The growth, inequality and poverty triangle in South Africa: A provincial analysis

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Economic growth, Gini coefficient, Human Development Index, Income inequality, Poverty, Provinces

Abstract

Purpose of research: *Poverty, widening income inequality and economic growth are crucial challenges in sustainable development. A significant fraction of the world's poorest population still struggles to achieve a minimal standard of living throughout emerging nations, particularly in Africa, despite decades of tremendous progress in reducing poverty and improving prosperity. Developing countries tend to have inconsistent progress in eliminating extreme poverty due to reasons specific to geographic and national identity. The study explored the growth, inequality, and poverty triangle. Thus, the objective of the study was to explore the impact of economic growth and income inequality on poverty by looking at the nine South African provinces, over the periods of 1995 to 2022.*

Design/methodology: *The study adopted the panel data methodologies of the pooled mean group, feasible generalized least squares, and panel-corrected standard error technique.*

Results/findings: *Empirical results obtained from the study revealed that as the economy positively progresses in the long run there is an increase in the human development index unlike the short run, implying a decline in poverty levels. Income inequality was found to positively affect the human development index in both short- and long-term. This shows that as income inequality intensifies, the poverty levels among the nine provinces in South Africa will continue to increase thus leading to a deterioration in the standard of living.*

Practical implications and Conclusions: *The outcome of the study suggests that economic growth must be stimulated and inclusive. Effective redistributive policies are required to ameliorate income inequality.*

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Introduction

The United Nations post-2015 agenda strives at enhancing the overall quality of life globally through the Sustainable Development Goals (SDGs) (Fofana et al., 2023). In this realm, economic growth, poverty and income distribution have continually been an issue of concern globally. Hence, three of the 17 SDGs namely, SDGs 1, 8 and 10, focus exclusively on growth, poverty, inequality and redistribution respectively (Fofana et al., 2023). It can be emphasised that research on the economic growth, inequality, and poverty nexus, that is, the Bourguignon triangle, has always been at the centre of development economics (Thorbecke & Ouyang, 2022). But, irrespective of the unprecedented accumulation of wealth globally, certain regions have remained anchored in states of deprivation of all kinds (Labidi et al., 2023). More than half the world's poor lived in sub-Saharan Africa (SSA), real gross domestic product growth in Africa was 0.25% during the period 2010 and 2019 and the pandemic deepened poverty in SSA and it was estimated that 31 million people lived in adject poverty by 2020 (Labidi et al., 2023). The poverty reduction progress has been slow for the SSA region which faces serious challenges in addressing inclusive growth (Fofana et al., 2023). SSA's annual average poverty reduction rate during 1981–2018 was less than half of that of the whole developing world (Thorbecke & Ouyang, 2022).

African countries generally, being characterized by the weakness of their political institutions, the benefits of growth are not distributed in the most egalitarian manner hence such countries would experience lower poverty if inequalities were low (Wale-Awe & Evans, 2023). With the current income growth and inequality performances of African countries, more than half (55%) of the African countries are off track to halving poverty between 2015 and 2030 (Fofana et al., 2023). In the same vein, South Africa is regarded as the most unequal country in the World by most contemporary measures with roots emanating from colonialism and apartheid (Chatterjee et al., 2020). Nevertheless, irrespective of having a progressive constitution and policy mandate underpinned by a radical Bill of Rights which foregrounds expanded socio-economic rights, South Africa seems to have reproduced inequality along similar lines (Webster & Francis, 2019; Chatterjee et al., 2020). In the democratic era, the richest 10% of the population earns 60% of the national income and owns 95% of all wealth and assets in South Africa (Webster & Francis, 2019). The income trajectories of the rich continue to diverge from the rest of the income distribution irrespective of South Africa's need for inclusive economic growth (Bassier & Woolard, 2021). Therefore, countries which have different historically determined wealth distributions, follow different growth paths and may even converge to different steady states (Galor & Zeira, 1993).

Despite the fact that empirical outcomes continue to contribute to the ongoing discussions on poverty and inequality in the developing world, and the debate on the robust strategies required to address the rising poverty and inequality in developing countries has become a point of contention (Amponsah et al., 2023). Unlike other studies a multi-analytical approach was employed to determine the growth-poverty-inequality nexus in South Africa using a panel data approach. Most studies used the Gini coefficient as a measure of income inequality and the poverty head count pegged at international poverty line as a proxy of poverty (Thorbecke & Ouyang, 2022; Amponsah et al., 2023). Others employed per capita consumption/Purchasing Power Parity – adjusted real consumption to stand for poverty in the model (Wan et al., 2021; Adeleye et al., 2020). The human development index (HDI) was employed as a proxy of poverty by other scholars who sometimes disaggregated the proxy to determine the HDI-economic growth or poverty relationship by including other variables unrelated to the triangular relationship (Castells-Quintana et al., 2019; Amaluis, 2024; Fitratul Nakyah et al., 2024). In this study HDI was used as a proxy of poverty when analysing the growth-income inequality-poverty nexus rather than the poverty head count pegged at international lines used to untangle the nexus by other scholars.

Panel studies that interrogated the growth-poverty-inequality mostly focused on group of countries rather than execute a provincial analysis within a country. Due to varied assumptions made by other scholars the growth-poverty-inequality trilemma yielded mixed results. Some studies' findings reinforced the a priori expectation that an increase in economic growth reduces poverty while income inequality intensifies poverty (Thorbecke & Ouyang, 2022; Wale-Awe & Evans, 2023). Although other studies confirmed that the effects of growth on the nexus is to induce a decrease in extreme poverty levels, income inequality was found to be poverty neutral (Doğan & Aslan, 2023; Labidi et al., 2023). Studies like that of Elkafrawy and Elsayed (2024) found economic growth to be poverty neutral and income inequality to be significant and negatively related to poverty and Wan et al. (2021) confirmed that both gross domestic product per capita and the Gini index help to promote human capital formation. On the contrary, Faisal

(2022) found GDP growth to be insignificant and negatively related the Human Development Index (a proxy for poverty), but income inequality was reported to moderate poverty.

Therefore, this study adds to the broader development economics on the growth-inequality-poverty trilemma by providing empirical evidence from a unique South African context through provincial data analysis. In this case, the understanding of provincial variation is advanced which can inform targeted policy interventions. Given the current inequality reduction performances, African countries should aim to realise higher income growth results, above 6% growth of annual gross domestic product on average, to be on track and achieve the Sustainable Development Goals target of halving poverty between 2015 and 2030 (Fofana et al., 2023). This target for most African countries and specifically for South Africa is a surmountable task given that GINI coefficient averaged 67.72%, the average GDP growth stood at 2.39% for the South African economy during the period 1995 to 2022 (World Bank, 2024; Quantec, 2024) while 71.1%, 60.9% and 55.5% South African population lived in poverty in the years 1993, 2010 and 2020 respectively (GCIS, 2024). It took South Africa 20 years to reduce the burden of poverty from 71.1% to 55.5% by 15.6% and to be conservative 71.1% must be halved to 35.55% by 20% in the remaining 10 years (2020 to 2030) for the SDG goal to become a reality. Such a growth-income inequality-poverty trilemma from a South African context calls for an investigation. Consequently, the study investigates the linkages that exists in the growth-income inequality-poverty triangle in South Africa for the period 1995 to 2022 using a panel data approach.

The rest of the paper is organised as follows: The interrogation of literature review is conducted in Section 2 while the research methodology of the study is presented in Section 3. Furthermore, the study results are discussed in Section 4 and the conclusion and policy implications is presented in Section 5.

Literature review

This section discusses both theoretical and empirical literature in order to lay a solid foundation of the growth-income inequality-poverty nexus.

Theoretical Literature

The Classical theory which was founded by Smith (1776) emphasises that savings rates are directly related to wealth and inequality, which calls for resources to be channelled towards individuals whose marginal propensity to save is higher. Galor and Moav (2004) assumes that an economy endogenously evolves through two fundamental regimes namely regime 1 (the early stage of development) and regime 2 (the mature stages of development). In the early development stage, the human capital rate of return is lower than physical capital rate of return hence the development process is driven by capital accumulation. Specifically, in the early stages of development, when physical capital accumulation is regarded as the prime source of economic growth with higher return, inequality accelerates the development process by channelling resources towards individuals whose appetite to save is higher. While in mature stages of development, human capital rate of return increases sufficiently so as to induce human capital accumulation, and the development process is generated by both human capital and physical capital accumulation. But the regime 2 (mature stage) is further divided into 3 stages, that is, investment in human capital is (i) selective and feasible only for the rich (ii) universal and suboptimal due to credit constraints and (iii) optimal given that credit constraints are no longer binding.

According to the Bourguignon's Triangle theory depicted in Figure 1, poverty reduction in any country, at a particular point in time is significantly determined by the growth rate of average income of the population and the change in the distribution of income (Bourguignon, 2004). Bourguignon when addressing the importance of either poverty, growth or inequality as the basis of a country's development strategies, he emphasised the importance of the prioritisation of the reduction of absolute poverty in order to develop a solid foundation for an economy (Doğan & Aslan, 2023). Hence, sustainable development can be realised through the reduction of inequality and the realisation of growth and policies must address all three dimensions (Doğan & Aslan, 2023). But it can be emphasised that an increase in income inequality can further aggravate poverty in the presence of growth when a country experiences limited development levels and poverty reduction policies (Bourguignon, 2004). The poverty incidence is influenced by both the economic growth dynamics and wealth distribution (Bourguignon, 2004) as depicted in Figure 1 (a). Nevertheless, the consequences of these occurrences will vary based on the beginning level of income and inequality (Elkafrawy & Elsayed, 2024).

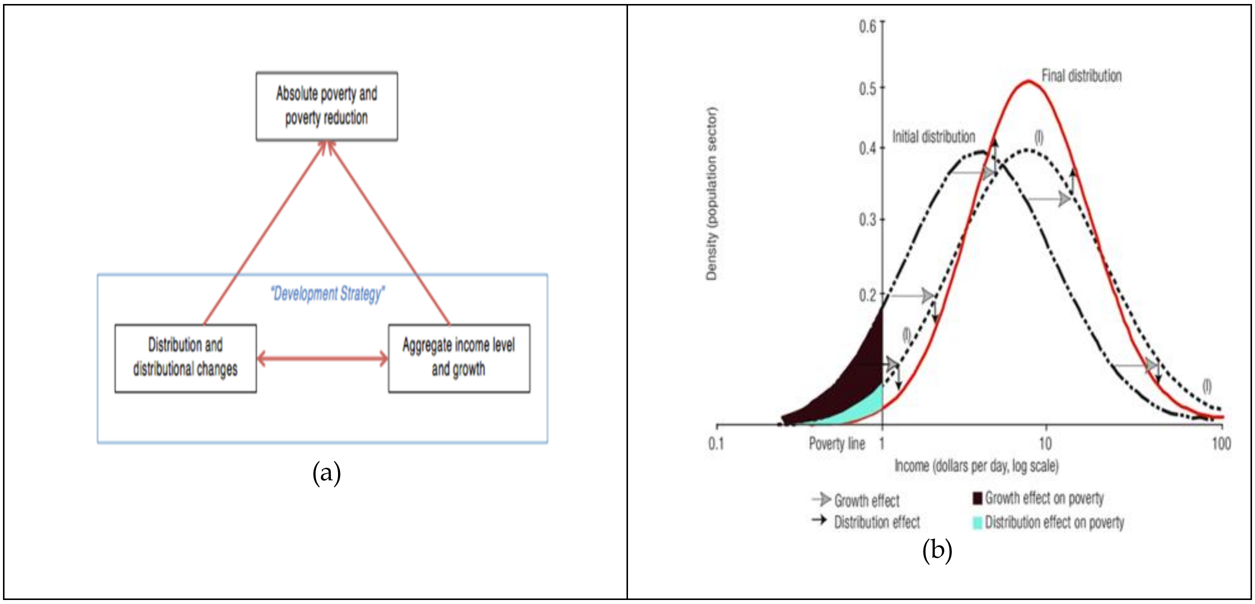

Figure 1: Bourguignon's Triangle of Poverty, Growth and Inequality
Key: (a)-Bourguignon's Triangle and (b)-Growth Incidence Curve: poverty changes decomposed due to economic growth and income distribution.
Source: Bourguignon's Triangle theory adapted from Bourguignon (2004)

The income distribution changes are evaluated through the growth effect and the distribution effect depicted in Figure 1(b) as initial distribution and final distribution respectively. The growth effect is experienced when the overall economic growth translates into relative changes in income without varying the distribution of relative incomes while the distribution effect manifests when the distribution of relative income is altered (Elkafrawy & Elsayed, 2024). The Growth Incidence Curve (GIC) captures income increase and decrease within every population segment across the desired period of time, and visually highlights the trends (Bourguignon 2004). Simultaneously, the GIC facilitates the analysis of the interactions between income growth, inequality and poverty decrease in a segment of the population (Michálek & Výbošťok, 2019). Therefore, this study is anchored by both the Classical theory and the Bourguignon's Triangle theory.

Empirical Literature

The Growth Incidence Curve technique employed by Michálek and Výbošťok (2019) was used to analyse the changes in economic growth, inequality and poverty across 28 EU member states for the period 2005 to 2015. The results showed that economic growth is connected with a decrease in poverty, however, as income inequality intensified, poverty intensifies also. The outcome was confirmed by Zaman et al. (2020) who examined the growth-inequality-poverty (GIP) triangle using data of 124 countries for the period 2010-2013 by employing the Pooled Mean Group (PMG) estimator. The results revealed that household income was significant and negatively related to poverty head count ratio and income inequality was also significant but positively associated with poverty which satisfied the a priori expectations. Income inequality intensified poverty while household income ameliorated poverty. Such an outcome was also supported by Thorbecke and Ouyang (2022) who explored empirically the relationship between poverty and growth by applying Ordinary least Squares (OLS) and Generalised method of Moments (GMM) techniques on 129 developing countries' data (44 in SSA) during the years 1981 to 2018. But in the 129 developing countries case, a 1% growth was found to increase the pace of poverty reduction by 3% in LDCs as a whole, yet by only 1% in SSA when poverty is measured against the $1.90 international line. Also, evidence continued to mount with regards to the support of the a priori expectation when Wale-Awe and Evans (2023) used 1 and 2 Step Systems Generalised method of Moments (SGMM) to investigate the causal relationship between digital financial inclusion and the growth-inequality-poverty triangle using panel data of 42 African countries for the years 1995 to 2018. In this case although growth in GDP per capita gives rise to the reduction in poverty, and income inequality proved to have a positive and significant effects on poverty but negative significant effects on growth, implying that an increase in the level of inequality exacerbates poverty and simultaneously diminishes economic growth.

Amponsah et al. (2023) used a 2-Step Instrumental Variables Generalised Method of Moments (2SIV-GMM) to estimate the poverty-growth-inequality triangle (PGIT) relationship by employing panel data of 35 SSA countries (1990-2018) and the outcome reinforced the a priori expectation. Results revealed that income inequality adversely impacts poverty and worsens inclusive growth, while inclusive growth assists in reducing poverty. Nevertheless, the echoes of the studies which contradicted the status quo (a priori expectation) were simultaneously mounting which includes Elkafrawy and Elsayed (2024) who explored the simultaneous relationships between PGIT in Egypt covering the years 1975 to 2019 by applying the 3-Stage Least Squares Method. The results showed that there is an insignificant but positive relationship between economic growth and poverty while income inequality is significant and negatively related to poverty. Given that economic growth is directly neutral to poverty reduction or intensification, it affects poverty indirectly through the income inequality channel. The expected PGIT outcome failed to hold entirely when Labidi et al. (2023) included lagged extreme poverty, lagged GDP growth and lagged income inequality (GINI) variables in the model. The results showed that the 1st lag of extreme poverty and 1st lag of economic growth were all significant but positively and negatively related to extreme poverty (independent variable), while the 1st lag of income inequality was found to be insignificant but negatively related to extreme poverty. Hence, in this case economic growth induces a decrease in extreme poverty levels of which income inequality remains neutral. This outcome was verified by Doğan and Aslan (2023), who examined the PGIT using selected developing countries between the years 2000 and 2020. In addition, the Dumistresu-Hurlin panel causality test results when poverty is considered as a dependent variable showed that no causality exists between income inequality and economic growth and poverty and economic growth but simply a bidirectional causality exists between economic growth and poverty.

The estimated poverty model continued to yield surprising results when the Human Development index and its variations were used as a proxy by other studies. Adeleye et al. (2020) conducted a comparative investigation of the PGIT trilemma using 58 SSA countries and Latin American countries (LAC) covering the years 2000 to 2015. The findings from the pooled OLS, Fixed Effects and SGMM estimates showed that economic growth is significant and positively related to poverty (per capita consumption expenditure) and income inequality is significant and negatively associated with poverty. That is, economic growth embodies poverty-reduction properties while the increasing income inequality considerably dwindles absolute poverty. Wan et al. (2021)'s study employed human capital as a proxy of poverty in an endeavour to disentangle the PGIT relationship in Asia by applying the 2-SLS technique for the period covering the 1960s and 2010s. The results revealed that both GDP per capita and the GINI index (income inequality) promotes human capital formation for the rest of the World but Asia. Another contradictory outcome to the PGIT a priori expectation was found by Faisal (2022) who used comprehensive measures of human development and applied the Panel Least Squares method, FE and RE Techniques to analyse SAARC's member states data covering the period 2000 to 2016. The results showed a negative but insignificant relationship between GDP and HDI while income inequality with single lag and poverty have a negative and a significant relationship. In this case, extreme inequality lowers HDI and vice versa while economic growth-poverty relationship is considered to be neutral.

Research methodology

The study examines the growth, inequality and poverty triangle, based on the panel dataset of the sample of nine South African provinces, namely, Limpopo, Eastern Cape, Free State, Gauteng, KwaZulu-Natal, Mpumalanga, Northern Cape, North West and Western Cape. The research methodology is fully discussed in this section, which includes the data source, model specification and estimation methods.

Data and model specifications

To achieve the aim of the study, secondary panel data was used from 1995 to 2022. Three indicators were used, namely economic growth, income inequality and poverty reduction/poverty proxied by the human development index (HDI). Economic growth and income inequality as the independent variables were proxied by gross domestic product (GDP) at market prices-constant 2015 prices and the Gini coefficient (Municipal Gini Coefficient for current income at 2016 municipal/ward-based metro region level). The data for the three variables were obtained from the Quantec EasyData. The priori expectations are that economic growth positively affects, while income inequality (GINI) negatively affects poverty (HDI). It can be stated that poverty is a function of economic growth and income inequality. The functional and level-log-level regression models (equation 1 and equation 2) are as follows:

$$HDI = f(GDP, GINI) \tag{1}$$

$$HDI_{it} = \beta_0 + \beta_1 LNGDP_{it} + \beta_2 GINI_{it} + \mu_{it} \tag{2}$$

In Equation 2, the LNGDP denotes the natural log of GDP, and the GINI represents the Gini coefficient while β_0 signifies the constant; β_1 and β_2 are population parameters, μ_{it} is the error term and it shows the analyses of the countries/provinces across time.

Estimation techniques

Econometric techniques conducted are presented in this section, namely, the descriptive statistic, correlation matrix, cross-sectional dependence test, panel first- and second-generation unit root tests, optimal lag selection, Pedroni's panel cointegration test, dynamic panel models (Mean Group, Dynamic Fixed Effect, Pooled Mean Group and Hausman test), Panel Corrected Standard Errors (PCSE) and Feasible generalized least squares (FGLS) Technique. Hsiao (2022) asserts that panel data set, is a collection of data that tracks a specific sample of individuals over time and offers several observations about each sample member. Usage of panel data sets have greater advantage as compared to the conventional cross-sectional or time series data set (Ahmad et al., 2021). Complicated behavioural models can be constructed and tested with panel data.

Descriptive statistic

Descriptive statistical analyses methods are used to conduct data analysis, provide a summary and description of a set of data (Salvatore, 2021; Yao et al., 2022). The descriptive statistics consists of three main varieties, namely; the measures of dispersion or variation as well as measures of central tendency, and measures of frequency (Mishra et al., 2019). It is thus important to have prior information on the past behaviour of the series before undertaking the other econometric tests. To establish basic characteristics of the data set, the descriptive statistic is conducted in the study.

Correlation matrix

The linear association between two variables is described by the correlation coefficient (Doku et al., 2019; Hadd & Rodgers, 2020). Furthermore, the test shows how the dependent variable will react when the independent variables changes. The correlation matrix is also deployed in this study to check if the variables are highly correlated or not.

Cross-sectional dependence

The cross-sectional dependence (CSD) test must be conducted before testing for stationarity, as the test shows whether the provinces are dependent or independent of each other. The Pesaran (2004, 2013) CSD-test for cross sectional dependence is conducted. Zhang et al. (2020) states that due to the consideration of open economies, globalization, international trade openness, financial crisis, and overlooked common factors, cross-sectional dependence arises among the countries and regional economies. Thus, depending on the outcome of the results, the first-generation and/or second-generation panel unit root tests will have to be conducted.

Panel stationarity tests

The first generation and second-generation panel unit root tests are performed to ensure stationarity of the variables and order of integration. Although the cross-sectional dependence test approves the application of the second-generation panel unit root. The panel unit root tests help uncover more information regarding the series. The following first-generation panel unit root tests are implemented, namely the Levin, Lin, and Chu test (2002) (LLC); and Im, Pesaran and Shin (2003) (IPS). Ali et al. (2022) asserts that the LLC unit root test is based on the homogeneity of the panel and tends to follow the procedures of the Augmented Dickey-Fuller (ADF). The IPS tests provides means in avoiding problems of the estimation of spurious regressions, which is a recurring issue in finance and macroeconomics (Im et al., 2023).

The Pesaran (CIPS) second generation unit root test will be conducted in this study. Shobande and Asongu (2022) asserts that there are implications that may occur when panel unit root tests are overlooked, such as possible usage of spurious regression; neglect of using a series that exhibits a random walk with long cycle without treatment, leading to results being invalid as the series will unlikely be normally distributed; and not checking stationarity may result in misinterpretation of results. The hypothesis rule of the abovementioned panel unit root tests is the same. The null hypothesis (H_0) is that the variable is non-stationary and has a unit root. The alternative hypothesis (H_1) is that the series is stationary and has no unit root. When variables are found to be stationary it shows that they have a linear association (Mohsin et al., 2019).

Optimal lag selection

The study also determines the optimal lag number of the model, in which the most common lags between provinces shall be chosen. Specifically, the most frequent number which appears for all provinces is selected and for each variable used by referring to the Akaike information criterion (AIC) criterion.

Pedroni's panel cointegration test

Panel cointegration tests will be performed to validate the long run association among the variables and whether the variables can converge to their long run mean. For the purpose of this study the Pedroni panel cointegration test was implemented. The Pedroni cointegration tests extends the framework of the Engle Granger. Sheikh and Hassan (2023) postulates that the Pedroni test is accommodative to heterogeneous intercepts and trend coefficients within cross-sections.

Dynamic panel Model: Mean Group, Dynamic Fixed Effect, Pooled Mean Group and Hausman test

The application of the autoregressive distributed lag (ARDL) method provides more insight into the short and long run relationship status of the variables. The ARDL method is suitable when the variables are found to be integrated of different orders, a mixture of $I(0)$ and $I(1)$ (Mohsin et al., 2019). To find the long and short run effects of economic growth, income inequality on HDI (poverty reduction/poverty) various estimations in the ARDL version can be implemented such as the mean group (MG), dynamic fixed effect (DFE) and pooled mean group (PMG) estimators. The three estimators were all conducted to check if there were any significant differences among the MG, DFE and PMG estimates. According to Pesaran and Smith's (1995) MG technique, each country's unique regressions must be estimated, and the coefficients must be determined as the invariant means of the calculated coefficients for each country. The MG does not impose any restrictions, as it permits all coefficients to be heterogenous in the short and long-term, unlike the DFE and PMG (Androniceanu & Georgescu, 2023).

The DFE is similar to the PMG, in such that it imposes restrictions in the long term on the error variances to be equal across countries and slope coefficients (Zardoub, 2023). The speed of adjustment and short run coefficients are also restricted under the DFE. The long-run coefficients of the PMG estimator are homogeneous across cross-sections, but the short-run coefficients are heterogeneous (Zhang et al., 2020; Zardoub, 2023). The PMG estimator is stated to be valid when the error correction term (ECT) is negative and greater than -1.2. The long-run Hausman test is conducted to determine and select the best estimator to find the long run impact of economic growth and income inequality on HDI (poverty reduction/poverty). The hypothesis rule of the Hausman test in this case, is that the null hypothesis (H_0) assumes that the PMG and MG estimators are not different and the alternative hypothesis (H_1) assumes that the PMG and MG estimators are different. This implies that the acceptance of H_0 means accepting the PMG estimator due to its efficiency. However, rejection of H_0 confirms significant differences between the PMG and MG estimators, thus the MG estimator will be preferred (Androniceanu & Georgescu, 2023).

The Hausman test can further be used to determine the difference among the MG and DFE estimators, including the PMG and DFE estimators.

Panel Corrected Standard Errors (PCSE) Technique

This study's approach is also based on the PCSE technique, which was used because it produces more accurate statistics and improves parameter efficiency by simultaneously correcting for autocorrelation, residual correlation, and heteroscedasticity (Iyika et al., 2021; Zidi & Hamdi, 2024). The PCSE technique was first presented by Beck and Katz in 1995. The technique proposes an estimator that aggregates data from many clusters to calculate error variances (Doku et al., 2019). The PCSE technique is an alternative to the FGLS technique.

Feasible generalized least squares (FGLS) Technique

The FGLS approach was also considered since it yields estimators that are efficient, accurate, and dependable. Additionally, by methodically projecting the enormous error covariance matrix, it has been demonstrated that the FGLS estimate outperforms the ordinary least squares (OLS) estimator in detecting the presence of heteroskedasticity, serial, and cross-sectional correlations (Bai et al., 2021; Igbinedion & Gozhak, 2023). The FGLS regression method was also applied to achieve the ultimate objective of the study.

Results and discussions

Descriptive statistic results

Short descriptions of the fundamental characteristics of the data in the study, including the mean and standard deviation (SD), are provided by descriptive statistics. A summary of the descriptive statistics is presented in Table 1.

Variable	Obs	Mean	Std.Dev	Min	Max
HDI	252	0.6048	0.0803	0.3831	0.7615
LNGDP	252	12.6516	0.7410	10.9931	14.2556
GINI	252	0.6772	0.0352	0.5922	0.7789

Table 1: Summary of descriptive statistics
Authors' computations.

The descriptive statistic results are reported in Table 1, for the three variables; HDI as the dependent variable representing the poverty reduction/poverty. The HDI has the mean of 0.60, and the Gini-coefficient average is reported in Table 1 to be 0.68. The average economic growth rate is 12.65% with a variability of 0.74%. Economic growth possesses the highest standard deviation of 0.74, unlike HDI (0.0803) and the Gini-coefficient (0.0352). The minimum and maximum values for HDI are 0.38 and 0.76, for economic growth 10.99 and 14.26, and the Gini 0.59 and 0.78 respectively.

Correlation matrix

It is important to check if the variables are highly or not highly correlated in the regression model. Highly correlated variables tend to result in unreliable and unstable estimates of regression coefficients. The correlation matrix results, provided in Table 2, in this case is used to check if there is multicollinearity or not.

	HDI	**LNGDP**	**GINI**
HDI	1		

LN GDP	0. 2654	1	
GINI	-0.3015	-0.2996	1

Table 2: Correlation analysis results
Authors' computations.

It is evident from the correlation matrix analysis that economic growth is positively correlated with HDI, unlike the Gini-coefficient which is adversely correlated with HDI. Furthermore, the correlation values are very low for both economic growth (0.2654) and the Gini-coefficient (-0.3015), which shows that there is no problem of multicollinearity between model variables.

Cross-sectional dependence

The cross-sectional dependence test assists in estimating if there is cross sectional dependence or cross-sectional independence among the South African provinces. Hence, the null hypothesis (H_0) states that there is no cross-sectional dependence but cross-sectional independence; while the alternative hypothesis (H_1) approves that there is cross-sectional dependence among the provinces. Table 3 reports the Pesaran (2004, 2013) CSD-test for cross sectional dependence results.

Variable	CD-test	P - value	Average Joint T	Mean ρ	Mean abs (ρ)
HDI	29.110	0.000***	28	0.92	0.92
LNGDP	31.563	0.000***	28	0.99	0.99
GINI	2.609	0.009***	28	0.08	0.50

Table 3: Pesaran (2004, 2013) CSD-test for cross sectional dependence results
Authors' computations. *** p<0.01 and ** p<0.05.

The cross-sectional dependence results in Table 3, provide that all the variables are significant at 1%. The results confirm that the null hypothesis of cross-sectional independence is rejected, and the alternative hypothesis accepted as there is existence of cross-sectional dependence among the variables with respect to South African nine provinces. With the existence of cross-sectional dependence, the second-generation panel unit root tests can be implemented.

Panel stationarity results

The unit root tests are used to avoid spurious regression. The cross-sectional dependence test approved the usage of the second generation, however the first- and second-generation panel unit root tests are conducted in this study for a comparative analysis. The first-generation panel unit root results in Table 4 included the LLC (2002) and IPS (2003). The first-generation panel unit root tests assume of cross-sectional independence, unlike the second generation based on cross-sectional dependence. The Pesaran (CIPS) second generation panel unit root test results are also presented in Table 4.

	1st Generation		**2nd Generation**	
Variables/Unit root tests	**LLC (Individual intercept and trend)**	**IPS (Individual intercept and trend)**	**CIPS w/o trend**	**CIPS w trend**
HDI	1.6604	1.5821	-1.174	-2.440

	$I(0)$ -1.8115*** $I(1)$	$I(0)$ -1.4957*** $I(1)$	$I(0)$ -4.685*** $I(1)$	$I(0)$ -4.672*** $I(1)$
LNGDP	-4.8487*** $I(0)$	-1.1488 $I(0)$ -4.8652*** $I(1)$	-2.966*** $I(0)$	-3.530*** $I(0)$
GINI	-1.5050 $I(0)$ -5.8982*** $I(1)$	-0.1236 $I(0)$ -6.0464*** $I(1)$	-1.782 $I(0)$ -4.624*** $I(1)$	-2.051 $I(0)$ -4.641*** $I(1)$

Table 4: First- and second-generation panel unit root tests results
Authors' computations. *** p<0.01, ** p<0.05 and * p<0.1.

According to the first-generation panel unit root test HDI is found to be non-stationary for both the LLC and IPS test at level [$I(0)$]. To induce stationarity HDI had to be differenced once. Similarly with the second-generation panel unit root test (CIPS), HDI is not stationary at levels with no trend and trend aspect, however, becomes stationary after first differencing [$I(1)$] at 1% significance level. Economic growth (LNGDP) on the other hand was found to be stationary at levels [$I(0)$] under the LLC test, however for IPS it was found to consist of a unit root. Economic growth had to be differenced once under the IPS test, thus the null hypothesis of non-stationarity was rejected at 1% significance level. In the second-generation test, economic growth is stationary at levels implying the alternative hypothesis is accepted at 1% significance level at the with no trend and trend aspect. Lastly for the Gini-coefficient (GINI), for both the first-and second-generation panel unit root tests, it was found to have a unit root at levels and the null hypothesis is not rejected. However, for stationarity, the Gini-coefficient was difference leading to the rejection of the null hypothesis at 1%. From the panel unit root results, it is evident that HDI and the Gini-coefficient are integrated of order one [$I(1)$] for the first- and second-generation test, unlike economic growth. Economic growth is integrated of order zero [$I(0)$].

Optimal lag length

The lag length selection test must also be conducted. The most common lags between provinces are chosen. The optimal lag selection outcome is presented in Table 5.

Code	Cross section\variable	HDI	LNGDP	GINI

1	Western Cape	1	0	0
2	Eastern Cape	1	1	0
3	Northern Cape	1	0	1
4	Free state	1	0	1
5	KwaZulu-Natal	2	0	0
6	North West	1	1	2
7	Gauteng	2	0	0
8	Mpumalanga	1	0	1
9	Limpopo	1	1	0
	Optimal	***1***	***0***	***0***

Table 5: Optimal Lag Selection Outcome (maxlag-2 2 2)
Authors' computations.

From the optimal lag selection outcome, under HDI, 7 provinces approve the usage of 1 lag and only 2 provinces confirm 2 lags. Under economic growth, 6 provinces confirm the application of 0 lags, while 3 provinces approve 1 lag. The Gini-coefficient, 0 lags are approved by 5 provinces, 1 lag by 3 provinces and 2 lags by 1 province. The results in Table 5 confirm that according to most frequent number for all provinces under each variable, that for HDI the optimal lag selected is 1, for economic growth and Gini-coefficient is 0. Thus, the optimal lag chosen is (1, 0, 0) which is used in the estimation of the MG, DFE and the PMG-ARDL.

Pedroni's panel cointegration results

To find out whether there is a long run cointegrating association between the variables, the Pedroni panel cointegration test was used in this study. The results are presented in Table 6.

Pedroni's PDOLS (Group mean average)		
No. of Panel Units: 9	**Lags and leads: 2**	
Number of obs: 207	**Avg obs per unit: 23**	
Data has been time-demeaned		
Variables	Beta	t - stat
LNGDP_td	-0.1616	-3.142
GINI_td	0.2651	4.633

Table 6: Pedroni's PDOLS (Group mean average)
Authors' computations.

From the Pedroni panel cointegration results, it is evident that the variables are cointegrated and that indeed a long-run association between the variables exists given that the absolute t-statistic values outweigh the bench mark of 2.

Dynamic panel Model: Mean Group, Dynamic Fixed Effect, Pooled Mean Group-ARDL and Hausman

To see whether there are significant differences between the MG, DFE and PMG, the three estimators were conducted, including the Hausman test to show the best estimator. The findings are shown in Table 7, which further shows the long and short effects of economic growth and income inequality on HDI (poverty reduction/poverty).

	MG Model (1)	**DFE Model (2)**	**PMG Model (3)**

VARIABLES	LR	SR	LR	SR	LR	SR
Short-Run (SR)						
ECT	-	-0.196***	-	-0.0997***	-	-0.101***
	-	(-6.628)	-	(-5.604)	-	(-6.383)
D.LNGDP	-	-0.131***	-	-0.0859*	-	-0.138***
	-	(-4.094)	-	(-1.913)	-	(-7.124)
D.GINI	-	0.0754	-	0.456***	-	0.219
	-	(0.397)	-	(5.768)	-	(0.949)
Long-Run (LR)						
LNGDP	0.710***	-	0.733***	-	0.798***	-
	(2.776)	-	(5.523)	-	(8.274)	-
GINI	2.595*	-	1.285***	-	2.140***	-
	(1.899)	-	(2.714)	-	(7.223)	-
Constant		-1.221***		-0.949***		-1.091***
		(-3.834)		(-9.597)		(-6.864)
Observations		243				243
Hausman Test		MG vs PMG		MG vs DFE		DFE vs PMG
		Chi2(2)=0.46		Chi2(2)=0.00		Chi2(2)=-11.29
		Prob>chi2=0.796		Prob>chi2=1.00		Prob>chi2=0.00

Table 7: MG, DFE and PMG-ARDL short-run and long-run results
Authors' computations. Z-statistics in parentheses, *** p<0.01, ** p<0.05 and * p<0.1.

According to the MG, DFE and PMG estimated results there is a negative and significant short run relationship between economic growth (D.LNGDP) and HDI at 1%, 10% and 1% respectively. This implies that an increase in economic growth with have an adverse effect on poverty reduction within the provinces in the short run. The Gini-coefficient, however, was found to have a positive association with HDI but was statistically insignificant in the short run in the MG aspect; although in the DFE is significant at 1%. This shows that income inequality is growth enhancing via higher propensity to save (Castells-Quintana et al., 2019). In the long-run, both economic growth and the Gini-coefficient, have a positive long run impact on HDI. The PMG results in the long term, show that there is a positive association between economic growth and HDI, including the Gini and HDI relationship. Comparatively, based on the MG, DFE and PMG long term results, income inequality increases poverty while economic growth accelerates poverty reduction in the long run. Since the estimated coefficient for inequality is positive and significant which concurs with Galor and Moav (2004) who associated physical capital accumulation as a source of economic growth in the early stages of development which inequality intensifies. Hence inequality is regarded as growth enhancing through higher propensity to save by the rich few.

The error correction term (ECT) is a useful tool for assessing long-term relationships based on short-term associations. The MG has an ECT of -0.196, the DFE of -0.0997, and PMG of -0.101, which are all significant at 1% level. These findings reveal that the estimated speed at which HDI will converge to its equilibrium state after a change in the other variables is at 20%, 10% and 10%, with respect to the MG, DFE and PMG estimators. The choice of the three estimators is made according to the Hausman test. From the Hausman results if we compare the PMG and MG, it is evident that the Hausman test probability value (p-value) is 0.796 and greater than 0.05, therefore the PMG estimator is the more efficient. Similarly the Hausman test probability value of 1.00 which outweighs the 0.05 level of significance when MG and DFE models are compared, indicates that DFE model outcome is preferred. But when PMG and DFE models are compared, DFE seem to be preferable since the probability value of 0.00 is less than 5% level as shown in Table 7.

Panel Data Models using Panel Corrected Standard Errors (PCSE) Technique

Results in Table 8 are estimated assuming that autocorrelation computations are based on single lag Ordinary Least Squares (OLS) of the residuals.

Model	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Error structure across the panels	**Panel Level heteroscedastic and correlated across panels**		**Panel Level heteroscedastic**		**Independent across panels**	
Form of Autocorrelation	**AR(1)**	**Panel level AR(1)**	**AR(1)**	**Panel level AR(1)**	**AR(1)**	**Panel level AR(1)**
VARIABLES	HDI	HDI	HDI	HDI	HDI	HDI
HDI						
LNGDP	0.0173	0.0237	0.0173	0.0237*	0.0173	0.0237*
	(0.622)	(1.451)	(0.924)	(1.833)	(0.902)	(1.763)
GINI	0.441***	0.445***	0.441***	0.445***	0.441***	0.445***
	(3.790)	(3.672)	(4.749)	(4.687)	(4.628)	(4.659)
Constant	0.127	0.0447	0.127	0.0447	0.127	0.0447
	(0.355)	(0.227)	(0.511)	(0.258)	(0.496)	(0.248)
Observations	252	252	252	252	252	252
R-squared	0.730	0.823	0.730	0.823	0.730	0.823
Number of Province	9	9	9	9	9	9
Wald statistic	15.11***	15.36***	23.00***	24.15***	21.72***	23.59***

Table 8: Panel Data Models using Panel Corrected Standard Errors (PCSE) Technique
Authors' computations. Z-statistics in parentheses, *** p<0.01, ** p<0.05 and * p<0.1.

From models 4, 5, 6 and 8 of the PCSE estimated results, the coefficient of LNGDP is positive but not significant, though the positive outcome indicates that it is a positive predictor of HDI. In respect to models 7 and 9 it is found to be statistically significant at 10%, confirming that economic growth does enhance HDI, thus having a poverty reduction effect. However, the GINI has a positive and significant coefficient at 1% level. This suggests that an increase income inequality worsens poverty and that a 10% in income inequality leads to a 4.4% increase in poverty, on average. This shows that as income inequality widens, the poverty levels among the nine provinces in South Africa will continue to increase thus leading to a deterioration in the standard of living poor (the majority). The R-squared are high and acceptable at 0.730 and 0.823, which shows that the model is fit. Further that the economic growth and income inequality will cumulatively explain about 73% and 82% true value of HDI (poverty reduction/poverty proxy) in the South African provinces. The Wald statistic values also confirms that the models are robust and of good fit, further showing the reliability of the results as the p-values are significant.

Feasible generalized least squares (FGLS) Technique

To test the robustness of the results, the FGLS technique was deployed. Similarly, Table 9 results are based on the single lag OLS of residuals as the method of computing autocorrelation.

	(10)	(11)	(12)	(13)	(14)	(15)
Error structure across the panels	**Independent and Identically distributed (IID)**		**Heteroscedastic but uncorrelated**		**Heteroscedastic and correlated**	
Form of Autocorrelation	**AR(1)**	**Panel-specific AR(1)**	**AR(1)**	**Panel-specific AR(1)**	**AR(1)**	**Panel-specific AR(1)**
VARIABLES	HDI	HDI	HDI	HDI	HDI	HDI
HDI						
LNGDP	0.0173	0.0237*	0.0144	0.0223*	0.0179***	0.0226***
	(0.902)	(1.763)	(0.797)	(1.745)	(10.47)	(20.90)
GINI	0.441***	0.445***	0.443***	0.419***	0.412***	0.378***
	(4.628)	(4.659)	(4.993)	(4.618)	(28.60)	(16.79)
Constant	0.127	0.0447	0.159	0.0815	0.122***	0.102***
	(0.496)	(0.248)	(0.666)	(0.479)	(3.508)	(4.906)
Observations	252	252	252	252	252	252
Number of Province	9	9	9	9	9	9
Wald statistic	21.72***	23.59***	25.18***	23.29***	1022***	635.7***

Table 9: Feasible generalized least squares (FGLS) Technique
Authors' computations. Z-statistics in parentheses, *** p<0.01, ** p<0.05 and * p<0.1.

FGLS results shows that the coefficient of LNGDP is positive and significant at 1% and 10% levels with respect to models 11, 13, 14 and 15, supporting the PCSE results that economic growth indeed has a direct effect on HDI. Similar to the PCSE results, the GINI is found to be a positive and significant predictor of HDI. The complementary roles of economic growth and income inequality, shows them to be essential factors that predicts the level of poverty reduction and poverty. The Wald statistic values further reveals the model is robust and of good fit.

Mean Group results

The provincial long run coefficients and ECT results are provided in Table 10 using the MG model results since the MG estimator assumes heterogeneity of the provinces both in the short run and long run.

		Long-Run		Short-Run
Code	**Cross section\variable**	**LNGDP**	**GINI**	**ECT**
1	Western Cape	0.013	-2.040**	-0.235**
2	Eastern Cape	0,438***	3.572***	-0.225***
3	Northern Cape	0.703***	2.079***	-0.195***
4	Free state	1.749***	4.772***	-0.125***
5	KwaZulu-Natal	0.305	-2.036	0.163***
6	North West	0.410***	2.279***	0.231***
7	Gauteng	2.197	10.283	-0.029
8	Mpumalanga	0.640***	-1.389**	-0.206***
9	Limpopo	-0.064	5.839***	-0.356***

Table 10: Mean Group (MG) long run and ECT estimates

Authors' computations. HDI is the independent variable, *** p<0.01, ** p<0.05 and * p<0.1

Economic growth might be cooperative in poverty reduction, particularly if it is not linked with increasing income disparity (Khan et al., 2022). When growth becomes inclusive it enhances the HDI, which means that the Western cape, KwaZulu Natal, Gauteng and Limpopo still have to look at how they can make economic growth inclusive. It is further evident from the results presented in Table 10, that issues of income inequality still need to be addressed in the Eastern Cape, Northern Cape, Free State, North West, Gauteng, and Limpopo. Prevailing severe income inequality is a major challenge to economic progress and is the reason behind the slowdown of poverty reduction in developing regions (Omar & Inaba, 2020). Eastern Cape, Northern Cape, Free State, North West and Mpumalanga are taking advantage of the growth of the respective provinces to reduce poverty while Western Cape and Mpumalanga are reducing inequality in order to promote inclusivity and ameliorate poverty in the process. In the short run, the speed of adjustments is negative and significant for 8 provinces excluding Gauteng, implying HDI shall converge back to its equilibrium state in the 8 provinces at different rates. Furthermore, if policies were to be applied to promote HDI it will take that rate (ECT) in those provinces for the polices to be fully effective.

Conclusion

The study investigated the linkages that exists in the growth-income inequality-poverty triangle in South Africa for the period 1995 to 2022, using a panel data approach. The descriptive statistic showed the overall perspective of the dataset, while no multicollinearity was detected among the variables. By using both the first- and second-generation panel unit roots test, a mixture of variables integrated at level and first differences were obtained. After applying the panel-ARDL in STATA, it was found that PMG estimator was preferred according to the Hausman test. The MG, DFE and PMG estimator revealed long term positive link between economic growth, income inequality and poverty. The PCSE, supported by the FGLS technique showed that economic growth intensifies poverty reduction while income inequality worsens poverty.

The outcome of the study suggests that economic growth must be stimulated and inclusive. Such a direct relationship between economic growth and poverty must be capitalised. Effective redistributive policies are required to ameliorate income inequality and hence poverty through possible targeted inventions in mostly affected regions and South Africa as a whole. The policy interventions should target mostly wealth inequality and address such anomaly that has been perpetual even after the dawn of democracy. Inequalities of opportunities or structural inequalities emanating from institutional structures and inequality that creates barriers for human capital accumulation should be removed. Investment by both the private and public sector should continue to be channelled in such a way that there is improvement in the basic dimensions of HDI in order to promote longevity and health life, knowledge and a decent standard of living in order to reverse the legacies of the past. Overall policies in the blue print (National Development Plan) should be implemented and targets inscribed in it be realised. Not implementing well designed polices backed by the constitution of the country, implies promoting the interests of the few at the expense of the majority's interest.

Limitations and direction of future research

The study focused on secondary panel data from 1995 to 2022 due to the limitation of available data. For future research, the growth-income inequality-poverty triangle can be explored focusing on different countries or regions, such as the Southern African Development Community (SADC) region.

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