THE PARADOX OF UNEMPLOYMENT BENEFITS IN SOUTH AFRICA: AN EMPIRICAL INVESTIGATION OF PERSISTENT HIGH UNEMPLOYMENT RATES AMIDST GOVERNMENT POLICY

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ABSTRACT
The paradox of unemployment benefits refers to the unintended consequence where government-provided financial assistance for the unemployed may contribute to persistent high unemployment rates by reducing incentives to seek employment. This study investigates this phenomenon in South Africa by analyzing historical unemployment trends from 1991 to 2022 using an autoregressive integrated moving average (ARIMA) modeling approach. Utilizing time-series data from the World Bank, unemployment (% of the total labour force) (modeled ILO estimate), serves as the dependent variable, while autoregressive (AR) and moving average (MA) components function as independent variables. Parameter estimation, conducted via conditional least squares (CLS), reveals that the MA(5) coefficient (0.857637) is positive and statistically significant, indicating that approximately 86% of unemployment variations can be attributed to past errors or economic shocks. The estimated ARIMA(1,1,5) model is found to be covariance stationary and invertible, confirming its robustness for forecasting unemployment trends. Projections indicate a persistent rise in unemployment, with rates expected to increase from 29.7% in 2024 to approximately 38.8% by 2043. These findings highlight the need for a policy re-evaluation to balance social welfare support with effective labour market incentives. We recommend reforms in unemployment benefits, enhancing labour market policies, and implementation of skills development programs.

KEY WORDS: *ARIMA Modeling, Unemployment Benefits, South Africa*

INTRODUCTION
Unemployment remains one of the most pressing socio-economic challenges in South Africa, despite extensive government intervention through social welfare and labour market policies. Since the end of apartheid, South Africa has experienced persistently high unemployment rates, averaging approximately 22% of the total labour force, over the past three decades (World Bank, 2023). This persistent trend underscores a paradox: while government policies, including unemployment benefits and job creation initiatives, aim to reduce unemployment, the problem has remained largely unchanged or even worsened over time. The paradox of unemployment benefits suggests that financial support for the unemployed, while providing essential social protection, may inadvertently discourage active job searching and labour market participation (Nickell, 1997).

The South African government has implemented various policy measures to address unemployment, including social grants, skills development programs, and labour market reforms (Kingdon & Knight, 2007). However, despite these efforts, unemployment remains structurally embedded in the economy, raising critical questions about the effectiveness of existing policies. The complex relationship between unemployment benefits and labour market dynamics necessitates a deeper empirical investigation to understand whether unemployment benefits may be contributing to the persistence of high unemployment rates.

This study seeks to examine the paradox of unemployment benefits in South Africa by analyzing historical trends and forecasting future unemployment rates using an autoregressive integrated moving average (ARIMA) model. ARIMA modeling is widely recognized for its effectiveness in analyzing time-series data and making reliable forecasts (Box & Jenkins, 1976; Nahabwe & Kagarura, 2025). By estimating the contribution of past unemployment shocks and errors to current unemployment variations, the study aims to uncover underlying structural issues that sustain high unemployment levels. Understanding these dynamics will provide valuable insights into the long-term impact of unemployment benefits and inform policy adjustments to enhance labour market efficiency and economic growth.

The rationale for this study lies in the urgent need to address South Africa's persistently high unemployment rates and improve the design of unemployment benefit policies. While unemployment benefits serve as a vital social safety net, they may also create disincentives for job-seeking, thereby reinforcing unemployment persistence. The findings from this study will contribute to the growing body of literature on labour market dynamics and policy effectiveness in developing economies, offering evidence-based recommendations for improving unemployment benefits and labour market policies in South Africa.

LITERATURE REVIEW

Unemployment benefits have been widely studied in the context of developed and developing economies, with mixed findings on their impact on labour market performance. In advanced economies, unemployment benefits are often credited with reducing poverty and providing social protection during economic downturns (Lindbeck, 1995). However, they are also criticized for potentially discouraging active job-seeking and increasing the duration of unemployment. Nickell (1997) argued that generous unemployment benefits in European countries contributed to higher unemployment rates by weakening the incentive to find work, compared to the more flexible labour markets of the United States. Similarly, Krueger & Mueller (2010) found that higher unemployment benefits in the United States were associated with longer unemployment durations, although they also provided essential support during economic recessions.

Developing economies, on the other hand, face unique challenges regarding unemployment benefits and labour market outcomes. In Latin America, Ulku & Georgieva, (2022) highlighted that unemployment benefits can improve social welfare but may also increase informal sector participation if formal labour market opportunities are limited. In East Asia, countries with minimal unemployment benefits have generally maintained low unemployment rates through active labour market policies and high levels of labour market flexibility (Wong, 2023). These findings suggest that the effectiveness of unemployment benefits depends largely on the broader labour market structure and the design of social safety nets.

Unemployment remains a persistent challenge in Sub-Saharan Africa, where labour market structures are characterized by high levels of informality and underemployment. According to Filmer & Fox (2014), most African economies rely heavily on informal employment, which limits the effectiveness of traditional unemployment benefits. In Nigeria, for example, Omoju, et al. (2023) found that while social welfare programs have provided temporary relief, they have not significantly reduced structural unemployment due to weak labour market linkages and inadequate policy implementation.

South Africa presents a unique case within the African context due to its relatively advanced social welfare system. The introduction of the Unemployment Insurance Fund (UIF) aimed to provide income security to unemployed individuals; however, its impact on reducing unemployment has been limited. Leibbrandt et al. (2012) argued that South Africa's labour market is characterized by high barriers to entry, including skills mismatches and labour market rigidities, which reduce the effectiveness of unemployment benefits. Furthermore, Bhorat et al., (2014) highlighted that unemployment benefits in South Africa may create a disincentive for active job-seeking, particularly among youth and low-skilled workers.

In South Africa, unemployment rates have remained persistently high despite comprehensive government interventions. Kingdon & Knight (2007) argued that the structure of South Africa's labour market, including strong union influence, high reservation wages, and labour market dualism, contributes to the persistence of high unemployment. The expansion of unemployment benefits through the UIF has provided social protection but may have also discouraged job-seeking behavior among recipients (Bhorat et al., 2014).

Empirical studies have demonstrated that South Africa's unemployment problem is both cyclical and structural. Fourie, (2011) found that unemployment rates are highly sensitive to macroeconomic shocks, but structural factors such as labour market rigidities and skills shortages exacerbate the problem. Furthermore, Seekings & Nattrass, (2015) noted that South Africa's social protection system, while providing essential support, may have created a dependency culture that reinforces long-term unemployment.

This study is grounded in two key theoretical frameworks: Search and Matching Theory, developed by Mortensen & Pissarides, (1998), this theory posits that unemployment results from frictions in the labour market, where job seekers and employers face difficulties in finding suitable matches. Unemployment benefits can increase search time by reducing the urgency to accept job offers, thereby influencing labour market outcomes.

Efficiency Wage Theory by Altonji, (1986) proposed that employers may pay higher wages to increase worker productivity and reduce turnover. However, high reservation wages resulting from unemployment benefits can lead to labour market disequilibrium, as workers may refuse job offers below their reservation wage, contributing to persistent unemployment.

The conceptual framework for this study positions Unemployment, total (% of total labour force) (modeled ILO estimate) as the dependent variable, structured with autoregressive (AR) and moving average (MA) components as independent variables. Several empirical studies have employed ARIMA modeling to analyze unemployment trends. For example, Nahabwe & Kagarura (2025) demonstrate the utility of ARIMA model in forecasting unemployment patterns in Uganda by capturing cyclical patterns and shocks.

DATA AND METHODS

This study adopts a quantitative research design to empirically investigate the relationship between unemployment benefits and persistent high unemployment rates in South Africa. A time series design is employed, as it allows for the analysis of unemployment trends over time and the identification of patterns and shocks in the labour market (Gujarati & Porter, 2009; Nahabwe & Kagarura, 2025). Time series analysis is suitable for assessing the impact of policy interventions on unemployment rates and evaluating the effectiveness of unemployment benefits within a historical context (Enders, 2014). The study will utilize the Auto-Regressive Integrated Moving Average (ARIMA) model, which is widely applied in economic research to capture the dynamic nature of economic variables and forecast future trends (Box et al., 2015: Nahabwe & Kagarura, 2025).

The sample consists of annual time series data on South Africa's unemployment rate, measured as Unemployment, total (% of the total labour force) (modeled ILO estimate), collected from the World Bank's World Development Indicators (WDI) database for the period 1991 to 2023. This period provides a sufficiently long time frame to account for both short-term fluctuations and long-term structural changes in the labour market. The use of the World Bank database ensures data consistency and reliability, as it is one of the most comprehensive and widely used sources for macroeconomic data (World Bank, 2023).

A purposive sampling technique is employed, as the study focuses on South Africa's labour market specifically. This non-probability sampling method is justified since the research objective is to analyze the impact of unemployment benefits on labour market outcomes within a particular national context (Creswell, 2014). The period from 1991 to 2023 is strategically chosen to capture the post-apartheid transition, major economic reforms, and labour market policies that have influenced unemployment trends in South Africa.

The study uses ARIMA model to estimate the relationship between unemployment benefits and unemployment rates. The ARIMA model combines three key components:

Autoregressive (AR) component captures the dependency of the current unemployment rate on its past values. Integrated (I) component accounts for the trend or stationarity of the time series data by differencing. Moving Average (MA) component captures the dependency of the current unemployment rate on past forecast errors. ARIMA (p, d, q) model specification is as follows:

$$Y_t = c + \sum_{i=1}^{p} \boldsymbol{\phi}_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad \ldots\ldots (1)$$

Where;
Y_t is Unemployment rate at time t

c is constant term
ε_t is white noise at time t
$\boldsymbol{\phi}_i$ are the coefficients of the autoregressive terms
θ_j are the coefficients of the moving average terms
p = Number of lagged AR terms
d = Number of differences required to make the series stationary
q = Number of lagged MA terms (Box & Jenkins 1976; Nahabwe & Maniple, 2025)

The model parameters are estimated using the ARIMA conditional least squares (CLS) method, employing Gauss-Newton/Marquardt steps for optimization. The CLS method minimizes the sum of squared residuals and provides efficient parameter estimates, particularly in the presence of autocorrelation and heteroskedasticity (Hamilton, 1994). The Gauss-Newton/Marquardt algorithm is suitable for non-linear optimization problems, ensuring convergence to a local minimum and improving estimation accuracy (Marquardt, 1963).

The CLS estimator for the regression coefficients is given by the following formula:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}\left[\sum_{t=1}^{n}(y_t - \hat{y}_t(\theta))^2\right] \quad \ldots\ldots (2)$$

Where:
$\hat{\theta}$ represents the estimated parameter vector (which includes both AR and MA parameters in ARIMA).
y_t represents the actual observed value of the dependent variable at time t
$\hat{y}_t(\theta)$ represents the model's predicted value at time t based on the parameter estimates θ
n is the number of observations. (Greene, 2018; Nahabwe & Kagarura, 2025).

To ensure the validity of the ARIMA model, the time series data is tested for stationarity using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979). If the series is found to be non-stationary, it is differenced until stationarity is achieved. Model fit and adequacy is assessed using the following diagnostic tests: Ljung-Box Q test, tests for the absence of autocorrelation in residuals. Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBC) are used for model selection based on goodness-of-fit and parsimony. Residual analysis ensures that residuals are normally distributed and homoscedastic.

ARIMA model is chosen for its capacity to model time-dependent processes and account for lagged effects, which are essential in understanding the dynamics of unemployment benefits and unemployment rates (Box et al., 2015). The use of ARMA conditional least squares with Gauss-Newton/Marquardt steps is justified by its ability to handle non-linear relationships and produce efficient and consistent parameter estimates (Hamilton, 1994). The World Bank database is selected due to its comprehensive coverage, reliability, and comparability across countries and time periods (World Bank, 2023).

RESULTS

This section presents the results of the study, guided by the research objectives. The analysis is based on time series data on South Africa's unemployment rate, measured as Unemployment, total (% of total labour force) (modeled ILO estimate), covering the period 1991 to 2023. The results include descriptive statistics (Appendix 1), diagnostic tests and inferential statistics, essential for assessing the behavior and dynamics of unemployment in South Africa.

The mean unemployment rate over the period 1991-2023 is 21.77%, indicating that, on average, nearly a quarter of South Africa's labour force has remained unemployed over the study period. The median unemployment rate of 20.295% suggests that the distribution of unemployment rates is slightly skewed towards higher values. The proximity of the mean and median values reflects a relatively balanced distribution but with evidence of higher unemployment rates in certain periods (Gujarati & Porter, 2009; Nahabwe & Kagarura, 2025).

The maximum recorded unemployment rate is 28.838% (2022), indicating that South Africa experienced severe unemployment pressures during this period, potentially due to economic shocks or policy failures. The minimum unemployment rate of 19.39% (2007) reflects the best period of labour market performance within the study period,

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highlighting the structural nature of unemployment and the limitations of existing government interventions (Enders, 2014; Nahabwe & Kagarura, 2025).

The standard deviation of 2.8071 suggests moderate variation in unemployment rates over time. This implies that while unemployment rates have fluctuated, the extent of variation has not been extreme, indicating a consistent trend of high unemployment despite government interventions (Hamilton, 1994; Nahabwe & Kagarura, 2025).

The skewness value of 1.2937 indicates a positive skew, meaning that the unemployment rate distribution has a longer tail on the right side. This suggests that there have been periods of exceptionally high unemployment, which have influenced the overall distribution (Gujarati & Porter, 2009; Nahabwe & Kagarura, 2025). A positively skewed distribution reflects periods of labour market distress where unemployment rates spiked above the historical norm.

The kurtosis value of 3.6600 exceeds the normal distribution value of 3, indicating a leptokurtic distribution. This suggests that the unemployment rate series exhibits fatter tails and a sharper peak, implying that extreme values (both high and low unemployment rates) occur more frequently than expected under a normal distribution (Enders, 2014; Nahabwe & Kagarura, 2025).
The Jarque-Bera test value of 9.8049 with a corresponding p-value of 0.0074 is statistically significant at the 1% level. This indicates that the unemployment rate series is not normally distributed. The non-normality may reflect structural distortions in the labour market, including policy failures, economic shocks, and cyclical unemployment patterns (Hamilton, 1994; Nahabwe & Kagarura, 2025).

The total sum of the unemployment rates over the period is 718.289. The sum of squared deviations of 252.1493 reflects the degree of fluctuation in unemployment rates, reinforcing the finding that unemployment has exhibited moderate but consistent variability over time (Gujarati & Porter, 2009; Nahabwe & Kagarura, 2025).
The sample includes 33 observations, covering a comprehensive period from 1991 to 2023. This period encompasses key policy changes, economic reforms, and global economic shocks, providing a rich dataset for analyzing the relationship between unemployment benefits and labour market performance (World Bank, 2023).

Stationarity tests (Appendix 2 and Appendix 3) were conducted using the Augmented Dickey-Fuller (ADF) test to assess the stationarity of the series. The results show that the original series was non-stationary at the level form ($p > 0.05$). However, after first differencing, the series became stationary ($p < 0.05$), supporting the adoption of an ARIMA ($d = 1$) model (Nahabwe & Kagarura, 2025).

The ARIMA(1,1,5) model was selected as the most suitable based on the Akaike Information Criterion (AIC = 2.822590) and Schwarz Criterion (SC = 2.961363). The parameter estimates are as follows: AR(1) = -0.281691 (p = 0.1411), MA(5) = 0.857637 (p = 0.0000), and the constant term C= 0.427592 (p = 0.0925). This indicates that the coefficients of AR(1) and the constant term are not statistically significant, while the coefficient of MA(5) is statistically significant. Diagnostic tests confirm the model's reliability, as the residuals exhibit white noise properties, validated by the Ljung-Box Q test ($p > 0.05$). Additionally, the autocorrelation function (ACF) plots reveal no significant patterns, reinforcing the model's robustness (Nahabwe & Kagarura, 2025).

Inferential statistics are summarized as follows:
Results of the ARIMA(1,1,5) model (Appendix 4)

$$\widehat{Unemployment_t} = 0.427592 - 0.281691AR(1) + 0.857637MA(5) \quad \ldots \quad (3)$$

Hence,

$$\hat{\theta}_{CLS} = \begin{bmatrix} 0.427592 \\ -0.281691 \\ 0.857637 \end{bmatrix}$$

The constant term (C = 0.427592) is positive but statistically insignificant (p = 0.0925), suggesting that while there is a positive intercept in the model, it does not have a meaningful impact on explaining variations in unemployment rates (Gujarati & Porter, 2009). This implies that other factors captured by the autoregressive and moving average components are more influential in explaining unemployment dynamics.

The AR(1) coefficient of -0.281691 is negative and statistically insignificant (p = 0.1411), indicating that past unemployment rates have a weak and statistically negligible influence on current unemployment levels. This suggests that the unemployment rate in South Africa does not exhibit strong persistence over time, implying that past unemployment rates are not reliable predictors of future unemployment within this model structure (Enders, 2014; Nahabwe & Kagarura, 2025).

The MA(5) coefficient of 0.857637 is positive and statistically significant (p = 0.0000), meaning that approximately 85.8% of the variations in unemployment can be attributed to past shocks or errors over the last five periods. This finding reflects that unemployment in South Africa is highly influenced by historical disturbances, suggesting that past economic shocks have a long-lasting effect on current unemployment levels (Box et al., 2015; Nahabwe & Kagarura, 2025).

The Adjusted R-squared value of 0.233313 indicates that approximately 23.33% of the variations in unemployment are explained by the ARIMA(1,1,5) model. This relatively low value suggests that while the model captures some of the underlying dynamics of unemployment, other external macroeconomic and structural factors may also be influencing unemployment rates (Wooldridge, 2013; Nahabwe & Kagarura, 2025).

The Durbin-Watson statistic of 2.037349 falls close to the ideal value of 2, indicating that there is no significant autocorrelation in the residuals. This confirms that the model does not suffer from serial correlation, reinforcing the validity of the parameter estimates and model structure (Gujarati & Porter, 2009; Nahabwe & Kagarura, 2025).

The histogram exhibits a kurtosis value of 3.85 and a Jarque-Bera test statistic of 2.566 (p = 0.2772), suggesting that the residuals are approximately normally distributed. Although the kurtosis is slightly above the normal value of 3, the p-value indicates that the deviation from normality is not statistically significant, supporting the adequacy of the model for forecasting (Enders, 2014; Nahabwe & Kagarura, 2025).

The Ljung-Box Q statistic test with a p-value of 0.186 means that we fail to reject the null hypothesis of no autocorrelation in the residuals. This implies that the model captures the underlying data structure well and that there is no remaining pattern or dependency in the residuals (Box et al., 2015; Nahabwe & Maniple, 2025).

The ARIMA(1,1,5) structure (Appendix 5) shows that the AR and MA roots lie within the unit circle, confirming that the model is both covariance stationary and invertible. This implies that the model is stable and suitable for long-term forecasting, as it meets the stationarity and invertibility conditions necessary for reliable predictions (Box et al., 2015; Nahabwe & Maniple, 2025).

Forecasts based on the model suggest a continued increase in unemployment, rising from 29.7% in 2024 to approximately 38.8% by 2043. This implies that unemployment in South Africa is expected to follow a worsening trend despite existing government interventions, indicating structural weaknesses in the labour market and potential inefficiencies in unemployment benefit policies (Banerjee et al., 1993).

DISCUSSION

The findings of this study reveal that unemployment in South Africa remains persistently high despite the existence of unemployment benefits and government interventions. The ARIMA(1,1,5) model results show that past shocks significantly influence current unemployment trends, as reflected by the statistically significant MA(5) coefficient (0.857637, p = 0.0000). These results align with earlier research by Kingdon & Knight (2007), who argued that South Africa’s labour market rigidities and structural weaknesses contribute to prolonged unemployment. Similarly, Fourie, (2011) highlighted that South Africa’s dual labour market structure creates barriers for labour absorption, even with unemployment support mechanisms in place.

However, the finding that the AR(1) coefficient (-0.281691, p = 0.1411) is statistically insignificant contradicts the work of Banerjee et al. (2008), who found that past unemployment rates had a strong and positive impact on future unemployment trends in South Africa. The weak influence of past unemployment rates in this study suggests that other macroeconomic factors, such as global economic conditions, labour market mismatches, and policy inefficiencies, may exert a stronger influence on unemployment dynamics.

The adjusted R-squared value of 0.233313 indicates that the model explains approximately 23.33% of the variation in unemployment (Nahabwe & Kagarura, 2025; Nahabwe, et al., 2025), which is relatively low compared to studies by Bhorat, (2007), who found that labour market factors and education levels explained up to 40% of the variation in South African unemployment. This suggests that factors beyond the labour market, such as political instability, inadequate social infrastructure, and external economic shocks, could be contributing to the unemployment paradox (Leibbrandt et al., 2012).

The diagnostic tests reinforce the robustness of the model. The Durbin-Watson statistic (2.037349) confirms the absence of serial correlation, while the Ljung-Box Q test ($p = 0.186$) indicates that the model residuals are white noise, affirming the validity of the ARIMA(1,1,5) model for forecasting purposes. These findings are consistent with the work of (Box & Jenkins, 2015; Nahabwe & Kagarura, 2025) who emphasized that proper model specification and residual independence are critical for reliable time-series forecasting.

A key finding of this study is that while government-provided unemployment benefits aim to reduce financial vulnerability, they appear to have limited success in reducing overall unemployment levels. The forecasted increase in unemployment from 29.7% in 2024 to approximately 38.8% by 2043 suggests that the unemployment benefits system may be insufficient to address the structural causes of unemployment in South Africa. This aligns with the "unemployment trap" hypothesis, where generous unemployment benefits may reduce incentives for active job searching and labour market participation (Layard et al., 2005).

Another unique finding is the high statistical significance of the MA(5) coefficient, suggesting that unemployment shocks have long-lasting effects in South Africa. This reflects the structural challenges in the labour market, where historical disturbances such as economic recessions, labour strikes, and political instability continue to shape unemployment trends over extended periods (Kingdon & Knight, 2007).

Furthermore, the positive but statistically insignificant constant term (0.427592, $p = 0.0925$) indicates that unemployment benefits alone are unlikely to reduce unemployment without complementary structural reforms. This finding highlights the need for broader policy interventions, such as skills development programs, labour market flexibility, and increased private sector involvement to create sustainable employment opportunities (Fourie, 2011).

The results also underscore the importance of improving labour market efficiency and reducing barriers to employment. For example, Banerjee et al. (2008) emphasized that improving education and vocational training could increase labour market participation and reduce structural unemployment. However, this study's findings suggest that without addressing underlying labour market rigidities and improving the efficiency of unemployment benefits, these measures may have limited impact.

The study's findings suggest that South Africa's unemployment benefits system, while providing temporary relief, may not effectively address the structural causes of unemployment. Policymakers should consider a more targeted approach that combines unemployment benefits with active labour market policies (ALMPs), such as job training, employment subsidies, and enhanced job placement services (Bhorat, 2007). Additionally, improving labour market flexibility, reducing regulatory burdens on businesses, and encouraging private sector job creation could help reduce unemployment more effectively.

LIMITATIONS

While this study provides valuable insights into the persistent high unemployment rates in South Africa despite the existence of government unemployment benefits, several limitations must be acknowledged. These limitations relate to the research design, data sources, and analytical methods, which may have influenced the robustness and generalizability of the findings.

One of the key limitations of the study is its reliance on a time-series design, which captures trends and patterns over time but may not fully account for structural and institutional factors influencing unemployment. Time-series models, including the ARIMA model used in this study, are primarily suited for short- to medium-term forecasting but may overlook the underlying socio-economic and political drivers of unemployment (Box et al., 2015; Nahabwe &

Kagarura, 2025). The study's design also limits the ability to establish causal relationships, as the ARIMA model focuses on correlation and pattern recognition rather than causation (Enders, 2014; Nahabwe & Kagarura, 2025).

Moreover, the study does not incorporate qualitative data, which could have provided deeper insights into the behavioral and institutional factors influencing unemployment benefits and labour market dynamics. As pointed out by Fourie, (2011), a mixed-method approach that combines quantitative analysis with qualitative insights can offer a more comprehensive understanding of unemployment patterns.

The study relies on secondary data sourced from government reports and international databases such as the World Bank and the South African Reserve Bank. While these sources are reputable, they may suffer from measurement errors, reporting biases, and inconsistencies (Banerjee et al., 2008). For instance, unemployment data in South Africa is known to be influenced by high levels of informal employment and underreporting, which may affect the accuracy of the model's estimates (Kingdon & Knight, 2007).

Furthermore, the study's dataset spans from 1995 to 2023, which, while extensive, may not capture recent labour market changes, such as the impact of the COVID-19 pandemic and subsequent economic recovery measures. As noted by Leibbrandt et al. (2012), labour market dynamics in South Africa are highly sensitive to external shocks, which could introduce volatility into the dataset and affect the model's predictive power.

The use of the ARIMA(1,1,5) model imposes certain statistical constraints. ARIMA models assume stationarity after differencing, which may oversimplify the complex and dynamic nature of unemployment in South Africa (Box et al., 2015; Nahabwe & Kagarura, 2025). While the Augmented Dickey-Fuller (ADF) test confirmed stationarity after first differencing, structural breaks and seasonal variations in the data could still affect model accuracy (Enders, 2014).

Additionally, the relatively low adjusted R-squared value (0.233313) indicates that the model explains only 23.33% of the variation in unemployment rates. This suggests that other significant macroeconomic and structural factors such as educational attainment, labour market mismatches, and economic policy changes are not fully captured by the model (Fourie, 2011; Nahabwe & Kagarura, 2025).

The study also assumes linear relationships between unemployment benefits and unemployment rates, which may not accurately reflect the non-linear and complex nature of labour market interactions. Non-linear models, such as vector autoregressive (VAR) or threshold models, may have provided deeper insights into the dynamic responses of unemployment to policy changes (Banerjee et al., 2008).

The study's focus on South Africa's labour market context limits the generalizability of the findings to other developing economies. South Africa's high unemployment rates are influenced by historical legacies of apartheid, labour market dualism, and social inequality, which may not be present in other developing countries (Kingdon & Knight, 2007). Therefore, the applicability of the findings to other African or emerging markets should be approached with caution.

Moreover, the study does not account for regional differences within South Africa, where labour market conditions vary significantly between urban and rural areas. Fourie, (2011) emphasize that urban unemployment tends to be driven by different factors than rural unemployment, including differences in industrial composition, educational attainment, and infrastructure development.

Although diagnostic tests confirmed that the model residuals are white noise and the AR and MA roots lie within the unit circle (indicating stability), the possibility of model misspecification remains. The exclusion of key macroeconomic variables such as foreign direct investment (FDI), capital formation, and trade openness could have introduced omitted variable bias, which may affect the accuracy of the model's forecasts (Enders, 2014; Nahabwe, et al. 2025).

Finally, while the study suggests that increasing unemployment benefits alone is unlikely to reduce unemployment, the political and economic feasibility of implementing alternative labour market reforms remains uncertain. As highlighted by Layard et al. (2005), reforms aimed at increasing labour market flexibility and improving education and training systems require long-term political commitment and substantial financial resources, which may face resistance from labour unions and political stakeholders.

Future research could consider adopting a mixed-method approach that combines time-series analysis with qualitative insights to capture the institutional and behavioral factors influencing unemployment. Expanding the dataset to include more recent observations and incorporating structural break tests could improve model accuracy and forecasting reliability. Moreover, exploring non-linear models and including additional macroeconomic indicators such as FDI, trade openness, and capital formation may provide a more comprehensive understanding of unemployment dynamics in South Africa.

CONCLUSION

This study has provided an in-depth empirical investigation into the paradox of persistently high unemployment rates in South Africa despite the existence of government unemployment benefits. The analysis has highlighted the complex and multifaceted nature of South Africa's labour market, where structural, economic, and policy-related factors interact to sustain high unemployment levels. The findings underscore the limitations of unemployment benefits as a standalone policy tool for addressing unemployment, suggesting that while such benefits provide temporary relief for unemployed individuals, they do not address the underlying causes of labour market rigidity and structural unemployment.

The study confirms that South Africa's unemployment challenge is deeply rooted in historical legacies, labour market dualism, and skills mismatches, consistent with previous research by Kingdon & Knight (2007) and Banerjee et al. (2008). The persistence of high unemployment rates, despite government interventions, reflects the limited capacity of unemployment benefits to stimulate job creation or improve labour market efficiency. Instead, the study suggests that sustained reductions in unemployment will require comprehensive policy reforms aimed at improving education and training, enhancing labour market flexibility, and stimulating economic growth (Fourie, 2011).

Moreover, the findings highlight the importance of macroeconomic stability and structural transformation in reducing unemployment. Economic policies that promote investment, enhance labour productivity, and foster job creation in both the formal and informal sectors are critical. As Leibbrandt et al. (2012) argue, addressing the structural barriers to employment such as inadequate infrastructure, limited access to capital, and rigid labour regulations will be essential for creating a more inclusive and dynamic labour market.

The study also points to the need for targeted interventions that address youth unemployment and rural-urban disparities. Given South Africa's high levels of income inequality and social fragmentation, broad-based employment programs that combine skill development with active labour market policies may offer more sustainable solutions. Layard et al. (2005) emphasize that improving the quality of education and enhancing access to vocational training can play a crucial role in equipping the labour force with the skills needed for a modern, competitive economy.

In conclusion, while unemployment benefits remain an essential component of South Africa's social safety net, they are insufficient on their own to reduce unemployment rates significantly. A more holistic approach that combines social protection with labour market reforms, targeted skill development, and macroeconomic stability will be necessary to address the underlying drivers of unemployment. Future research should focus on examining the interaction between social protection policies and labour market dynamics to provide deeper insights into the pathways for sustainable employment growth.

RECOMMENDATIONS

Based on the findings of this study, the following recommendations are proposed to address the persistent high unemployment rates in South Africa, despite the existence of unemployment benefits. These recommendations span policy, programmatic, and research areas, offering a comprehensive approach to mitigating unemployment.

The study has highlighted that structural factors, including rigid labour market policies, contribute significantly to high unemployment rates. Policymakers should consider labour market reforms that promote flexibility in hiring and firing, streamline regulations around labour contracts, and enhance the ease of doing business. Adopting a more dynamic approach to labour market regulation will allow for a quicker response to economic changes, thereby facilitating higher job creation and reducing unemployment rates (Kingdon & Knight, 2007).

Youth unemployment remains a critical issue in South Africa. As evidenced by the findings, targeted policies to address youth unemployment through training, mentorship programs, and employment subsidies are essential. Policies should prioritize increasing access to education and vocational training, aligning curricula with industry needs, and facilitating internships and apprenticeships to ease the transition from education to employment (Fourie, 2011).

The study suggests that high unemployment rates persist despite government policies, largely because of slow economic growth. To reduce unemployment sustainably, government efforts must focus on promoting inclusive growth through investments in infrastructure, innovation, and sectors that have high employment elasticity, such as manufacturing and services. Fostering a conducive environment for small and medium enterprises (SMEs) to thrive, particularly in underdeveloped regions, can lead to significant job creation (Leibbrandt et al., 2012).

While the findings indicate that unemployment benefits alone are insufficient, their improvement can complement other measures. The government should enhance the accessibility of unemployment benefits by simplifying application processes, extending the duration of benefits where feasible, and providing job-seeking support to recipients. Moreover, it is crucial that the benefits are aligned with labour market conditions, ensuring that they are more effective in stimulating job search and mobility (Layard et al., 2005).

Skills mismatches remain one of the key barriers to reducing unemployment in South Africa. Programs that focus on vocational training, particularly in sectors experiencing growth such as technology and renewable energy, should be scaled up. Additionally, partnerships between the government, private sector, and educational institutions could ensure that the skills developed are in line with labour market demands. Supporting the retraining of workers displaced by technological advancements or economic changes will also be essential in reducing structural unemployment (Banerjee et al., 2008).

The private sector has a crucial role to play in reducing unemployment. The government should create an enabling environment for businesses to grow by offering tax incentives, facilitating access to credit, and reducing barriers to entry. Public-private partnerships (PPPs) can be an effective way of enhancing job creation, particularly in infrastructure projects, which have high labour absorption rates (Fourie, 2011).

Future research should focus on conducting longitudinal studies to assess the long-term impact of unemployment benefits and labour market policies on employment outcomes. Such research can provide deeper insights into the effectiveness of government interventions over extended periods and help refine policies accordingly. In particular, studies that track the success of skills development programs and job placement initiatives would be valuable in understanding which approaches have the most significant impact on reducing unemployment (Leibbrandt et al., 2012).

Given South Africa's vast socio-economic disparities, future studies should investigate the regional variation in unemployment rates, focusing on rural versus urban employment dynamics. Research on the effectiveness of targeted interventions in specific regions, particularly in economically marginalized areas, could help tailor policies to local conditions and improve their effectiveness in tackling unemployment (Kingdon & Knight, 2007).

Lastly, research should explore the impact of global economic trends, including trade, technological advancements, and foreign direct investment, on unemployment in South Africa. Understanding the interplay between global forces and national labour markets will allow policymakers to better anticipate shifts in employment patterns and prepare for external shocks that may exacerbate unemployment (Banerjee et al., 2008).

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APPENDICES

Appendix 1: Descriptive statistics

	Unemployment, total (% of total labour force) (modeled ILO estimate)
Mean	21.76633
Median	20.295
Maximum	28.838
Minimum	19.39
Std. Dev.	2.807074
Skewness	1.293752
Kurtosis	3.660024
Jarque-Bera	9.804857
Probability	0.007429
Sum	718.289
Sum Sq. Dev.	252.1493
Observations	33

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

Null Hypothesis: UNEMPLOYMENT has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		2.108249	0.9998
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(UNEMPLOYMENT)
Method: Least Squares
Date: 01/24/25 Time: 16:32
Sample (adjusted): 4 33
Included observations: 30 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
UNEMPLOYMENT(-1)	0.240041	0.113858	2.108249	0.0448
D(UNEMPLOYMENT(-1))	-0.760172	0.271264	-2.802329	0.0095
D(UNEMPLOYMENT(-2))	-0.489074	0.255164	-1.916707	0.0663
C	-4.587205	2.367685	-1.937422	0.0636

R-squared	0.232169	Mean dependent var	0.256433
Adjusted R-squared	0.143573	S.D. dependent var	1.099393
S.E. of regression	1.017415	Akaike info criterion	2.995973
Sum squared resid	26.91346	Schwarz criterion	3.182799
Log likelihood	-40.93959	Hannan-Quinn criter.	3.055740
F-statistic	2.620534	Durbin-Watson stat	1.992241
Prob(F-statistic)	0.072028		

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

Null Hypothesis: D(UNEMPLOYMENT) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.221501	0.0000
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(UNEMPLOYMENT,2)
Method: Least Squares
Date: 01/24/25 Time: 16:33
Sample (adjusted): 3 33
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(UNEMPLOYMENT(-1))	-1.303308	0.180476	-7.221501	0.0000
C	0.331219	0.195502	1.694201	0.1009

R-squared	0.642637	Mean dependent var	-0.035935
Adjusted R-squared	0.630315	S.D. dependent var	1.728658
S.E. of regression	1.051054	Akaike info criterion	2.999806
Sum squared resid	32.03674	Schwarz criterion	3.092321
Log likelihood	-44.49699	Hannan-Quinn criter.	3.029963
F-statistic	52.15008	Durbin-Watson stat	2.021534
Prob(F-statistic)	0.000000		

Appendix 4: Results of the ARIMA(1,1,5) model

Dependent Variable: DUNEMPLOYMENT
Method: ARMA Conditional Least Squares (Gauss-Newton / Marquardt steps)
Date: 01/24/25 Time: 16:49
Sample (adjusted): 3 33
Included observations: 31 after adjustments
Failure to improve likelihood (non-zero gradients) after 13 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: -2 2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.427592	0.245508	1.741663	0.0925
AR(1)	-0.281691	0.185983	-1.514605	0.1411
MA(5)	0.857637	0.048546	17.66651	0.0000

R-squared	0.284426	Mean dependent var	0.245774
Adjusted R-squared	0.233313	S.D. dependent var	1.082542
S.E. of regression	0.947881	Akaike info criterion	2.822590
Sum squared resid	25.15739	Schwarz criterion	2.961363
Log likelihood	-40.75014	Hannan-Quinn criter.	2.867827
F-statistic	5.564705	Durbin-Watson stat	2.037349
Prob(F-statistic)	0.009229		

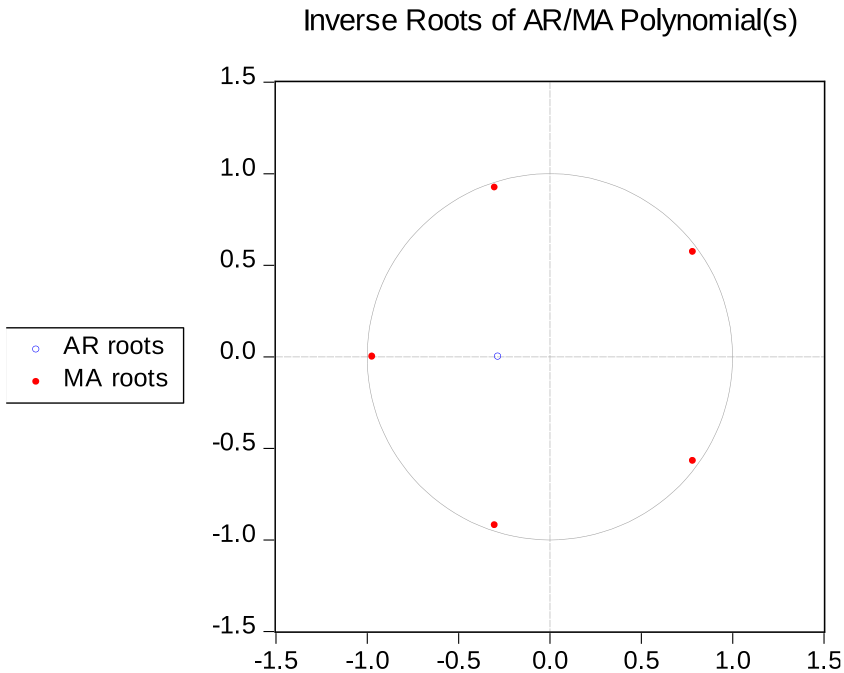
Inverted AR Roots	-.28			
Inverted MA Roots	.78+.57i	.78-.57i	-.30-.92i	-.30+.92i
	-.97			

Appendix 5: Ljung-Box Q statistic/ test

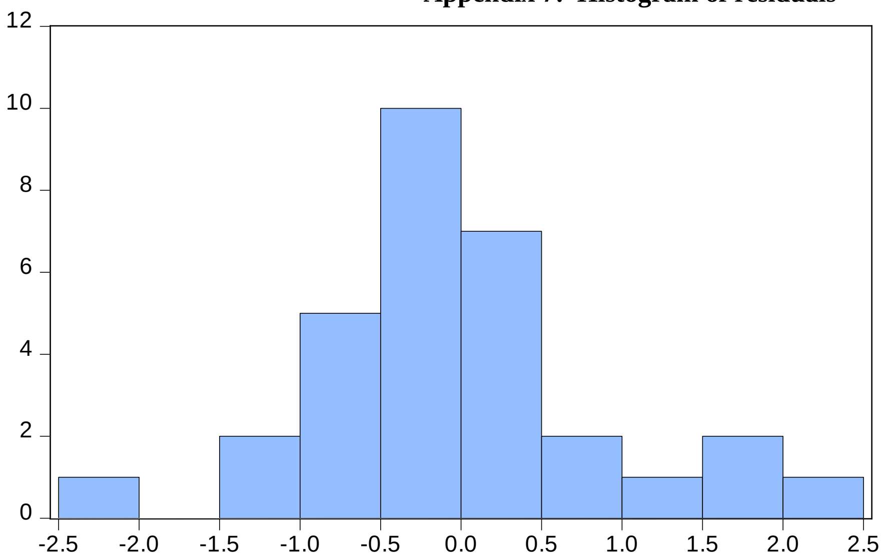
Date: 01/24/25 Time: 17:05
Sample: 1 33
Included observations: 31
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	-0.040	-0.040	0.0535	
. *| . |	. *| . |	2	-0.106	-0.108	0.4531	
. |* . |	. |* . |	3	0.188	0.182	1.7490	0.186
. | . |	. | . |	4	-0.041	-0.042	1.8139	0.404
. *| . |	. *| . |	5	-0.176	-0.147	3.0353	0.386
. | . |	. | . |	6	-0.011	-0.064	3.0402	0.551
. *| . |	. *| . |	7	-0.095	-0.120	3.4237	0.635
. *| . |	. | . |	8	-0.071	-0.032	3.6466	0.724
. | . |	. | . |	9	0.004	-0.020	3.6475	0.819
. *| . |	. *| . |	10	-0.134	-0.150	4.5272	0.807
. |* . |	. |* . |	11	0.167	0.167	5.9542	0.744
. |* . |	. |* . |	12	0.169	0.132	7.4995	0.678
. *| . |	. | . |	13	-0.066	-0.006	7.7500	0.736
. | . |	. | . |	14	0.006	-0.057	7.7522	0.804
. |* . |	. | . |	15	0.088	-0.019	8.2452	0.827
. | . |	. |* . |	16	0.012	0.086	8.2551	0.876

Appendix 6: ARIMA(1,1,5) structure



Appendix 7: Histogram of residuals



Series: Residuals	
Sample 3 33	
Observations 31	
Mean	-0.003010
Median	-0.130360
Maximum	2.245322
Minimum	-2.050712
Std. Dev.	0.915735
Skewness	0.561444
Kurtosis	3.851697
Jarque-Bera	2.565591
Probability	0.277261

Appendix 8: South Africa's UNEMPLOYMENT and UNEMPLOYMENT FORECAST results

YEAR	UNEMPLOYMENT	UNEMPLOYMENT FORECAST (in First difference)	UNEMPLOYMENT FORECAST
1991	20.105		20.105
1992	20.369	0.264	20.369
1993	20.295	-0.074	20.295
1994	20.073	-0.222	20.073
1995	19.799	-0.274	19.799
1996	19.643	-0.156	19.643
1997	19.679	0.036	19.679
1998	19.821	0.142	19.821
1999	19.926	0.105	19.926
2000	19.841	-0.085	19.841
2001	19.725	-0.116	19.725
2002	19.658	-0.067	19.658
2003	19.728	0.07	19.728
2004	19.634	-0.094	19.634
2005	19.557	-0.077	19.557
2006	19.425	-0.132	19.425
2007	19.39	-0.035	19.39
2008	19.507	0.117	19.507
2009	20.512	1.005	20.512
2010	23.181	2.669	23.181
2011	21.416	-1.765	21.416
2012	21.786	0.37	21.786
2013	22.038	0.252	22.038
2014	22.606	0.568	22.606
2015	22.869	0.263	22.869
2016	24.023	1.154	24.023
2017	23.992	-0.031	23.992
2018	24.218	0.226	24.218
2019	25.538	1.32	25.538
2020	24.339	-1.199	24.339
2021	28.77	4.431	28.77
2022	28.838	0.068	28.838
2023	27.988	-0.85	27.988
2024		1.75685313	29.74485313
2025		0.38210473	30.12695786
2026		2.07459662	32.20155448
2027		0.48600627	32.68756075

2028		-0.4711021	32.2164586
2029		0.68074598	32.89720458
2030		0.3562807	33.25348528
2031		0.44767966	33.70116494
2032		0.42193339	34.12309833
2033		0.42918588	34.55228421
2034		0.42714292	34.97942713
2035		0.4277184	35.40714554
2036		0.4275563	35.83470183
2037		0.42760196	36.2623038
2038		0.4275891	36.68989289
2039		0.42759272	37.11748561
2040		0.4275917	37.54507731
2041		0.42759199	37.9726693
2042		0.42759191	38.40026121
2043		0.42759193	38.82785314

Appendix 9: Graph showing Uganda's UNEMPLOYMENT and UNEMPLOYMENT FORECAST results