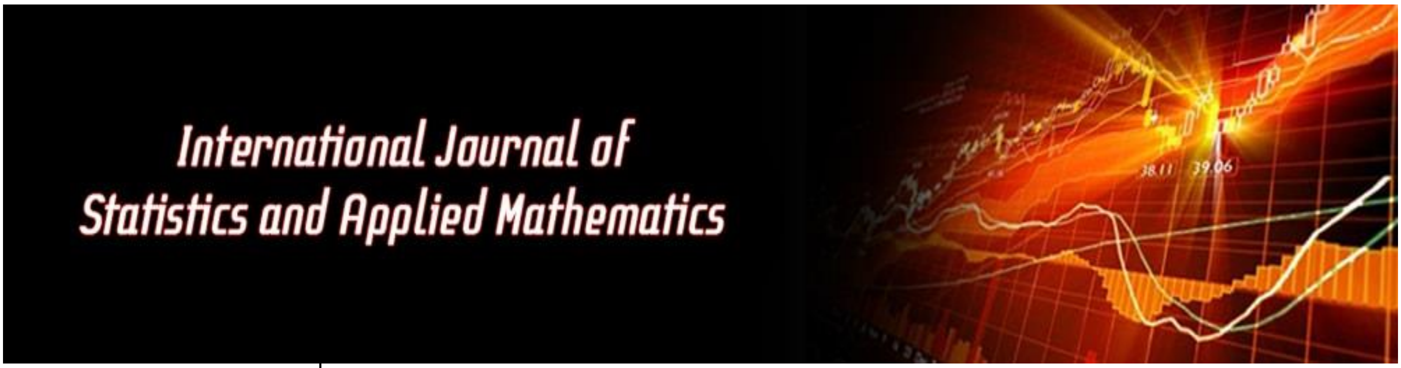

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Autoregressive distributed lag cointegration analysis of youth unemployment in Kenya

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Abstract
In this paper we consider cointegration analysis in an autoregressive distributed lag (ARDL) structure. First, logarithmic transformation is performed on the series to reduce outlier effects and have elasticity interpreted in terms of percentage. Second, the variables are tested for stationarity using Augmented Dickey-Fuller test. Third, the Johansen Cointegration test is carried out to examine cointegration of the series. Fourth, cointegrated dynamic ARDL model is estimated using ordinary least squares (OLS) and effects of variables and their lags interpreted. The results indicate that Gross Domestic Product (GDP) and its two-year lag are the only ones having negative effect on youth unemployment, that is, one unit increase in GDP and GDP two-year lag reduce youth unemployment by 0.207922% and 0.2052705% respectively. Also, one unit increase in External Debt (ED) and ED two-year lag reduce youth unemployment by 0.07303% and 0.009116% respectively. Furthermore, unit increase in one-year lag of youth literacy rate is the only one which reduces youth unemployment by 0.0892691%; one-year and three-year lag of population (POP) reduce youth unemployment by 0.2590455% and 4.3093119% respectively**.** The Foreign Direct Investment (FDI) and Private Investment (PI) do not have significant effects on youth unemployment. In the long run, increase in GDP causes increase in youth unemployment by 0.09148447%. The long run result explains that GDP growth in the country is "jobless growth" mainly in less labour intensive sectors.

Keywords: ARDL, cointegration, youth unemployment

1. Introduction
Unemployment occurs when a person who is actively searching for employment is unable to find work (Davidson, 1998) [2]. Unemployment rate is the number of unemployed persons expressed as a percentage of number of people in the labor force. Although definition of youth varies from one country to another (United Republic of Tanzania, 1995) [26], the United Nations defines youth as persons aged between 15-24 years. However, the Kenya Constitution (GoK, 2010) defines youth as persons aged between 18 and 35 years. In this study, youth unemployment rate is taken as the number of persons aged between 18-35 years and actively looking for employment but unable to find work expressed as a percentage of number of people in the labour force.

In most countries, more young people are unemployed and disenchanted. However, the youth unemployment challenge has been underestimated (Azeng and Yogo, 2013). Youth accounts for 35% of Kenya's population and represent 67% of unemployment (Kenya Population Census, 2009). The youth population growth rate at 4% is higher than national growth rate at 2.9%. The "youth bulge" is a source of distress for governments and non-state actors as unemployment pushes young people to engage in illegal activities like touting, stealing, armed robbery, dealing in drugs, gambling and prostitution (Okojie, 2003). Young people without jobs are prone to crime as a result of psychological hitch and depression (Australia National Health Survey, 1989-90).

In addition, political instability is African governments' worrying concern where large numbers of young people are unemployed. According to (Urdal, 2006) [12] youth bulges favour the risk of three forms of political violence: rioting, civil war, and terrorism. The unemployed youth bulge becomes supply for politicians and extremist groups for political unrest.

Kenya has experienced incessant Islamic terrorist attacks among other internal organized crime with youth as either victims or perpetrators. These social evils are linked to economic conditions of the youth which make them idle. As such, the startling youth unemployment in Kenya needs urgent intervention through policies supported by evidence from research studies.

In the considered literature, the main factor of youth unemployment is GDP. The relationship between GDP and employment has been researched based on Okun's law. Okun (1962) [20] described a coefficient that gives the rate of change of real GDP for a unit in the unemployment rate. According to the law, an increase in the economic growth rate by 3%, above the normal growth rate, reduces the unemployment rate by 1%. The rate of GDP growth must be commensurate with potential growth in order to keep the unemployment rate constant. To reduce unemployment, the rate of GDP growth must be above the growth rate of potential output.

Gul *et al.* (2012) noted that the Phillips curve was a chronological contrary association between the rate of unemployment and the rate of inflation in an economy. It is clearly acknowledged that the lower the unemployment in an economy, the higher the rate of inflation.

Past studies have been conducted to establish economic determinants of unemployment. Valadkhani (2003) [28] verified major determinants of Iranian youth unemployment using simultaneous equation model and time series data between 1968 and 2000. He used consumer price index, output gap, total investment and the exchange rate as variables. He found out that these factors influence youth unemployment rate.

Kabaklarli *et al.* (2011) [8, 17] employed long term cointegration analysis from an econometric analysis perspective to determine the effects of GDP, Price Index, Gross Fixed Capital Formation and Productivity on youth unemployment. The results indicated that inflation and productivity had positive effects on youth unemployment rate even though GDP and investment had negative effects on the long-run.

Based on reviewed literature, the most frequently used variables of youth unemployment are population, GDP, Foreign Direct Investment (FDI), Private Investment (PI), and External Debt (ED). In this study considers education as one of the key determinants of youth unemployment in a mathematical model.

Uwe and Jurgen (2010) considered cointegration analysis within an ARDL structure and the review of cointegration tests based on EC regression paying particular attention to linear time series without detrending. The results indicated that conditional error correction model is superior to unconditional one. This study adopts the dynamic ARDL to analyze detrended variables.

In order to avoid spurious regression, variables are tested for stationarity and cointegration before analysis. Further, Engle and Granger (1987) [6, 7]; Johansen (1991) [13]; Phillip (1991) [21, 23]; Phillip and Hansen (1990) [22]; and Phillips and Loretan (1991) [21, 23]; Dickey and Fuller (1979 and 1981) provide tests for unit roots.

2. Methodology

Data

To conduct estimation procedure of ARDL that would determine the contribution pattern of GDP, ED, FDI, PI, LR and POP to youth unemployment in Kenya, annual data covering the period between 1979 and 2015 is used. The logarithm transformation is applied to macroeconomic data obtained from World Bank and Kenya National Bureau of Statistics (KNBS). The transformation enables interpretation of elasticity in terms of percentage and reduces effects of outlier data points. In some cases, log transformation solves the problem of heteroskedastisity.

Model

The functional form of the model is given in equation,

$$YUN = f\,(GDP, FDI, PI, ED, LR, POP) \tag{1}$$

The general form of ARDL model with both dependent and independent variables lagged up to *p* and *q* respectively is given by

$$Y_t = \delta + \sum_{i=1}^{p} \theta_i\, Y_{t-i} + \sum_{j=1}^{q} \beta_j X_{t-j} + \in_t \tag{2}$$

Where,

y_t is the dependent variable, $\mathrm{x_t}$ is independent variable, δ is the impact multiplier, θ_i is the distributed lag weight of Y_t, p is the lag length of $\mathrm{Y_t}$, q is the lag length of X_t, $\in_t$ is the error term, t is time.

Assumptions of ARDL:

1. $t = q+1, \cdots, T$, Y_t and X_t are stationary random variables
2. $\in_t$ is independent of current past and future values of X_t.
3. $\mathrm{E}(\in_t) = 0$, $\mathrm{Var}(\in_t) = \sigma^2, cov(\in_t, \in_s) = 0, t \neq s, \in_t \sim N(0, \sigma^2)$

Choosing the length of lags p and q

The study uses Akaike Information Criterion (AIC), Bayesian Information Criteria (BIC), and Final Prediction Error (FPE). These involve choosing lags *p* and *q* that minimizes the sum of squared errors (SSE) subject to increase in number of parameters. This involves deciding on trade-off between number of parameters and sum of squared errors. In most economic autoregressive (AR) models, the number of lag on unemployment is taken to be one (1). In this case our *p* is one. Choosing the order *q* of an autoregression requires balancing the marginal benefit of including more lags against the marginal cost of additional estimation uncertainty (Stock and Watson, 2007) [14]. Increasing lag lengths increases the number of parameters but reduces sum of squared errors (SSE). However, if the order of an estimated autoregression is too low, you may omit valuable information contained in the more distant lagged values. Also, if the order is too high, you will estimate more coefficients than necessary. The Schwarz Criterion estimates SC(*q*) by minimizing an information

$$I(q) = ln(q) + \ln(q+1) \quad (3)$$

Where Residual Sum of Squares (RSS (q)) is the sum of squared residuals of the estimated autoregression (AR(q)). The BIC estimator of p,
q is the value that minimizes BIC (q) among the possible choices q = 0,1, …q_{max}, which is the largest value of q considered. Since the regression coefficients are estimated using OLS, the sums of squared residuals necessarily decrease when you add a lag. The second term is the log of the number of estimated regression coefficients (the number of lags, q, plus one for the intercept) times the factor$\frac{lnT}{T}$. This second term increases when a lag is added. The SC trades off these two forces so that the number of lags that minimizes the SC is a consistent estimator of the true lag length.

$$AIC = ln\left(\frac{SSE}{T}\right) + \frac{2K}{T} \quad (4)$$

Where,$K = q + p + 2$ the number of coefficients estimated, SSE is sum of squared error.

$$BIC = ln\left(\frac{SSE}{T}\right) + \frac{Kln(T)}{T} \quad (5)$$

$$FPE = \det\{\left[1 + \left(\frac{qk}{T}\right)\right]\}SSE \quad (6)$$

The FPE is recommended by Akaike (1971) for vector AR(m) lag selection.
Since $\frac{\text{KlnT}}{\text{T}} > \frac{2K}{T}$ for $T > 8$ the B IC restricts additional lags more than AIC.
From the functional form of the model in (1),
Our equation of interest is given by:
The ARDL being autoregressive (AR), has previous values of YUN_t among explanatory variables.

$$lnYUN_t = \beta_0 + \beta_1 \Delta lnYUN_{t-i} + \beta_2 \Delta lnGDP_t + \beta_3 \Delta lnPOP_t + \beta_4 \Delta lnFDI_t + \beta_5 \Delta lnED_t + \beta_6 \Delta lnPI_t + \beta_7 \Delta lnLR_t + \epsilon_t \quad (7)$$

Incase every variable is lagged up to t-p for independent and t-q for dependent variable.

$$lnYUN = \beta_0 + \beta_1 \Delta lnYUN_{t-p} + \beta_2 \Delta lnGDP_{t-q} + \beta_3 \Delta lnPOP_{t-q} + \beta_4 \Delta lnFDI_{t-q} + \beta_5 \Delta lnED_{t-q} + \beta_6 \Delta lnPI_{t-q} + \beta_7 \Delta lnLR_{t-q} + \epsilon_t \quad (8)$$

The ARDL Model
1. ARDL captures dynamic effects from lagged x's and y's
2. Serial correlation can be eliminated if sufficient number of lags of x's and y's are included.
3. ARDL can be transformed into infinite distributed lags with lagged x's only which extend into infinite past.

Estimation of ARDL model parameters
The estimation and inference concerning the long-run properties of ARDL model are then carried out using maximum likelihood function developed by Sargan (1964) and standard asymptotic normal theory, Hendry, Pagan and Sargan (1984) as,

$$K(\alpha^{2'} - \alpha^{3'}) = O_p\left(\frac{1}{T}\right) \quad (9)$$

Where, $\alpha^{2'}$ and $\alpha^{3'}$ are vectors of matrices $A^{2'}$ and $A^{3'}$, $O_p\left(\frac{1}{T}\right)$ is $A^{2'} - A^{3'}$,T is total time, and K is a square matrix of order equal to the number of unknown coefficients in the equation. It is viewed as obtained by taking the Frobenius matrix product and picking only those rows and columns corresponding to unknown coefficients. K is partitioned as shown below,

$$K = \begin{pmatrix} K_{11} & K_{12} & K_{13} & \cdots & K_{1n} \\ K_{21} & K_{22} & K_{23} & \cdots & K_{2n} \\ K_{31} & K_{32} & K_{33} & \cdots & K_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ K_{n1} & K_{n2} & K_{n3} & \cdots & K_{nn} \end{pmatrix}$$

Inference on long run and short run coefficients
Lag operator notation:

Let $ly_t = Ly_{t-1}$

$$L^p(y_t) = y_{t-p} \quad (10)$$

Re-writing the ARDL in terms of lag operator notation and factoring out tx_t and y_t,

$$\left(1-\theta_1 L-\theta_2 L^2-\cdots-\theta_p L^p\right) y_t=\delta+\left(\delta_0+\delta_1 L+\delta_2 L^2+\cdots+\delta_q L^q\right) x_t+\epsilon_t \quad (11)$$

From Okun's Law (1962) [20]:

$$\Delta YUN_t=\delta+\theta_1 \Delta YUN_{t-1}+\delta_0 G_t+\delta_1 G_{t-1}+\epsilon_t \quad (12)$$

Rewriting and factoring the like terms,

$(1-\theta_1 L) DYUN_t=\delta+(\delta_0+\delta_1 L) G_t+\epsilon_t$ (21)

We write the inverse of $(1-\theta_1 L)$ which is $(1-\theta_1 L)^{-1}$
And gives $(1-\theta_1 L)(1-\theta_1 L)^{-1}=1$
Rewriting (11)

$$\Delta YUN_t=(1-\theta_1 L)^{-1} \delta+(1-\theta_1 L)^{-1}(\delta_0+\delta_1 L+\delta_2 L^2+\cdots) G_t+(1-\theta_1 L)^{-1}+\epsilon_t \quad (13)$$

Equating (11) to infinite distributed lag,

$DYUN_t=\alpha+\beta_0 G_t+\beta_1 G_{t-1}+\beta_2 \beta_{t-2}+\cdots+e_t$
$DYUN_t=\alpha+(\beta_0+\beta_1 L^2+\beta_2 L^2+\cdots) G_t+e_t$=$(1-\theta_1 L)^{-1} \delta+(1-\theta_1 L)^{-1}(\delta_0+\delta_1 L+\delta_2 L^2+\cdots) G_t+(1-\theta_1 L)^{-1}+\epsilon_t$
(12) and ((13) are identical where,
$\alpha=(1-\theta_1 L)^{-1} \delta, e_t=(1-\theta_1 L)^{-1} \in_t$

$$\beta_0+\beta_1 L+\beta_2 L^2+\cdots=(1-\theta_1 L)^{-1}(\delta_0+\delta_1 L+\delta_2 L^2+\cdots) \quad (14)$$

so,

$$\alpha=\frac{\delta}{1-\theta_1}$$

To obtain βs we multiply (13) by $(1-\theta_1 L)$

$$\delta_0+\delta_1 L+\delta_2 L^2+\cdots=(1-\theta_1 L)(\beta_0+\beta_1 L+\beta_2 L^2+\beta_3 L^3+\cdots) \quad (15)$$

$$=\beta_0+\beta_1 L+\beta_2 L^2+\beta_3 L^3-\theta_1 \beta_0 L-\theta_1 \beta_1 L^2-\theta_1 \beta_2 L^3-\theta_1 \beta_3 L^4-\cdots$$

$$=\beta_0+(\beta_1-\theta_1 \beta_0) L+(\beta_2-\theta_1 \beta_1) L^2+(\beta_3-\theta_1 \beta_2) L^3-\theta_1 \beta_3 L^4$$

$$\delta_0+\delta_1 L+\delta_2 L^2+0 L^3+0 L^4=\beta_0+(\beta_1-\theta_1 \beta_0) L+(\beta_2-\theta_1 \beta_1) L^2+(\beta_3-\theta_1 \beta_2) L^3-\theta_1 \beta_3 L^4$$

From (15),

$\delta_0=\beta_0$
$\delta_1=\beta_1-\theta_1 \beta_0 \rightarrow \beta_1=\delta_1+\theta_1 \beta_0$
$=\beta_2-\theta_1 \beta_1 \rightarrow \beta_2=\delta_2+\theta_1 \beta_1$
$0=\beta_3-\theta_1 \beta_2) \rightarrow \beta_3=-\theta_1 \beta_2$
$0=-\theta_1 \beta_3 \rightarrow \beta^{-3}=-\theta_1$

To determine the effects of change in individual independent variable on dependent variable Multiplier analysis is used. From equation two,

$$y_t=\delta+\alpha y_{t-i}+\beta_0 x_t+\beta_1 x_{t-1}+\beta_2 x_{t-2}+\beta_3 x_{t-3}+\cdots+\epsilon_t \; i=1,2, \ldots p$$

The multipliers are given by,

$\beta_s=\frac{\partial y_t}{\partial x_{t-s}}$, is the s period delay multiplier

$\sum_{j=0}^q \beta_j$ is the total period interim multiplier

Or
From (3) above we have:

$$C(L) y_t=\delta+\beta(L) x_t+\epsilon_t \quad (16)$$

where

$$C(L) = 1 - \theta_1 L - \theta_2 L^2 - \theta_p L^p$$
$$B(L) = \beta_0 + \beta_1 L + \beta_2 L^2 + \cdots + \beta_q L^q$$

The equilibrium multiplier (long- run effects of a change in x) in the ARDL model generally is,

Long Run Multiplier $\sum_{i=0}^{\infty} \alpha_1 = \frac{B(1)}{C(1)} = A(1) = \frac{\sum_i^p \beta_i}{1-\sum_i^q \theta_1}$ where $A(L) = \frac{B(L)}{C(L)}$

Given stationarity of variables, and no shocks, the long run relationship in a regression is given by:

$$\bar{y} = \frac{B_0}{C(1)} + \frac{B_1(1)}{C(1)} x_1 + \frac{B_2(1)}{C(1)} x_2 + \cdots + \frac{B_k(1)}{C(1)} \quad (17)$$

$\bar{y}$ is constant value of y and x

Mean Lag is $\frac{B(L)}{C(L)}$

3. Unit Root Tests

The times series variables are tested for unit roots to verify their stationarity at level. Preceding the unit root test is the need to ascertain whether the variables are correlated to establish causality-effect in the subsequent sections. The models considered by this study require additional tests including cointegration test of macroeconomic data used. The purpose of the tests is to ensure validity and replicability of the results.

Correlation

The correlation test is conducted on the variable to establish existing relationship in such a way that the regression foreseen in ARDL is considered valid. The relationship between the dependent variable Youth Unemployment (YUN) and each of the six independent variables (GDP, ED, FDI, PI, LR, POP) is scrutinized using R software correlation test at 1% CL.

Table 1: Correlation between dependent variable and each independent variable

R-codes	Result
>cor(YUN,GDP)	0.294
>cor(YUN,ED)	0.44
>cor(YUN,FDI)	-0.094
>cor(YUN,PI)	0.48
>cor(YUN,LR)	0.22
>cor(YUN,POP)	0.27

In the result, the correlation of dependent variable is being tested with each independent variable. From the table, it is evident that none of the variables explains more than 50% variation in youth unemployment. To get more accurate results, we compute the multiple regression equation to examine the adjusted R^2 and comment on the elasticity of each regression coefficient. By computing the multiple regression, we are able to comment on the magnitude of adjusted R^2 to determine extent of the variation in YUN being explained by independent variables.

Multiple Correlation

The multiple correlation test is done by estimating regression equation and observing adjusted R^2. The multiple regression is done using lmtest as follows:

Table 2: *Multiple correlation test*

Variable	Estimate	Std. Error	t-value	
Intercept	14.808212	3.833368	3.863	0.000556 ***
GDP	0.169736	0.036054	4.708	5.31e-05 ***
ED	0.038800	0.008756	4.431	0.000115 ***
FDI	0.001253	0.0001431	8.76	0.0388176 **
PI	0.014296	0.006801	2.10	0.050627*
LR	0.02003	0.009138028	2.19	0.051986*
POP	-0.114248	0.053802	-2.123	0.042075 *

The standard errors are in the parenthesis.

$$YUN = 0.169736GDP_{(0.036054)} + 0.0388ED_{(0.008756)} + 0.001253FDI_{0.001431} + 0.014296PI_{(0.006801)} + 0.02003LR_{(0.009138028)} - 0.114258POP_{(0.053802)} \quad (18)$$

The multiple regression adjusted R squared is 0.7787 revealing that 77.87% of variation in YUN is explained by the explanatory variables.The stationarity test is conducted to ensure that variables used do not exhibit spurious regression. The Augmented

Dickey-Fuller unit root test is used to verify stationarity status of each variable at level. The variables are checked for unit roots. The study uses Augmented Dickey-Fuller Test. Also, when the variables are not of the same stationary process, we may still perform cointegration test to construct ARDL model. The results for stationary test are presented in *Table 3*.

Table 3: stationarity tests of variables

Variable	p-value	Tau	1st diff Tau		Lag Order
			P-value	Tau	
YUN	0.99	3.0023	0.01	-4.9328	3
GDP	0.04211	-3.6641	NA	NA	3
ED	0.02464	-3.9058	NA	NA	3
FDI	0.01	-5.7999	NA	NA	3
PI	0.6188	-1.8831	0.01	-5.573	3
LR	0.6146	-1.894	0.01	-5.0686	3
POP	0.2925	-2.7199	0.01	-5.0035	3

From the results presented in the table, and focusing on p-values, the variables are either I (0) or I(1) stationary. These results allow cointegration analysis of ARDL. I(0) variables are stationary at level, that is, without differencing; I(1) variables are stationary after the first difference.

Time plot

The time plots for all variables at level are generated complementing stationarity test as indicated below:

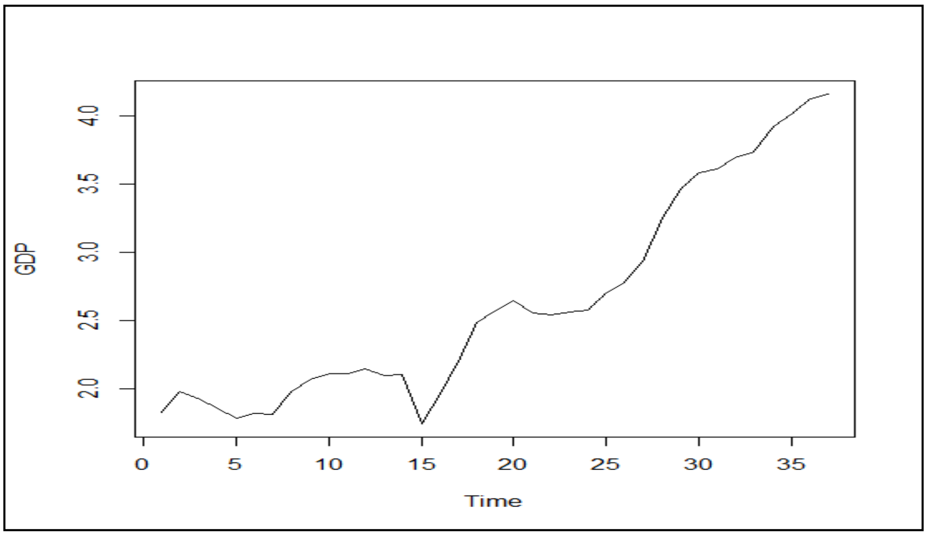

Fig 1: *Time plot of GDP*

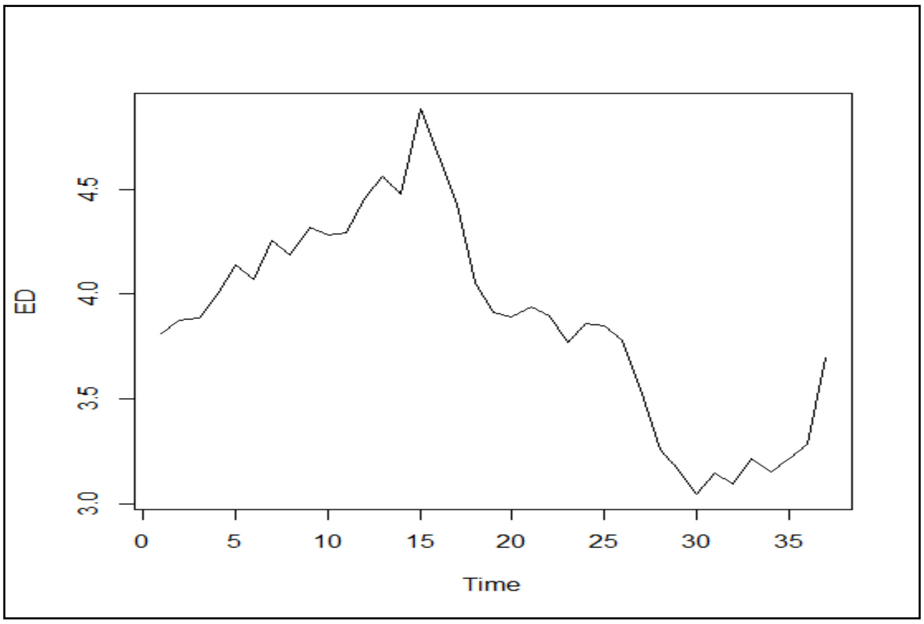

Fig 2: *Time plot of External Debt(ED) Investment (FDI)*

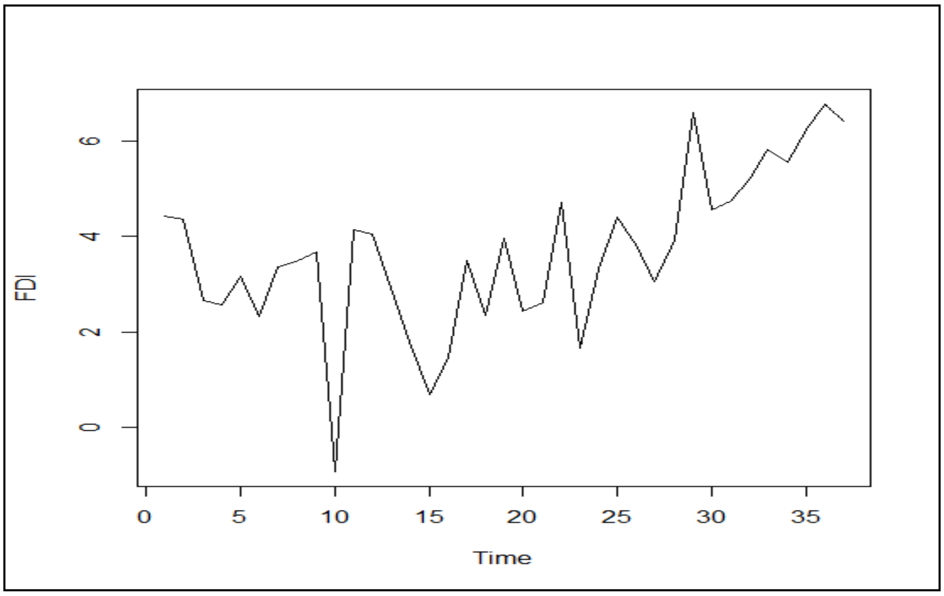

Fig 3: Time plot of Foreign Direct

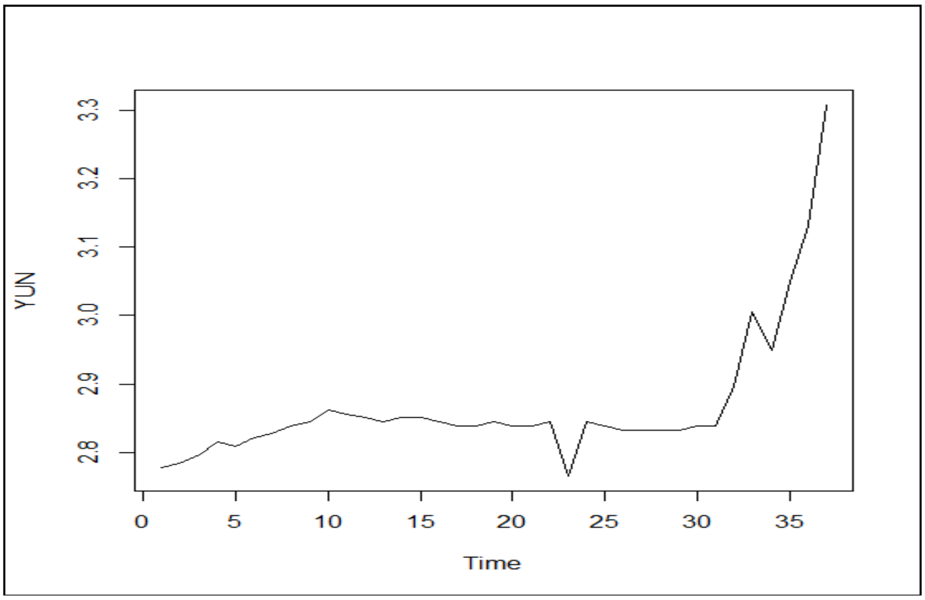

Fig 4: Youth Unemployment (YUN) (PI)

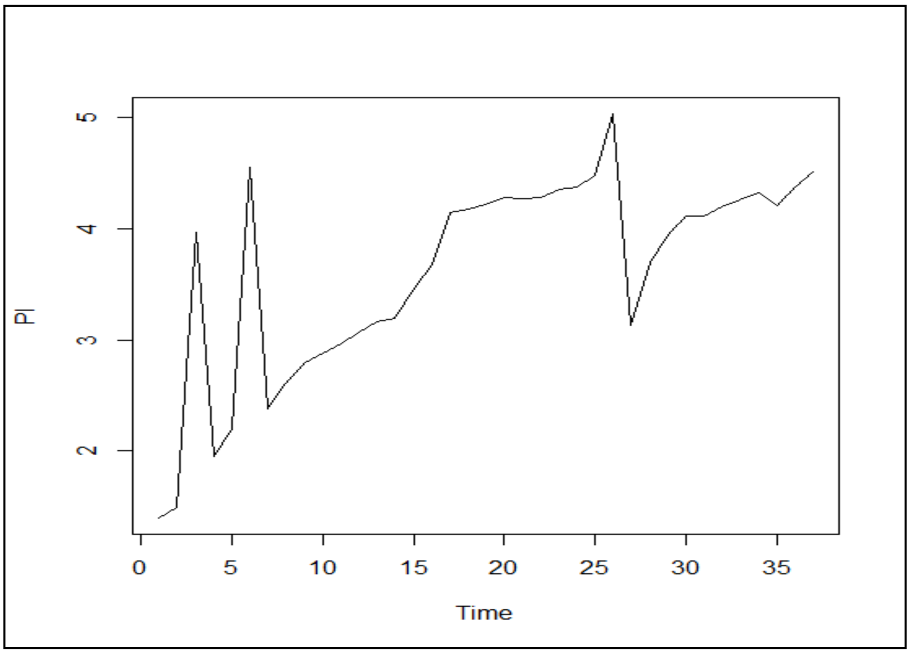

Fig 5: Time plot of Private Investment

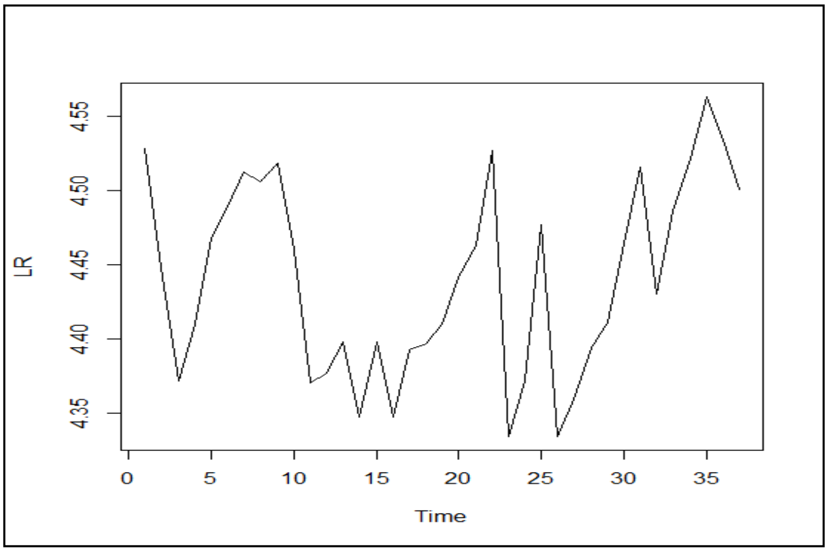

Fig 6: Time plot of Literacy Rate (LR) *Population (POP)*

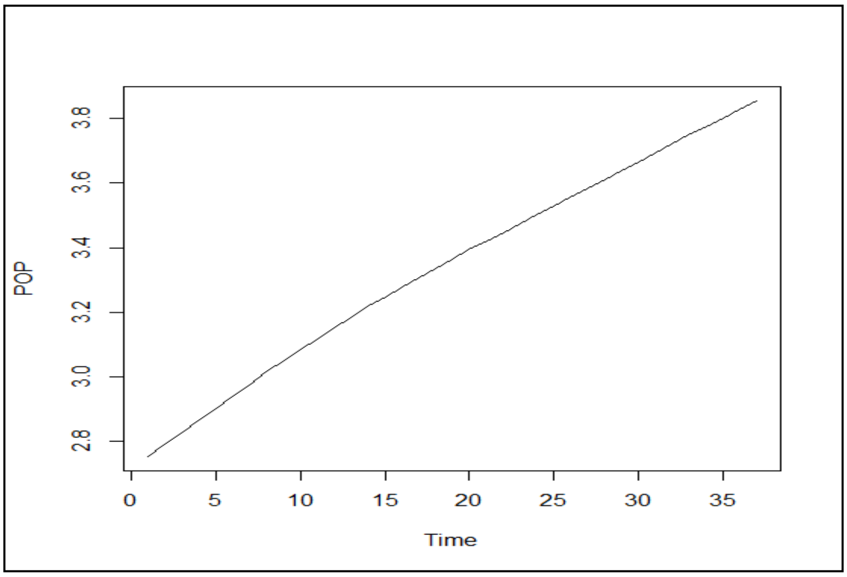

Fig 7: Time plot of

Choosing lag length

When the data VAR is applied to the variables to determine the most appropriate lag, the results are obtained as shown on the table below. We then choose FPE suggesting 3 lags in line with stationarity results.

Table 4: Lag selection criteria

Lag	AIC	HQ	SC	FPE
1	-3.633133e+01	-3.553215e+01	-3.364367e+01	1.893163e-16
2	-3.837335e+01	-3.687489e+01	-3.333399e+01	5.824986e-17
3	NaN	NaN	NaN	-1.300749e-47 *

Serial Correlation Test

The independence of observations and efficiency of labour market is tested using serial correlation test which is tested using Peirce-Box test in R. It is also a diagnostic test for residuals of OLS.

Table 5: *serial correlation test*

Variable	X-squared stat	P-value
GDP	142.16	0.2475
ED	138.05	0.2565
FDI	39.219	0.1566
YUN	30.138	0.8133
PI	51.501	0.1287
LR	21.126	0.02023
POP	155.99	0.0475

Null Hypothesis: NO serial correlation up to lag 10.
Alternative Hypothesis: There is serial correlation up to lag 10.
According to this test, there is no serial correlation up to lag 10 in GDP, ED, FDI, YUN and PI whose p-values are greater than 0.05%. However, literacy rates and population have serial correlation up to lag 10 since their p-values are less than 0.05%.

4. Cointegration Analysis

The study conducts both Phillips-Ouliaris (PO) test and Johansen cointegration test. The PO test verifies the cointegration relations between two variables at a time whereas the Johansen test verifies collectively the cointegration relations between all variables.

Johansen Cointegration Rank Test

The Johansen (1991) cointegration rank test has the ability to perform cointegration test for more than two variables. In *Table 6* below, cointegration test is done for six variables at 95% significance level. Using maximum eigen value test, we reject the null hypothesis when the test statistics take on a value below the critical value at 95%. The results are presented in table 6 below. Test type: maximal eigenvalue statistic (lambda max), without linear trend.

Table 6: Values of test statistic and critical values of test:

r (cointegration rank)	Test Stats	10%	5%	1%
r<=6	5.37	7.52	9.24	12.97
r<=5	10.07	13.75	15.67	20.20
r<=4	15.58	19.77	22.00	26.81
r<=3	17.17	25.56	28.14	33.24
r<=2	40.13	31.66	34.40	39.79
r<=1	57.15	37.45	40.30	46.82
r<=0	66.89	43.25	46.45	51.91

H0:r≤3, the critical value is less than the test statistics (28.14>17.17) at 95%, we fail to reject null hypothesis and conclude that there are 3 cointegration relationships. The study rejects the null hypothesis and concludes that there are r=3cointegrating vectors. The test statistics reveals the existence of three cointegrating relationships among the six variables. With 3 cointegrating vectors, there is basis for ARDL estimation.

Estimation of autoregressive distributed lag (ARDL)

The study uses FPE criteria to choose 3 lags of each variable with exception of 1 lag for dependent variable. $YUN = \alpha YUN_{t-1} + \beta_1 GDP_t + \beta_2 GDP_{t-1} + \beta_3 GDP_{t-2} + \beta_4 GDP_{t-3} + \gamma_1 ED_t + \gamma_2 ED_{t-1} + \gamma_3 ED_{t-2} + \gamma_2 ED_{t-3} + \theta_1 FDI_t + \theta_2 FDI_{t-1} + \theta_3 FDI_{t-2} + \mu_1 PI_t + \mu_2 PI_{t-1} + \mu_3 PI_{t-2} + \mu_4 PI_{t-3} + \pi_1 LR_t + \pi_2 LR_{t-1} + \pi_3 LR_{t-2} + \pi_4 LR_{t-3} + \varphi_1 POP_t + \varphi_2 POP_{t-1} + \varphi_3 POP_{t-2} + \varphi_4 POP_{t-3} + \epsilon_t$ (19)
Every independent variable is lagged 3 times while the dependent variable is lagged once. The results are tabulated below

Table 7: Results of ARDL estimation

Variable	Estimate	Std. Error	t- value	Pr(>|t|)
Intercept	3.1881443	1.1867684	2.731	0.06930 **
Lag(YUN,-1)	0.6580734	0.2268072	2.90	0.1090 .
GDP	-0.2079220	0.040073	-5.19	0.0406 ***
Lag(GDP,-1)	0.3848136	0.0917367	4.19	0.0796 *
Lag(GDP,-2)	-0.2052705	0.0673422	-3.05	0.1548 *
Lag(GDP,-3)	0.1208412	0.0257892	-4.69	0.03694***
ED	-0.073030	0.0149475	-4.89	0.00235 ***
Lag(ED,-1)	0.0214684	0.0110151	1.95	0.1369 .
Lag (ED,-2)	-0.009116	0.00325426	-2.91	0.09087*
Lag(ED,-3)	0.0094806	0.0125552	0.76	0.4718
FDI	0.0020017	0.0010008	1.99	0.3159 .
Lag(FDI,-1)	0.0025032	0.0012111	2.07	0.1787*
Lag(FDI,-2)	0.0006147	0.001649	0.37	0.7234
Lag(FDI,-3)	0.0027486	0.0010519	2.61	0.1145 *
PI	0.0107310	0.0054604	1.97	0.1946 .
Lag(PI,-1)	0.0069095	0.0067884	1.018	0.3385
Lag(PI,-2)	0.0144567	0.0059603	2.403	0.0539 *
Lag(PI,-3)	0.0083734	0.0073051	1.146	0.2848
LR	0.0116937	0.003686	3.17	0.07589 *
Lag(LR,-1)	-0.0892691	0.0373312	-2.391	0.0438 **
Lag(LR,-2)	0.0557574	0.0456325	1.222	0.2565
Lag(LR,-3)	0.0169212	0.0389834	0.434	0.6757
POP	2.0186805	2.0022926	1.0813	0.4396
Lag(POP,-1)	-0.2590455	0.036858	-7.03	0.9457**
Lag(POP,-2)	4.2498754	3.3935272	0.663	0.5260
Lag(POP,-3)	-4.3093119	4.1772794	-1.032	0.3324

Where significance codes are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Adjusted R-squared = 0.9406
F-value computed 7.909 on 25 and 8 DF, F-value critical=2.34
F-value computed 7.909>F-value critical 2.34

$H_0 = \beta_1 = \beta_2 \dots \beta_k$

H_A: H_0 is not true

The null hypothesis is rejected and the equation was declared statistically significant at 5% level.
p-value is 0.002519

The estimated ARDL equation is:

$$YUN = 3.1881443_{1.1867684} + 0.6580734_{0.2268072}\,YUN_{t-1} - 0.2079220_{0.040073}\,GDP_t + 0.3848136_{0.0917367}\,GDP_{t-1} - 0.2052705_{0.0673422}\,GDP_{t-2} + 0.1208412_{0.0257892}\,GDP_{t-3} - 0.073030_{0.0149475}\,ED_t + 0.0214684_{0.0110151}\,ED_{t-1} - 0.009116_{0.00325426}\,ED_{t-2} + 0.0094806_{0.0125552}\,ED_{t-3} + 0.0025032_{0.0012111}\,FDI_{t-1} + 0.0006147_{0.001649}\,FDI_{t-2} + 0.0107310_{0.0054604}\,PI_t + 0.0069095_{0.0067884}\,PI_{t-1} + 0.0144567_{0.0059603}\,PI_{t-2} + 0.0083734_{0.0073051}\,PI_{t-3} + 0.0116937_{0.003686}\,LR_t - 0.0892691_{0.0373312}\,LR_{t-1} + 0.0557574_{0.0456325}\,LR_{t-2} + 0.016921_{0.0389834}\,LR_{t-3} + 2.0186805_{2.0022926}\,POP_t - 0.2590455_{0.036858}\,POP_{t-1} + 2.2498754_{3.3935272}\,POP_{t-2} - 4.3093119_{4.1772794}\,POP_{t-3} \quad (20)$$

Table 8: The estimated long Run coefficient for selected ADRL Model

Regressors	Coefficient	Prob
Intercept	4.8447	0.041
GDP	0.09148447	0.05
ED	-0.0512	0.036
FDI	0.01196	0.02
PI	0.0615	0.04
LR	-0.0154	0.01
POP	1.762635	0.01

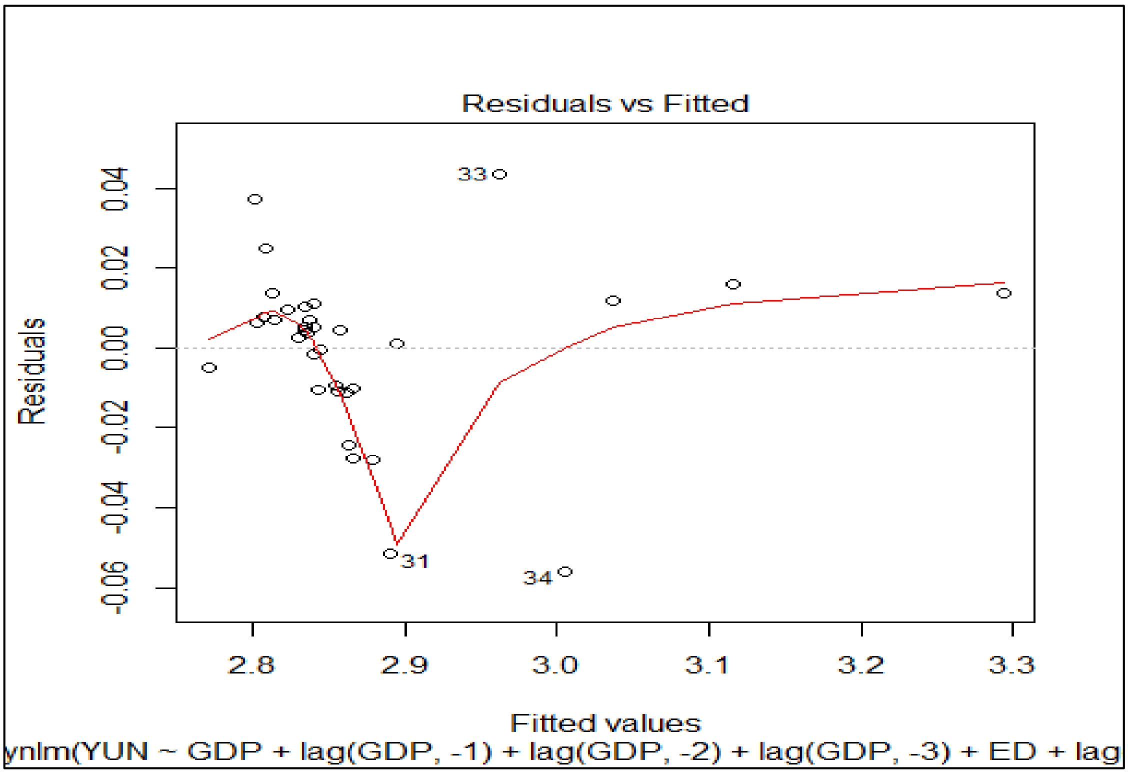

Fig 8: Plot of residual vs fitted

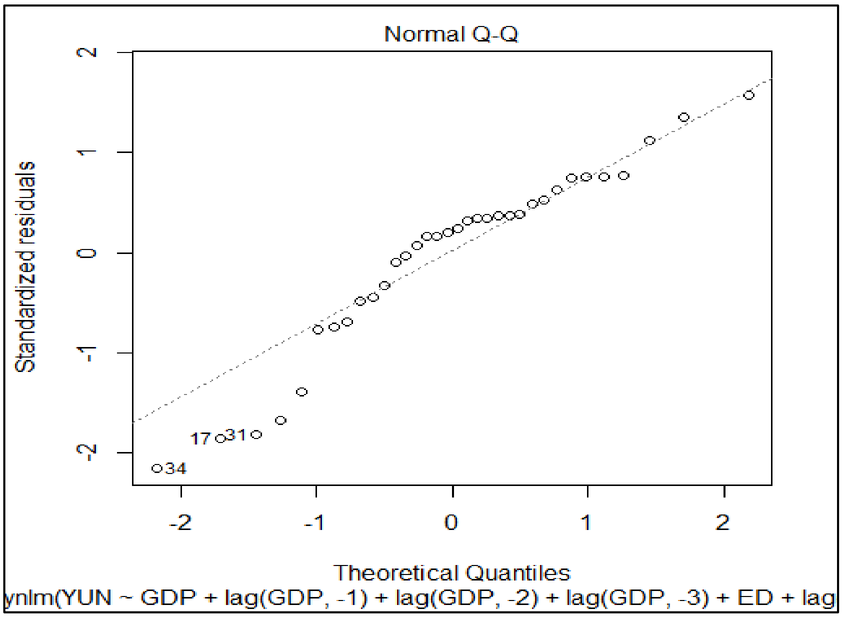

Fig 9: Plot of normality of residuals

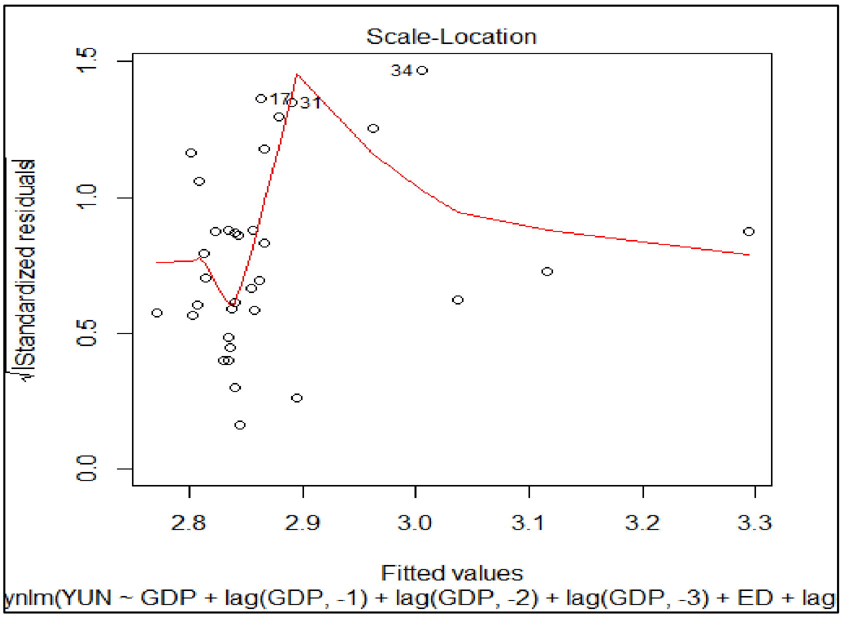

Fig 10: *Plot of scale versus location of residuals*

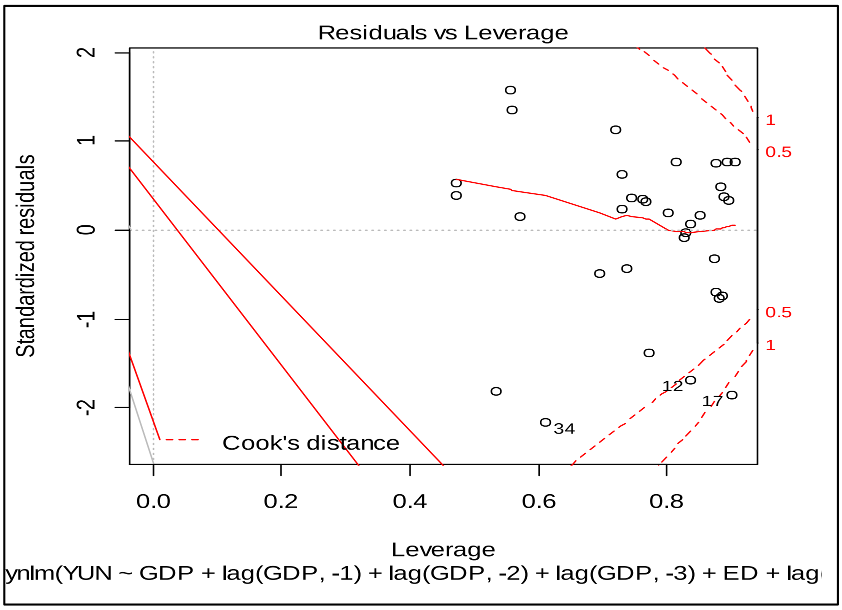

Fig 11: Plot of residual vs leverage

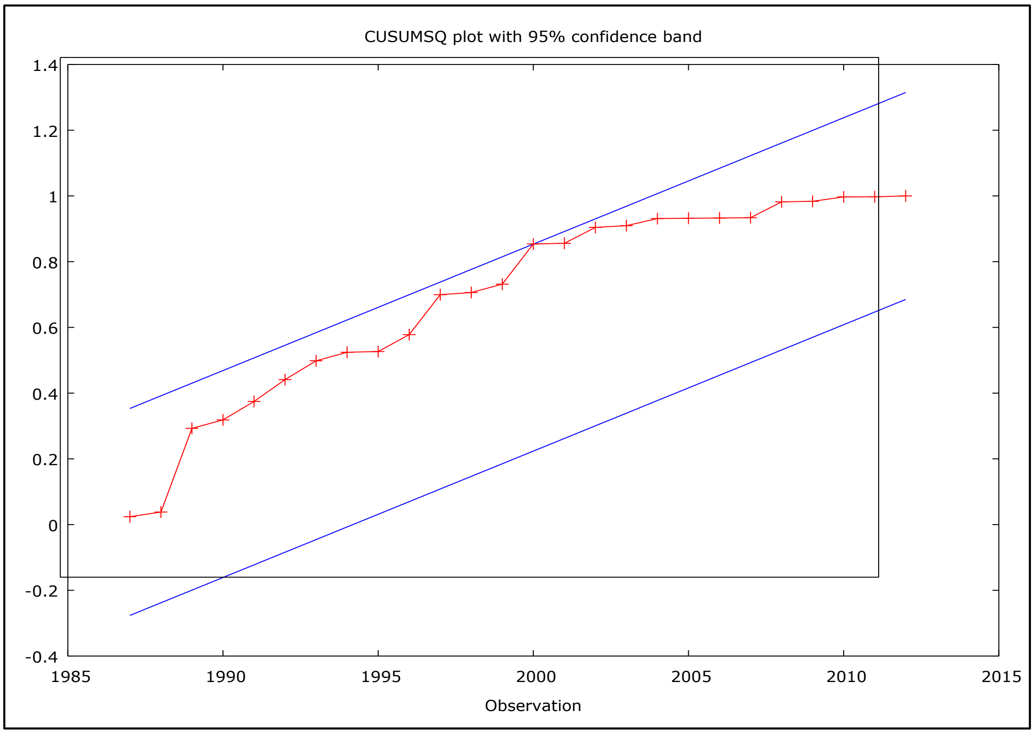

Fig 12: Plot of Cumulative Sum of Squares of Recursive Residuals

6. Discussion

After the data is taken through Box-Pierce serial correlation test, multiple correlation test, stationarity test and Johansen cointegration test, ARDL is estimated. The results reveal that GDP and its second lag have negative effect on youth unemployment, that is, one unit increase in GDP and GDP two-year lag reduce youth unemployment by 0.207922% and 0.2052705% respectively. This can be explained as decrease in unemployment due to increase in productivity. Also, one unit of ED and ED two-year lag reduce youth unemployment by 0.07303% and 0.009116% respectively. The external debt effect on youth unemployment occurs when money borrowed from foreign institutions is invested in employment intensive sectors to create more jobs. Furthermore, unit increase in one-year lag of youth literacy level reduces youth unemployment by 0.0892691%. The reduction is explained by government interventions like *Kazi Kwa Vijana*, Youth Enterprise Development Fund (YEDP), National Youth Service programs among others to address backlog in unemployed youth in the previous year(s). The same reason is given for one-year lag and three-year lag of population which reduce unemployment by 0.2590455% and 4.3093119% respectively**.** The Foreign Direct Investment (FDI) and Private Investment (PI) do not have statistically significant effects on youth unemployment but increase by 0.01196 and 0.0615 respectively in the long run. F-test shows that ARDL model estimated in this paper is significant while CUSUM test indicates its stability. Except for FDI, the results are consistent with Muhammad et al (2013) [19] which used (ARDL) approach and found that GDP, population, inflation, and FDI are significant determinants of youth unemployment in Pakistan. In the long run, increase in GDP causes increase in youth unemployment by 0.09148447%. It is explained that GDP growth in the country is " jobless growth" as found by Ajilore and Yinusa (2011) in Botswana. However, the findings are contrary to Kabaklarli *et al* (2011) [8, 17] in which 1% increase in GDP growth in Turkey reduces youth unemployment by 3.07%. Also, increase in previous literacy rates by one unit in the long run, reduces youth unemployment by 0.0154% contrary to study by Guillermo *et al* (2012) [11] in Brazil whose findings revealed that higher educational levels do not compensate for unemployment episode in the past.

7. Conclusion

The study of unemployment requires a dynamic model that generates results for autoregression. The beauty of ARDL is that nonstationary series can be used without detrending if the series are cointegrated as shown in this paper without encountering the problem of spurious regression. If the series are cointegrated of different order I(0) and I(1) ARDL can be estimated. Also, lags of autoregressing dependent variable is equally included and estimated among other independent variables. The model eliminates serial correlation when appropriate number of lags are included. From the F-test results the ARDL model used in this study is significant.

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