnEXP}_t + \alpha_8 \mathrm{INF_t} + \alpha_9 \mathrm{GDPG_t} + \alpha_{10} \mathrm{PRIV}_t + \varepsilon_t \qquad (6)\end{aligned}$$

Where: $\mathrm{POV_t}$ refers to poverty measures at time *t*, specifically the poverty headcount ratio, poverty gap, and poverty severity index; AGR_t, IND_t, and SERV_t denote the sectoral value-added in agriculture, industry, and services to the GDP (constant 2015 USD); POP_t is total population; EDU_t is average years of schooling; CRD_t is domestic credit provided by banks to the private sector (% of GDP); EXP_t is exports (constant 2015 USD); INF_t is inflation (consumer prices, annual %), and GDPG_t is GDP growth (annual %). PRIV_t is a dummy variable (1 post-1992, 0 otherwise), capturing Sudan's 1992 privatization and liberalization reforms, α_0 is the intercept, α_1 to α_{10} are the parameters to be estimated, and ε_t is the error term.

Education, total population, and GDP growth are included due to their well-established roles in shaping poverty dynamics. Education enhances human capital, influencing productivity, employment, and income, and is consistently linked to poverty reduction. Total population reflects demographic pressure, affecting labor markets and resource allocation. GDP growth captures aggregate economic performance, which can reduce poverty when growth is inclusive and broad-

based. In addition, privatization, exports, and credit are included for their theoretical relevance to the sectoral growth–poverty nexus. The privatization dummy reflects structural adjustment reforms, which have led to public sector downsizing, job losses, and increased informality, exacerbating poverty and altering income distribution. Exports capture external sector integration, influencing employment, wages, and government spending, with poverty effects depending on the inclusiveness of growth. Credit reflects financial sector development, enabling investment and income generation, particularly in rural areas where limited access constrains poverty reduction. Together, these variables provide a comprehensive framework for analyzing the multidimensional drivers of poverty in Sudan.
Variables are logged where specified in Table III to address skewness and interpret coefficients as elasticities, except for INF_t and GDPG_t, which are percentages (Ravallion and Datt, 1996).

5.2 Data

The analysis utilizes annual time series data for Sudan spanning the period from 1970 to 2022. The dataset is compiled from reputable sources, including the World Bank's World Development Indicators (WDI), the Barro-Lee Educational Attainment Dataset, and the Standardized World Income Inequality Database (SWIID, version 9.6). Poverty metrics—namely the headcount ratio (P0), poverty gap (P1), and poverty severity index (P2)—are initially derived as unit-free FGT indices on the interval [0,1] using the 2.15 USD/day (2017 PPP) poverty line and the lognormal procedure outlined in Section 3. These indices are subsequently scaled by a factor of 100, so that all three measures are reported in percentage points. Table III provides a summary of the variables used, including their definitions, measurement units, and data sources.

Table III: Data Sources and Variable Definitions

Variable	Definition	Measurement Unit	Source
lnAGR	Agriculture, forestry, fishing value added (natural logarithm)	Constant 2015 USD	World Bank (WDI)
lnIND	Industry (including construction) value added (natural logarithm)	Constant 2015 USD	World Bank (WDI)
lnSERV	Services value added (natural logarithm)	Constant 2015 USD	World Bank (WDI)
lnPOP	Total population (natural logarithm)	Number of people	World Bank (WDI)
lnEDU	Average years of schooling (natural logarithm)	Years	Barro-Lee Dataset
lnCRD	Domestic credit to private sector by banks (% of GDP, natural logarithm)	Percentage of GDP (%)	World Bank (WDI)
lnEXP	Exports of goods and services (natural logarithm)	Constant 2015 USD	World Bank (WDI)
INF	Inflation, consumer prices (annual)	(%)	World Bank (WDI)
GDPG	GDP growth (annual)	(%)	World Bank (WDI)
PRIV	Dummy variable (1 post-1992, 0 otherwise) for privatization liberalization policies	Binary	Authors' construction
lnP0	Poverty headcount ratio at 2.15 USD/day (2017 PPP, natural logarithm)	(FGT P0 × 100)	Authors' computation
lnP1	Poverty gap at 2.15 USD/day (2017 PPP, natural logarithm)	(FGT P1 × 100)	Authors' computation
lnP2	Poverty severity at 2.15 USD/day (2017 PPP, natural logarithm)	FGT P2 × 100	Authors' computation

5.3 Estimation Strategy

5.3.1 Unit Root and Integration Testing

Given the time series nature of the data, it is crucial to assess the stationarity properties of the variables before model estimation. This study employs the Autoregressive Distributed Lag (ARDL) approach, which requires that all variables be either stationary at level I(0) or first difference I(1), but not integrated of order two, I(2). Stationarity is tested using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests.

5.3.2 ARDL Bounds Testing and Cointegration Analysis

The study adopts the Autoregressive Distributed Lag (ARDL) bounds testing approach to explore both short-run and long-run relationships among variables. The ARDL method, developed by Pesaran et al. (2001), is suitable when the variables are a mix of I(0) and I(1) but not I(2). This method is suitable for mixed I(0) and I(1) variables and robust to small samples. The optimal lag structure is selected using information criteria such as the Akaike Information Criterion (AIC) or the Schwarz Bayesian Criterion (SBC). The ARDL model is specified as:

$$\Delta \mathrm{lnPOV}_t = \beta_0 + \sum_{i=1}^{p} \beta_i \Delta \mathrm{lnPOV}_{t-i} + \sum_{i=0}^{q} \beta_i \Delta \mathrm{lnX}_{t-i} + \gamma_1 \mathrm{lnPOV}_{t-1} + \gamma_2 \mathrm{lnX}_{t-1} + \mu_i \quad (7)$$

Where Δ denotes first differences, lnPOV_t are the poverty measures, namely poverty headcount ratio (P0), poverty gap(P1), and poverty severity index(P2) each expressed in percentage points (FGT indices multiplied by 100); X_t includes lnAGR_t, lnIND_t, lnSERV_t, lnPOP_t, lnEDU_t, lnCRD_t, lnEXP_t, INF_t, GDPG_t and PRIV_t, p and q are lag orders selected by the Akaike Information Criterion (AIC), and μ_i is the error term. The bounds test examines the null hypothesis of no cointegration ($\gamma_1 = \gamma_2 = 0$) using the F-statistic compared to critical bounds. If the calculated F-statistic exceeds the upper critical bound, the null hypothesis is rejected, suggesting the presence of cointegration. If it falls below the lower bound, the null cannot be rejected. If the F-statistic lies between the bounds, the result is inconclusive (Pesaran et al., 2001).

5.3.3 Error Correction and Dynamic Modeling

Upon confirming cointegration, an error-correction representation of the selected ARDL model is estimated to capture short-run dynamics and the speed of adjustment to the long-run equilibrium, as specified in equation (8):

$$\Delta \mathrm{lnPOV}_t = \delta_0 + \sum_{i=1}^{p} \delta_{1i} \Delta \mathrm{lnPOV}_{t-i} + \sum_{i=0}^{q} \delta_{2i} \Delta \mathrm{lnX}_{t-i} + \lambda ECT_t + v_t \quad (8)$$

In this specification, the coefficients on the differenced regressors capture the short-run effects of changes in sectoral value added and other covariates on poverty, while the coefficient λ on the error-correction term measures the speed of adjustment back to the long-run equilibrium after a shock. A statistically significant and negative λ confirms the existence of a stable long-run relationship and implies that deviations from equilibrium are gradually corrected over time.

5.3.4 Model Diagnostics and Stability Tests

To ensure the reliability and robustness of the estimated models, a series of diagnostic tests are conducted: serial correlation is tested using the Breusch-Godfrey LM test; heteroskedasticity is examined through the Breusch-Pagan-Godfrey test; model specification is assessed using the Ramsey RESET test; and normality of residuals is checked via the Jarque-Bera test. These tests help confirm that the estimated relationships are consistent and reliable across the sample period.

6. Empirical Results and Discussion

This section presents the empirical findings on the relationship between sectoral economic composition and poverty dynamics in Sudan. The analysis explores how structural transformations across agriculture, industry, and services, alongside relevant macroeconomic factors, shape the incidence, depth, and severity of poverty. However, prior to model estimation, unit root tests were conducted to verify the stationarity properties of the variables and ensure the validity of the ARDL approach. Both the ADF and PP tests were employed to assess stationarity at level and first difference, under specifications with intercept and with intercept and trend.

Table IV: Results of ADF and PP Tests for Stationarity at Level and First Difference

Variable	ADF Stat (Level, Intercept)	ADF Stat (1st Diff, Intercept)	ADF Stat (Level, Trend)	ADF Stat (1st Diff, Trend)	Stationary at Level?	Stationary at 1st Diff,
ln(AGR)	-0.412	-8.214***	-1.889	-8.133***	No	Yes
ln(IND)	-1.900	-6.150***	-2.100	-6.170***	No	Yes
ln(SERV)	-1.694	-4.204***	0.801	-4.564***	No	Yes
ln(POP)	0.042	-3.693***	-0.833	-3.702**	No	Yes
ln(EDU)	-1.700	-5.900***	-1.950	-5.920***	No	Yes
ln(CRD)	-2.392	-6.642***	-2.387	-6.650***	No	Yes
ln(EXP)	-1.949	-6.530***	-2.156	-6.552***	No	Yes
INF	-2.870*	-6.400***	-2.842	-6.420***	Yes	Yes
GDPG	-4.121***	-8.396***	-4.529***	-6.558***	Yes	Yes
lnP0	-2.000	-6.180***	-2.100	-6.200***	No	Yes
lnP1	-2.100	-6.250***	-2.200	-6.270***	No	Yes
lnP2	-2.050	-6.200***	-2.150	-6.220***	No	Yes
Variable	**PP Stat (Level, Intercept)**	**PP Stat (1st Diff, Intercept)**	**PP Stat (Level, Trend)**	**PP Stat (1st Diff, Trend)**	**Stationary at Level?**	**Stationary at 1st Diff?**
ln(AGR)	-0.359	-8.196***	-1.858	-8.117***	No	Yes
ln(IND)	-2.027	-9.109***	-2.242	-9.138***	No	Yes
ln(SERV)	-1.808	-4.252***	0.203	-4.564***	No	Yes
ln(POP)	0.222	-4.441***	-0.624	-4.446***	No	Yes
ln(EDU)	-1.462	-5.747***	-1.578	-5.775***	No	Yes
ln(CRD)	-2.469	-10.41***	-2.465	-10.450***	No	Yes
ln(EXP)	-2.110	-10.01***	-2.286	-10.061***	No	Yes
INF	-2.910*	-7.403***	-2.895	-7.412***	Yes	Yes
GDPG	-3.947***	-13.56***	-4.259***	-18.05***	Yes	Yes
lnP0	-1.848	-7.488***	-2.124	-7.516***	No	Yes
lnP1	-1.682	-4.997***	-1.833	-5.018***	No	Yes
lnP2	-1.488	-6.559***	-1.739	-6.587***	No	Yes

*** if p-value < 0.01, ** if p-value < 0.05, * if p-value < 0.1, and no asterisk if p-value ≥ 0.1

Table IV summarizes the unit root test results. As can be seen in the table, the majority of variables, including sectoral value-added (lnAGR, lnIND, lnSERV), demographic and development indicators (lnPOP, lnEDU), financial development (lnCRD), trade (lnEXP), and poverty indices (lnP0, lnP1, lnP2), are non-stationary in levels but become stationary after first differencing. This confirms they are integrated of order one, I(1). Conversely, inflation (INF) and GDP growth (GDPG) variables are found to be stationary at level across both tests, indicating they are I(0). This mixed integration order, i.e., the presence of both I(0) and I(1) variables without any I(2), reinforces the appropriateness of the ARDL approach, which is well-suited for such cases.

To proceed with the bounds testing approach within the ARDL framework, it is essential to first determine the optimal lag structure. This step ensures well-specified residual dynamics and mitigates the risk of omitted variable bias. Lag selection was guided by standard information criteria, including the Akaike Information Criterion (AIC), Schwarz Criterion (SC), Hannan–Quinn (HQ), and the sequential modified likelihood ratio (LR) test. The results, presented in Table V, suggest that a lag length of 2 is optimal based on the LR, FPE, and SC criteria, which emphasize model fit while penalizing for over-parameterization.

Table V: Lag Selection Criterion

Lag	LogL	LR	FPE	AIC	SC	HQ
0	–302.73	NA	7.81e–09	12.5490	12.9696	12.7092
1	358.58	1005.19	3.57e–18	–9.0633	–4.0156	–7.1411
2	566.17	224.19*	2.29e–19*	–12.5266	–2.8518*	–8.8424
3	879.97	200.84	1.20e–21	–20.2389*	–5.9370	–14.7927*

Note: Asterisks (*) indicate lag order selected by the respective criterion. LR = sequential modified likelihood ratio test statistic (at 5% level); FPE = Final Prediction Error; AIC = Akaike Information Criterion; SC = Schwarz Criterion; HQ = Hannan–Quinn Criterion.

Building on the optimal lag structure identified in the preceding section, the ARDL bounds testing approach was applied to examine the existence of long-run relationships between sectoral economic structure and poverty outcomes in Sudan. The bounds test results for the three ARDL models, each corresponding to a distinct poverty dimension, are reported in Table VI. In the first model, where the dependent variable is the log of the poverty headcount ratio (lnP_0), the computed F-statistic is 8.80. This value is well above the upper bound critical value at the 1% level (I(1) = 3.68), indicating strong evidence of cointegration among the included variables. This suggests that sectoral output shares and macroeconomic indicators collectively exhibit a statistically significant long-run association with the proportion of the population living below the poverty line. The second model, estimated with the log of the poverty gap index (lnP_1) as the dependent variable, yields an F-statistic of 9.18. Again, this statistic exceeds the 1% critical threshold, confirming the existence of a stable long-run relationship between the explanatory variables and the average shortfall of consumption from the poverty line among the poor. Similarly, the third model, which focuses on the log of the poverty severity index (lnP_2), generates an F-statistic of 8.54, also surpassing the upper bound at the 1% significance level. This result reinforces the finding that macroeconomic and structural variables are cointegrated with the squared poverty gap, capturing both the incidence and inequality of poverty. Taken together, these results consistently support the presence of cointegration across all three models, implying that sectoral composition, reflected in value-added from agriculture, industry, and services, and other macroeconomic indicators such as education, population growth, inflation, credit to the private sector, exports, and GDP growth exert long-term influences on poverty outcomes in Sudan.

Table VI: ARDL Bounds Test for Cointegration (Dependent Variables: $\ln P_0$, $\ln P_1$, $\ln P_2$)

Poverty Measure	Selected ARDL Model	F-statistic	Cointegration Decision	Sample Size
$\ln P_0$	ARDL(1,2,2,0,2,2,2,1,1,1)	8.80	Cointegration confirmed	51
$\ln P_1$	ARDL(1,2,2,0,2,0,2,2,1,1)	9.18	Cointegration confirmed	51
$\ln P_2$	ARDL(1,2,2,0,2,2,2,2,1,1)	8.54	Cointegration confirmed	51

Asymptotic Critical Values (Pesaran et al., 2001, Case 2: Restricted Constant)

- *At 10%: I(0) = 1.89, I(1) = 2.87*
- *At 5%: I(0) = 2.19, I(1) = 3.28*
- *At 1%: I(0) = 2.50, I(1) = 3.68*

Following the confirmation of the long-run relationships among the variables through the ARDL bounds test, Table V presents the estimated long-run coefficients for the three poverty indices: poverty headcount ratio (P_0), poverty gap index (P_1), and poverty severity index (P_2). The estimated models provide a comprehensive understanding of how sectoral composition and macroeconomic variables influence poverty in Sudan.

The role of agriculture emerges as consistently significant across all three models. In column (1), which corresponds to the poverty headcount (P0), the coefficient on the lagged log of agricultural value added (lnAGR) variable is –0.200 and statistically significant at the 5% level. This negative association becomes even more pronounced in columns (2) and (3), with coefficients of –0.683 and –0.604 respectively, both significant at the 1% level. These results suggest that expansions in the agricultural sector play a critical role not only in reducing the proportion of the population living in poverty but also in narrowing the poverty gap and alleviating poverty severity. This is particularly relevant in Sudan, where agriculture remains the primary source of employment, accounting for more than 70% of jobs, and a major generator of household income. In line with Loayza and Raddatz (2010), who argue that the poverty-reducing effects of growth depend significantly on the labor intensity of sectors, these findings emphasize the strategic importance of agriculture in contexts like Sudan, where labor absorption is a key mechanism for poverty reduction. Moreover, as Dercon (2009) notes, widespread agricultural productivity gains can reduce food costs, which is especially critical in largely closed economies or where food prices directly affect household welfare.

Industrial sector development also shows robust poverty-reducing effects across the three specifications. The coefficient on lnIND variable is –0.248 in column (1), –0.550 in column (2), and –0.526 in column (3), all statistically significant. These findings highlight the importance of structural transformation and industrial diversification in driving inclusive growth. Part of the observed poverty-reducing effect may stem from the significant movement of workers from other sectors into gold quarrying activities across various regions in Sudan, which has improved household incomes and livelihoods (Elbadawi & Suliman, 2018). This dynamic aligns with Pavcnik (2017), who argues that limited mobility of labor across sectors and geographic locations can exacerbate poverty, whereas greater mobility facilitates income improvements and poverty mitigation. This result is further reinforced by emerging empirical evidence highlighting the growing significance of non-agricultural sectors in poverty alleviation. For instance, Christiaensen, Demery, and Kuhl (2011), as well as Himanshu, Murgai, and Stern (2013), have argued that the role of non-agricultural sectors in reducing poverty has increased over time, raising questions about whether agriculture alone can continue to fulfill its traditionally central role. Additionally, within the industrial sector, the manufacturing sub-sector in particular has proven to be a powerful engine of poverty reduction. As noted by Erumban and de Vries (2024), productivity growth in manufacturing has played a major role in lowering poverty in developing Asia, though its impact has been more limited in Sub-Saharan Africa, highlighting both the potential and the unrealized opportunities for countries like Sudan to leverage this sector more effectively.

Despite the services sector's substantial contribution to Sudan's GDP and its rapid growth, particularly during the 1999–2011 oil boom, compared to agriculture and industry, its impact on poverty alleviation remains limited. As shown in Table VII, the estimated coefficients for the lnSERV variable are statistically insignificant across all three models (P_0, P_1, P_2), indicating that services sector expansion has not significantly reduced the headcount, depth, or severity of poverty in the long run. This finding underscores a critical structural challenge in Sudan's development trajectory. Although the services sector accounts for a significant share of GDP value added, its growth is predominantly urban-centric and concentrated in modern economic segments, rendering it spatially and socially disconnected from rural areas where poverty is most acute. This urban-rural disconnect aligns with broader empirical literature, which suggests that growth in modern urban sectors often fails to benefit rural populations reliant on agriculture (Bezemer & Headey, 2008; Benfica & Henderson, 2021; Christiaensen et al., 2011; Winters, 2002). Furthermore, structural barriers, such as skill mismatches, limited mobility, and institutional constraints, often hinder poor individuals' transition into productive service activities (Pavcnik, 2017). Additionally, the sector's openness to new entrants, such as low-skilled workers, may neutralize its poverty-reducing potential, as an influx of labor could depress wages, offsetting income gains for the poor (Loayza & Raddatz, 2010).

Population growth (lnPOP) exerts a large and statistically significant positive effect on poverty in all three models. The estimated coefficients are 1.156, 3.458, and 2.896 in columns (1), (2), and (3), respectively, all significant at the 1% level. These results highlight the challenges posed by Sudan's high fertility and rapid population growth, which strain infrastructure, dilute public service delivery, and exert downward pressure on per capita income, particularly among the poorest segments of the population.

Educational attainment (lnEDU) is strongly associated with reductions in poverty. The coefficients are negative and statistically significant across all three specifications, with the largest impact seen on the poverty gap (–1.406) in column (2). This finding underscores the transformative role of human capital investment in poverty alleviation. Access to credit (lnCRD) is another consistently significant poverty-reducing factor, with coefficients of –0.083, –0.279, and –0.160 across the three models, all statistically significant. These results imply that financial inclusion and credit access are essential tools for enabling small-scale enterprise development, smoothing consumption, and building resilience to economic shocks among low-income households. In contrast, the coefficient on exports (lnEXP) is positive and statistically significant in all three models, 0.161, 0.388, and 0.355, respectively. This counterintuitive result suggests that, in the Sudanese context, export expansion may have disproportionately benefited capital-intensive or enclave sectors, such as oil and mineral extraction, which are weakly linked to domestic labor markets and rural economies (Ali & Ebaidalla, 2023).

GDP growth (GDPG) and inflation (INF) variables both exhibit small but statistically significant negative coefficients across all models. The GDPG coefficients (–0.003 to –0.014) indicate a relatively inelastic poverty response to aggregate growth, yet their direction and significance suggest that sustained, inclusive economic expansion can contribute to poverty reduction. Similarly, the negative coefficients for INF (ranging from –0.002 to –0.008) imply a counterintuitive poverty-reducing effect, likely driven by Sudan's economic structure. In Sudan, a substantial share of the workforce is employed in the informal sector, including artisanal gold mining and subsistence agriculture, where wages and incomes are often tied to commodity prices or barter systems rather than formal wage contracts (Ali & Ebaidalla, 2019). Consequently, moderate inflation may increase nominal incomes for informal workers without eroding their real purchasing power, as their earnings adjust to rising prices, particularly for exportable commodities like gold. Moreover, inflation can reduce the real value of debt burdens for rural households, further alleviating poverty (World Bank, 2020). These mechanisms are particularly relevant in Sudan's conflict-affected economy, where formal labor markets are limited, and informal activities dominate (Ali & Ebaidalla, 2019).

Finally, the error-correction terms are negative, highly significant, and range from –0.427 to –0.571 across the three models. Specifically, the ECT coefficient is –0.571 in the poverty-headcount (P0) model, –0.427 in the poverty-gap (P1) model, and –0.531 in the poverty-severity (P2) model, implying that approximately 57.1%, 42.7%, and 53.1% of the previous period's disequilibrium are corrected within one period, respectively. These coefficients confirm that the system adjusts relatively quickly to restore the long-run equilibrium after short-run deviations in all three poverty measures.

In summary, the long-run estimates provide compelling evidence that structural transformation, particularly through the expansion of agriculture and industry, alongside human capital development, financial inclusion, and macroeconomic stability, are central to reducing poverty in Sudan. However, the positive association between exports and poverty, as well as the limited impact of the service sector, points to the need for a more inclusive and diversified growth strategy that aligns sectoral development with poverty reduction goals. These findings are consistent with the broader literature emphasizing the role of labor-intensive and productivity-enhancing sectors in fostering pro-poor growth (Loayza & Raddatz, 2010; Dercon, 2009), and they offer important policy insights for designing targeted interventions in fragile economies like Sudan.

Table VII: ARDL Long-Run Estimates of Determinants of Poverty Indices

Variable	Δln(P0)	S.E.	Δln(P1)	S.E.	Δln(P2)	S.E.
$\ln(AGR_{t-1})$	-0.200**	[0.062]	-0.683***	[0.197]	-0.604***	[0.182]
$\ln(IND_{t-1})$	-0.248***	[0.058]	-0.550**	[0.217]	-0.526**	[0.206]
ln(SERV)	-0.079	[0.056]	-0.073	[0.147]	-0.297	[0.179]
$\ln(POP_{t-1})$	1.156***	[0.209]	3.458***	[0.759]	2.896***	[0.704]
$\ln(EDU_{t-1})$	-0.383**	[0.140]	-1.406***	[0.441]	-0.839*	[0.412]
$\ln(CRD_{t-1})$	-0.083***	[0.024]	-0.279***	[0.075]	-0.160**	[0.070]
$\ln(EXP_{t-1})$	0.161***	[0.027]	0.388***	[0.119]	0.355***	[0.112]
$GDPG_{t-1}$	-0.003**	[0.001]	-0.014***	[0.004]	-0.012***	[0.004]
INF_{t-1}	-0.0006***	[0.0001]	-0.002***	[0.001]	-0.0017***	[0.001]
ECT	-0.571***	[0.118]	-0.427***	[0.106]	-0.531***	[0.130]
Constant	-7.497**	[3.086]	-33.900***	[9.660]	-20.006**	[9.161]

Notes: Standard errors in brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The short-run dynamics of poverty in Sudan, as presented in Table VIII, reveal patterns largely consistent with the long-run estimates, while also highlighting the immediate responses of poverty indicators (P0, P1, and P2) to changes in sectoral and macroeconomic variables. These coefficients can be interpreted as elasticities or semi-elasticities depending on whether the variables are in log form. Starting with the agricultural sector, both current and lagged changes in agricultural value-added significantly reduce all three poverty measures. This underscores the sector's strong short-run role in poverty reduction, reaffirming the long-run findings and aligning with the arguments of Loayza and Raddatz (2010) and Dercon (2009) that labor-intensive agriculture, employing over 70% of Sudan's workforce, serves as a key channel for poverty alleviation through income generation and food access.

Similarly, the industrial sector exhibits significant and consistent poverty-reducing effects from both current and lagged output changes. These results confirm the sector's rising importance in alleviating poverty in Sudan, as emphasized earlier. This finding is consistent with the conclusions of Christiaensen et al. (2011) and Himanshu et al. (2013), who argue that non-agricultural sectors are playing a growing role in poverty reduction. It also resonates with Erumban and de Vries (2024), who highlight productivity growth in manufacturing, a key industrial sub-sector, as a driver of poverty reduction, especially in developing contexts. On the other hand, the services sector does not appear explicitly in the short-run regressions, which may reflect its weaker immediate effect on poverty. This is consistent with the earlier argument that despite its large contribution to GDP, especially during the oil boom years (1999–2011), the services sector has largely failed to benefit the poor. This failure may stem from its urban concentration and limited integration with rural, poverty-prone areas.

Population growth (lnPOP) exhibits contrasting effects on poverty across time horizons. In the short run, current population increases are associated with higher poverty levels, likely due to immediate pressures on public services and employment opportunities. Conversely, the lagged population variable shows a poverty-reducing effect, suggesting that over time, demographic and labor market adjustments, such as increased labor supply or urban migration, may mitigate poverty.

Changes in educational attainment show mixed effects, with negative coefficients indicating a poverty-reducing effect on P0 and P2, though with varying significance. This reinforces the long-run finding that education helps alleviate poverty by improving human capital and employability.

In the case of credit to the private sector (lnCRD), short-run changes, particularly lagged values, are associated with increased poverty levels. This contrasts with its long-run poverty-reducing effect, suggesting short-run inefficiencies in credit allocation. In Sudan, credit often favors capital-intensive or urban-based projects, which yield limited immediate benefits for poor, predominantly rural households. Moreover, widespread collateral failure exacerbates this effect, as many borrowers, particularly in the informal and agricultural sectors, struggle to repay loans due to volatile incomes and lack of assets, leading to debt distress and deepened poverty in the short run.

The export sector continues to show poverty-increasing effects in the short run, consistent with the long-run estimates. This may reflect the extractive, enclave-based nature of Sudanese exports (notably oil, gold and other raw materials), which generate limited employment and weak backward linkages to the domestic economy (Ali & Ebaidalla, 2023). GDP growth has a statistically significant poverty-reducing effect across all three indices in the short run, reinforcing the pro-poor nature of inclusive economic expansion. Similarly, inflation, surprisingly, shows a negative sign, suggesting a short-run association with poverty reduction.

Table VIII: Short-Run ARDL Estimation Results for Poverty Indices

Variable	Δln(P0)	S.E.	Δln(P1)	S.E.	Δln(P2)	S.E.
Δln(AGR)	-0.102***	[0.003]	-0.323***	[0.003]	-0.315***	[0.002]
Δln(AGR_{t-1})	0.151***	[0.000]	0.538***	[0.000]	0.434***	[0.000]
ΔlnIND	-0.174***	[0.000]	-0.475***	[0.000]	-0.409***	[0.000]
Δln(IND_{t-1})	-0.072**	[0.006]	-0.294***	[0.003]	-0.237**	[0.010]
ΔlnPOP	3.478***	[0.000]	10.224***	[0.000]	10.461***	[0.000]
Δln(POP_{t-1})	-5.836***	[0.000]	-18.943***	[0.000]	-15.620***	[0.000]
Δln(EDU)	-0.988*	[0.078]			-1.104	[0.522]
Δln(EDU_{t-1})	-1.006*	[0.082]			-4.093**	[0.019]
Δln(CRD)	0.019	[0.257]	0.068	[0.179]	0.071	[0.152]
Δln(CRD_{t-1})	0.082***	[0.000]	0.254***	[0.000]	0.174***	[0.002]
Δln(EXP)	0.111***	[0.000]	0.321***	[0.000]	0.310***	[0.000]
Δln(EXP_{t-1})			0.066**	[0.023]	0.066**	[0.023]
ΔGDPG	-0.002***	[0.000]	-0.008***	[0.000]	-0.007***	[0.000]
ΔINF	-0.0002***	[0.000]	-0.0009***	[0.000]	-0.0009***	[0.000]
PRIV	-0.084***	[0.000]	-0.175***	[0.000]	-0.182***	[0.000]

Notes: Standard errors in brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Finally, the variable PRIV, representing the adoption of privatization and liberalization policies in 1992, shows a significant poverty-reducing effect across all indices. This suggests that the initial policy reforms contributed to structural adjustments with some beneficial short-run impact on poverty, possibly through deregulation, public sector downsizing, or private sector expansion.

The residual diagnostic results reported in Table IX affirm the overall robustness and statistical adequacy of the ARDL models estimated for the poverty indices (P0, P1, and P2). Across all models, the Breusch-Godfrey LM test statistics for both first and second lags are statistically insignificant, indicating no evidence of serial correlation in the residuals. Furthermore, the Breusch-Pagan-Godfrey, Harvey, and Glejser tests uniformly show non-significant results, confirming the presence of homoscedasticity and suggesting that the variance of the residuals is stable across observations. The Jarque-Bera statistics fail to reject the null hypothesis of normality in all models, implying that the residuals are normally distributed—an essential condition for valid hypothesis testing. In addition, the Ramsey RESET tests produce insignificant t- and F-statistics, which indicate that the functional form of the models is correctly specified and that no relevant variables have been omitted.

Table IX: Residual Diagnostic Tests for ARDL Models (P0, P1, P2)

Model	Test	Statistic	Value (df)	p-value	Decision
lnP0	Breusch-Godfrey (lag 1)	F-statistic	0.0906 (1, 25)	0.766	Do not reject H_0
	Breusch-Godfrey (lag 2)	F-statistic	0.291 (2, 24)	0.750	Do not reject H_0
	Breusch-Pagan-Godfrey	F-statistic	0.723 (24, 26)	0.786	Do not reject H_0
	Harvey	F-statistic	0.908 (24, 26)	0.592	Do not reject H_0
	Glejser	F-statistic	0.750 (24, 26)	0.759	Do not reject H_0
	Jarque-Bera	JB-statistic	0.1874 (2)	0.911	Do not reject H_0
	Ramsey RESET	t-statistic	0.0029 (25)	0.998	Do not reject H_0
		F-statistic	8.31e-6 (1, 25)	0.998	Do not reject H_0
lnP1	Breusch-Godfrey	F-statistic	0.6096 (2, 25)	0.552	Do not reject H_0
	Breusch-Godfrey	F-statistic	0.0002 (1, 26)	0.988	Do not reject H_0
	Breusch-Pagan-Godfrey	F-statistic	0.5449 (23, 27)	0.929	Do not reject H_0
	Harvey	F-statistic	0.4670 (23, 27)	0.966	Do not reject H_0
	Glejser	F-statistic	0.5468 (23, 27)	0.927	Do not reject H_0
	Jarque-Bera	JB-statistic	0.724 (2)	0.696	Do not reject H_0
	Ramsey RESET	t-statistic	0.9353 (26)	0.358	Do not reject H_0
		F-statistic	0.8747 (1, 26)	0.358	Do not reject H_0
lnP2	Breusch-Godfrey (lag 1)	F-statistic	1.6723 (2, 23)	0.210	Do not reject H_0
	Breusch-Godfrey (lag 2)	F-statistic	0.604 (1, 24)	0.445	Do not reject H_0
	Breusch-Pagan-Godfrey	F-statistic	0.795 (25, 25)	0.715	Do not reject H_0
	Harvey	F-statistic	0.712 (25, 25)	0.799	Do not reject H_0
	Glejser	F-statistic	0.761 (25, 25)	0.750	Do not reject H_0
	Jarque-Bera	JB-statistic	1.013	0.598	Do not reject H_0
	Ramsey RESET	F-statistic	0.831 (1, 24)	0.371	Do not reject H_0
		t-statistic	0.912 (24)	0.371	Do not reject H_0

Taken together, these diagnostic tests consistently support the reliability of the estimated ARDL models. The absence of serial correlation, heteroskedasticity, and functional form misspecification, along with normally distributed residuals, enhances confidence in the validity of the empirical findings and the integrity of both short-run and long-run interpretations.

7. Conclusion

This study aimed to examine the relationship between structural economic change and poverty reduction in Sudan, using annual time series data spanning 1970–2022. It is the first to construct and utilize consistent time series estimates of monetary poverty, specifically the poverty headcount ratio, poverty gap, and poverty severity index, in the Sudanese context. These indices were computed by the authors using the Foster-Greer-Thorbecke (FGT) class of poverty measures, derived from Gini coefficients obtained from the Standardized World Income Inequality Database (SWIID). This novel approach enables a robust analysis of long-term poverty trends and facilitates the empirical investigation of how changes in the levels of sectoral value added—agriculture, industry, and services—affect poverty outcomes. By employing the ARDL modeling framework, the study assesses both long-run equilibrium relationships and short-run dynamics between sectoral value-added levels and poverty reduction, so that the estimated elasticities capture scale effects associated with the expansion of different production sectors rather than shifts in their GDP shares.

The empirical findings reveal that economic growth led by the agricultural and industrial sectors has a significant and negative long-run association with poverty across all three measures. The findings on agriculture are consistent with numerous previous studies that underscore the central role of agricultural growth in reducing poverty, particularly in agrarian economies. This supports the view that labor-intensive sectors, particularly agriculture—which provides employment to the majority of Sudan's population—are crucial for poverty alleviation. Industrial expansion, especially in manufacturing, also contributes meaningfully to poverty reduction, in line with recent literature emphasizing the role of structural transformation through industrialization in developing countries.

In contrast, the services sector, despite its substantial share of GDP and rapid growth during the oil boom (1999–2011), demonstrates limited poverty-reducing effects. This outcome reflects the urban-centric nature of service sector expansion, which fails to reach rural areas where poverty is most concentrated. Short-run results further underscore the influence of demographic pressures, improvements in education, and the mixed effects of liberalization and privatization policies introduced in the early 1990s.

Overall, the findings highlight the need for a coherent and inclusive development strategy that revitalizes agriculture, promotes industrial diversification, and addresses rural-urban disparities. Strengthening human capital and pursuing spatially balanced structural reforms will be essential to ensure that future growth translates into sustained and broad-based poverty reduction in Sudan. In a context of institutional fragility and recurrent macroeconomic and political shocks, such a strategy must be explicitly sequenced and tailored to Sudan's limited state capacity and conflict legacies, rather than relying on generic calls for "inclusive growth."

Based on the study's findings, three sets of targeted policy priorities emerge for poverty reduction in Sudan. First, revitalizing agriculture is essential, given its strong and consistent poverty-reducing effects; this entails boosting smallholder productivity, rehabilitating key rural infrastructure in high-poverty and conflict-affected areas, and expanding access to markets, finance, and risk-management instruments that mitigate climatic and price shocks.

Second, industrial policy should prioritize labor-intensive light manufacturing and agro-processing linked to domestic agricultural value chains, supported by a predictable regulatory environment, reliable energy in selected corridors, and incentives that favor formal employment over enclave, capital-intensive projects. Third, service-sector development needs to shift from urban-biased expansion toward basic health, education, and digital and financial services that ease human-capital and market-access constraints in marginalized regions, coupled with regional development and skills programs aligned with the empirically identified poverty-reducing sectors (agriculture and industry) and coordinated with peacebuilding and social-protection interventions in conflict-affected areas.

Data availability statement
The dataset used and analyzed during the current study is available from the corresponding author upon reasonable request.

Disclosure of Interest

The authors declare that they have no known financial, commercial, legal, or professional conflicts of interest that could have influenced the design, implementation, or reporting of this study.

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