Modeling the effect of devolution on youth unemployment rates in Kenya using autoregressive integrated moving average - intervention model

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ABSTRACT

Youth unemployment remains a major concern, particularly in African countries with the youngest population globally. In Kenya, youth unemployment rate has shown fluctuations despite several government efforts such as the Youth Enterprise Development Fund (YEDF), Kenya Youth Empowerment Project (KYEP) and the Youth Employment Scheme Abroad (YESA). The impact of devolution on youth unemployment in Kenya has had little investigation on, which is the reason for this study. The study aims to assess the effect of devolution on youth unemployment rates in Kenya, utilizing Autoregressive Integrated Moving Average-Intervention model. This research was informed by the Keynesian and Decentralization theories of employment, which collectively illustrate how government efforts, like introduction of devolution, are anticipated to influence labor market results. This study used the yearly secondary data on youth unemployment rates from the World Bank covering the period from 1991 to 2022. Computational analysis was done using Python programming. An ARIMA (0, 0, 0)(0,0,1)[4] was selected as the most suitable model for the youth unemployment rates prior to devolution (noise model) due to its lowest Akaike Information Criterion (AIC) value of 234.746 in comparison to other identified candidate models. By including devolution as an intervention in the selected noise model, its statistical significance was established at the 0.05 level of significance. Comparative analysis findings revealed that the average youth unemployment rate increased from 6.67% prior to devolution to 10.19% during the devolution period. The projected counterfactual rate during devolution was approximated to be 8.583%, which confirmed the observed increase as statistically significant. In conclusion, the effect of devolution was found to be statistically significant, implying that youth unemployment rates increased during devolution, as confirmed by the fitted ARIMA - Intervention model. Based on the upward trend in youth unemployment rates, the study recommended that policymakers prioritize other context specific and targeted interventions to address structural barriers in the youth labour markets. These should include expanding access to skills training and vocational education, fostering youth entrepreneurship through financing and mentorship programs, and aligning education curriculum with labour market needs.

Keywords: ARIMA-Intervention Model, Devolution, Kenya, Time Series, Youth Unemployment

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I. INTRODUCTION

Youth unemployment remains a significant issue worldwide, particularly in Sub-Saharan Africa, where population pressures intensify the challenges within labour markets. In Kenya, despite various employment-related policy initiatives, youth unemployment remains a major concern. One of the most impactful governance reforms in Kenya was the implementation of devolution following the 2010 Constitution's passage.

Unemployment is a vital economic indicator, showcasing the health of a country's economy. Higher unemployment rates are closely tied to poverty, increased crime rates and socio-political challenges. The increasing youth unemployment is rapidly becoming a serious problem. Achieving employment is essential for the transition from youth to adulthood and for attaining financial independence. This rising unemployment threatens Kenya's economic development, underscoring the necessity for government interventions (Dritsakis & Klazoglou, 2018; Mlatsheni & Leibbrandt, 2011).

Despite witnessing significant Gross Domestic Product (GDP) growth since 2000, Kenya's youth unemployment rate has surged by 42% since then. From 2006 to 2013, Kenya's growing economy experienced an annual employment growth rate of 45%. However, this growth has been inadequate to accommodate the 500,000 to 800,000 Kenyan youth entering the job market annually. The exact number of new entrants into the labour force is uncertain, leading to considerable inconsistencies in employment data (Hall, 2017).

In the last three decades, numerous African nations have pursued devolution reforms. These initiatives aim to enhance governance efficiency and tailor policies to better address the needs of local communities, particularly the underprivileged. Nevertheless, there is a lack of organized research on devolution in Africa and its impact on service delivery and poverty relief. The citizens of Kenya sought a devolved governance system to facilitate easier and closer access to public services. Devolution was perceived as a mechanism to stimulate economic and social development, generating new job opportunities and investment prospects that could lead to further advancement (Lidia, 2011; Ngigi & Busolo, 2019).

However, the degree to which devolution has influenced youth employment in Kenya remains largely unexplored. Therefore, this study aimed at assessing the effect of devolution on youth unemployment rates in Kenya using a time series methodology, specifically an Autoregressive Integrated Moving Average (ARIMA) - Intervention model.

1.1 Statement of the Problem

Youth unemployment has resulted in higher levels of poverty, escalated crime rates, social alienation and emotional distress, all of which affect national economic progress. According to the Kenya National Bureau of Statistics (KNBS) 2019 report, individuals aged 20 to 24 experienced the highest unemployment rate at 16.8%, followed by those in the 15 to 19 age bracket at 11.1%. Conversely, the unemployment rate for those aged 35 to 64 was considerably lower, at 2.8% or less. The report also revealed that the long-term unemployment rate was highest among those aged 20 to 24 at 8.8%, while individuals aged 60 to 64 had a long-term unemployment rate of under 1.0%. In 2022, youth aged 20 to 24 maintained the highest long-term unemployment rate at 9.9% (KNBS, 2019; KNBS, 2022).

Research has focused on how unemployment impacts youth, as well as the significant factors leading to it. However, the influence of devolution on youth unemployment in Kenya has not been thoroughly investigated. As a result, this study sought to analyze the effect of devolution on youth unemployment in Kenya by utilizing an Autoregressive Integrated Moving Average - Intervention model. While other factors, such as economic downturns, contribute to the situation, devolution stands out as a policy issue with an anticipated effect on employment, warranting close examination.

1.2 Research Objective

The main aim of this study was to model the effect of devolution on youth unemployment rates in Kenya using ARIMA-Intervention model.

II. LITERATURE REVIEW

2.1 Theoretical Review

2.1.1 ARIMA Model

ARIMA modeling is a helpful *tool for assessing large-scale time series data when other methods fails. It takes into consideration the underlying trends and autocorrelation*, and it offers flexible ways to model various types of impacts. $ARIMA(p,d,q)$ is a combination of the Autoregressive (AR) model of order p, Moving Average model (MA) of order q and the differencing (I) component of order d needed to arrive at stationary $ARMA(p,q)$ model (Box & Jenkins, 1970).

$ARIMA(p,d,q)$ model is given by the following expression;

$$(1-B)^d Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \quad (1)$$

$$\left(Y_t - \phi_1 Y_{t-1} - \phi_2 Y_{t-2} - \ldots - \phi_p Y_{t-p}\right)(1-B)^d = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \quad (2)$$

Rewriting Equation (2) using the backshift operator technique, that is, $Y_{t-k} = B^k Y_t$;

$$Y_t - \phi_1 B Y_t - \phi_2 B^2 Y_t - \ldots - \phi_p B^p Y_t)(1-B)^d = e_t - \theta_1 B e_t - \theta_2 B^2 e_t - \ldots - \theta_q B^q e_t \quad (3)$$

$$\left(1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p\right)(1-B)^d Y_t = \left(1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q\right) e_t \quad (4)$$

$$\phi(B)(1-B)^d Y_t = \theta(B) e_t \quad (5)$$

Where:

Y_t represents non-stationary time series, $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$ is the autoregressive component polynomial of order p, $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$ is the moving average component of order q, $(1-B)^d$ is the trend difference operator of order d, B is the backshift operator and e_t is the white noise process.

2.1.2 Seasonal ARIMA (SARIMA) Model

SARIMA model builds on the basic ARIMA model and is specifically developed to work with a time series data that show both trends and seasonality. It is useful for data values that experience regular highs and lows at certain times of the year. Seasonal $ARIMA(p,d,q)(P,D,Q)[s]$ model is given by;

$$\Phi_P(B^s)\phi(B)(1-B^s)^D(1-B)^d Y_t = \Theta_Q(B^s)\theta(B) e_t \quad (6)$$

Where;

Y_t is the non-stationary time series, $\phi(B)$ is the usual Autoregressive component polynomial, $\theta(B)$ is the Moving Average component polynomial, $\Phi_P(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \ldots - \Phi_P B^{Ps}$ is the seasonal Autoregressive component of order P, $\Theta_Q(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \ldots - \Theta_Q B^{Qs}$ is the seasonal Moving Average component of order Q, $(1 - B^s)^D$ is the seasonal difference operator of order D, $(1 - B)^d$ is the ordinary difference operator and e_t is the usual white noise process.

2.1.3 ARIMA – Intervention Model

ARIMA - *Intervention modeling is a robust statistical technique used to evaluate the effect of a significant policy change or event on a time series of interest. Based on the study by Box and Tiao, it is of interest to determine whether there is any evidence of a change* or effect, of an expected kind on the time series associated with the event (Box & Tiao, 1975).
The general structure of the model they developed is of the form;

$$Y_t = \frac{\omega(B)}{\delta(B)} I_{t-b} + \frac{\Theta(B)}{\Phi(B)(1 - B)^d} e_t \tag{7}$$

Where;
Y_t represents a time series variable of interest (dependent variable).
I_t represents the intervention variable. In the case of a step intervention, I_t takes only the values 0 and 1, denoting non-occurrence and occurrence of the intervention event respectively, and it is defined as;

$$\mathrm{I_t} = \begin{cases} 1, & \text{if } t \geq T \\ 0, & \text{if } t < T \end{cases} \tag{8}$$

And in the case of a ramp intervention;

$$\mathrm{I_t} = \begin{cases} f(t - T), & \text{if } t \geq T \\ 0, & \text{if } t < T \end{cases} \tag{9}$$

With T being the time of intervention when it first occurred.
$\delta(B) = 1 - \delta_1 B - \delta_2 B^2 - \ldots - \delta_r B^r$ is the slope parameter. Considering a step intervention, if δ is near 0, the effect of intervention remains constant over time and if δ is near 1, the effect of intervention increases over time.
$\omega(B) = \omega_0 - \omega_1 B - \omega_2 B^2 - \ldots - \omega_s B^s$ is the impact parameter, which explains a change due to the intervention effect (the change might be positive or negative). b is the delay parameter, which usually takes values 0, 1, and so on. If $b = 0$, it implies that the effect of intervention has occurred at the time of intervention, and if $b = 1$, it implies that the effect of intervention is felt after a delay of one period and so on.
B is the backshift operator. e_t is the usual white noise process, and they are independently and identically distributed (iid), i.e. $e_t \sim N(0, \sigma^2)$

For simplicity; we employ the backshift operator to rewrite the intervention component in Equation (7), i.e. $I_{t-b} = B^b I_t$, such that;

$$Y_t = \frac{\omega(B)}{\delta(B)} B^b I_t + \frac{\Theta(B)}{\Phi(B)(1 - B)^d} e_t \tag{10}$$

Further, let $\frac{\omega(B)}{\delta(B)} B^b = \omega$, since it does not contain any variable, i.e. it is a coefficient of the intervention variable I_t ; and we know that $\frac{\Theta(B)}{\Phi(B)(1-B)^d} e_t$ follows the Box - Jenkins $ARIMA(p, d, q)$, which forms the noise component of the model. Hence, Equation (10) translates to;

$$Y_t = \omega I_t + ARIMA(p, d, q) \tag{11}$$

Equation (11) Forms a Simplified ARIMA-Intervention Model: This theoretical overview has proven that ARIMA model and its versions, particularly ARIMA–Intervention model provide a strong statistical basis for analyzing how interventions such as devolution affect youth unemployment. Even though conventional ARIMA and SARIMA models are accurate at identifying seasonality and temporal trends in unemployment facts, they're not excellent at incorporating structural effects of governance policies. An ARIMA–Intervention framework based on the study of Box and Tiao (1975) gives a methodological advantage by allowing the explicit evaluation of the policy shocks. Therefore, an ARIMA–Intervention model guided this study as the most appropriate theoretical tool to capture the effect of devolution on youth unemployment rates behavior in Kenya.

2.1.4 Decentralization and Keynesian Theories of Employment

2.1.4.1 Decentralization

Decentralization is the process by which subnational governmental entities, such counties, municipalities or local authorities, receive political, administrative and financial authority from the central government. Decentralization's primary justification is that local governments are better equipped to recognize and respond to the particular requirements of their communities, such as job creation and economic development (Rondinelli *et al.*, 1983).

Decentralization is argued to boost local labor markets in the context of employment by promoting local development projects that generates jobs suited to the unique needs and resources of local communities, fostering participatory governance, which gives citizens a say in policies that impact labor market outcomes and improving resource allocation efficiency, which permits focused investments in sectors like infrastructure, education and employment-generating industries (Smoke, 2003; Faguet, 2014; Oates, 1999).

2.1.4.2 Keynesian Theory of Employment

The classical view that markets self-correct to full employment is challenged by the Keynesian theory of employment, by John Maynard Keynes in *The General Theory of Employment, Interest and Money (1936)*. Keynes maintained that aggregate labor demand is what drives employment, and not price and pay flexibility. The Keynesian perspective states that government interventions should use fiscal policies (such as public works and social programs) to increase labor demand in order to create jobs during periods of high unemployment. Additionally, an increase in government expenditures boosts economic activities beyond the initial investments by creating more job opportunities and income (Keynes, 1936).

The function of government interventions in promoting labor demand and job creation is where decentralization and Keynesian theories of employment intersect. Decentralization increases the efficacy of these interventions by making them more context-specific and sensitive to local labor market dynamics.

2.2 Empirical Review

2.2.1 International Evidence

Karlson and Javed evaluated the predictive accuracy of Seasonal Autoregressive Integrated Moving Average (SARIMA), Self-Exciting Threshold AutoRegressive (SETAR) and VAR time series models using the Sweden's unemployment rates. This method sought to select an appropriate and straightforward model, producing insightful ideas and recommendations. The models' fit was demonstrated using secondary data on unemployment rates from 1983 to 2010 obtained from the Organization for Economic Cooperation and Development (OECD). A recursive approach for out-of-sample assessment used the data from 2011 to 2015 to evaluate the forecasting performance of the models. The study found that, especially in short-term forecasting, the Self-Exciting Threshold AutoRegressive (SETAR) and SARIMA models performed better than the VAR model (Karlson & Javed, 2016). The study did not, however, take intervention analysis into account, which would have enhanced comprehension of the consequences of policy.

Three primary objectives of a study using ARIMA model were; to forecast the unemployment rates of Saudi workers by 2030; to investigate the relationship between the unemployment rate, GDP and population growth; and to provide an explanation for the declining trend in the Saudi labor market's unemployment rate. The dataset used in this analysis included population growth, GDP and Saudi Arabia's unemployment rates from 1999 to 2019. The statistical data under examination had a noteworthy pattern and was best suited for forecasting over the ensuing decade using the ARIMA (1, 0, 0) model. According to the analysis, unemployment rates was predicted to surpass the Saudi Vision 2030 target by 2030, reaching 10.99%. Contrary to popular economic beliefs, GDP and population expansion also had negligible effects on unemployment (Sharahiley, 2020). However, policy initiatives like devolution, which can have an impact on unemployment trends, were not examined in the study.

2.2.2 African and Regional Evidence

Didiharyono and Syukri conducted applied research using quantitative secondary data on unemployment rates from South Sulawesi's Central Statistics Agency. The study objective was to use an ARIMA model to forecast South Sulawesi's open unemployment rates. Based on their research findings, they concluded that ARIMA (1, 2, 1) was the best time series model for forecasting the future unemployment rates. The results of their study showed that unemployment rates had shown an increasing trend annually. They hoped that the government, especially the South Sulawesi provincial administration, would develop efficient plans and policies to address the unemployment problem. The results underlined the necessity of government initiatives to generate employment opportunities, including trainings in entrepreneurship, the growth of tourism and greater funding for the agricultural and marine sectors (Didiharyono & Syukri, 2020).

Nigerian unemployment rates were analyzed using ARIMA model. The analysis used annual secondary data from 1972 to 2014. In order to analyze Nigeria's unemployment rates, four distinct ARIMA models were identified and examined. The findings showed that an ARIMA (2, 1, 2) model was the most effective option among the identified options for analyzing Nigeria's unemployment rates over the studied period. The chosen ARIMA model was used to forecast Nigeria's unemployment rates from 2015 to 2018. From 2015 to 2017, Nigeria's projected unemployment rates increased; however, in 2018, they somewhat decreased. The rates stayed rather high between 2015 and 2018. The selected ARIMA model was shown to be stable upon analysis of its diagnostics (Adenomon, 2017). However, they did not consider the role of devolution or government interventions in unemployment fluctuations.

A study fitted a model, examined the pattern and forecasted Nigeria's unemployment rates. The primary statistical technique employed was a univariate time series modeling (Autoregressive Integrated Moving Average model). The secondary data obtained from the World Economic Outlook Database, CBN publications, the International Monetary Fund and the NBS bulletin was used in this study. Nigerian unemployment rates from 2000 to 2018 were included in the data. Differentiating was used to achieve stability since the time series plots showed that the unemployment rates varied over time. ARIMA (1,1,1), ARIMA (2,1,1), ARIMA (2,1,2), ARIMA (2,2,1) and ARIMA (2,2,2) were among the various ARIMA models that were taken into consideration. The models had the following log-likelihood and AIC values: (111.08, -50.54,) (109.22, -50.61), (111.36, -50.68) and (107.52, -50.76), respectively. An ARIMA (1, 1, 1) model was selected since it had the highest log likelihood and the lowest AIC value among the examined models. According to the study's findings, the fitted model can be used to forecast, monitor and control Nigeria's unemployment rates. To combat unemployment, the report suggested curriculum improvements, economic diversification and industrialization (Adesegun *et al.*, 2020).

2.2.3 Kenyan Evidence

Using the Autoregressive Distributed Lag (ARDL) model, the association between Kenya's youth unemployment rate and per capita income was investigated. The model was chosen due to its flexibility in analyzing the short-term and long-term effects of both stationary and non-stationary variables. The study was anchored on Okun's law, which states that a 2% rise in Gross Domestic Product (GDP) is equivalent to a 1% drop in unemployment (a 1% rise in employment). The World Bank database provided secondary time series data for the study, which covered the years 1991 to 2021. The results showed that youth unemployment rates increased by 4.88% for every 1% increase in per capita income. The surprising conclusion was that Kenya is experiencing *"jobless growth,"* in which economic expansion does not result in a significant number of new jobs (Okuom *et al.*, 2023). Nevertheless, the impact of devolution on youth employment was not taken into account in the study.

In order to ascertain how non-technological factors, such as labor supply, affect young people's employability, a Probit model was used to analyze the determinants impacting youth unemployment in Kenya. The model was used to assess how youth's family background and personal circumstances affect their employment prospects in Kenya. According to the study, there is skills mismatch in the labor market since young people with only secondary or vocational education had greater unemployment rates compared to those with tertiary education. Key drivers of employment were found to include household factors (financial status and family size) and personal characteristics (age, gender, location and educational attainment) (Wamalwa, 2009). The study did not, however, look at how devolution has influenced the development of youth employment prospects.

The macroeconomic variables affecting youth unemployment (YUN) in Kenya were evaluated using applied cointegration analysis. Gross domestic product (GDP), external debt (ED), private investment (PI), Foreign Direct Investment (FDI), youth population (POP) and youth literacy rate (LR) were considered as the independent variables. According to the study, GDP, external debt, foreign direct investment, private investment, literacy rates and youth population growth all accounted for 84.08% of the differences in youth unemployment. According to the study results, youth unemployment rates rose by 1.3225%, 0.356204%, 0.269%, 0.002441% and 0.154216% respectively, for every 1% increase in GDP, ED, FDI, PI and LR. The *"jobless growth"* theory was further supported by the thought – provoking finding that there was a positive correlation between GDP growth and youth unemployment (Sam *et al*, 2020). The study however, did not account for the role of devolution in shaping labour market dynamics.

A study looked at the connection between Kenya's economic growth and youth unemployment. The Granger causality test and the Ordinary Least Squares (OLS) methods were used to demonstrate the relationships between the variables using secondary data. Keynesian theory, Okun's law, the Solow-Swan model and surplus-value theory were among the theories that guided the study. These theories aid in the explanation of economic growth and unemployment. According to the study, Okun's law does not apply to youth unemployment in the Kenyan economic context. The correlation between economic growth and youth unemployment was found to be 0.708, far larger than the 0.03 suggested by Okun's law. Furthermore, Okun's inverse relationship between youth unemployment and economic growth did not hold. The results demonstrated that economic growth by itself is insufficient to explain trends in youth unemployment; thus, it was recommended that additional factors be examined in order to have a more thorough understanding of the changes in youth unemployment (Katumo, 2021). This emphasizes the necessity of investigating policy measures like decentralization and governance in order to alleviate youth unemployment.

The impact of youth unemployment on Africa's economic development was examined using the classical theory. The information was gathered, examined and disseminated using both quantitative and qualitative research approaches. With a sample size of 384 participants, this study used primary data that was collected using questionnaires and interviews. Officials from non-governmental organizations (NGOs) that assist young people in Nairobi, as well as community leaders, youth and religious leaders, were selected through the use of purposeful sampling techniques. Microsoft Excel and the Scientific Package for Social Sciences (SPSS) were used to conduct the analysis. According to the report, growing unemployment impeded economic growth and retarded development. The study criticized the absence of follow-up procedures in current government programs, while also recognizing Kenya's efforts to combat youth unemployment (Munyao, 2019). The study did not, however, examine how devolution contributes to the development of jobs.

Kenyan youth unemployment was predicted using a multivariate linear regression model that took into account population growth, GDP and Foreign Direct Investments (FDI). The World Bank databank provided secondary data for this study, including data on youth population, GDP growth rate and FDI from 2000 to 2017. SPSS software and E-Views 8 were used for data analysis. According to the study findings, youth unemployment and GDP are positively correlated ($B_1 = 0.027$). Additionally, the study discovered that a one-unit shift in FDI would result in a 0.034 unit increase in youth unemployment, provided all other parameters remained constant. On the other hand, youth unemployment would drop by 1.543 units for every unit increase in population growth. According to the study, strategies that draw in foreign direct investment should be taken into account by both national and local governments. These investments can boost GDP growth by adding value and utilizing funds from external debt (Monari *et al.*, 2020). Devolution, however, was not taken into consideration as a variable in the analysis of the study.

In Kwale County, Kenya, the relationship between youth unemployment and insecurity was investigated between 2010 and 2018. The research design used in this study was mostly descriptive. Youth leaders, police officers, Kwale County government representatives, Kwale County national government administration personnel and members of the religious community participated in the focus group. Focused group discussions, interviews and questionnaires were employed in the study to gather primary data. According to the survey, majority of the youths in Kwale County were either unemployed or working in low-wage formal occupations like fishing, boat riding, *boda* riding and small-scale trading (Riechi, 2019). Although this study emphasized the security threats linked to youth unemployment, it did not investigate how devolution can help address the issue.

The effect of devolution on Kenya's economic development was assessed using a descriptive research design, with a particular emphasis on the Nakuru East sub - county. The results of the study demonstrated that the situation had clearly improved following the introduction of devolution. The results of the survey also showed that devolution had improved the social and economic standing of the residents of the Nakuru - East constituency. The study's conclusion demonstrated that devolution greatly enhanced social and economic circumstances, but they also highlighted the necessity of greater policy execution and accountability (Nimrod, 2016).

A study was carried out to determine the impact of decentralized funds on Kenya's economic growth from 1993 to 2012. Research techniques based on the secondary data were used. The study findings supported the arguments made by those who opposed that devolution had led to economic growth. Fiscal decentralization was accomplished through decentralized finance. As recommended by the two distinct schools of thought on fiscal decentralization, it was divided into capital finance and recurrent finance in order to isolate the effects of each on economic growth. All of the model's fiscal decentralization components had a negative correlation with economic growth. This suggested that poor management of devolved resources may have hampered development and that fiscal decentralization had a detrimental effect on economic growth (Nzau, 2014).

It is clear from this literature analysis that devolution has not been taken into consideration as an intervention when modeling Kenya's youth unemployment rates. This study therefore aimed at bridging this gap by fitting a suitable time series model (ARIMA-Intervention model) to explain the effect of devolution on Kenya's youth unemployment rates. Periods before (1991 - 2012) and during (2013 - 2022).

III. METHODOLOGY

This study applied quantitative time series analysis to model the effect of devolution on youth unemployment. Secondary data from the World Bank databank, covering youth unemployment rates in Kenya from 1991 to 2022 was used. The yearly data was interpolated into quarterly observations using a stochastic approach based on the Skewed Generalized Error Distribution (SGED) so as to enhance temporal resolution. In this study, the adoption of devolution, implemented in 2013 following the enactment of Kenya's 2010 Constitution, was treated as the intervention variable and youth unemployment rates as the time series variable of interest (dependent variable), hence justifying the use of ARIMA - Intervention model. Python programming was used for computational analysis.

To measure the effect of devolution starting in 2013, a ramp function was used; and the intervention variable I_t was defined as:

$$I_t = \begin{cases} t - 2013, & \text{if } t \geq 2013 \\ 0, & \text{if } t < 2013 \end{cases} \quad (12)$$

Where; $t = 1991, 1992, \dots, 2022$

The intervention-enhanced model was specified as;

$$Y_t = \mu + \omega I_t + N_t \quad (13)$$

where Y_t is the youth unemployment rate at time t, μ is the intercept value, ω is the intervention effect parameter (measuring the effect of devolution on youth unemployment rates), I_t is the intervention variable (representing the occurrence of devolution) and N_t is the noise component (pre – intervention model) modeled as ARIMA(p, d, q)(P, D, Q)[s]. The presence of the seasonality component is as a result of using the quarterly data.

Rewriting the model in Equation (13), we obtained a full ARIMA – Intervention model as;

$$Y_t = \mu + \omega I_t + \text{ARIMA}(p, d, q)(P, D, Q)[s]. \quad (14)$$

Where:

p is the order of Autoregressive component polynomial, d is the ordinary differencing order, q is the order of the Moving Average component, P is the order of the Seasonal Autoregressive component, D is the order of Seasonal differencing, Q is the order of the Seasonal Moving Average component and s represents a seasonality pattern.

Pre-Intervention Model Identification

The Box-Jenkins methodology was used to identify $ARIMA\ (p, d, q)\ (P, D, Q)\ [s]$ model. The Box-Jenkins methodology involved three systematic approaches, that is, model identification, model comparison and selection, and diagnosing to validate the model (Box, *et al*., 1976).

Model Identification Stage: This stage involved analysing the data on youth unemployment rates before devolution so as to identify the order of autoregressive, moving average and differencing components that best fits the data.

Testing for Stationarity: Stationarity is a fundamental assumption in time series analysis, ensuring that the statistical properties of a time series such as mean and variance remain constant over time. A stationary time series simplifies modelling by maintaining consistency in its behaviour. Augmented Dickey-Fuller (ADF) test was employed to determine whether the time series data was stationary. The test detected for the presence of a unit root (a sign of non - stationarity) in the youth unemployment rates, that is, when the statistical properties such as the mean and variance change over time.

Model Comparison and Selection: Several ARIMA models were identified and compared based on their Akaike Information Criterion (AIC) values. The model with the lower AIC was selected as the best-fitting model. This approach balances model accuracy with parsimony. AIC is straightforward in that it provides a quick assessment of the model without requiring data splitting, making it more flexible for practical applications. Also, it prioritizes models that offer the best predictive accuracy, more lenient in penalizing complexity and often used in situations where the goal is prediction, not necessarily finding the fit model (Burnham & Anderson, 2004).

The AIC value of the model is computed as:

$$AIC = n\, log(\sigma_e^2) + 2(k + 1) \quad (15)$$

Where;

n is the number of observations used for parameter estimation, σ_e^2 denote the error variance and k is the number of parameters estimated in the model.

Diagnostic Checking Stage: Having selected and estimated the suitable model parameters, the model residuals were examined to assess the adequacy and stability of the fitted model. This involved checking whether the residuals are white noise, meaning they don't show any patterns, that is, if they are uncorrelated (*independently and identically distributed (iid)*) and normally distributed with zero mean (approximately).

Estimation of ARIMA - Intervention Model Parameters: Having identified and selected the noise model at the pre-intervention analysis stage, the parameters of full regression form of the ARIMA - Intervention model which incorporated devolution policy I_t as an intervention (Equation (14)) were estimated over the entire data period (1991 - 2022) using maximum likelihood estimation (MLE) method, under the assumption that $e_t \sim N(0, \sigma_e^2)$.

IV. FINDINGS & DISCUSSION

4.1 Pre – Intervention (Noise) Model

To assess the effect of devolution on youth unemployment rates in Kenya, an ARIMA model was first fitted to the quarterly interpolated data covering 1991 to 2012 so as to obtain the pre-intervention model. Following the Box-Jenkins methodology, the time series data was first tested for stationarity and structural patterns.

4.1.1 Testing for Stationarity

The Augmented Dickey-Fuller (ADF) test was employed to check if the series was non-stationary, i.e. if the statistical properties such as the mean and variance changed over time. The following hypotheses at 5% level of significance guided the test:

H_0: The time series is not stationary
Vs
H_a: The time series is stationary

Table 1 displays the results of the Augmented Dickey-Fuller (ADF) test at the 5% level of significance.

Table 1
Augmented Dickey-Fuller (ADF) Test Results

ADF Stat	Critical value	P-value
-9.0931	-2.850	3.7782e-15

From Table 1, the p-value of the ADF test, 3.7782e-15 ≈ 0.0000 is less than the significance level of 5%, the null hypothesis was therefore rejected in favour of the alternative hypothesis. Since the series is already stationary, further transformations like differencing were unnecessary (which implies that *d=0* and *D=0*).

Seasonality: Seasonal Autocorrelation function (ACF) and Partial Autocorrelation function (PACF) plots suggested a seasonal structure with a quarterly lag of 4. A significant spike at lag 4 in the seasonal ACF plot suggested the presence of a seasonal moving average component. As a result, the pre-intervention model identified through the Box-Jenkins methodology was ARIMA(0,0,0)(0,0,1)[4]. This specification implies that there is no non-seasonal autoregressive (AR) or moving average (MA) components, but includes a seasonal MA (1) term with quarterly seasonality.

4.1.2 Diagnostic Checking of the Noise Model

Here, the study examined how well the selected noise model fits the data, i.e. if the residuals of the selected model are white noise (if they are independently and identically distributed (iid)) and normally distributed with mean 0 and variance σ_e^2.

The Ljung-Box test was conducted, Q - Q plot of residuals was examined and also looked at the histogram of residuals overlaid with a normal curve. The results are presented in Table 2, Figure 1 and Figure 2.

Ljung-Box Test: To assess the adequacy of the selected time series model, Lung-Box test was applied to the model residuals. This test was used to evaluate whether the residuals exhibit significant autocorrelation at different lag levels. The following hypotheses were tested at $\alpha = 0.05$.

H_0: The residuals are white noise
Vs
H_a: The residuals are not white noise.

Table 2 presents the Ljung-Box test statistics and their corresponding p-values for lag 1 - 10. Stopping at lag 10 is a practical choice to detect autocorrelation while maintaining statistical reliability, avoiding over fitting and ensuring the test remains meaningful for model diagnostics.

Table 2
Ljung-Box Test Results for the Noise Model Residuals.

Lag (k)	Test statistic	P-value
1	0.045972	0.830228
2	0.201101	0.904340
3	0.431557	0.933649
4	1.347016	0.853350
5	1.638560	0.896547
6	1.671012	0.947337
7	1.700811	0.974533
8	1.834562	0.985670
9	2.891880	0.968428
10	3.070372	0.979719

The results presented in Table 2 shows that the p-values across different lags are greater than 0.05, hence we fail to reject the null hypothesis indicating that the residuals are white noise. This suggests that the noise model sufficiently captures the data before devolution, validating its adequacy.

4.1.3 Normal Q-Q Plot of Residuals

Figure 1 presents a Quantile-Quantile plot, which was used to assess the normality assumption of residuals from the fitted model. The plot compared the quantiles of the residuals against the theoretical quantiles of a normal distribution.

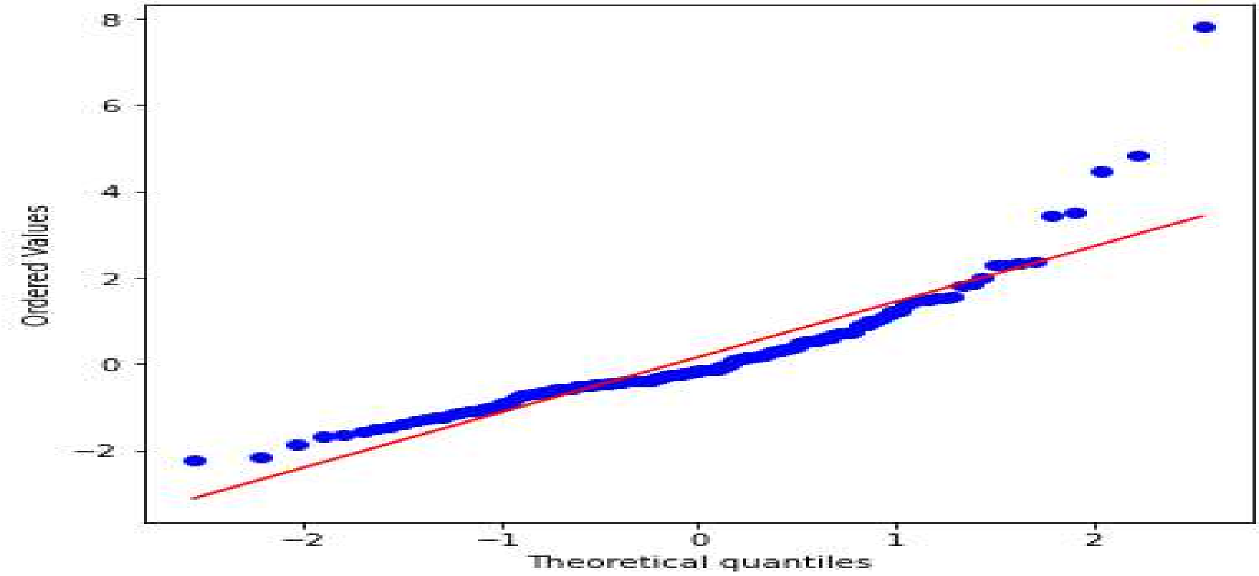

Figure 1
Normal Q - Q Plot of Residuals

It is clear from Figure 1 that the points align closely along the reference line, indicating that the residuals are normally distributed.

4.1.4 Histogram of Residuals

Figure 2 presents a histogram of residuals for the fitted model. The histogram provided a visual assessment of the residuals' distribution, helping to evaluate whether they follow a normal distribution with mean zero.

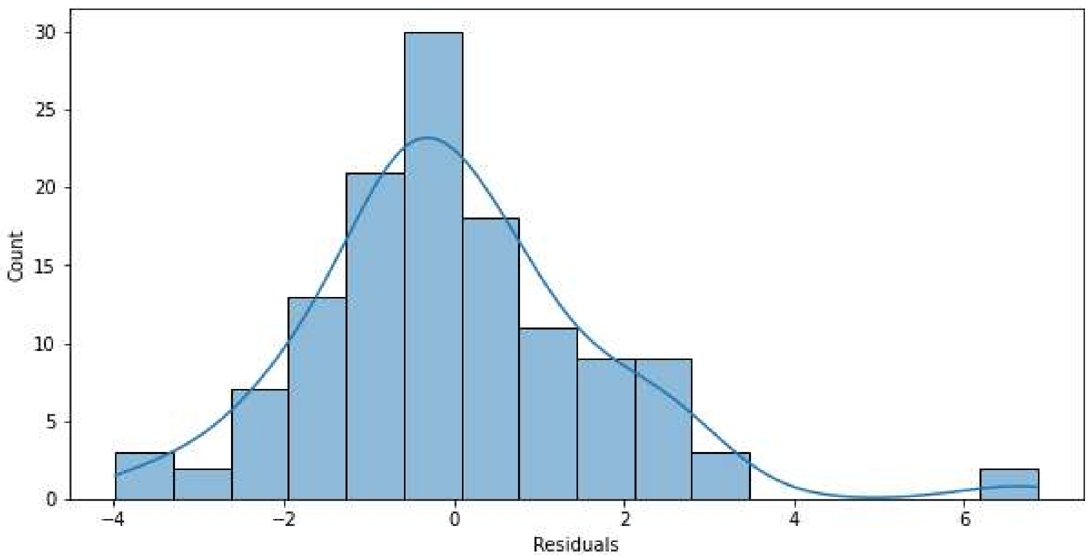

Figure 2
Histogram of Residuals for the Noise Model

It appears from Figure 2 that the histogram is symmetric and bell-shaped, which indicates that the residuals are normally distributed with an average value centred around zero, which is in line with our assumption that $e_t \sim N(0, \sigma_e^2)$.

These diagnostics validate that the noise model is appropriate since the residuals behave like white noise.

4.2 ARIMA-Intervention Model

After identifying the order of the noise model, parameter estimates for ARIMA (0, 0, 0) (0, 0, 1) [4] model incorporating devolution as an intervention variable were estimated and the results are shown in Table 3. The primary objective was to assess whether devolution had a statistically significant effect on youth unemployment rates by evaluating the significance of the intervention effect parameter. The following hypotheses were tested at 5% significance level:

H_0 : There is no intervention effect ($\omega = 0$)
Vs
H_a : There is intervention effect ($\omega \neq 0$)

The estimated parameters of ARIMA (0, 0, 0) (0, 0, 1) [4] model with devolution intervention are presented in Table 3.

Table 3
Estimated Parameters of ARIMA (0, 0, 0) (0, 0, 1) [4] *Model Incorporating Devolution Intervention.*

Parameter	Estimate	Std. Error	t-statistic	p-value	Significance
Intercept (μ)	6.4982	0.189	34.36	<0.001	Significant
Intervention effect (ω)	0.2004	0.010	19.83	<0.001	Significant
SMA(1)	0.2127	0.104	2.038	0.042	Significant
MSE	1.4543	0.157	9.256	0.000	Significant

According to the ARIMA-Intervention analysis presented in Table 3, devolution, which was implemented in 2013, had a considerable effect (statistically significant) on the dependent variable of youth unemployment rates. Devolution, considered as the independent variable, is associated with higher youth unemployment rates as indicated by the positive coefficient of the intervention effect parameter (0.2004, $p < 0.001$).
From Table 3, the noise model becomes:

$$N_t = 6.4982 + 0.2127 e_{t-4} + e_t \quad (16)$$

Rewriting Equation (14) using the estimated model parameters in Table 3 and the specified noise model in Equation (16), the fitted ARIMA – Intervention model was obtained as:

$$Y_t = 6.4982 + 0.2004\, I_t + 0.2127 e_{t-4} + e_t \quad (17)$$

Where Y_t represents youth unemployment rate at time t, I_t is the occurrence of devolution at time t and e_t is the white noise process.

4.2.1 Model Diagnostics of ARIMA – Intervention Model

Diagnostic checks were conducted on the residuals of the fitted ARIMA-Intervention model to validate model assumption, i.e. $e_t \sim N(0, \sigma_e^2)$. Figure 3 show the PACF of residuals. Figure 4 presents the Q - Q plot for residual normality check. Additionally, the Ljung-Box test was conducted to check if the residuals are white noise and its results are presented in Table 4.

4.2.2 Partial Autocorrelation Function (PACF) Plot of Residuals

Figure 3 presents the PACF plot, which illustrates the correlation between the model residuals and their lagged values. It was used to determine whether the residuals (differences between observed and predicted values) exhibit autocorrelation, which would indicate a violation of the *iid* assumption in the model residuals.

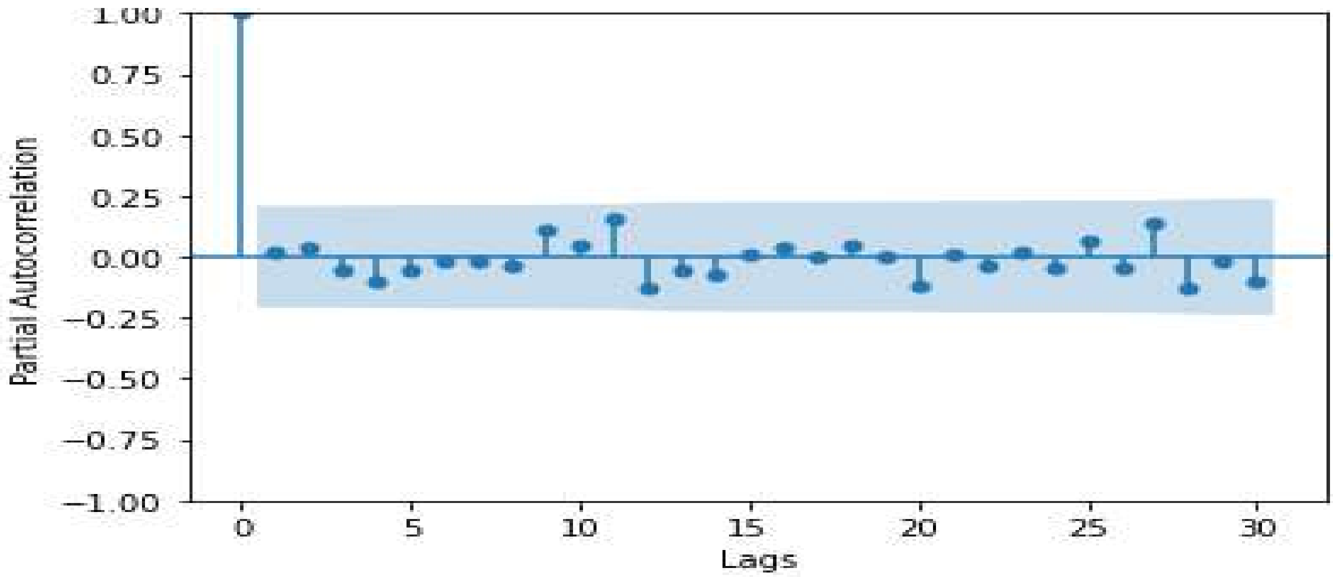

Figure 3
PACF Plot of Residuals for ARIMA - Intervention Model.

From Figure 3, all the estimated autocorrelations of the residuals for lags 1-30 are within the 95% significance bounds. Since all the lags with autocorrelations does not fall outside these bounds, it suggests that there is no significant relationship between the residuals, which led to a conclusion that they are *iid*.

4.2.3 Normal Q-Q Plot of Residuals

Figure 4 presents a Quantile - Quantile plot, which was used to assess the normality assumption of residuals from the fitted model. The plot compared the quantiles of the residuals against the theoretical quantiles of a normal distribution.

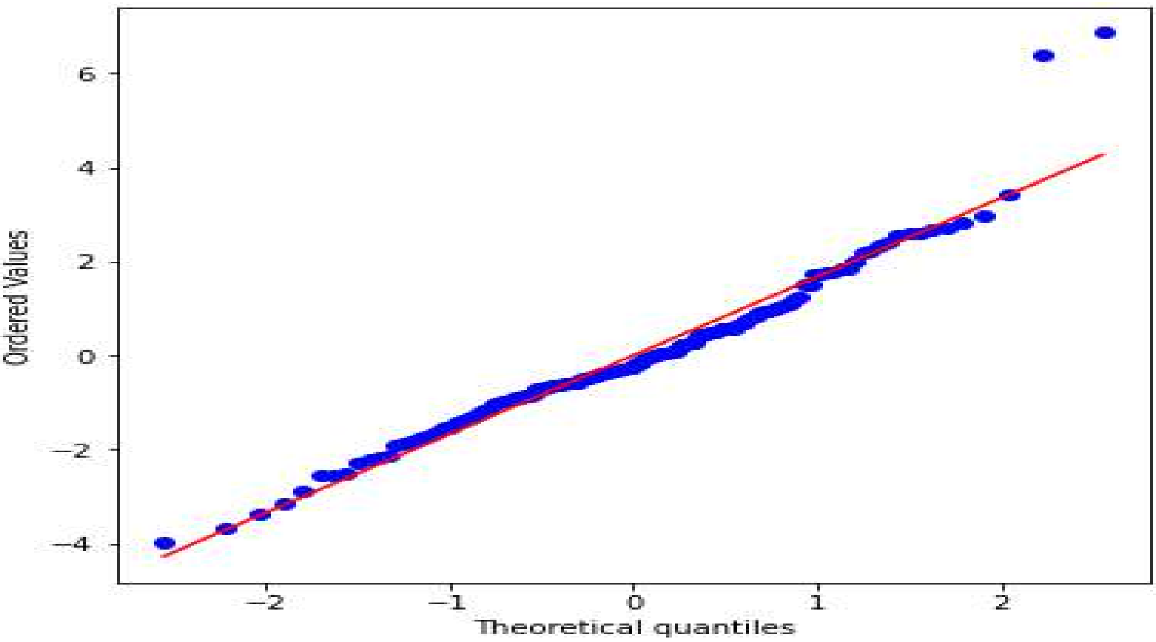

Figure 4
Q-Q Plot of ARIMA-Intervention Model Residuals.

It is clear from Figure 4 that the points align closely along the reference line, indicating that the residuals are normally distributed.

4.2.4 Ljung - Box Test

This test was used to evaluate whether the residuals exhibit significant autocorrelation at different lag levels, i.e. if they are white noise. Tested hypotheses at 5% significance level:

H_0: The residuals are white noise
Vs
H_a: The residuals are not white noise.
The Ljung - Box test results are summarized in Table 4.

Table 4
Ljung - Box Test Results for Model Residuals, for White Noise Assumption.

Lag (k)	Test statistic	P-value
1	0.011993	0.912796
2	0.556732	0.757020
3	1.356709	0.715713
4	1.358038	0.851454
5	1.367066	0.927882
6	1.383118	0.966877
7	1.685359	0.975191
8	1.861703	0.984962
9	1.954703	0.992164
10	2.239935	0.994148

The results in Table 4 show that the p-values from lag 1 to lag 10 are all greater than 0.05. The study therefore failed to reject the null hypothesis and concluded that the residuals are white noise, which implies that they show no autocorrelation and therefore they are independently and identically distributed *(iid).*

4.3 Comparative Analysis

4.3.1 Evaluating the Effect of Devolution on Youth Unemployment Rates

The pre-intervention noise model was employed to forecast counterfactual youth unemployment rates for the devolution period. These forecasts served as a baseline for comparison, enabling a qualitative assessment of the observed deviations and thereby facilitating a deeper understanding of the intervention's effect.

Youth unemployment rates over time are illustrated in **Figure 5**, where a red-dotted vertical line marks the onset of devolution in 2013. This visual comparison highlighted potential shifts attributable to the policy change.

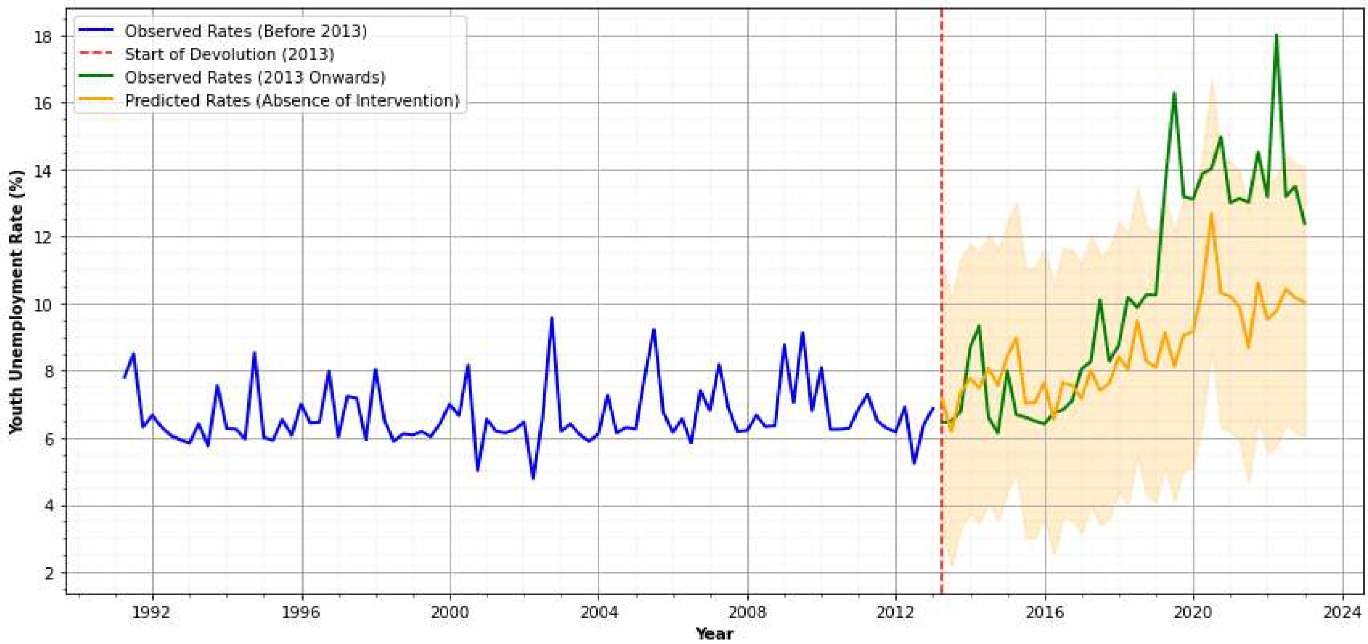

Figure 5
Observed and Predicted Youth Unemployment Rates in Kenya (1991 - 2022)

From Figure 5, the blue line represents the observed youth unemployment rates before devolution, while the green line shows the observed rates during the devolution period. Prior to 2013, unemployment rates generally fluctuated between 6% and 8%. However, following the onset of devolution in 2013, there is a noticeable upward trend, with rates gradually increasing and peaking between 16% and 18%. The orange line indicates the predicted youth unemployment rates, based on the fitted ARIMA - Intervention model (in Equation (17)), assuming there was no intervention effect.

The shaded orange region represents the associated 95% confidence interval, illustrating the range within which the predicted values would likely fall suppose devolution was not implemented.

The intersection points effectively mark transitions between periods where devolution appeared to be outperforming expectations (green line observed below the orange line) and under-performing expectations (green line observed above the orange line). The initial intersection occurred shortly after the devolution policy implementation. At this point, the observed and predicted values were almost similar (approximately 6% to 7%), which represents the moment before devolution effect became apparent. At the second intersection (2015 - 2016), the observed rates temporarily dropped below predictions. This could indicate a brief period where devolution appeared to be working as intended or where other economic factors temporarily counteracted negative effects. The third intersection occurred at around late 2016 - 2017, after which the observed rates crossed above the predicted line. This marked the beginning of a sustained period where actual unemployment rates significantly exceeded predictions.

The fact that the observed line (green) spends significantly more time above the predicted line (orange), particularly with substantial magnitude, suggests that devolution policy likely had an overall negative effect on youth employment outcomes compared to what would have been expected suppose it was not implemented. This unexpected rise contradicts expectations, as devolution aimed to create more job opportunities. For instance, macroeconomic shocks such as inflation, exchange rate volatility and slow economic growth could have constrained policy implementation hindering job creation, making it harder for youth to find employment despite devolution efforts. Additionally, corruption, political instability during election cycles and anti-government demonstrations may have disrupted economic activities and discouraged investments which may have affected job creation. Structural factors such as skills gap between graduates and labor market demands, could also have played a role, limiting the effectiveness of devolution in addressing youth unemployment. These findings implies that while devolution has had a notable effect, additional measures are necessary to optimize its benefits for youth employment.

4.3.2 Youth Unemployment Rates before and during Devolution

To further assess the effect of devolution, this subsection compares youth unemployment rates during the pre and post-intervention periods. The analysis incorporated a counterfactual scenario to estimate what the unemployment trend might have looked like in the absence of devolution.

Figure 6 presents a flow chart illustrating the trend in youth unemployment rates before and during the devolution period, alongside a counterfactual mean projection representing the expected rate had the devolution intervention not occurred.

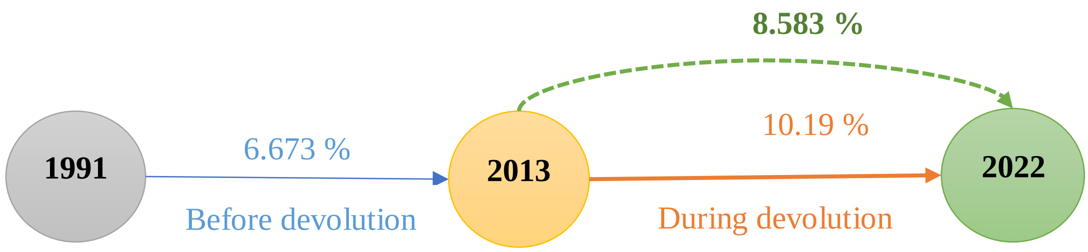

Figure 6
A Flow Chart Summarizing the Comparative Analysis Results.

As illustrated in Figure 6, the average youth unemployment rate before the implementation of devolution was approximately 6.67%. Following the introduction of devolution, this rate increased to about 10.19%. In comparison, the counterfactual scenario assuming devolution had not been implemented suggests an expected average unemployment rate of 8.583%, which is notably lower than the observed rate during devolution. The estimated absolute effect of devolution on youth unemployment is therefore approximately 1.607%. In relative terms, this reflects an increase of 24.09 %. Given the low likelihood of this change occurring due to random fluctuations alone, the results implies that the increase in youth unemployment during the devolution period was statistically significant and likely attributable to the intervention (which aligns with the tested significance of the intervention effect parameter, ω in the fitted ARIMA - Intervention model, see Table 3).

4.4 Discussion

According to this study findings, youth unemployment rates significantly rose during devolution. This finding is consistent with other research that emphasized the inefficiencies of devolved governance. While Monari *et al.* (2020) and Sam *et al.* (2020) demonstrated that Kenya is experiencing a *"jobless growth,"* where macroeconomic progress does not transfer into sufficient youth employment opportunities. Also, Nzau (2014) contended that poor management of devolved funds hindered economic growth. These similarities imply that structural inefficiencies and governance issues within devolved entities may be the cause of the observed increase in youth unemployment during devolution.

However, the findings contradicts those of Nimrod (2016), who concluded that devolution has enhanced socioeconomic performance in the Nakuru East sub-county. This significant difference may be due to methodological differences, that is, the current time series analysis representing the nationwide outcomes, which may be more impacted by systemic problems like political instability, corruption and weak institutional capacity, whereas localized studies capture context - specific improvements.

Methodologically, by incorporating devolution as a structural intervention in the ARIMA framework, the current study builds on earlier research on unemployment forecasting (Adesegun *et al*. 2020; Adenomon, 2017; Karlson & Javed, 2016). This demonstrates how effective time series intervention modeling is at reflecting how significant governance reforms will affect the labor market.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

The impact of devolution on youth unemployment rates depends on how effectively local governments manage resources and implement policies for job creation. Devolution may offer opportunities to develop regionally tailored employment solutions, however, if poorly handled, it may lead to a rise in youth unemployment. How successfully devolution is applied, including governance, funding distribution and job market alignment, determines the effectiveness of policy achievements.

The impact of a particular event on the time series of interest can be assessed with the aid of intervention modeling. An ARIMA - Intervention model was used in this study to analyze the effect of devolution on Kenya's youth unemployment rates. Implementation of devolution was viewed as a means of generating job opportunities, hence justifying it as an appropriate intervention in this study. The World Bank data bank (1991 - 2022) provided annual data on Kenya's youth unemployment rates, which were utilized in interpolation of the quarterly data, so as to achieve the minimum sample size requirement of at least 50 data points for time series modeling. Python programming was utilized for computational analysis. From the suggested and assessed candidate models, an ARIMA (0, 0, 0) (0, 0, 1) [4] model was selected as the optimal noise model based on its lowest Akaike Information Criterion (AIC) value.

The effect of devolution was found to be statistically significant, as confirmed by the fitted ARIMA-Intervention model. According to the comparative analysis results, following the introduction of devolution in 2013, the mean unemployment rate surged from 6.67% in the pre - devolution period to 10.19% during the devolution period. The observed rise seemed unlikely to be as a result of random fluctuations. Given the counter factual estimate, assuming devolution was not implemented, youth unemployment rate was roughly 8.583%.

5.2 Recommendations

Based on the upward trend in youth unemployment rates, the study recommended that policymakers prioritize other proactive and targeted interventions to address structural barriers in the youth labour markets. These should include expanding access to skills training and vocational education, fostering youth entrepreneurship through financing and mentorship programs, and aligning education curriculum with labour market needs. Additionally, efforts to stimulate job creation in high potential sectors such as technology and manufacturing will be critical. Taking action in the short term when forecasts are more stable may offer the best opportunity to alter the projected trajectory and prevent youth unemployment from escalating to more critical levels in the long run.

The complicated socioeconomic impact of devolution on youth unemployment rates may not have been adequately captured by the study's assumption of a linear relationship between devolution and youth unemployment rates. In order to capture non - linear correlations and interactions between variables, the study suggests taking into account different machine learning techniques like Random Forests. Furthermore, methods such as Elastic Net Regression may offer flexibility in data modeling without requiring rigid linearity assumptions, enabling a more thorough comprehension of the intricate and dynamic relationship between youth unemployment and devolution.

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