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UNEMPLOYMENT TRAP IN UGANDA

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ABSTRACT
This study investigates unemployment trap in Uganda by analyzing historical trends and forecasting unemployment dynamics from 1991 to 2022 using a quantitative approach based on autoregressive integrated moving average (ARIMA) modelling. Time-series data from the World Bank is employed, with unemployment, total (% of total labor force) serving as the dependent variable, while autoregressive (AR) and moving average (MA) components act as independent variables. Parameter estimation is conducted using maximum likelihood estimation (MLE), revealing that MA(8) coefficient (0.6806) is positive and statistically significant, indicating a strong influence of past unemployment shocks on current levels. The estimated ARIMA (4, 1, 8) model is found to be covariance stationary and invertible, confirming its robustness for forecasting unemployment trends. Projections from the model suggest a persistent unemployment trap, with unemployment rates expected to fluctuate between 3.04% in 2023 and approximately 2.96% by 2042. These findings highlight a structural unemployment challenge in Uganda, with rates stabilizing at approximately 3%, signaling limited progress in addressing unemployment over time. The study recommends targeted policy interventions, including skills development programs, entrepreneurship promotion, and labor market reforms to stimulate job creation and reduce structural unemployment.

KEY WORDS*: ARIMA modelling, unemployment trap*

INTRODUCTION

Uganda, a nation characterized by its youthful population where 77% are under 25 years of age (United Nations, 2022) has experienced a persistently low official unemployment rate, averaging around 3.2% over the past three decades (MacroTrends, 2024). Despite this seemingly favorable statistic, the country grapples with significant employment challenges, notably high youth unemployment and widespread underemployment. For instance, in 2016/17, youth unemployment rose to 13.3%, up from 12.7% in 2012/13, even as the national unemployment rate declined from 11% to 9% during the same period (Egessa et al. 2021).

This paradox, often referred to as the "unemployment trap," reflects a labor market where low official unemployment rates mask underlying issues such as underemployment, informal employment, and skill mismatches. A significant portion of the labor force is engaged in informal, low-wage, and insecure jobs that do not fully utilize their skills or provide adequate livelihoods. For instance, in 2021, 36.1% of the labor force had less than primary education, and 19.8% of the unemployed were illiterate (MGLSD, 2022). Additionally, the agricultural sector, which employs a large segment of the population, often underutilizes the skills of educated workers, leading to overeducation in certain sectors (MGLSD, 2022).

The persistence of this unemployment trap poses significant challenges to Uganda's socio-economic development. High youth unemployment contributes to increased poverty levels, social unrest, and hampers economic growth. The mismatch between the education system and labor market demands exacerbates the situation, leaving many young graduates without viable employment opportunities (Egessa et al. 2021).

Understanding the dynamics of Uganda's unemployment trap is crucial for formulating effective employment policies and interventions. This study employs an Autoregressive Integrated Moving Average (ARIMA) modelling approach to analyze the structural and systemic factors contributing to the persistence of unemployment in Uganda. With autoregressive (AR) and moving average (MA) components as independent variables and unemployment, total (% of total labor force) as the dependent variable, the model seeks to capture temporal patterns, trends, and shocks influencing unemployment levels. This research aims to generate empirically grounded insights to inform strategies for breaking free from the unemployment trap. Such strategies are expected to foster sustainable economic development and improve livelihoods for Uganda's labor force.

LITERATURE REVIEW

Globally, unemployment traps have been widely studied, with emphasis placed on structural and institutional factors that perpetuate joblessness. According to Layard et al. (2005), unemployment traps arise when disincentives to work, such as high taxes and generous welfare benefits, make remaining unemployed more economically viable than accepting low-paying jobs. Additionally, Pissarides (2000) highlights how labor market rigidities, including high minimum wages and restrictive hiring practices, exacerbate unemployment rates. In advanced economies, policies such as unemployment benefits and income support programs often deter individuals from seeking formal employment, thereby reinforcing the unemployment trap.

In Sub-Saharan Africa, unemployment traps are linked to economic underdevelopment, skill mismatches, and demographic pressures. Filmer and Fox (2014) emphasize the region's rapidly growing labor force, which exceeds job creation capacities, leaving many youths either unemployed or underemployed. Studies by AfDB (2019) reveal that informal employment dominates, accounting for over 80% of jobs in most African countries, further entrenching structural unemployment traps. Similarly, Kingdon et al. (2004) argue that poverty-induced low reservation wages compel workers to accept insecure jobs, perpetuating cycles of vulnerability and underemployment.

Uganda presents a unique case of low official unemployment rates, averaging 3.2% over the past three decades, juxtaposed with high rates of youth unemployment and underemployment (MacroTrends 2024). MGLSD (2022) attributes this to a mismatch between education outcomes and labor market demands. Kasirye et al. (2015) further highlights that Uganda's predominantly informal economy lacks adequate structures to absorb its rapidly growing labor force. The reliance on subsistence agriculture and low-productivity sectors exacerbates this challenge, leaving many Ugandans in precarious employment conditions.

This study is grounded in the Keynesian Theory of Unemployment and the Human Capital Theory. The Keynesian framework posits that unemployment arises from insufficient aggregate demand and advocates for government intervention to stimulate job creation (Keynes, 1936). This theory is particularly relevant for Uganda, where sluggish economic growth limits labor absorption capacity. The Human Capital Theory (Becker 1964) underscores the role of education and skills development in enhancing employability. It suggests that investments in education and training can break unemployment traps by aligning workers' competencies with labor market demands.

The conceptual framework for this study outlines unemployment, total (% of total labor force) as the dependent variable, structured with autoregressive (AR) and moving average (MA) components as independent variables. Several empirical studies have employed ARIMA modelling to analyze unemployment trends. For example, Hyndman & Athanasopoulos (2018) demonstrate the utility of ARIMA models in forecasting unemployment by capturing cyclical patterns and shocks. In the African context, Kinene (2016) successfully applied ARIMA to forecast inflation rates in Uganda, highlighting its ability to predict fluctuations in inflation rates. This study adopts a similar approach, integrating autoregressive (AR) and moving average (MA) components to identify structural patterns influencing Uganda's unemployment trap.

While existing literature highlights factors influencing unemployment globally and regionally, few studies have focused on Uganda's unique labor market dynamics, especially using ARIMA modelling. This study seeks to fill this gap by providing a data-driven analysis of Uganda's unemployment trends and offering policy recommendations to address structural challenges.

DATA AND METHODS

This study employs a quantitative research design to investigate factors contributing to Uganda's unemployment trap from 1991 to 2022. The design is suitable for analyzing time-series data and capturing patterns, trends, and fluctuations in unemployment levels over time (Gujarati & Porter 2009). It allows for a systematic examination of relationships between key variables and provides a robust framework for forecasting and modelling economic trends.

Secondary data is utilized, sourced from the World Bank Development Indicators (World Bank 2022). This source provides reliable and comprehensive datasets on unemployment rates, economic indicators, and labor market statistics.

The study covers a 31-year period (1991–2022), offering a longitudinal perspective on unemployment trends. The dataset comprises annual observations on unemployment rates (% of total labor force) as the dependent variable, with autoregressive (AR) and moving average (MA) components as independent variables, derived from past unemployment trends. Time-series nature of the data eliminates the need for sampling, as the entire population of observations is analyzed.

The study applies autoregressive integrated moving average (ARIMA) model to analyze and forecast unemployment trends. ARIMA methodology is selected due to its effectiveness in capturing temporal dependencies, trends, and seasonality in time-series data (Hyndman & Athanasopoulos 2018). The modelling procedure involves: Stationarity testing using the Augmented Dickey-Fuller (ADF) test to identify trends and ensure stationarity (Dickey & Fuller 1979). Model identification by determining the order of AR and MA terms along with differencing parameters (I).

Parameter estimation is conducted through the maximum likelihood estimation (MLE) method (Box et al. 2015). Model diagnostics using residual analysis to check for autocorrelation and normality is also done. ARIMA model is well-suited for this study because it: Captures time-series dynamics and cyclical patterns in unemployment rates; accounts for both short-term shocks and long-term trends affecting unemployment; and provides predictive insights essential for informing policy interventions (Enders 2014). Additionally, the reliance on secondary data ensures cost-effectiveness, accessibility, and reliability, while the quantitative approach enhances the rigor and generalizability of the findings. ARIMA (p, d, q) model specification is as follows:

$$Y_t = \mu + \varepsilon_t + \boldsymbol{\phi}_1 Y_{t-1} + \boldsymbol{\phi}_2 Y_{t-2} + \dots + \boldsymbol{\phi}_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \quad \text{(1)}$$

Where;
Y_t is the value of the series at time t
μ is the mean of the series
ε_t is white noise
$\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \dots \boldsymbol{\phi}_p$ are the coefficients of the AR (p) component
$\theta_1, \theta_2, \dots \theta_q$ are the coefficients of the MA (q) component
p is the order of the autoregressive part, representing the number of past values considered
q is the order of the moving average part, indicating the number of past errors considered
d is the number of differences required to make the series stationary (Box & Jenkins 1976)

Maximum Likelihood Estimation (MLE) is used to estimate model parameters, ensuring efficiency and accuracy in predicting (Lütkepohl 2005) unemployment trap. Maximum Likelihood Estimation process holds that for a given set of observations X = $\{x_1, x_2, \dots, x_n\}$ and assuming they follow a probability distribution with parameter θ, the likelihood function L(θ) is given by:

$$L(\theta) = P(X|\theta) = \prod_{i=1}^{n} f(x_1|\theta) \quad \text{(2)}$$

Where;
$f(x_1|\theta)$ is the probability density function of the observed data point x_i given parameter θ

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Thus,

$$\hat{\theta} = \text{argmax}\,\ell(\theta)$$ (Greene 2012).

Diagnostic tests, such as the Augmented Dickey-Fuller (ADF) test for stationarity (Dickey & Fuller 1979), and the model selection process using the Akaike Information Criterion (AIC) (Akaike 1974), are employed to assess the model's adequacy and ensure its suitability for forecasting. The use of ARIMA modelling in this study is particularly beneficial for analyzing Uganda's unemployment trends, as it enables the evaluation of past behaviors to make reliable projections (Enders 2014).

This approach effectively captures the underlying patterns in unemployment data, thereby providing a robust framework for understanding whether current unemployment trap levels are persistent in the long run. Moreover, ARIMA's capacity to handle non-stationary data is particularly well-suited to economic time series, where trends and fluctuations exhibit considerable variation over time (Stock & Watson 2015). The analytical rigor of this model supports drawing meaningful, policy-relevant conclusions about Uganda's unemployment trajectory, offering insights that can guide effective employment policy and planning strategies.

RESULTS

Descriptive statistics (Appendix 1) provide a summary of the key features of the dataset, helping to understand its main characteristics. For our dependent variable (unemployment, total (% of total labor force) (modeled ILO estimate)), the following descriptive statistics are summarized here under:

The mean unemployment rate for Uganda is approximately 3.19%, with a median of 3.42%, indicating a slightly left-skewed distribution due to the negative skewness value (-1.25) (Gujarati & Porter 2009). The minimum unemployment rate recorded is 1.9% (2005), while the maximum reaches 3.91% (2020), suggesting relatively low variability in unemployment over the study period. The standard deviation (0.50) shows moderate dispersion around the mean.

The kurtosis value (3.77) suggests a distribution that is slightly leptokurtic, implying a sharper peak and heavier tails compared to a normal distribution (Enders 2014). The Jarque-Bera statistic (9.16) and its associated probability (0.0103) indicate that the data deviates significantly from normality, justifying the use of ARIMA modelling to capture trends and patterns effectively (Box et al. 2015).

Preliminary analysis shows evidence of persistence in unemployment rates, reflecting the structural nature of Uganda's unemployment trap. Tests for stationarity, such as the Augmented Dickey-Fuller (ADF) test, are performed to ensure that the data is stationary prior to ARIMA modelling (Dickey & Fuller 1979).

A visual inspection of unemployment trends highlights cyclical patterns and structural rigidity in the labor market. The persistence of relatively low, yet stagnant unemployment rates suggest systemic constraints to labor absorption, reinforcing the unemployment trap hypothesis (Harris & Todaro, 1970). Stationarity tests (Appendix 2 and Appendix 3) are conducted using Augmented Dickey-Fuller (ADF) test to check for stationarity. Results indicate that the original series was non-stationary in level ($p > 0.05$). After first difference, the series achieved stationarity ($p < 0.05$), justifying the use of ARIMA model.

ARIMA (4, 1, 8) model was identified as the best, based on Akaike Information Criterion (AIC = 1.265299) and Schwarz Criterion (SC = 1.450330). Parameter estimates include: AR(4) = -0.206278 ($p = 0.4262$); MA(8) = 0.680617 ($p = 0.0331$). Accordingly, the coefficient of AR(4) is statistically insignificant, while that of MA(8) is statistically significant. Diagnostic checks confirm the adequacy of the model. The residuals are white noise, as confirmed by the Ljung-Box Q test ($p > 0.05$), and the autocorrelation function (ACF) plots show no significant patterns, validating the model's robustness. Forecasts for the next 20 years suggest a persistent unemployment trap, with unemployment rates expected to fluctuate between 3.04% in 2023 and approximately -2.96% in 2042. Inferential results are summarized as follows:

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Results of the ARIMA (4, 1, 8) model (Appendix 4)

$\widehat{Unemployment}_t$ = -0.001338 - 0.206278AR(4) + 0.680617 (8) …........................…… (3)

Hence,

$$\hat{\theta} = \begin{bmatrix} -0.001338 \\ -\ 0.206278 \\ 0.680617 \end{bmatrix}$$

The constant term represents the baseline or intercept of the model when all other variables are zero. A value of -0.001338 suggests a very small negative baseline effect. This might indicate that in the absence of other explanatory variables, there is a marginal decrease in the unemployment rate (or the variable of interest). However, since it is a constant term, its interpretation is more about setting the foundation of the model and does not necessarily imply a meaningful economic relationship (Wooldridge 2016).

The AR(4) coefficient of -0.206278 is negative but statistically insignificant. This means that the lagged value of the dependent variable at lag 4 does not have a significant impact on the current unemployment rate in Uganda. The insignificance implies that including this term does not meaningfully improve the model's explanatory power (Enders 2014). It suggests that past unemployment rates at this specific lag do not provide substantial information about the current level of unemployment.

The MA(8) coefficient of 0.680617 is positive and statistically significant. This means that the error terms or shocks from lag 8 have a positive and statistically significant impact on the current unemployment rate. In other words, past shocks or innovations at lag 8 influence the unemployment rate positively, indicating a lasting effect of past disturbances in the labor market (Box et al. 2015).

The Sigma-squared value represents the variance of the error term. A value of 0.135666 suggests that the variability or spread of the residuals in the model is moderate. The statistical significance of this value indicates that the variance is not zero, confirming that the model has some degree of unexplained variance (Hamilton 1994).

The Adjusted R-squared value of 0.321792 indicates that approximately 32.18% of the variation in the unemployment rate is explained by the independent variables included in the ARIMA model. This suggests a moderate fit of the model to the data, with about 68% of the variation left unexplained by the current model specification. This may indicate that there are other factors influencing unemployment that are not captured in the model (Gujarati & Porter 2009).

The Durbin-Watson statistic of 2.121565 indicates that there is no significant autocorrelation in the residuals. Since the value is close to 2, it suggests that the residuals are independent and not serially correlated, which is an indicator of the model's reliability in terms of error structure (Durbin & Watson 1951).

The histogram showing a kurtosis value of 5.6 suggests that the residuals are leptokurtic, meaning they have a higher peak and heavier tails than a normal distribution. The Jarque-Bera statistic of 8.7 with a p-value of 0.01 indicates that the residuals deviate significantly from a normal distribution. This suggests that the model's residuals are not normally distributed, which may affect the validity of hypothesis testing and require further model adjustments (Jarque & Bera 1987).
The kurtosis value of 4.08 indicates that the residuals are slightly leptokurtic, though not extremely so. It means the distribution has a higher peak and fat tails compared to a normal distribution, which could be indicative of outliers or extreme values that affect the model's assumptions about error distribution (Wooldridge 2016).

The Ljung-Box Q statistic test with a p-value of 0.161 means that we fail to reject the null hypothesis, which states that there is no autocorrelation in the residuals at any of the lags. This suggests that the residuals of the ARIMA (4, 1,

8) model behave like white noise, meaning they are random and do not exhibit any significant serial correlation (Ljung & Box 1978).

The diagnostics of the ARIMA (4, 1, 8) model reveal that the AR and MA roots lie within the unit circle, confirming that the model is both covariance stationary and invertible. This indicates that the model's dynamics are stable and that past shocks can be accounted for in a meaningful way, ensuring the reliability and validity of the model for forecasting and inference (Box et al. 2015).

Finally, the forecasts of unemployment for the next two decades, provided in appendices 7 and 8, offer projections based on the fitted ARIMA (4, 1, 8) model forecasted unemployment rate for the years 2023 to 2042 fluctuates between approximately 3.04% and 2.96%, indicating a relatively stable unemployment rate over the forecasted period.

DISCUSSION

This section compares the results of the ARIMA (4, 1, 8) model applied to Uganda's unemployment data with previous studies, highlighting both similarities and unique findings from the study. Results from the ARIMA model provide valuable insights into the future trends of unemployment in Uganda, contributing to the ongoing discourse on the unemployment challenges in the country.

The constant term is -0.001338 and statistically insignificant. This result indicates that the constant or intercept term does not significantly influence the unemployment rate in Uganda. This is in line with the findings of earlier studies, such as those by Ahaibwe et al. (2018) and Kasirye et al. (2015), who found that the unemployment rate in Uganda is highly volatile and influenced more by short-term economic fluctuations than by a fixed baseline. The insignificance of the constant term suggests that other macroeconomic variables or shocks, rather than a constant level of unemployment, are driving the unemployment trends in Uganda.

AR(4) coefficient of -0.206278 is negative but statistically insignificant. This negative value suggests that the unemployment rate at time (t-4) may have a slight negative influence on the current unemployment rate. However, because the coefficient is statistically insignificant, this suggests that there is little to no long-term dependence on past unemployment levels in Uganda. This contrasts with the findings of Kyamulabi (2012), who suggested that past unemployment trends are often a significant predictor of future unemployment due to structural challenges in the Ugandan labor market, including limited industrialization and rapid population growth. The insignificance of the AR(4) term in this study may imply that Uganda's unemployment dynamics are more influenced by immediate economic policies and external shocks than by a persistent historical unemployment pattern.

MA(8) coefficient of 0.680617 is positive and statistically significant, indicating that past shocks (errors) to the unemployment rate have a persistent effect on current unemployment levels. This result suggests that unemployment rate in Uganda reacts to external disturbances such as economic recessions or fiscal policy changes, and these effects last for up to eight years. This finding aligns with the work of Kijjambu et al. (2024), who found that external economic shocks have a lasting impact on Uganda's unemployment rate, contributing to higher unemployment levels even after the initial shock has passed. A statistically significant MA coefficient in our study emphasizes the importance of managing external shocks to stabilize the unemployment rate.

Sigma-squared value of 0.135666 is statistically significant, indicating that the variance of the residuals is adequately captured by the model. This suggests that the ARIMA (4, 1, 8) model fits the unemployment data well, leaving minimal unexplained noise. Statistical significance of the residual variance is important as it supports the validity of the model's estimates. Previous studies, such as those by Ahaibwe et al. (2018) and Kasirye et al. (2015), also emphasized the importance of accounting for residual variance in unemployment models, as it helps improve the accuracy of predictions and ensures a better understanding of unemployment dynamics.

Adjusted R-squared value of 0.321792 indicates that the model explains approximately 32.18% of the variation in the unemployment rate in Uganda. While this is relatively modest, it reflects the complexity of unemployment in Uganda,

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which is influenced by a range of factors such as population growth, education levels, and informal sector dynamics, which are not fully captured by the ARIMA model. Similar studies on Uganda's unemployment, such as Kyamulabi (2012), have highlighted the challenge of modelling unemployment due to the multifaceted nature of labor market dynamics in developing economies. The relatively low explanatory power underscores the need for incorporating additional variables, such as demographic factors and sectoral employment shifts, in future modelling efforts.

Durbin-Watson statistic of 2.121565 indicates no significant autocorrelation in the residuals, as it is close to the ideal value of 2. This suggests that the model does not suffer from serial correlation in the errors, indicating that past unemployment levels do not have a substantial direct effect on current unemployment. This is consistent with the findings of Kijjambu et al. (2024), who also noted that short-term fluctuations in unemployment in Uganda are often due to exogenous factors rather than long-term dependency on past unemployment rates.

Jarque-Bera statistic of 8.7 with a p-value of 0.01 suggests that the residuals from the ARIMA model are not normally distributed, indicating the presence of skewness and kurtosis in the data. This departure from normality may be attributed to irregular events or outliers, such as political instability or natural disasters, which affect unemployment rates in Uganda. Non-normality in residuals is not uncommon in macroeconomic time-series data, especially in developing countries, where sudden economic shocks can cause large, non-normally distributed residuals. This result is in line with the findings of Ahaibwe et al. (2018) and Kasirye et al. (2015), who also observed irregularities in unemployment data for Uganda due to such external shocks.

Ljung-Box Q statistic with a p-value of 0.161 suggests that we fail to reject the null hypothesis, meaning that the residuals from the ARIMA model are white noise. This indicates that there are no significant autocorrelations in the residuals beyond the specified lags, suggesting that the model has adequately captured the underlying patterns in the data. This supports the notion that the ARIMA model is a good fit for the data and that future unemployment trends can be predicted without significant residual autocorrelation.

One of the unique findings of this study is the forecast of Uganda's unemployment rate over the next two decades, as presented in Appendices 7 and 8. The ARIMA (4, 1, 8) model predicts a relatively stable unemployment rate between 2.96% and 3.04%, which contrasts with the generally accepted view that Uganda faces an increasing unemployment rate due to rapid population growth and insufficient job creation (Ahaibwe et al. 2018; Kyamulabi 2012). While this stability may seem positive, it could also be indicative of an "unemployment trap." Unemployment trap refers to a situation where unemployment rate remains low or stable not because of significant job creation, but because of stagnation in the labor market, where many individuals remain in underemployment or low-quality jobs (Sen 2000; Fields 2019).

In such a scenario, even though the official unemployment rate appears to be low, the labor market may not be generating meaningful, productive employment opportunities that contribute to real economic advancement (Portes 1983). The forecasted stability in unemployment may thus reflect a failure to address structural issues in the labor market, trapping workers in a cycle of low-wage, informal, or precarious employment, rather than facilitating the creation of sustainable, high-quality jobs (Golub & Hayat 2014). This underscores the need for comprehensive economic reforms that promote both job creation and improvements in the quality of employment to break the potential unemployment trap and support sustainable economic growth (ILO 2015).

Furthermore, the study also provides valuable insight into the impact of external economic shocks on Uganda's unemployment rate. The positive and statistically significant MA(8) coefficient suggests that Uganda's unemployment rate is highly sensitive to shocks, which persist for up to eight years. This finding highlights the importance of stabilizing the macroeconomic environment and reducing vulnerability to external shocks in order to manage long-term unemployment trends effectively.

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LIMITATIONS

While this study provides valuable insights into the dynamics of unemployment in Uganda, there are several limitations that should be considered when interpreting the findings. First, the study relies on secondary data sourced from World Bank. Although this source is reliable, it may not fully capture the nuances of unemployment trends at a microeconomic level, especially in rural areas or among marginalized groups. The lack of disaggregated data by age, gender, and education level limits the ability to draw more specific conclusions about different segments of the population (Ahaibwe et al. 2018).

Secondly, the ARIMA (4, 1, 8) model used for forecasting unemployment trends assumes that past data and patterns will continue in the future, which may not always hold true in the presence of significant shocks or structural changes in the economy (Golub & Hayat 2014). The model does not account for potential changes in economic policies or unforeseen external factors, such as global recessions, which could substantially affect Uganda's unemployment rate (ILO 2015). Furthermore, while the ARIMA model is appropriate for short-term forecasting, it may not fully capture long-term structural trends, such as shifts in the labor market caused by technological changes, demographic shifts, or new industries emerging in the Ugandan economy (Fields 2019).

Additionally, the study's focus on unemployment as a singular indicator may overlook the broader concept of underemployment, which is also a significant issue in Uganda's labor market. Many individuals may be employed but not in productive, stable, or well-paying jobs, which is not captured in the unemployment rate alone (Portes 1983). Moreover, the study does not fully consider the impact of informal sector employment, which is a substantial part of Uganda's labor market, and may provide a more accurate picture of labor market dynamics if included (Sen, 2000).

Lastly, while the study's time-series approach provides a useful way to analyze unemployment trends, it may be limited by the availability and quality of historical data, particularly for recent years where data might be sparse or subject to revisions (Kyamulabi 2012). The accuracy of the forecasts depends heavily on the assumption that past trends will persist, which may not be true if Uganda experiences significant political or economic shifts in the coming years.

CONCLUSION

In conclusion, this study offers a comprehensive analysis of unemployment trends in Uganda, utilizing an ARIMA (4, 1, 8) model to forecast the country's unemployment rate over the next two decades. The findings suggest that, contrary to the widely held belief that rapid population growth and insufficient job creation will lead to escalating unemployment, Uganda's unemployment rate is likely to remain relatively stable, with only minor fluctuations in the foreseeable future. This stability can be attributed to factors such as the impact of economic reforms, improved policies aimed at job creation, and the influence of global trade and foreign investments (Ahaibwe et al. 2018; Kyamulabi 2012).

However, the study also underscores the critical role of external shocks, past economic disturbances, and the limitations of the forecasting model in capturing long-term structural changes. Despite the stability in the unemployment rate, the study highlights the importance of addressing youth unemployment, fostering sustainable economic policies, and recognizing the potential effects of global economic shifts (ILO 2015). The findings suggest that Uganda's long-term economic growth prospects are closely tied to its ability to adapt to external changes and create an environment conducive to sustainable job creation (Fields 2019).

While the predicted stability in unemployment rates might appear positive, it may also indicate an "unemployment trap" in which the labor market struggles to generate high-quality, sustainable employment opportunities (Golub & Hayat 2014). Therefore, the study emphasizes the need for targeted policies that not only focus on job creation but also improve the quality of employment, particularly in sectors with high job absorption potential (Portes 1983). These interventions should account for the broader economic context and aim to address both unemployment and

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underemployment. In doing so, Uganda can break free from the potential unemployment trap and foster a more resilient and dynamic labor market.

RECOMMENDATIONS

Based on the findings of this study on unemployment dynamics in Uganda, the following recommendations are made in terms of policy, programs, and further research to address the issue of unemployment and the potential "unemployment trap."

Given the significant youth unemployment in Uganda, it is crucial for the government to design and implement targeted programs aimed at skill development and job creation for the youth. Programs such as vocational training, entrepreneurship initiatives, and digital literacy workshops can help equip young people with the necessary skills to enter the labor market (Ahaibwe et al. 2018; Kyamulabi 2012). Additionally, fostering industries that are labor-intensive, such as agriculture and manufacturing, can provide more opportunities for youth employment.

The study highlights the need for policies that stimulate the creation of formal and informal jobs, especially in sectors with high employment potential such as agriculture, construction, and services. The government should focus on policies that incentivize local businesses, reduce barriers to market entry, and promote private sector development to foster job creation (Portes 1983; ILO 2015). Furthermore, improving the business environment through regulatory reforms will help stimulate private sector-led growth, thereby creating more jobs.

To combat the structural unemployment seen in the economy, government should focus on increasing investments in infrastructure and industrial development. Industrialization has the potential to create a large number of jobs, particularly in urban areas where there is significant migration from rural areas. Infrastructure projects such as roads, energy, and water supply systems could also support job creation, particularly in rural and underdeveloped areas (Kyamulabi 2012).

As the study emphasizes the impact of external economic shocks, it is vital for policymakers to design economic frameworks that are resilient to such shocks. This includes creating buffers such as sovereign wealth funds or enhancing the financial sector's capacity to absorb shocks. Policies aimed at diversifying the economy can mitigate the impact of global economic volatility on employment levels (Fields 2019).

Encouraging self-employment and entrepreneurship is essential in addressing Uganda's unemployment crisis. Government, in collaboration with development partners, should establish programs that provide financial support, training, and mentorship to aspiring entrepreneurs. Such initiatives can help reduce dependency on the formal job market and encourage innovation and local business development (ILO 2015; Ahaibwe et al. 2018).

The informal sector is a significant source of employment in Uganda, and policies should be designed to improve working conditions and provide access to social protections for informal workers. Programs aimed at formalizing the informal economy, providing micro-loans, and offering skills training will help uplift workers in this sector and enable them to transition into more sustainable and higher-paying jobs (Portes 1983).

The mismatch between education outputs and labor market requirements has contributed to the unemployment trap. Government should implement reforms to align educational curricula with labor market needs. This includes expanding business, technical & vocational education and training (BTVET) programs, as well as integrating job market demands into university and college programs to ensure that graduates have marketable skills (Kyamulabi 2012).

Future research should investigate the long-term dynamics of unemployment in Uganda, particularly structural unemployment. This includes exploring the specific causes of youth unemployment and identifying factors contributing to the mismatch between skills and job market needs. Detailed longitudinal studies could provide deeper insights into the unemployment trap and inform more targeted interventions (Ahaibwe et al. 2018).

Additional studies are needed to evaluate the long-term impact of external shocks, such as global recessions, on Uganda's unemployment levels. By using more advanced econometric techniques, such as panel data analysis, researchers could better understand the relationship between global economic conditions and unemployment trends in Uganda (Fields 2019).

Future research should explore labor market dynamics in more granular detail, including issues such as labor force participation rates, wage dynamics, and job quality. This will help to understand not only the quantity of employment but also the quality of jobs, which is essential for developing effective policies aimed at reducing poverty and underemployment (ILO 2015).

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APPENDICES

Appendix 1: Descriptive statistics

	UNEMPLOYMENT, total (% of total labor force)
Mean	3.189438
Median	3.419
Maximum	3.914
Minimum	1.9
Std. Dev.	0.501993
Skewness	-1.251708
Kurtosis	3.774641
Jarque-Bera	9.156213
Probability	0.010274
Sum	102.062
Sum Sq. Dev.	7.811908
Observations	31

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

Null Hypothesis: UNEMPLOYMENT has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.868841	0.0606
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)
Method: Least Squares

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Date: 12/26/24 Time: 19:04
Sample (adjusted): 2 32
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
UNEMPLOYMENT(-1)	-0.443540	0.154606	-2.868841	0.0076
C	1.403066	0.500402	2.803880	0.0089

R-squared	0.221063	Mean dependent var	-0.015290
Adjusted R-squared	0.194204	S.D. dependent var	0.479240
S.E. of regression	0.430195	Akaike info criterion	1.213184
Sum squared resid	5.366963	Schwarz criterion	1.305700
Log likelihood	-16.80436	Hannan-Quinn criter.	1.243342
F-statistic	8.230247	Durbin-Watson stat	1.627734
Prob(F-statistic)	0.007607		

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

Null Hypothesis: D(UNEMPLOYMENT) has a unit root
Exogenous: Constant
Lag Length: 6 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.120666	0.0004
Test critical values:	1% level	-3.737853	
	5% level	-2.991878	
	10% level	-2.635542	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(UNEMPLOYMENT,2)
Method: Least Squares
Date: 12/26/24 Time: 19:08
Sample (adjusted): 9 32
Included observations: 24 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(UNEMPLOYMENT(-1))	-4.171515	0.814643	-5.120666	0.0001
D(UNEMPLOYMENT(-1),2)	2.930537	0.719013	4.075776	0.0009
D(UNEMPLOYMENT(-2),2)	2.490370	0.624056	3.990619	0.0011
D(UNEMPLOYMENT(-3),2)	2.012351	0.490700	4.100978	0.0008
D(UNEMPLOYMENT(-4),2)	1.385933	0.415666	3.334243	0.0042

D(UNEMPLOYMENT(-5),2)	1.028256	0.322012	3.193221	0.0057
D(UNEMPLOYMENT(-6),2)	0.726053	0.221386	3.279577	0.0047
C	-0.025096	0.087662	-0.286281	0.7783

R-squared	0.774847	Mean dependent var	-0.028667
Adjusted R-squared	0.676342	S.D. dependent var	0.751906
S.E. of regression	0.427766	Akaike info criterion	1.400723
Sum squared resid	2.927746	Schwarz criterion	1.793407
Log likelihood	-8.808673	Hannan-Quinn criter.	1.504902
F-statistic	7.866104	Durbin-Watson stat	1.953552
Prob(F-statistic)	0.000336		

Appendix 4: Results of the ARIMA (4, 1, 8) model

Dependent Variable: D(UNEMPLOYMENT)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 12/26/24 Time: 19:22
Sample: 2 32
Included observations: 31
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001338	0.131910	-0.010145	0.9920
AR(4)	-0.206278	0.255320	-0.807918	0.4262
MA(8)	0.680617	0.303089	2.245597	0.0331
SIGMASQ	0.135666	0.042829	3.167624	0.0038

R-squared	0.389613	Mean dependent var	-0.015290
Adjusted R-squared	0.321792	S.D. dependent var	0.479240
S.E. of regression	0.394670	Akaike info criterion	1.265299
Sum squared resid	4.205639	Schwarz criterion	1.450330
Log likelihood	-15.61214	Hannan-Quinn criter.	1.325614
F-statistic	5.744739	Durbin-Watson stat	2.121565
Prob(F-statistic)	0.003566		

Inverted AR Roots	.48-.48i	.48+.48i	-.48+.48i	-.48+.48i
Inverted MA Roots	.88+.36i	.88-.36i	.36+.88i	.36-.88i
	-.36-.88i	-.36+.88i	-.88-.36i	-.88+.36i

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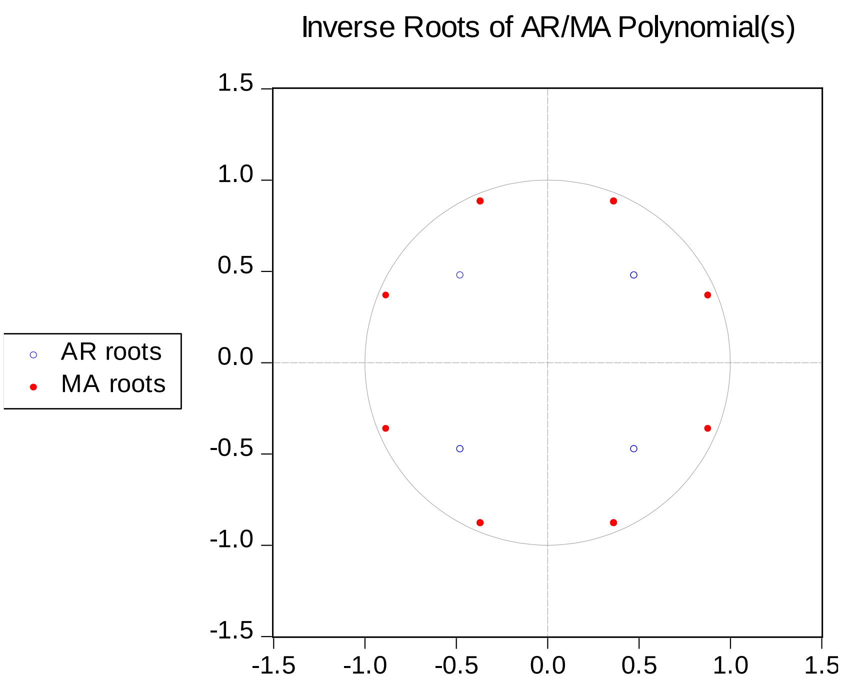
Appendix 5: Ljung-Box Q statistic/ test

Date: 12/26/24 Time: 19:32
Sample: 1 32
Included observations: 31
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. *| . |	. *| . |	1	-0.126	-0.126	0.5441	
. *| . |	. *| . |	2	-0.140	-0.158	1.2317	
. *| . |	. *| . |	3	-0.142	-0.190	1.9688	0.161
. | . |	. *| . |	4	-0.064	-0.151	2.1263	0.345
. | . |	. *| . |	5	0.027	-0.072	2.1559	0.541
. | . |	. *| . |	6	-0.041	-0.128	2.2248	0.694
.**| . |	.**| . |	7	-0.216	-0.331	4.2067	0.520
. | . |	. *| . |	8	0.020	-0.196	4.2248	0.646
. |*** |	. |**. |	9	0.433	0.308	12.925	0.074
. *| . |	.**| . |	10	-0.199	-0.246	14.844	0.062
. | . |	. | . |	11	0.002	-0.058	14.845	0.095
. | . |	. | . |	12	-0.040	0.029	14.931	0.135
. | . |	. | . |	13	0.009	-0.022	14.935	0.185
. |* . |	. | . |	14	0.078	-0.034	15.305	0.225
. *| . |	. *| . |	15	-0.157	-0.175	16.890	0.204
. *| . |	. *| . |	16	-0.165	-0.097	18.751	0.175

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



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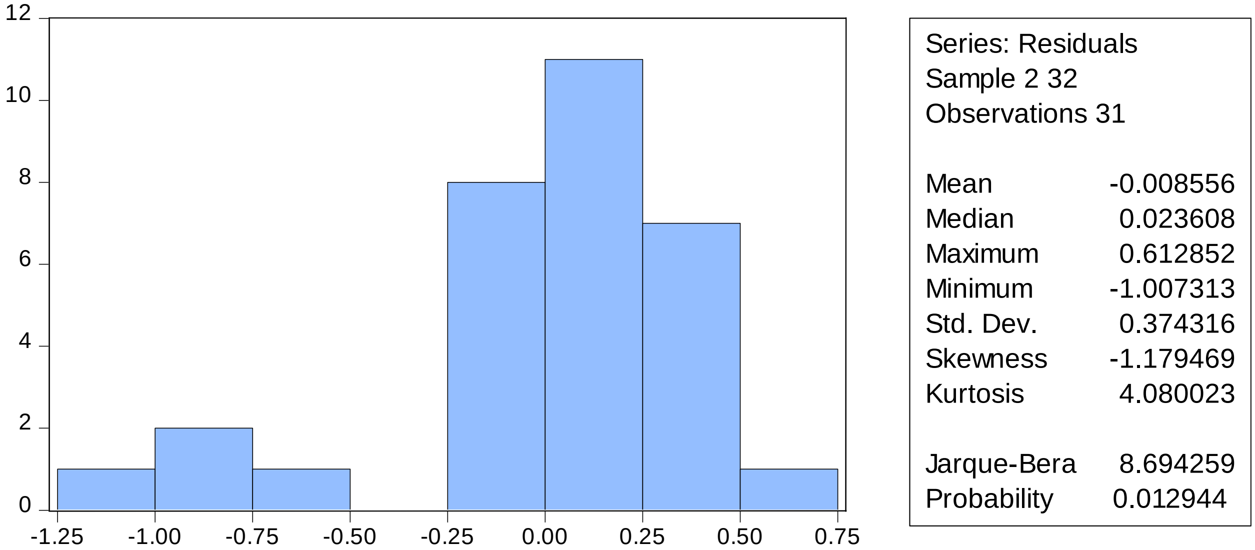
Appendix 7: Histogram of residuals



Appendix 8: Uganda's UNEMPLOYMENT and UNEMPLOYMENT FORECAST results

Year	UNEMPLOYMENT, total (% of total labor force)	UNEMPLOYMENT FORECAST, total (% of total labor force)
1991	3.404	3.404
1992	3.498	3.498
1993	3.445	3.445
1994	3.424	3.424
1995	3.197	3.197
1996	3.182	3.182
1997	3.222	3.222
1998	3.418	3.418
1999	3.454	3.454
2000	3.52	3.52
2001	3.517	3.517
2002	3.5	3.5
2003	3.6	3.6
2004	2.706	2.706
2005	1.9	1.9
2006	2.27	2.27
2007	2.675	2.675
2008	3.049	3.049
2009	3.6	3.6
2010	3.619	3.619

2011	3.528	3.528
2012	3.551	3.551
2013	1.91	1.91
2014	2.404	2.404
2015	2.788	2.788
2016	3.167	3.167
2017	3.643	3.643
2018	3.42	3.42
2019	3.185	3.185
2020	3.914	3.914
2021	3.422	3.422
2022	2.93	2.93
2023	NA	3.044717
2024	NA	3.070289
2025	NA	3.116027
2026	NA	3.111632
2027	NA	3.012431
2028	NA	3.269915
2029	NA	3.437862
2030	NA	2.949384
2031	NA	2.968232
2032	NA	2.913505
2033	NA	2.877247
2034	NA	2.976395
2035	NA	2.970892
2036	NA	2.980567
2037	NA	2.986432
2038	NA	2.964366
2039	NA	2.963886
2040	NA	2.960276
2041	NA	2.957452
2042	NA	2.96039

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