Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 5 | May 2026 -Peer-Reviewed Journal

YOUTH UNEMPLOYMENT VERSUS EDUCATION ATTAINMENT IN SOUTH AFRICA: AN EMPIRICAL INVESTIGATION

Muhangi Elian[1], Nahabwe Patrick Kagambo John[2]
[1]*Kabale University, Uganda*
[2]*Kabale University, Uganda*

ABSTRACT

We empirically analyze the relationship between youth unemployment and education attainment in South Africa, using quarterly data from 2001 to 2024 obtained from the World Bank. Employing Autoregression Distributed Lags (ARDL) model, we treat Unemployment, youth total (% of total labor force ages 15-24) (national estimate) as dependent variable and educational attainment, at least completed lower secondary, population 25+, total (%) (cumulative) as independent variable. ARDL results show that lagged Unemployment (lag 1) is positive and statistically significant, meaning that unemployment is persistent. The coefficient of education (0.208554) is positive and statistically significant. This implies that a one year increase in education leads to increase in unemployment by 0.21%. We recommend that policymakers strengthen the quality and relevance of education through skills development, vocational training, and stronger alignment between educational institutions and labor market demands. In addition, broader economic policies aimed at promoting investment, entrepreneurship, and job creation are necessary to effectively reduce youth unemployment in South Africa.

KEY WORDS: *Autoregression Distributed Lags, Unemployment, Education, South Africa*

INTRODUCTION

Youth unemployment and educational attainment are among the most critical socio-economic indicators used to evaluate labour market performance and inclusive economic development (Ladaru et al., 2026). Within the framework of human capital theory, education is widely regarded as a key determinant of employability, as it enhances skills, productivity, and an individual's capacity to participate effectively in the labour market (Suleman, 2018). Consequently, policymakers have consistently emphasized expanding access to education as a primary strategy for reducing youth unemployment (Giwah et al., 2021). However, recent empirical evidence, particularly from developing economies, suggests that the relationship between education and unemployment is not always straightforward, as increases in educational attainment have not necessarily translated into improved employment outcomes for young people (Vivarelli, 2014).

South Africa presents a particularly striking case in this regard. Despite substantial progress in expanding access to education since the end of apartheid, the country continues to experience persistently high levels of youth unemployment (Fourie, 2017). This paradox is further compounded by the growing incidence of unemployment among individuals with secondary and even tertiary qualifications (Livingstone, 2019). While higher education generally improves employment prospects, a significant proportion of educated youth remain unemployed, raising concerns about the effectiveness of the education system in preparing individuals for the labour market (Sanyal, 2024). These patterns suggest that structural issues, such as skills mismatch, low economic growth, and limited job creation, may weaken the expected inverse relationship between educational attainment and unemployment (Adely et al., 2021). The South African labour market is characterized by deep structural and institutional challenges that shape the education-employment nexus (Zinatsa & Saurombe, 2022). Inequalities in the quality of education, limited access to work experience, and a mismatch between the skills produced by the education system and those demanded by employers continue to constrain employment opportunities for young people (Green, 2017). Furthermore, the slow pace of economic growth and insufficient labour market absorption capacity exacerbate the problem, resulting in a situation where even qualified individuals struggle to secure employment (Narula, 2004). These complexities raise important questions about whether educational attainment alone can effectively reduce youth unemployment or whether broader economic and institutional reforms are required.

This study empirically examines the relationship between youth unemployment and educational attainment in South Africa using the Autoregressive Distributed Lag (ARDL) modelling approach (Das & Raju, 2025). The ARDL technique is particularly suitable for this analysis as it allows for the estimation of both short-run and long-run dynamics between variables, regardless of whether they are integrated of different orders (Nkoro & Uko, 2016). By applying the ARDL framework, this study provides robust insights into the nature and direction of the relationship between education and youth unemployment over time. The findings are expected to contribute to policy discussions by offering evidence on whether improving educational attainment can serve as an effective strategy for addressing youth unemployment in South Africa.

LITERATURE REVIEW

Youth unemployment remains one of the most pressing socio-economic challenges globally, particularly in developing regions (Mago, 2018). The relationship between educational attainment and youth unemployment has attracted extensive scholarly attention, with education traditionally viewed as a key pathway to improved labour market outcomes (Brzinsky-Fay, 2017). However, empirical evidence increasingly suggests that the relationship is complex, context-specific, and mediated by structural economic factors (Dogru et al., 2025).

Globally, the dominant theoretical framework underpinning the relationship between education and employment is human capital theory (Tonini, 2021). This theory posits that investments in education enhance individuals' productivity, thereby increasing their employability and earnings potential (Azatovna Galiakberova, 2019). Empirical studies across both developed and developing countries generally support this proposition, showing that higher levels of educational attainment, particularly tertiary education, are associated with lower unemployment rates (Liefner & Schiller, 2008). However, the global literature also highlights several emerging challenges. One such challenge is credential inflation, where the expansion of educational systems has outpaced job creation, leading to rising levels of graduate unemployment (Hassan, 2025). Additionally, the phenomenon of skills mismatch has become increasingly prominent, referring to a situation where the skills possessed by graduates do not align with labour market demands (Moloto et al., 2025). Consequently, education alone is no longer a sufficient guarantee of employment, particularly in economies experiencing slow structural transformation (Lin, 2011).

In the African context, the relationship between education and youth unemployment is further complicated by demographic and economic dynamics (Anyanwu, 2013). The continent is experiencing rapid population growth, resulting in a disproportionately large youth population entering the labour market each year (Lam & Leibbrandt, 2023). While educational access has improved significantly in many African countries, the quality and relevance of education remain critical concerns (Adeniyi et al., 2024). Studies across the continent reveal a growing trend of "educated unemployment," where individuals with secondary or even tertiary qualifications struggle to secure employment (Xibao & Ping, 2025). This paradox is often attributed to weak industrialization, limited formal sector job creation, and education systems that are poorly aligned with labour market needs (Allais, 2022). Furthermore, the dominance of the informal sector in many African economies means that a large proportion of youth are either underemployed or engaged in low-productivity activities that do not match their level of education (Sumberg et al., 2020).

Within Southern Africa, the challenge of youth unemployment is particularly acute, despite relatively higher levels of educational attainment compared to other regions on the continent (De Lannoy et al., 2020). Countries such as South Africa, Namibia, and Botswana exhibit persistently high unemployment rates among young people, reflecting deep structural inequalities and limited economic diversification (Naape, 2026). The literature in this region emphasizes the existence of dual labour markets, characterized by a small, highly skilled formal sector and a large, low-skilled informal sector (Ugargol & Parvathy, 2023). Educational attainment alone does not guarantee access to the formal sector, as employment outcomes are also influenced by factors such as the quality of education, field of study, and access to social networks (Werquin, 2012). Moreover, historical inequalities continue to shape both educational opportunities and labour market outcomes, reinforcing patterns of exclusion among disadvantaged groups (Hadjar, 2019).

South Africa provides a particularly compelling case study within this broader context, as it combines relatively high levels of educational participation with exceptionally high rates of youth unemployment (Ngcaweni, 2016). Empirical studies consistently show that the relationship between education and unemployment in South Africa is non-linear (Ngubane et al., 2023). While individuals with tertiary education generally experience better employment prospects, those with only secondary education often face higher levels of unemployment (Van Broekhuizen, 2016). This suggests that the labour market places a premium on advanced skills, while individuals with lower levels of education struggle to compete for limited opportunities. Furthermore, the South African labour market is characterized by significant skills mismatch, with employers frequently reporting shortages of appropriately skilled workers despite high unemployment rates (Daniels, 2007).

A key theme in the South African literature is the distinction between the quantity and quality of education (Spaull, 2015). Although access to education has improved significantly since the end of apartheid, disparities in educational quality persist across different socio-economic groups (Mzangwa, 2019). Many students, particularly those from disadvantaged backgrounds, attend under-resourced schools that fail to equip them with the skills required for the modern labour market (Woldegiorgis & Chiramba, 2025). As a result, even individuals who have completed secondary education may lack the competencies needed to secure employment. In contrast, graduates from higher-quality institutions, particularly those with specialized or technical qualifications, tend to fare better in the labour market (Rasool & Botha, 2011).

In addition to educational factors, structural and macroeconomic conditions play a critical role in shaping youth unemployment outcomes in South Africa (Dunga & Maloma, 2024). The economy has experienced relatively low levels of growth and job creation, limiting the absorption capacity of the labour market (Mncayi & Shuping, 2021). Historical legacies of inequality, spatial disparities, and labour market rigidities further exacerbate the problem (Yolusever, 2025). Consequently, youth unemployment in South Africa cannot be understood solely as a function of educational attainment; rather, it reflects a complex interplay of educational, economic, and institutional factors (Lam et al., 2009).

DATA AND METHODS

We adopt a quantitative time-series research design grounded in econometric analysis to empirically examine the relationship between youth unemployment and educational attainment in South Africa. The choice of a quantitative approach is motivated by the need to analyze numerical macroeconomic indicators and their dynamic interactions over time using formal statistical techniques (Sheya, 2020).

The study utilizes secondary data obtained from the World Development Indicators (WDI) database of the World Bank (World Bank, 2023). The analysis focuses on two key variables: **youth unemployment**, defined as unemployment among individuals aged 15–24 as a percentage of the total youth labor force (dependent variable), and **educational attainment**, measured as the percentage of the population aged 25 and above that has completed at least lower secondary education (independent variable). The dataset spans the period 2001 to 2024.

Given the limited number of annual observations, the data is transformed into quarterly frequency using linear interpolation. This technique preserves the overall structure of the data while increasing the number of observations, thereby improving the robustness of econometric estimation (Vera-Jaramillo, 2025). This results in a quarterly time series spanning from 2021Q1 to 2024Q1 yielding 93 observations for each variable.

A purposive sampling approach is employed, with South Africa selected due to its persistently high youth unemployment rates and ongoing policy emphasis on education as a tool for labor market improvement (Mseleku, 2022). This context provides a suitable case for examining the linkage between human capital development and employment outcomes.

To provide preliminary insights into the data, descriptive statistics-including mean, median, standard deviation, skewness, and kurtosis-are computed (Chatterjee, 2025). The results indicate moderate variability in both variables, with youth unemployment exhibiting slight positive skewness and educational attainment showing slight negative skewness. The Jarque-Bera statistics suggest that both series are approximately normally distributed, as the null hypothesis of normality cannot be rejected at conventional significance levels (Bokhari & Ali, 2025).

To avoid spurious regression and ensure the validity of time-series analysis, stationarity tests are conducted using the Augmented Dickey-Fuller (ADF) test (Ghouse et al., 2021). The results reveal that both youth unemployment and educational attainment are non-stationary in levels but become stationary after first differencing, implying that both variables are integrated of order one, I(1) (Mehmetaj & Xhindi, 2022). This justifies the use of econometric techniques capable of handling variables with mixed integration orders.

To examine both short-run and long-run dynamics between the variables, the study employs the Autoregressive Distributed Lag (ARDL) bounds testing approach developed by Pesaran et al. (Shahid et al., 2025). The ARDL model is particularly suitable given its flexibility in handling small sample sizes and variables integrated of order I(0) and I(1), but not I(2) (Ghouse, 2018). Based on the Akaike Information Criterion (AIC), the optimal model selected is ARDL(1,1).

The general ARDL model estimated in this study is specified as follows:

$$\Delta Unemployment_t = \sum_{i=1}^{p} \beta_i \Delta Unemployment_{t-i} + \sum_{j=1}^{q} \gamma_i \Delta Education_t + \varepsilon_t \text{ ....(1)}$$

Where;
Δ denotes the first difference operator
$Unemployment_t$ is Unemployment, youth total (% of total labor force ages 15-24) (national estimate)
$Education_t$ is educational attainment, at least completed lower secondary, population 25+, total (%) (cumulative)
ε_t is the white noise error term (Roschitsch, n.d.).

The estimated ARDL results indicate that past values of unemployment significantly influence current unemployment dynamics, as evidenced by the statistically significant lagged dependent variable. In the short run, changes in educational attainment have a positive and statistically significant effect on youth unemployment, suggesting that increases in education levels may initially coincide with higher unemployment, possibly due to skill mismatches or delays in labor market absorption (Mroz & Savage, 2006). However, the lagged effect of education appears negative, indicating potential long-run benefits of education in reducing unemployment.

To ensure the reliability and adequacy of the model, several diagnostic tests are conducted (Campbell et al., 2015). The Breusch-Pagan-Godfrey test for heteroskedasticity fails to reject the null hypothesis of homoskedasticity, indicating constant variance of residuals (Ohaegbulem & Iheaka, 2024). The Breusch-Godfrey Serial Correlation LM test shows no evidence of autocorrelation, confirming that the residuals are independent (Chaudhary et al., 2022). These results suggest that the estimated ARDL model is statistically robust and well-specified.

Overall, the ARDL framework is appropriate for this study as it captures the dynamic interactions between education and youth unemployment without imposing restrictive assumptions about variable integration orders (Mazorodze & Siddiq, 2018). The use of quarterly data enhances the degrees of freedom and allows for more reliable inference, particularly in the context of limited original observations (Leone et al., 2019)

RESULTS

This section presents and interprets the empirical findings of the study, guided by the core objective of examining the relationship between youth unemployment and educational attainment in South Africa using quarterly data from 2001 to 2024. The analysis begins with descriptive statistics, followed by unit root tests and the estimation of the ARDL model, and concludes with diagnostic tests to assess model adequacy.

The descriptive statistics (Appendix 1) provide insight into the distributional characteristics of the variables. Youth unemployment exhibits a relatively high mean value of 54.92%, highlighting the persistent and severe nature of youth joblessness in South Africa (Makananise, 2023). The standard deviation of 4.64 indicates moderate variability, with values ranging from a minimum of 45.59% to a maximum of 65.22%. This suggests that although unemployment levels are consistently high, fluctuations over time are relatively contained (Elsby et al., 2013).

Educational attainment, on the other hand, records a mean of 71.77%, reflecting gradual improvements in access to and completion of lower secondary education (Abbasi, 2025). The standard deviation of 6.24 indicates slightly higher variability compared to unemployment, with values ranging between 55.59% and 85.43%. This suggests a steady upward trend in educational outcomes over the study period (Nkoane & Seeletse, 2021).

The skewness values reveal that youth unemployment is slightly positively skewed (0.23) (Singh & Chiloane-Tsoka, 2015), while educational attainment is slightly negatively skewed (-0.21), indicating relatively symmetric distributions

for both variables (Montanari & Viroli, 2010). Kurtosis values for both series are below 3, suggesting platykurtic distributions with thinner tails compared to a normal distribution. The Jarque-Bera statistics are statistically insignificant ($p > 0.05$), implying that both series are approximately normally distributed (Glinskiy et al., 2024). This supports the reliability of subsequent econometric analysis.
To ensure the validity of the time-series analysis, stationarity tests are conducted using the Augmented Dickey-Fuller (ADF) test (Mushtaq, 2011). The results (Appendices 2 and 4) indicate that both youth unemployment and educational attainment are non-stationary in their levels, as the null hypothesis of a unit root cannot be rejected ($p > 0.05$). Specifically, the ADF statistic for unemployment (-0.2115) and education (1.5017) fall above their respective critical values (Mabengwana, 2024).
However, after first differencing, both variables become stationary (Appendices 3 and 5). The ADF test statistics for the differenced series are -2.9766 for unemployment and -2.4579 for education, both of which are statistically significant at the 5% level ($p < 0.05$). This indicates that both variables are integrated of order one, I(1), thereby satisfying the requirements for applying the ARDL bounds testing approach (Rehman et al., 2020).
The ARDL model estimation results (Appendix 6) are presented as follows:

$$\widehat{Unemployment}_t = -0.023507 + 0.765089 Unemployment_{t-1} + 0.208554 Education_t + -0.135308 Education_{t-1} \quad \text{......(2)}$$

Hence,

$$\hat{\beta}_{ARDL} \begin{bmatrix} -0.023507 \\ 0.765089 \\ 0.208554 \\ -0.135308 \end{bmatrix}$$

The coefficient of the lagged dependent variable (0.7651) is positive and highly statistically significant ($p < 0.01$), indicating strong persistence in youth unemployment. This suggests that past unemployment levels play a substantial role in determining current unemployment, reflecting structural rigidities in the labor market (Dadam & Viegi, 2024). The contemporaneous effect of educational attainment on youth unemployment is positive (0.2086) and statistically significant ($p < 0.01$). This implies that, in the short run, increases in educational attainment are associated with higher youth unemployment. This seemingly counterintuitive result may reflect labor market frictions, such as skill mismatches, where the education system produces graduates whose skills do not align with labor market demands (Sloane, 2020).

In contrast, the lagged effect of education (-0.1353) is negative and weakly significant ($p \approx 0.07$), suggesting that over time, improvements in educational attainment may contribute to reducing unemployment. This supports the notion that education has delayed but beneficial effects on employment outcomes, as individuals gradually integrate into the labor market (Bol et al., 2019).

The model exhibits a relatively strong explanatory power, with an R-squared value of 0.6223 and an adjusted R-squared of 0.6093, indicating that approximately 61% of the variation in youth unemployment is explained by the model (Kim, 2025). The overall model is statistically significant, as indicated by the F-statistic (47.79, $p < 0.01$).
To validate the robustness of the model, several diagnostic tests are conducted. The Breusch-Pagan-Godfrey test for heteroskedasticity (Appendix 8) shows that the null hypothesis of homoskedasticity cannot be rejected, as both the F-statistic ($p = 0.3084$) and the Obs*R-squared probability ($p = 0.2999$) are greater than 0.05. This indicates that the variance of the residuals is constant (Abdul-Hameed & Matanmi, 2021).

Similarly, the Breusch-Godfrey Serial Correlation LM test (Appendix 9) indicates no evidence of autocorrelation, as the null hypothesis of no serial correlation cannot be rejected ($p = 0.2399$ for the F-statistic and $p = 0.2224$ for the Chi-square statistic). This confirms that the residuals are independent across time (Test, n.d.).

Overall, the diagnostic results suggest that the ARDL model is well-specified, stable, and reliable for inference (Hendricks, 2021). The findings highlight a complex relationship between education and youth unemployment in South Africa, characterized by short-run increases in unemployment following improvements in education, but potential long-run reductions as the labor market adjusts. This underscores the importance of aligning educational outcomes with labor market needs to fully realize the employment benefits of human capital development (Ntsanwisi, 2025).

DISCUSSION

This study set out to empirically examine the relationship between youth unemployment and educational attainment in South Africa using a time-series framework based on the Autoregressive Distributed Lag (ARDL) model. The analysis was motivated by the human capital theory, which posits that higher levels of education should enhance employability and reduce unemployment (Adejumo et al., 2021). However, the empirical findings from this study reveal a more nuanced and somewhat counterintuitive relationship between education and youth unemployment.

The results indicate a positive and statistically significant short-run relationship between educational attainment and youth unemployment. This finding contradicts the conventional expectation that increased education directly leads to lower unemployment (Ferrante, 2017). Instead, it suggests that improvements in educational attainment are associated with rising youth unemployment in the short term. This outcome is consistent with studies conducted in developing and structurally constrained economies, where expansion in education does not immediately translate into job creation (Mascherini et al., 2017). One plausible explanation is the presence of skill mismatches, where the education system produces graduates whose skills are not aligned with labor market demands (Cappelli, 2015). In such cases, higher education levels may actually increase the pool of job seekers without a corresponding increase in employment opportunities.

In the South African context, this finding aligns with existing literature highlighting structural challenges in the labor market, including rigidities, limited absorption capacity, and a disconnect between educational curricula and industry needs (Wolff et al., 2025). The economy may not be generating sufficient high-quality jobs to accommodate the growing number of educated youth, leading to increased competition and higher unemployment rates among this group (Sparreboom & Staneva, 2014).

However, the lagged effect of education is negative, albeit weakly significant, suggesting that education may reduce unemployment over time. This supports the long-run benefits of human capital development, where the positive effects of education materialize gradually as individuals gain experience, adapt to labor market conditions, and transition into employment (Wilson & Briscoe, 2004). This delayed impact is consistent with the human capital framework, which emphasizes that the returns to education are not always immediate but accumulate over time (Belzil et al., 2017).

The strong persistence in youth unemployment, as indicated by the highly significant lagged dependent variable, reflects deep-rooted structural issues within the South African labor market. This persistence suggests that unemployment is not merely cyclical but structural in nature, influenced by factors such as slow economic growth, inequality, and institutional constraints. Similar findings have been reported in studies on labor markets in developing economies, where unemployment tends to exhibit inertia due to long-term structural imbalances (Kingdon & Knight, 2004).

Unlike traditional expectations of a straightforward inverse relationship, the findings of this study point to a complex and dynamic interaction between education and unemployment (Blasques et al., 2021). The short-run positive relationship may reflect transitional dynamics, where increased education initially raises expectations and labor force participation among youth, thereby increasing measured unemployment. Over time, however, the labor market begins to absorb these individuals, leading to a reduction in unemployment (Danziger & Ratner, 2010).

The diagnostic tests further reinforce the reliability of these findings. The absence of heteroskedasticity and serial correlation suggests that the estimated ARDL model is well-specified and that the results are not driven by econometric issues (Maponya, 2025). This strengthens confidence in the observed relationship between the variables.

Overall, the findings challenge the simplistic view that expanding education alone is sufficient to address youth unemployment. Instead, they highlight the importance of complementary **policies**, such as improving the quality and relevance of education, promoting skills development aligned with industry needs, and fostering job creation through economic growth and investment (Jafarov, 2025). This supports broader arguments in the literature that emphasize the role of structural reforms and labor market flexibility in translating educational gains into employment outcomes (Woldemichael et al., 2019).

In conclusion, while education remains a critical tool for long-term economic development, its effectiveness in reducing youth unemployment in South Africa depends on the extent to which it is aligned with labor market demands (Habiyaremye et al., 2022). The study underscores the need for integrated policy approaches that combine education reform with active labor market strategies to achieve meaningful reductions in youth unemployment (Radha et al., 2024).

LIMITATIONS

While this study provides important empirical insights into the relationship between youth unemployment and educational attainment in South Africa, several limitations should be acknowledged when interpreting the findings. The study employed a quantitative time-series econometric approach using the Autoregressive Distributed Lag (ARDL) model. Although the ARDL framework is appropriate for analyzing relationships among variables integrated of order zero and one and performs well with relatively small sample sizes (Kripfganz & Schneider, 2023), it assumes linearity and stability in the relationship between variables over time. In the context of South Africa's labor market, the relationship between educational attainment and youth unemployment may be influenced by structural inequalities, labor market rigidities, technological changes, and institutional factors that are potentially nonlinear or regime dependent (Baldry, 2016). Consequently, the linear ARDL specification may oversimplify the complexity of labor market dynamics and fail to fully capture asymmetric or threshold effects that characterize youth employment outcomes (Salah, 2025).

Furthermore, the study relied on quarterly time-series data from 2001Q3 to 2024Q1, producing 93 observations after adjustments. Although this sample size is adequate for ARDL estimation, it remains relatively limited for capturing long-run structural transformations in education and labor market conditions (Djamal et al., 2023). The period under review also includes major economic disruptions such as the global financial crisis, the COVID-19 pandemic, electricity supply constraints, and changes in labor market policies in South Africa. These events may have introduced structural breaks or shifts in the underlying economic relationships. However, the estimated model did not explicitly test for structural breaks or regime changes, which may affect the stability and reliability of the estimated coefficients (Casini & Perron, 2018). Failure to account for such discontinuities may therefore reduce the explanatory power of the model.

Another limitation relates to data measurement and variable specification. The study used educational attainment measured as the proportion of the population aged 25 years and above that completed at least lower secondary education, while youth unemployment was measured as the percentage of the labor force aged 15–24 that is unemployed. Although these indicators are widely accepted and sourced from internationally recognized databases, they may not fully capture the quality of education, skills mismatch, or employability of graduates in South Africa (Yu, 2020). Educational attainment alone does not necessarily reflect labor market readiness, technical competencies, or differences in school quality between urban and rural areas. Similarly, youth unemployment statistics may underestimate labor market distress due to discouraged work seekers, informal employment, or underemployment, which are significant features of the South African labor market (Alenda-Demoutiez & Mügge, 2020).

The econometric results further reveal certain methodological limitations. Unit root tests indicated that both unemployment and education variables were non-stationary at levels but became stationary after first differencing, implying integration of order one, I(1). Although this justified the use of the ARDL framework, the possibility of information loss through differencing remains a concern, particularly regarding long-run dynamics between variables (Aich et al., 2025). Additionally, the selected ARDL(1,1) model included only one explanatory variable, education attainment, in explaining youth unemployment. This parsimonious specification may result in omitted variable bias because several other determinants of youth unemployment such as economic growth, labor market regulations, wage dynamics, industrial structure, technological advancement, population growth, and political uncertainty were excluded from the analysis (Soliman & Beram, 2025). The exclusion of these relevant macroeconomic and institutional variables may limit the comprehensiveness of the findings.

Although diagnostic tests suggested that the estimated model satisfied several classical assumptions, some concerns remain. The Breusch-Pagan-Godfrey heteroskedasticity test largely supported homoskedasticity, and the Breusch-Godfrey LM test indicated absence of serial correlation (OLANIYI et al., 2024). However, the scaled explained sum of squares statistic in the heteroskedasticity test was statistically significant, suggesting the possible presence of residual variance instability. In addition, while the Jarque-Bera statistics suggested approximate normality of the

Journal DOI: 10.36713/epra1013|SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 5|May 2026 -Peer-Reviewed Journal

variables, normality of residuals in small samples may still be sensitive to outliers and structural disturbances. Therefore, caution should be exercised when generalizing the findings or drawing strong policy conclusions from the estimated coefficients (Hodge, 2009).

Lastly, the study focused exclusively on South Africa, which limits the external validity and generalizability of the results to other countries. South Africa has unique socioeconomic characteristics, including persistently high inequality, dual labor markets, historical disparities in education access, and exceptionally high youth unemployment rates (Tivaringe, 2019). These structural conditions may produce relationships between education and unemployment that differ significantly from those observed in other developing or developed economies (Mpendulo & Mang'unyi, 2018). Consequently, the findings should be interpreted within the specific institutional and economic context of South Africa and may not necessarily apply to other countries with different labor market structures or educational systems.

CONCLUSION

This study examined the relationship between youth unemployment and educational attainment in South Africa using quarterly time series data and the ARDL model. The main objective was to determine whether improvements in educational attainment influence youth unemployment levels in South Africa, a country characterized by persistently high youth unemployment despite rising educational participation (Baah-Boateng, 2016).

The findings revealed that both variables were non-stationary at levels but became stationary after first differencing, confirming that they are integrated of order one, I(1). This justified the use of the ARDL approach. The estimated ARDL(1,1) model showed that educational attainment has a significant effect on youth unemployment in the short run. The results further indicated that youth unemployment is highly persistent, suggesting that labor market challenges among young people are influenced not only by education but also by broader structural economic factors (Ismail & Kollamparambil, 2015).

The study also found that although higher educational attainment may improve employability over time, education alone is insufficient to solve the youth unemployment problem in South Africa (Graham & Mlatsheni, 2015). Factors such as slow economic growth, limited job creation, skills mismatches, and labor market inefficiencies continue to constrain employment opportunities for young people (Horwitz, 2013).

Diagnostic tests confirmed that the estimated model was reliable, with no serious problems of heteroskedasticity or serial correlation (Samantaraya, 2024). Therefore, the findings are considered robust for policy analysis and interpretation.

RECOMMENDATIONS

Based on the findings of this study, several policy and research recommendations are proposed to address the challenge of youth unemployment in South Africa. Since the results show that educational attainment alone is insufficient to significantly reduce youth unemployment, policymakers should complement education policies with broader job-creation strategies aimed at stimulating economic growth and expanding employment opportunities for young people (Mehta & Awasthi, 2025).

The government should strengthen the alignment between the education system and labor market requirements by promoting technical, vocational, and skills-based training programs (Lumadi, 2025). This would help reduce the mismatch between graduates' skills and employer expectations while improving youth employability. In addition, stronger partnerships between educational institutions and the private sector should be encouraged to provide internships, apprenticeships, and workplace experience for graduates (Jackson, 2016).

Given the persistence of youth unemployment revealed by the ARDL results, labor market policies should focus on supporting entrepreneurship, small business development, and innovation among young people. Access to finance, business training, and youth-targeted employment programs can assist in absorbing unemployed graduates into productive economic activities (Sele & Mukundi, 2024).

The study also recommends increased investment in sectors with high employment potential such as manufacturing, technology, agriculture, and infrastructure development. Expanding these sectors can create sustainable employment opportunities for the growing youth population in South Africa (Geza et al., 2022).

From a research perspective, future studies should incorporate additional macroeconomic variables such as economic growth, inflation, investment, government expenditure, and labor market regulations to provide a broader understanding of the determinants of youth unemployment (Muhammad, 2023). Further research may also apply advanced econometric techniques such as Vector Error Correction Models (VECM) or Structural VAR models to examine long-run relationships and dynamic interactions more comprehensively (Majka, n.d.).

REFERENCES

1. *Abbasi, A. A. (2025). Investment in Education and Its Impact on Lower Secondary School Completion in Low and Middle-Income Countries: A Pre-and Post-SDG Comparison. Hamad Bin Khalifa University (Qatar).*
2. *Abdul-Hameed, A. B., & Matanmi, O. G. (2021). A modified Breusch–Pagan test for detecting heteroskedasticity in the presence of outliers. Retrieved Online from the Website: Http://Article. Pamathj. Net/Pdf/10.11648. j. Pamj, 20211006.*
3. *Adejumo, O. O., Asongu, S. A., & Adejumo, A. V. (2021). Education enrolment rate vs employment rate: Implications for sustainable human capital development in Nigeria. International Journal of Educational Development, 83, 102385.*
4. *Adely, F. I. J., Mitra, A., Mohamed, M., & Shaham, A. (2021). Poor education, unemployment and the promise of skills: The hegemony of the "skills mismatch" discourse. International Journal of Educational Development, 82, 102381.*
5. *Adeniyi, I. S., Al Hamad, N. M., Adewusi, O. E., Unachukwu, C. C., Osawaru, B., Onyebuchi, C. N., & David, I. O. (2024). Educational reforms and their impact on student performance: A review in African Countries. World Journal of Advanced Research and Reviews, 21(2), 750–762.*
6. *Aich, B. R., Tareque, M., & Rahman, M. M. (2025). Testing the modeling relevance for growth, inflation, and unemployment: analysis using VAR, ARDL, and DOLS. Quality & Quantity, 1–28.*
7. *Alenda-Demoutiez, J., & Mügge, D. (2020). The lure of ill-fitting unemployment statistics: How South Africa's discouraged work seekers disappeared from the unemployment rate. New Political Economy, 25(4), 590–606.*
8. *Allais, S. (2022). Skills for industrialisation in sub-Saharan African countries: why is systemic reform of technical and vocational systems so persistently unsuccessful? Journal of Vocational Education & Training, 74(3), 475–493.*
9. *Anyanwu, J. C. (2013). Characteristics and macroeconomic determinants of youth employment in Africa. African Development Review, 25(2), 107–129.*
10. *Azatovna Galiakberova, A. (2019). Conceptual analysis of education role in economics: the human capital theory. Journal of History, Culture & Art Research/Tarih Kültür ve Sanat Arastirmalari Dergisi, 8(3).*
11. *Baah-Boateng, W. (2016). The youth unemployment challenge in Africa: What are the drivers? The Economic and Labour Relations Review, 27(4), 413–431.*
12. *Baldry, K. (2016). Graduate unemployment in South Africa: Social inequality reproduced. Journal of Education and Work, 29(7), 788–812.*
13. *Belzil, C., Hansen, J., & Liu, X. (2017). Dynamic skill accumulation, education policies, and the return to schooling. Quantitative Economics, 8(3), 895–927.*
14. *Blasques, F., Hoogerkamp, M. H., Koopman, S. J., & van de Werve, I. (2021). Dynamic factor models with clustered loadings: Forecasting education flows using unemployment data. International Journal of Forecasting, 37(4), 1426–1441.*
15. *Bokhari, S. W. A., & Ali, N. (2025). Normality Testing in Medical Data: Classical vs. Adapted Jarque-Bera. Research Journal of Social Sciences and Economics Review, 6(1), 48–66.*
16. *Bol, T., Ciocca Eller, C., Van De Werfhorst, H. G., & DiPrete, T. A. (2019). School-to-work linkages, educational mismatches, and labor market outcomes. American Sociological Review, 84(2), 275–307.*
17. *Brzinsky-Fay, C. (2017). The interplay of educational and labour market institutions and links to relative youth unemployment. Journal of European Social Policy, 27(4), 346–359.*
18. *Campbell, J. M., Klugar, M., Ding, S., Carmody, D. P., Hakonsen, S. J., Jadotte, Y. T., White, S., & Munn, Z. (2015). Diagnostic test accuracy: methods for systematic review and meta-analysis. JBI Evidence Implementation, 13(3), 154–162.*
19. *Cappelli, P. H. (2015). Skill gaps, skill shortages, and skill mismatches: Evidence and arguments for the United States. ILR Review, 68(2), 251–290.*
20. *Casini, A., & Perron, P. (2018). Structural breaks in time series. ArXiv Preprint ArXiv:1805.03807.*
21. *Chatterjee, M. (2025). Comprehensive Guide to Statistics. Educohack Press.*
22. *Chaudhary, A. A., Nazir, N., Riaz, A., Sadiq, N., & Riaz, N. (2022). Autocorrelation: what happens if the error or disturbance terms are correlated in time-series data. Competitive Education Research Journal, 3(2), 154–163.*
23. *Dadam, V., & Viegi, N. (2024). Investigating unemployment hysteresis in South Africa. South African Journal of Economics, 92(3), 331–353.*
24. *Daniels, R. (2007). Skills shortages in South Africa: A literature review.*
25. *Danziger, S., & Ratner, D. (2010). Labor market outcomes and the transition to adulthood. The Future of Children, 133–158.*
26. *Das, T., & Raju, S. (2025). Nexus Between Public Education Expenditure, Educational Attainment, and Youth Unemployment in Bangladesh: Empirical Evidence from an ARDL Approach. Educational Attainment, and Youth Unemployment in Bangladesh:*

Empirical Evidence from an ARDL Approach (November 09, 2025).
27. *De Lannoy, A., Graham, L., Patel, L., & Leibbrandt, M. (2020). Why is youth unemployment so intractable in South Africa? A synthesis of evidence at the micro-level. Journal of Applied Youth Studies, 3(2), 115–131.*
28. *Djamal, D., Fariou, C., & Brahim, L. (2023). Effect of human capital on economic growth in South Africa: An ARDL approach.*
29. *Dogru, A. K., Gong, K., Peyrefitte, J., Scrimpshire, A., & Lai, F. (2025). The context-dependent role of innovation as a mediator between firm capabilities and performance. Innovation, 1–29.*
30. *Dunga, H., & Maloma, I. (2024). Exploring the multifaceted dynamics of unemployment in South Africa: an investigation into the interplay of economic, social, and policy factors. International Journal of Research in Business & Social Science, 13.*
31. *Elsby, M. W. L., Hobijn, B., & Şahin, A. (2013). Unemployment dynamics in the OECD. Review of Economics and Statistics, 95(2), 530–548.*
32. *Ferrante, F. (2017). Great expectations: The unintended consequences of educational choices. Social Indicators Research, 131(2), 745–767.*
33. *Fourie, J. (2017). The long walk to economic freedom after apartheid, and the road ahead. Southern Journal for Contemporary History, 42(1), 59–80.*
34. *Geza, W., Ngidi, M. S. C., Slotow, R., & Mabhaudhi, T. (2022). The dynamics of youth employment and empowerment in agriculture and rural development in South Africa: A scoping review. Sustainability, 14(9), 5041.*
35. *Ghouse, G. (2018). ARDL model as a remedy for spurious regression: problems, performance and prospectus.*
36. *Ghouse, G., Khan, S. A., Rehman, A. U., & Bhatti, M. I. (2021). ARDL as an elixir approach to cure for spurious regression in nonstationary time series. Mathematics, 9(22), 2839.*
37. *Giwah, M. L., Nwokediegwu, Z. S., Etukudoh, E. A., & Gbabo, E. Y. (2021). A strategic blueprint model for poverty and unemployment reduction through public policy interventions. International Journal of Multidisciplinary Futuristic Development, 2(2), 1–6.*
38. *Glinskiy, V., Ismayilova, Y., Khrushchev, S., Logachov, A., Logachova, O., Serga, L., Yambartsev, A., & Zaykov, K. (2024). Modifications to the Jarque–Bera test. Mathematics, 12(16), 2523.*
39. *Graham, L., & Mlatsheni, C. (2015). Youth unemployment in South Africa: Understanding the challenge and working on solutions. South African Child Gauge, 2, 51–59.*
40. *Green, A. (2017). The crisis for young people: Generational inequalities in education, work, housing and welfare. Springer.*
41. *Habiyaremye, A., Habanabakize, T., & Nwosu, C. (2022). Bridging the labour market skills gap to tackle youth unemployment in South Africa. The Economic and Labour Relations Review, 33(4), 786–805.*
42. *Hadjar, A. (2019). Educational expansion and inequalities: how did inequalities by social originand gender decrease in modern industrial societies? In Research handbook on the sociology of education (pp. 173–192). Edward Elgar Publishing.*
43. *Hassan, M. (2025). Higher Education and Labor Market Outcomes: Investigating the Rise of Educated Unemployment. Universal Insights in Research and Innovation, 1(01), 1–13.*
44. *Hendricks, C. J. (2021). Employment growth intensity in South Africa.*
45. *Hodge, D. (2009). Growth, employment and unemployment in South Africa. South African Journal of Economics, 77(4), 488–504.*
46. *Horwitz, F. M. (2013). An analysis of skills development in a transitional economy: the case of the South African labour market. The International Journal of Human Resource Management, 24(12), 2435–2451.*
47. *Ismail, Z., & Kollamparambil, U. (2015). Youth unemployment duration and competing exit states: What hides behind long spells of black youth unemployment in South Africa? African Development Review, 27(3), 301–314.*
48. *Jackson, L. S. (2016). Public-Private Partnerships: Instruments to Enhance Education, Training and Employment Opportunities in the Republic of South Africa.*
49. *Jafarov, S. (2025). Education and skill development: A pathway to sustainable growth. International Journal of Scientific Research and Management, 13(2), 3963–3969.*
50. *Kim, M. S. (2025). Comparative R-Squared. Available at SSRN 3790200.*
51. *Kripfganz, S., & Schneider, D. C. (2023). ardl: Estimating autoregressive distributed lag and equilibrium correction models. The Stata Journal, 23(4), 983–1019.*
52. *Ladaru, G.-R., Petre, I. L., Mocanu, S., & Popescu, A. S. (2026). EU Labour Market in the Context of Sustainable Development. Merits, 6(1), 4.*
53. *Lam, D., & Leibbrandt, M. (2023). Demographic challenges for global labor markets in the 21st century, Africa in a changing world.*
54. *Lam, D., Leibbrandt, M., & Mlatsheni, C. (2009). Education and youth unemployment in South Africa. In Labor markets and economic development (pp. 90–109). Routledge.*
55. *Leone, A. J., Minutti-Meza, M., & Wasley, C. E. (2019). Influential observations and inference in accounting research. The Accounting Review, 94(6), 337–364.*
56. *Liefner, I., & Schiller, D. (2008). Academic capabilities in developing countries—A conceptual framework with empirical illustrations from Thailand. Research Policy, 37(2), 276–293.*
57. *Lin, J. Y. (2011). New structural economics: A framework for rethinking development. The World Bank Research Observer, 26(2), 193–221.*

58. *Livingstone, D. W. (2019). Underemployment of highly qualified labour in advanced capitalism: Trends and prospects. Journal of Education and Work, 32(4), 305–319.*
59. *Lumadi, R. I. (2025). Bridging the skills divide: Evaluating the effectiveness of lifelong learning initiatives in South Africa. South African Journal of Education, 45(4), 1–11.*
60. *Mabengwana, A. C. (2024). Impact analysis of disaggregated government spending shocks on unemployment: evidence from South Africa.*
61. *Mago, S. (2018). Urban Youth Unemployment in South Africa: Socio-Economic and Political Problems. Commonwealth Youth & Development, 16(1).*
62. *Majka, M. (n.d.). Vector Autoregression.*
63. *Makananise, M. A. (2023). Graduate unemployment: an exploration into the experiences and coping among South African youth. University of Johannesburg (South Africa).*
64. *Maponya, L. (2025). Examining the determinants of Human Development Index in South Africa: an econometric model.*
65. *Mascherini, M., Ledermaier, S., Vacas-Soriano, C., & Jacobs, L. (2017). Long-term unemployed youth: Characteristics and policy responses.*
66. *Mazorodze, B. T., & Siddiq, N. (2018). On the unemployment–output relation in South Africa: a nonlinear ARDL approach. Journal of Economics and Behavioral Studies, 10(5), 167–178.*
67. *Mehmetaj, N., & Xhindi, N. (2022). Public expenses in education and youth unemployment rates – a vector error correction model approach. Economies, 10(12), 293.*
68. *Mehta, B. S., & Awasthi, I. C. (2025). Policy Recommendations for Youth Education, Skill, and Employment. In Indian Youth's Journey from Education to Decent Work: Issues and Challenges (pp. 181–197). Springer.*
69. *Mncayi, P., & Shuping, K. (2021). Factors affecting labour absorption in South Africa. Journal of Economic and Financial Sciences, 14(1), 10.*
70. *Moloto, A. N., Ramasimu, N. F., Motsei, L. L., & Muchie, M. (2025). Graduate Unemployment, Skills Mismatch, and the Dynamics of Labour Mobility in South Africa: A Systematic Literature Review. International Journal of Applied Research in Business and Management, 6(5).*
71. *Montanari, A., & Viroli, C. (2010). A skew-normal factor model for the analysis of student satisfaction towards university courses. Journal of Applied Statistics, 37(3), 473–487.*
72. *Mpendulo, G., & Mang'unyi, E. E. (2018). Exploring relationships between education level and unemployment. Journal of Social Sciences (COES&RJ-JSS), 7(2), 86–102.*
73. *Mroz, T. A., & Savage, T. H. (2006). The long-term effects of youth unemployment. The Journal of Human Resources, 259–293.*
74. *Mseleku, Z. (2022). Youth high unemployment/unemployability in South Africa: the unemployed graduates' perspectives. Higher Education, Skills and Work-Based Learning, 12(4), 775–790.*
75. *Muhammad, A. A. (2023). Examining the relationship among unemployment, inflation, and economic growth. Journal of Business and Economic Options, 6(2), 23–31.*
76. *Mushtaq, R. (2011). Augmented dickey fuller test.*
77. *Mzangwa, S. T. (2019). The effects of higher education policy on transformation in post-apartheid South Africa. Cogent Education, 6(1), 1592737.*
78. *Naape, B. (2026). Exploring South Africa's Policy Dilemmas and Strategic Pathways. International Journal of Business, Economics, and Social Development, 7(1), 102–113.*
79. *Narula, R. (2004). Understanding Absorptive Capacities is an" Innovation Systems" Context: Consequences for Economic and Employment Growth.*
80. *Ngcaweni, B. (2016). Understanding youth unemployment and social inclusion in South Africa. Africanus: Journal of Development Studies, 46(2), 1–28.*
81. *Ngubane, M. Z., Mndebele, S., & Kaseeram, I. (2023). Economic growth, unemployment and poverty: Linear and non-linear evidence from South Africa. Heliyon, 9(10).*
82. *Nkoane, S. S., & Seeletse, S. M. (2021). Forecasting unemployment rate in South Africa with unexpected events using robust estimators. International Journal of Economics and Finance Studies, 13(2), 199–222.*
83. *Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. Journal of Statistical and Econometric Methods, 5(4), 63–91.*
84. *Ntsanwisi, S. (2025). Defending the Role of Formal Education in South Africa: A Theoretical and Ar etical and Argumentativ gumentative Perspectiv erspective on Reform. Educational Considerations, 50(3).*
85. *Ohaegbulem, E. U., & Iheaka, V. C. (2024). On remedying the presence of heteroscedasticity in a multiple linear regression modelling. Afr. J. Math. Stat. Stud, 7, 225–261.*
86. *OLANIYI, O. A., ADEKANMBI, A. M., OPADEJI, S. A., & SHALLIE, A. D. (2024). JOURNAL OF APPLIED ECONOMIC RESEARCH. JOURNAL OF APPLIED ECONOMIC RESEARCH Учредители: Уральский Федеральный Университет Им. Первого Президента России БН Ельцина, 23(3), 623–641.*
87. *Radha, P., Nirubarani, J., & Mekala, S. (2024). A Study on Addressing Unemployment: Strategies and Policies for Enhancing Job Creation. NPRC Journal of Multidisciplinary Research, 1(9), 96–105.*

88. *Rasool, F., & Botha, C. J. (2011). The nature, extent and effect of skills shortages on skills migration in South Africa. SA Journal of Human Resource Management, 9(1), 1–12.*
89. *Rehman, A., Irfan, M., Hena, S., & Chandio, A. A. (2020). By applying an ARDL bounds testing approach and causality test to investigate the electricity consumption and production with economic growth: Empirical evidence from Pakistan. World Journal of Science, Technology and Sustainable Development, 17(2), 182–199.*
90. *Roschitsch, U. (n.d.). M-Estimation for Time Series.*
91. *Salah, A. R. M. (2025). Unemployment Dynamics: Labor Markets, Skills, and Economic Growth.*
92. *Samantaraya, A. (2024). Diagnostic Tests in Regression Analysis. Basic Econometric Tools and Techniques in Data Analytics, 50.*
93. *Sanyal, B. C. (2024). Higher education and employment: An international comparative analysis. Routledge.*
94. *Sele, J. P., & Mukundi, M. B. (2024). Education and economic empowerment: How political policies shape the future of youth employment. Greener Journal of Social Sciences.*
95. *Shahid, M., Jehan, N., & Hussain, A. (2025). A Time Series Anaylsis Of Autoregressive Distributed Lag (ARDL) To Co Integration Technique: The Results Applications. Advance Journal of Econometrics and Finance, 3(3), 2094–2302.*
96. *Sheya, E. (2020). Foreign Direct Investment, Economic Growth and Employment creation: A Causality Analysis from Namibia.*
97. *Singh, I., & Chiloane-Tsoka, E. (2015). Youth Unemployment and effects of education as global entrepreneurial determinants: Case of South Africa. The Business & Management Review, 6(2), 251.*
98. *Sloane, P. J. M. (2020). Overeducation, skill mismatches, and labor market outcomes for college graduates. IZA World of Labor.*
99. *Soliman, P. E. N., & Beram, R. S. (2025). Sustainable development goals and unemployment: worldwide evidence. Journal of the Knowledge Economy, 1–51.*
100. *Sparreboom, T., & Staneva, A. (2014). Is education the solution to decent work for youth in developing economies. Work4Youth Publication Series, 23(1), 1–60.*
101. *Spaull, N. (2015). Education quality in South Africa and sub-Saharan Africa: An economic approach. Stellenbosch: Stellenbosch University.*
102. *Suleman, F. (2018). The employability skills of higher education graduates: insights into conceptual frameworks and methodological options. Higher Education, 76(2), 263–278.*
103. *Sumberg, J., Flynn, J., Mader, P., Mwaura, G., Oosterom, M., Sam-Kpakra, R., & Shittu, A. I. (2020). Formal-sector employment and Africa's youth employment crisis: Irrelevance or policy priority? Development Policy Review, 38(4), 428–440.*
104. *Test, B.-G. S. C. L. M. (n.d.). As with the first regression, the autocorrelation and partial autocorrelation functions of the residuals shows that there is no serial correlation in the residuals.*
105. *Tivaringe, T. (2019). The social unemployment gap in South Africa: Limits of enabling socio-economic redress through expanding access to higher education. Education Policy Analysis Archives, 27, 155.*
106. *Tonini, D. C. (2021). Human capital theory in comparative and international education. The Bloomsbury Handbook of Theory in Comparative and International Education, 69–86.*
107. *Ugargol, A. P., & Parvathy, L. (2023). Precarity of informal work, absence of social security, and ageism: The persistence of social inequalities and challenges for older adults' labor force participation in India. In Handbook of aging, health and public policy: Perspectives from Asia (pp. 1–29). Springer.*
108. *Van Broekhuizen, H. (2016). Graduate unemployment, Higher Education access and success, and teacher production in South Africa. Stellenbosch: Stellenbosch University.*
109. *Vera-Jaramillo, J. (2025). tempdisagg: A Python Framework for Temporal Disaggregation of Time Series Data. ArXiv Preprint ArXiv:2503.22054.*
110. *Vivarelli, M. (2014). Innovation, employment and skills in advanced and developing countries: A survey of economic literature. Journal of Economic Issues, 48(1), 123–154.*
111. *Werquin, P. (2012). The missing link to connect education and employment: recognition of non-formal and informal learning outcomes. Journal of Education and Work, 25(3), 259–278.*
112. *Wilson, R. A., & Briscoe, G. (2004). The impact of human capital on economic growth: a review. Impact of Education and Training, Third Report on Vocational Training Research in Europe: Background Report. Luxembourg: Office for Official Publications of the European Communities, Cedefop Reference Series, 54, 377–382.*
113. *Woldegiorgis, E. T., & Chiramba, O. (2025). Access and success in higher education: fostering resilience in historically disadvantaged students in South Africa. Journal of Applied Research in Higher Education, 17(2), 759–771.*
114. *Woldemichael, A., Jodlowski, M., & Shimeles, A. (2019). Labor Market Flexibility and Jobs in Select African Countries. Working Paper 330. African Development Bank.*
115. *Wolff, K., Hattingh, T., & Smith, L. (2025). Global challenges, local responses: Exploring curriculum reform in South African engineering education. Journal of Engineering Education, 114(3), e70006.*
116. *Xibao, G., & Ping, L. (2025). Educated Unemployment. In Dictionary of Contemporary Chinese Economics (pp. 535–536). Springer.*
117. *Yolusever, A. (2025). Economic Inequality: History, Case Studies and Policies. Ekonomi-Tek, 14(1), 154–190.*
118. *Yu, D. (2020). Employment quality index for the South African labour market. Development Southern Africa, 37(2), 276–294.*

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 5 | May 2026 -Peer-Reviewed Journal

119. *Zinatsa, F., & Saurombe, M. D. (2022). Tied migrant labor market integration: Deconstructing labor market subjectivities in South Africa. Frontiers in Psychology, 13, 806436.*

APPENDICES

Appendix 1: Descriptive statistics

	Unemployment, youth total (% of total labor force ages 15-24) (national estimate)	**Educational attainment, at least completed lower secondary, population 25+, total (%) (cumulative)**
Mean	54.91891	71.76912
Median	53.5825	72.46298
Maximum	65.219	85.42796
Minimum	45.585	55.58894
Std. Dev.	4.642415	6.241658
Skewness	0.228293	-0.214276
Kurtosis	2.097286	2.761904
Jarque-Bera	3.965535	0.931345
Probability	0.137688	0.627713
Sum	5107.459	6674.529
Sum Sq. Dev.	1982.785	3584.163
Observations	93	93

Appendix 2: Unit root test, Unemployment (in Level)

Null Hypothesis: UNEMPLOYMENT has a unit root
Exogenous: None
Lag Length: 5 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.211530	0.6073
Test critical values:	1% level	-2.591813	
	5% level	-1.944574	
	10% level	-1.614315	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(UNEMPLOYMENT)
Method: Least Squares
Date: 04/26/26 Time: 11:46
Sample (adjusted): 2002Q3 2024Q1
Included observations: 87 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 5 | May 2026 -Peer-Reviewed Journal

UNEMPLOYMENT(-1)	-0.000185	0.000877	-0.211530	0.8330
D(UNEMPLOYMENT(-1))	0.859043	0.105603	8.134672	0.0000
D(UNEMPLOYMENT(-2))	8.89E-05	0.133286	0.000667	0.9995
D(UNEMPLOYMENT(-3))	8.89E-05	0.133286	0.000667	0.9995
D(UNEMPLOYMENT(-4))	-0.431253	0.133476	-3.230953	0.0018
D(UNEMPLOYMENT(-5))	0.302737	0.104499	2.897021	0.0048

R-squared	0.635873	Mean dependent var	-0.001356
Adjusted R-squared	0.613396	S.D. dependent var	0.718250
S.E. of regression	0.446590	Akaike info criterion	1.292118
Sum squared resid	16.15482	Schwarz criterion	1.462181
Log likelihood	-50.20715	Hannan-Quinn criter.	1.360597
Durbin-Watson stat	1.932873		

Appendix 3: Unit root test, unemployment (in First difference)

Null Hypothesis: D(UNEMPLOYMENT) has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.976604	0.0033
Test critical values:	1% level	-2.591813	
	5% level	-1.944574	
	10% level	-1.614315	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(UNEMPLOYMENT,2)
Method: Least Squares
Date: 04/26/26 Time: 11:46
Sample (adjusted): 2002Q3 2024Q1
Included observations: 87 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(UNEMPLOYMENT(-1))	-0.270770	0.090966	-2.976604	0.0038
D(UNEMPLOYMENT(-1),2)	0.129796	0.103346	1.255937	0.2127
D(UNEMPLOYMENT(-2),2)	0.129796	0.103346	1.255937	0.2127
D(UNEMPLOYMENT(-3),2)	0.129796	0.103346	1.255937	0.2127
D(UNEMPLOYMENT(-4),2)	-0.301361	0.103688	-2.906436	0.0047

R-squared	0.267713	Mean dependent var	-0.003905
Adjusted R-squared	0.231992	S.D. dependent var	0.506619
S.E. of regression	0.443981	Akaike info criterion	1.269682
Sum squared resid	16.16374	Schwarz criterion	1.411401
Log likelihood	-50.23117	Hannan-Quinn criter.	1.326748

Durbin-Watson stat	1.932407

Appendix 4: Unit root test, Education (in Level)

Null Hypothesis: EDUCATION has a unit root
Exogenous: None
Lag Length: 9 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.501654	0.9663
Test critical values:	1% level	-2.593121	
	5% level	-1.944762	
	10% level	-1.614204	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EDUCATION)
Method: Least Squares
Date: 04/26/26 Time: 11:47
Sample (adjusted): 2003Q3 2024Q1
Included observations: 83 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EDUCATION(-1)	0.001418	0.000944	1.501654	0.1375
D(EDUCATION(-1))	0.830396	0.099006	8.387367	0.0000
D(EDUCATION(-2))	-0.000950	0.112505	-0.008446	0.9933
D(EDUCATION(-3))	-0.000950	0.112505	-0.008446	0.9933
D(EDUCATION(-4))	-0.826123	0.118534	-6.969476	0.0000
D(EDUCATION(-5))	0.661569	0.133275	4.963942	0.0000
D(EDUCATION(-6))	-0.000481	0.114955	-0.004183	0.9967
D(EDUCATION(-7))	-0.000481	0.114955	-0.004183	0.9967
D(EDUCATION(-8))	-0.780070	0.122731	-6.355938	0.0000
D(EDUCATION(-9))	0.607174	0.111113	5.464486	0.0000

R-squared	0.768199	Mean dependent var	0.256595
Adjusted R-squared	0.739620	S.D. dependent var	0.977343
S.E. of regression	0.498713	Akaike info criterion	1.559009
Sum squared resid	18.15614	Schwarz criterion	1.850436
Log likelihood	-54.69887	Hannan-Quinn criter.	1.676088
Durbin-Watson stat	1.890205		

Appendix 5: Unit root test, Unemployment (in First difference)

Null Hypothesis: D(EDUCATION) has a unit root
Exogenous: None
Lag Length: 8 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.457881	0.0144
Test critical values:	1% level	-2.593121	
	5% level	-1.944762	
	10% level	-1.614204	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EDUCATION,2)
Method: Least Squares
Date: 04/26/26 Time: 11:48
Sample (adjusted): 2003Q3 2024Q1
Included observations: 83 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(EDUCATION(-1))	-0.349243	0.142091	-2.457881	0.0163
D(EDUCATION(-1),2)	0.234123	0.124536	1.879964	0.0640
D(EDUCATION(-2),2)	0.234123	0.124536	1.879964	0.0640
D(EDUCATION(-3),2)	0.234123	0.124536	1.879964	0.0640
D(EDUCATION(-4),2)	-0.599294	0.129048	-4.643959	0.0000
D(EDUCATION(-5),2)	0.118465	0.095091	1.245797	0.2168
D(EDUCATION(-6),2)	0.118465	0.095091	1.245797	0.2168
D(EDUCATION(-7),2)	0.118465	0.095091	1.245797	0.2168
D(EDUCATION(-8),2)	-0.670608	0.103637	-6.470715	0.0000

R-squared	0.600940	Mean dependent var	0.021973
Adjusted R-squared	0.557798	S.D. dependent var	0.756296
S.E. of regression	0.502924	Akaike info criterion	1.565335
Sum squared resid	18.71698	Schwarz criterion	1.827619
Log likelihood	-55.96140	Hannan-Quinn criter.	1.670706
Durbin-Watson stat	1.929587		

Appendix 6 Results of the ARDL model

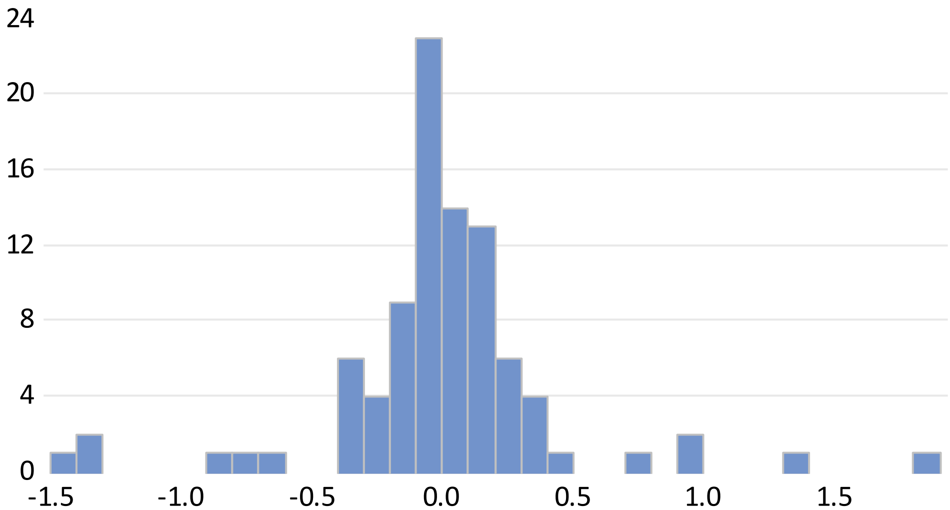
Dependent Variable: D(UNEMPLOYMENT)
Method: ARDL
Date: 04/26/26 Time: 11:54
Sample: 2001Q3 2024Q1
Included observations: 91
Dependent lags: 4 (Automatic)
Automatic-lag linear regressors (4 max. lags): D(EDUCATION)
Deterministics: Restricted constant and no trend (Case 2)
Model selection method: Akaike info criterion (AIC)
Number of models evaluated: 20
Selected model: ARDL(1,1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
D(UNEMPLOYMENT(-1))	0.765089	0.068408	11.18429	0.0000
D(EDUCATION)	0.208554	0.070619	2.953219	0.0040
D(EDUCATION(-1))	-0.135308	0.073416	-1.843032	0.0687
C	-0.023507	0.050292	-0.467409	0.6414

R-squared	0.622332	Mean dependent var	0.034255
Adjusted R-squared	0.609309	S.D. dependent var	0.723881
S.E. of regression	0.452464	Akaike info criterion	1.294742
Sum squared resid	17.81094	Schwarz criterion	1.405110
Log likelihood	-54.91078	Hannan-Quinn criter.	1.339269
F-statistic	47.78712	Durbin-Watson stat	1.807585
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent test results do not account for model selection.

Appendix 7: Normality of Residuals



Series: Residuals	
Sample 2001Q3 2024Q1	
Observations 91	
Mean	-4.27e-18
Median	-0.007070
Maximum	1.860203
Minimum	-1.494091
Std. Dev.	0.444859
Skewness	0.236438
Kurtosis	8.618996
Jarque-Bera	120.5626
Probability	0.000000

Appendix 8: Heteroskedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	1.217171	Prob. F(3,87)	0.3084
Obs*R-squared	3.665551	Prob. Chi-Square(3)	0.2999
Scaled explained SS	12.76329	Prob. Chi-Square(3)	0.0052

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 04/26/26 Time: 11:58
Sample (adjusted): 2001Q3 2024Q1
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.207152	0.060165	3.443083	0.0009
D(UNEMPLOYMENT(-1))	-0.086437	0.081837	-1.056213	0.2938
D(EDUCATION)	-0.140413	0.084483	-1.662039	0.1001
D(EDUCATION(-1))	0.118068	0.087828	1.344300	0.1823

R-squared	0.040281	Mean dependent var	0.195725
Adjusted R-squared	0.007187	S.D. dependent var	0.543242
S.E. of regression	0.541287	Akaike info criterion	1.653226
Sum squared resid	25.49025	Schwarz criterion	1.763593
Log likelihood	-71.22178	Hannan-Quinn criter.	1.697752
F-statistic	1.217171	Durbin-Watson stat	2.159121
Prob(F-statistic)	0.308354		

Appendix 9: Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	1.451946	Prob. F(2,85)	0.2399
Obs*R-squared	3.006172	Prob. Chi-Square(2)	0.2224

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 04/26/26 Time: 12:00
Sample (adjusted): 2001Q3 2024Q1
Included observations: 91 after adjustments
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(UNEMPLOYMENT(-1))	-0.155181	0.113956	-1.361766	0.1769

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 5 | May 2026 -Peer-Reviewed Journal

D(EDUCATION)	-0.009656	0.070485	-0.136996	0.8914
D(EDUCATION(-1))	0.040556	0.076844	0.527776	0.5990
C	-0.003221	0.050069	-0.064339	0.9489
RESID(-1)	0.233791	0.150323	1.555259	0.1236
RESID(-2)	0.173121	0.138505	1.249928	0.2148

R-squared	0.033035	Mean dependent var	-4.27E-18
Adjusted R-squared	-0.023845	S.D. dependent var	0.444859
S.E. of regression	0.450131	Akaike info criterion	1.305106
Sum squared resid	17.22256	Schwarz criterion	1.470657
Log likelihood	-53.38231	Hannan-Quinn criter.	1.371895
F-statistic	0.580778	Durbin-Watson stat	2.041235
Prob(F-statistic)	0.714583		