Innovations

An Empirical Study of the Long and Short Run Causation between Being without a job and Inflation in Ethiopia

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Abstract
A country's unemployment rate is an essential macroeconomic indicator. It is seen as a red flag that prevents the key resources from being allocated for the creation of the economy. Thus, the aim of the study was to investigate both long and short-term causality between unemployment rate and macroeconomic factors. After applying the augmented dickey-fuller for unit root detection, this investigation used the auto regressive distributed lag model testing approach and the vector error correction model for granger causality analysis. The time arrangement information between 1984/85 and 2018/19 is examined. The result suggests that unemployment rate and macroeconomic variables have been connected for a long run. Foreign direct investment, inflation rate, and unemployment rate all have a direct causal effect on the short run. Furthermore, unemployment drives real gross domestic product to decline and external debt to rise. Finally, the study recommends that government should build the degree of total harmony, create a favorable business climate that entices more foreign direct investment, and borrow just for good reasons to acclimatize a cost pool of unemployed people.The government should reduce spending on cosmetic projects that are not profitable.

Key words: ARDL model, Granger causality, Vector error correction model, Unemployment.

1. Introduction

The level of unemployment is considered a major macroeconomic indicator of the economic wellbeing and progress of a country's economy. It is seen as a barrier to government earnings that hamper the creation of the economy. According to Asif and Aurangzeb (2013), one of the strong facts about the labor market in Ethiopia is the rapid growth of labor supply. Due to the young demographic composition, the labor force is growing much more rapidly than the population as a whole.

This leads to problems such as poverty, crime, financial hardships, homelessness, frustration, as well as social isolation and low self-esteem, a breakdown of families, and a loss of confidence. In the end, all of these lead to the erosion of a well-functioning society (Muhammad et al., 2013).Previous studies were no longer viewed causally with the spirit of this research. As a result, we used both theoretical and empirical departures from the traditional version of Philips (1958) and Okunlaw (1962).Literatures on this particular subject were limited, and when combined with the limitations of previous studies provided additional impetus for this study Gobebo et al. (2017) and Bimal (2014). Among the determinants of unemployment, the study considers global external debt, inflation rate, real gross domestic product, population growth, and foreign direct investment. This selection is based on the relevance of each factor and previous studies in this area. It was decided to use the dataset from 1984 to 2018, i.e.35 years, because there were no organized sources of unemployment prior to the 1980s. Henceforth, the researcher researches log run and short run causality of macroeconomic factors and unemployment in Ethiopia from 1984/85-2018/19.

2. Literature Review

Okun (1962) examined the relationship between employment and economic growth in the United States following World War II. According to him, a 3 percent increase in output growth corresponded to a one percent decrease in unemployment rate. This law basically states that the unemployment rate remains unchanged if the economy grows rapidly, regardless of how small the growth is or how negative it is. This is commonly referred to as the Okun law and is unique in that it is quantitative rather than simply monetary.

Using Phillips curve as a starting point, market analysts have endeavored to establish the correlation between inflation and unemployment. Economically, these two segments are connected together. The associations between them are reciprocally related. These segments are essentially used to measure the difficulty in making economies.According to Friedman (1977), in the social and natural sciences, there is no such thing as certain knowledge; there are only tentative hypotheses that can never be proved or rejected, but we may have some confidence in,Several aspects may influence the acceptance of such a hypothesis, such as the range of their experience in comparison to their own complexity and alternative hypotheses, and the number of occasions on which they have come close to rejection.In both social and natural science, knowledge is gained through the failure of a tentative hypothesis to predict phenomena that it claims to explain.By patching up the hypothesis until someone comes up with a new hypothesis that embodies the troubling phenomenon more elegantly, and so on indefinitely. In both cases, the experiment is sometimes possible, sometimes not.

In our world, the issue of work has become increasingly essential as showcase economies become increasingly prominent.The unemployment rate can be a sign that the financial circumstances of a government are deteriorating when the economies of many nations are on the verge of a crisis. There are almost no segments of society unaffected by it, from students to seniors, and it is an excellent economic indicator that can identify the strength and weakness of an economy (Nasridini and Behrooz, 2015).As per Alraba (2017), there is a unidirectional causal relationship between investment and unemployment rate.The findings of Dilek (2016) show that GDP has a negative and significant relationship with China's unemployment rate.There is a positive and immaterial relationship between inflation and foreign direct investment and unemployment. In the short-run, GDP, inflation, and foreign direct investment are all negative, and the lagged error correction term is also negative and statistically significant.

3. Materials and Methods

3.1. Data Source and Type

Throughout the study, secondary time series data is used for all variables from 1984/85 to 2018/19, which is about 35 years. Data were collected from domestic and foreign organizations. A few of the main sources include World Development Indicators, Ethiopia's national bank, and the United Nation Conference on Trade and Development (UNCTAD), as well as published reports and studies.Many studies have utilized data published by WDI, NBE, and UNCTAD, thus making the data sources reliable. To complete the data, the researcher used Stata-v-15.0 econometric software for the entire analysis.

3.2. Model Specification

A macroeconomic model of unemployment in Pakistan was used by Muhammad et al. (2013), and it was adapted to this study with a few alterations. The model takes the form of:

$$UNR_t = f(RGDP_{t,} INFR_t, EXD_t, FDI_t, POP_t)$$

Where t = time period (1984/85-2018/19), UNR is unemployment rate, f is a function of, RGDP is real gross domestic product (%), INFR is inflation rate, EXD is external debt % of GNI and FDI is foreign direct investment (Millions of US$) and POP is population growth rate. Here is what the econometric state of the model looks like:

$$UNR_t = \alpha + \beta_1 RGDP_t + \beta_2 INFR_t + \beta_3 EXD_t + \beta_4 FDI_t + \beta_5 POP_t + \varepsilon$$

The logarithmic type of the model is:

$$UNR_t = \beta_0 RGDP_t^{\beta_1} INFR_t^{\beta_2} EXD_t^{\beta_3} FDI_t^{\beta_4} POP^{\beta 5} \varepsilon^{\mu t}$$

$$LnUNR_t = \beta_0 + \beta_1 LnRGDP_t + \beta_2 LnINFR_t + \beta_3 LnEXD_t + \beta_4 LnFDI_t + \beta_5 LnPOP_t + \mu_t$$

Ln represents the logarithmic expressions of $UNR_t, RGDP_t, INF_t, EXD_t, FDI_t and\ POP_t$. $\mu_t$is the white noise error term, and the parameters $\beta_1 to\ \beta_5$, are the long run elasticity's of the independent variables; and the constant term β_0, is a value that the dependent variable assumes when values of all the independent variables are zero or near zero.

There are two primary benefits to converting variables to natural logarithms. Firstly, slope coefficients in a non-logarithmic linear equation measure only the rate of change of the mean of the dependent variable.The slope coefficients can measure both the change in mean as well as the elasticity of the dependent variable in relation to the percentage change in the independent variables after transforming variables to their natural log.Furthermore, the log transformation reduces the problem of heteroscedasticity since it compresses the scale of the variables (Damodar, 2004). The study used the following equation to convert some negative observations of inflation and real gross domestic product into logarithmic figures (Matthias and Carsten, 2007).

$$y = \ln(x + \sqrt{x^2 + 1})$$

3.3. Stationary

In the case of non-stationary variables, there may be a possibility of a spurious regression. Without a real relationship between them, the variables may move together if they are not stationary. Alrabba (2017) points out that one of the most common tests for time series stationary is the Augmented Dickey-Fuller test, which examines the existence of a unit root hypothesis as a null hypothesis. Testing has been completed by(Dickey & Fuller, 1979). To test for a unit root, we use three different regression equations with the ADF test.

- Without drift and trend

$$\Delta X_t = \gamma X_{t-1} + \sum_{i=1}^{p} \beta_i \Delta X + e_t$$

- With intercept

$$\Delta X_t = \alpha_0 + \gamma X_{t-1} + \sum_{i=1}^{p} \beta_i \Delta X + e_t$$

- With drift and trend

$$\Delta \boldsymbol{X_t} = \boldsymbol{\alpha_0} + \boldsymbol{\gamma X_{t-1}} + \boldsymbol{\theta T} + \sum_{i=1}^{p} \boldsymbol{\beta_i} \, \Delta \boldsymbol{X_{t-i}} + \boldsymbol{e_t}$$

Where, Δ is difference operator, α_0 is drift term, P is the lag order of the auto-regressive process, T = trend term/trend variable, t = time subscribe, β_i = is a measure of lag length, $\gamma = \delta - 1$, the coefficient of X_{t-1}which measures the unit root, e = the error term / is the white noise, θ = the coefficient on a time trend series, $\Delta X_t = X_t - X_{t-1}$, are first difference of X_t, X_{t-1} = Are lagged values of order one of X_t, ΔX_{t-i}= are changes in lagged values, $\Delta X_{t-1} = X_{t-1} - X_{t-2}$, $\Delta X_{t-2} = X_{t-2} - X_{t-3}$, the null and alternative hypotheses can be written as follows:

H_o: $\gamma = 0$, Non-stationary time series, so it has a unit root problem.

H_a: $\gamma < 0$,The time series is stationary, so it doesn't have a unit root problem.

If the t-statistics are greater than the ADF critical value, then the null hypothesis should be rejected. This shows that the series is stationary. The null hypothesis will not be rejected if t-statistics are less than ADF critical value. This shows that the series is not stationary. The unit root tests on unemployment, external debt, real gross domestic product, foreign direct investment, inflation rate, and population growth are performed including the three common options (Sirah et al., 2021).

3.4. Long run Autoregressive Distributed Lag Model (ARDLM)

ARDL bounds test approach is used to determine whether the long-run relationship exists using Wald test or F-statistic. The researcher has to compare the calculated F-statistics (Wald test) value with the critical values reported in the paper of (Pesaran et al., 1999) to decide whether the variables have co-integration or not. In the case of a value greater than the upper-bound critical value, the null hypothesis of no co-integration is rejected. This implies that the variables have a long-term relationship with each other. As a result, if the F-statistics value falls below the lower bound critical value, then the null hypothesis of no co-integration cannot be removed. Thus, the variables included in the model do not share long-run relationships with one another. Furthermore, if the F-statistics value falls within the lower or upper bound critical values, this indicates that the long-run relationship cannot be confirmed or denied. The ARDL method is applied when the order of integration of all variables is different, for example, I (0) and I(1) (Dilek,2016). The general form of ARDL (p, q) is as:

$$Y_t' = \gamma_{0i} + \sum_{i=1}^{P} \delta_i \, Y_{t-i} + \sum_{j=0}^{q} \beta_i' X_{t-i} + \varepsilon_{ti}$$

Where,Y_t' is a vector, $(X_t')'$ are allowed purely $I(0)$ or I (1) or $cointegrated$; δ and β are coefficients; γ is the constant; $i = 1, \ldots\ldots, K; p$;is optimal lag order used for dependent variables;q is optimal lag orders used for independent variable; ε_{ti} is a vector of error terms- unobservable zero mean white noise vector process. Following is the bound test co-integrations models. So, the model can be framed as follow.

$$D\big(Ln\,(UNR_t)\big) = \beta_1 + \alpha_{11}Ln(UNR_{t-1}) + \alpha_{21}Ln(RGDP_{t-1}) + \alpha_{31}Ln(INFR_{t-1}) + \alpha_{41}Ln(ED_{t-1}) + \alpha_{51}Ln(FDI_{t-1}) + \alpha_{61}Ln(POP_{t-1}) + \sum_{i=1}^{p}\theta_{1i}\,D(Ln(UNR_{t-i})) + \sum_{i=1}^{q}\theta_{2i}\,D\big(Ln(RGDP_{t-i})\big) + \sum_{i=1}^{q}\theta_{3i}\,D\big(Ln(INFR_{t-i})\big) + \sum_{i=1}^{q}\theta_{4i}D\big(Ln(EXD_{t-i})\big) + \sum_{i=1}^{q}\theta_{5i}D\big(Ln(FDI_{t-i})\big) + \sum_{i=1}^{q}\theta_{6i}\,D(Ln(POP_{t-i})) + \varepsilon_{1i}$$

Where, 'D' is difference operator; $\beta_j(j = 1, \dots\dots, 6)$ denotes intercept; q is the maximum lag length: i is number of lags;$\theta_{jk}(j, k = 1, \dots\dots\dots, 6)$ denotes the short run coefficients of the variables;$\alpha_{jk}(j, k = 1, \dots\dots\dots, 6)$; denotes the long run coefficients of the variables; and $\varepsilon_{jt}(j = 1, \dots\dots, 6)$ presents the serial independent random error with mean zero a finite covariance matrix. The null hypothesis of co-integration states that there is no co-integration against the alternative hypothesis of there exist co-integration between variables. If there is an evidence of long-run relationship of the variables, the following long-run ARDL model was estimated (Abdulbaset et al., 2013; Sirah et al., 2021).

$$D\big(Ln\,(UNR_t)\big) = \beta_1 + \sum_{i=1}^{p}\theta_{1i}\,(Ln(UNR_{t-i})) + \sum_{i=1}^{q}\theta_{2i}\,\big(Ln(RGDP_{t-i})\big) + \sum_{i=1}^{q}\theta_{3i}\,\big(Ln(INFR_{t-i})\big) + \sum_{i=1}^{q}\theta_{4i}\big(Ln(EXD_{t-i})\big) + \sum_{i=1}^{q}\theta_{5i}\big(Ln(FDI_{t-i})\big) + \sum_{i=1}^{q}\theta_{6i}\,\big(Ln(POP_{t-i})\big) + \varepsilon_{1i}$$

3.5. Short Run Autoregressive Distributed Lag Model (ARDLM)

Following the confirmation of long-run co-integration between unemployment and other macroeconomic variables, the researcher uses an error correction model to estimate the short-run dynamic coefficients and determine the adjustment speed associated with the short-run estimates. The adjustment speed represents the speed at which variables adjust from a short-run equilibrium to a long-run equilibrium (Bekhet and Al-Smadi, 2015; Sirah et al., 2021). An error correction model is used for this study to identify short run co-integration.

Impact multiplier measures the instant impact that change in $X_t$will have on change in Y_t and adjustment effect shows how much of disequilibrium is being corrected.

$$\mu_{t-1} = Y_{t-1} - \beta_1 - \beta_2 X_{t-1}$$

In this equation β_2 being the long run response.

$$\mathrm{D}\big(\mathrm{Ln}\,(\mathrm{UNR_t})\big) = \theta_0 + \sum_{i=1}^{p}\theta_{1i}\,\mathrm{D(Ln(UNR_{t-i}))} + \sum_{i=1}^{q}\theta_{2i}\,\mathrm{D\big(Ln(RGDP_{t-i})\big)} + \sum_{i=1}^{q}\theta_{3i}\,\mathrm{D\big(Ln(INFR_{t-i})\big)} + \sum_{i=1}^{q}\theta_{4i}\mathrm{D\big(Ln(EXD_{t-i})\big)} + \sum_{i=1}^{q}\theta_{5i}\mathrm{D\big(Ln(FDI_{t-i})\big)} + \sum_{i=1}^{q}\theta_{2i}\,\mathrm{D\big(Ln(POP_{t-i})\big)} + \lceil \mathrm{ECT_{t-1}} + e_t$$

Here D is the difference operator; θ_i's the coefficients relating to the short -run dynamics of the model's convergence to equilibrium, $\lceil$measures the speed of adjustment, where ECT_{t-1} is the error correction term (Pesaran et al., 2001). This is defined as;

$$ECT_{t-1} = Ln(UNR_{t-i}) - [\theta_0 + \sum_{i=1}^{q} \theta_{1i}\big(Ln(UNR_{t-i})\big) + \sum_{i=1}^{q} \theta_{2i}\,\big(Ln(RGDP_{t-i})\big) + \sum_{i=1}^{q} \theta_{3i}\,\big(Ln(INFR_{t-i})\big) + \sum_{i=1}^{q} \theta_{4i}\big(Ln(EXD_{t-i})\big) + \sum_{i=1}^{q} \theta_{5i}\,(Ln(POP_{t-i})) + \sum_{i=1}^{q} \theta_{6i}\,(Ln(FDI_{t-i}))$$

3.6. The Granger Causality Test

Granger (1969) contended that vector error correction model (VECM) is more fitting to look at the causality. VECM Granger causality is used to determine the direction of causality between unemployment and other macroeconomic variables. This is done once co-integration among the variables mentioned above has been confirmed.Therefore, the generalized vector error correction model is as follows;

$$D\big(Ln\,(UNR_t)\big) = \theta_0 + \sum_{i=1}^{p} \theta_{1i}\,D(Ln(UNR_{t-i})) + \sum_{i=1}^{q} \theta_{2i}\,D\big(Ln(RGDP_{t-i})\big) + \sum_{i=1}^{q} \theta_{3i}\,D\big(Ln(INFR_{t-i})\big) + \sum_{i=1}^{q} \theta_{4i} D\big(Ln(EXD_{t-i})\big) + \sum_{i=1}^{q} \theta_{5i} D\big(Ln(FDI_{t-i})\big) + \sum_{i=1}^{q} \theta_{6i}\,D(Ln(POP_{t-i})) + \theta ECT_{t-1} + e_t$$

$$D\big(Ln\,(RGDP_t)\big) = \theta_0 + \sum_{i=1}^{p} \theta_{1i}\,D(Ln(RGDP_{t-i})) + \sum_{i=1}^{q} \theta_{2i}\,D\big(Ln(UNR_{t-i})\big) + \sum_{i=1}^{q} \theta_{3i}\,D\big(Ln(INFR_{t-i})\big) + \sum_{i=1}^{q} \theta_{4i} D\big(Ln(EXD_{t-i})\big) + \sum_{i=1}^{q} \theta_{5i} D\big(Ln(FDI_{t-i})\big) + \sum_{i=1}^{q} \theta_{6i}\,D(Ln(POP_{t-i})) + \theta ECT_{t-1} + e_t$$

$$D\big(Ln\,(INFR_t)\big) = \theta_0 + \sum_{i=1}^{p} \theta_{1i}\,D(Ln(INFR_{t-i})) + \sum_{i=1}^{q} \theta_{2i}\,D\big(Ln(RGDP_{t-i})\big) + \sum_{i=1}^{q} \theta_{3i}\,D\big(Ln(UNR_{t-i})\big) + \sum_{i=1}^{q} \theta_{4i} D\big(Ln(EXD_{t-i})\big) + \sum_{i=1}^{q} \theta_{5i} D\big(Ln(FDI_{t-i})\big) + \sum_{i=1}^{q} \theta_{6i}\,D(Ln(POP_{t-i})) + \theta ECT_{t-1} + e_t$$

$$D\big(Ln\,(FDI_t)\big) = \theta_0 + \sum_{i=1}^{p} \theta_{1i}\,D(Ln(FDI_{t-i})) + \sum_{i=1}^{q} \theta_{2i}\,D\big(Ln(RGDP_{t-i})\big) + \sum_{i=1}^{q} \theta_{3i}\,D\big(Ln(INFR_{t-i})\big) + \sum_{i=1}^{q} \theta_{4i} D\big(Ln(EXD_{t-i})\big) + \sum_{i=1}^{q} \theta_{5i} D\big(Ln(UNR_{t-i})\big) + \sum_{i=1}^{q} \theta_{6i}\,D\big(Ln(POP_{t-i})\big) + \theta ECT_{t-1} + e_t$$

$$D\big(Ln\,(EXD_t)\big) = \theta_0 + \sum_{i=1}^{p} \theta_{1i}\,D(Ln(EXD_{t-i})) + \sum_{i=1}^{q} \theta_{2i}\,D\big(Ln(RGDP_{t-i})\big) + \sum_{i=1}^{q} \theta_{3i}\,D\big(Ln(INFR_{t-i})\big) + \sum_{i=1}^{q} \theta_{4i} D\big(Ln(UNR_{t-i})\big) + \sum_{i=1}^{q} \theta_{5i} D\big(Ln(FDI_{t-i})\big) + \sum_{i=1}^{q} \theta_{6i}\,D(Ln(POP_{t-i})) + \theta ECT_{t-1} + e_t$$

$$D\big(Ln\,(POP_t)\big) = \theta_0 + \sum_{i=1}^{p} \theta_{1i}\,D(Ln(POP_{t-i})) + \sum_{i=1}^{q} \theta_{2i}\,D\big(Ln(RGDP_{t-i})\big) + \sum_{i=1}^{q} \theta_{3i}\,D\big(Ln(INFR_{t-i})\big) + \sum_{i=1}^{q} \theta_{4i} D\big(Ln(EXD_{t-i})\big) + \sum_{i=1}^{q} \theta_{5i} D\big(Ln(FDI_{t-i})\big) + \sum_{i=1}^{q} D(Ln(UNR_{t-i}) + \theta ECT_{t-1} + \mathrm{e_t}$$

According to Granger (1969), if there is a confirmation of a long-run relationship among the variables, there must either be a bidirectional, unidirectional or neutral causal relationship between them. In order to determine short run causality, the researcher used an unrestricted vector auto-regressive model. On the other hand, if the coefficients for lagged error correction terms are significant, this indicates that long run causality exists among variables.Short-term causality is captured by F - statistics (or Wald statistics). Long-term causality is captured by t-statistics on the coefficient of the lagged error correction. The following table 1 shows the order of lags suggested by each criteria.

4. Estimation Results

4.1. Lag Length Determination

Table 1 ︰ Lags order suggested by each criterion

Lag Order	LOGL	LR	FPE	AIC	SC	*HQ*
0	-194.7781	NA	0.182108	12.48613	12.71515	12.56204
1	-136.5185	94.67171	0.023295	10.40741	11.78154[a]	10.86289
2	-98.80853	49.49440[a]	0.011909	9.613033	12.13227	10.44809
3	-66.67363	32.13490	0.010789[a]	9.167102[a]	12.83144	10.38173[a]

[a] shows orders of lag selected by the criterion

Source: E-views-v-10

Specifically, Alemu et al. (2016) found that the optimum candidate for lags size determination is when AIC is minimized, a condition also met by this study at an optimal lag order of three.The ADF unit root tests for stationary of the variables at levels and at the first difference are shown in table 2.

4.2. ADF Unit Root Test of Variables at Level and First Difference

Table 2 : ADF unit root tests results for stationary of the variables at levels and first difference

Variables	Levels		First difference		
	Constant	Constant and trend	Constant	Constant and trend	Order of integration
LnUNR	(2.751582)	(2.734954)	(7.697294)*	(7.609472)*	Stationary at I(1)
	[0. 0761]	[0.2299]	[0.0000]	[0.0000]	
LnRGDP	(4.201534)*	(6.038616)*	(5.014189)*	(4.907468)*	Stationary at I(0) and I(1)
	[0.0023]	[0.0001]	[0.0003]	(0.0024)	
LnFDI	(1.382028)	(3.516594)	(5.883800)*	(5.803385)*	Stationary I(1)
	[0.5786]	[0.0481]	[0.0000]	[0.0002]	
LnINF	(4.168996)*	(7.536394)*	(7.691951)*	(7.536394)*	Stationary at I(0) and I(1)
	[0.0026]	[0.0000]	[0.0000}	[0.0000]	
LnPOP	(0.263257)	(4.212254)	(4.323737)*	(4.332646)*	Stationary at I(1)
	[0.9198]	[0.2116]	[0.0018]	[0.0087]	
LnEXD	(1.472761)	(2.574466)	(4.247948)*	(4.191843)*	Stationary I(1)
	[0.5347)	[0.2934]	[0.0021]	[0.0118]	
MacKinnon (1996) with constant, no trend, ( ) indicates t-statistics with absolute value, [ ] indicates p-value.			A null hypothesis states that all variables have a unit root at the level and first difference. A * means that the null hypothesis is rejected at the level and first difference levels of significance.		

Source: E-views-v-10

The unit root tests make sure that there no I (2) variable. For that reason, an ARDL procedure of co-integration test can be applied for this study with consideration of constant term (Yelwa et al., 2015).

4.3. ARDL Bounds Test Result for Co-integration

The estimation of equation tests for the existence of a long-run relationship among the variables is by conducting an F-test for the joint significance of the coefficients of the lagged levels of the variables, that is;

$$Ho: a1i=a2i=a3i=a4i=a5i=a6i=0$$

$$Ha: a1i \neq a2i \neq a3i \neq a4i \neq a5i \neq a6i \neq 0, \text{ for } i = 1, 2,3,4,5 \text{ and } 6$$

The calculated F-statistics are reported in table 3 when each variable is considered as a dependent variable in the ARDL regressions.

Table 3: ARDL bound testing to co integration results

Model	f-statistic	inference
$F_{LnUNR}(LnUNR \backslash LnRGDP, LnPOP, LnFDI, LnEXD, LnINFR)$	7.276699*	yes
$F_{LnPOP}(LnPOP \backslash LnRGDP, LnUNR, LnFDI, LnEXD, LnINFR)$	8.891138*	yes
$F_{LnRGDP}(LnRGDP \backslash LnUNR, LnPOP, LnFDI, LnEXD, LnINFR)$	8.742264*	yes
$F_{LnFDI}(LnFDI \backslash LnRGDP, LnPOP, LnUNR, LnEXD, LnINFR)$	13.25035*	yes
$F_{LnEXD}(LnEXD \backslash LnRGDP, LnPOP, LnFDI, LnUNR, LnINFR)$	4.957683*	yes
$F_{LnINFR}(LnINFR \backslash LnRGDP, LnPOP, LnFDI, LnEXD, LnUNR)$	5.071352*	yes

Critical value bounds of the F-statistic and T-statistic: unrestricted intercept and no trend

		F-statistic						T-statistic					
K = 5	Sign-level	99%		95%		90%		99%		95%		90%	
		I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(10	I(0)	I(1)	I(0)	I(1)
		3.41	4.68	2.62	3.79	2.26	3.35	3.43	4.79	2.86	4.19	2.57	3.86

Note: 1) K is the number of regressors 2) * denote statistically significance at 1 percent levels of significance.

From the above table, obviously there is a long run relationship amongst the variables. This imply that the null hypothesis (Ho) of no co-integration among the variables is not accepted.

4.4. Granger Causality Tests

Based on the coefficients on the lagged values of the dependent variables, we can say that the independent variable granger is caused by the dependent variable. In addition to checking for unidirectional causality, we should check for bidirectional causality, in which Yt causes Xt and Xt causes Yt. At last, we have to check whether there exists no granger causality effect (Min and Guna, 2018).

4.5. Granger Short Run Causality Tests

Table 4：Results of short run granger causality (Wald F-Test)

		F-statistics						Direction of causality
		A	*B*	*C*	*D*	*E*	*F*	
Dependent variable		*LnUNR*	LnRGDP	LnINFR	LnFDI	LnEXD	LnPOP	
LnUNR	*a*	-----	1.960057 (0.1603)	3.312775 (0.0444)	3.539446 (0.0365)	2.777179 (0.0721)	4.463240 (0.0545)	C to a D to a
LnRGDP	*b*	4.459322 (0.0173)	--------	15.92104 (0.0001)	7.015871 (0.0031)	7.239743 (0.0001)	5.588139 (0.0110)	A to b
LnINFR	*c*	2.124081 (0.1459)	3.488410 (0.0536)	----------	2.251744 (0.1295)	4.811222 (0.0173)	1.427886 (0.2887)	None
LnFDI	*d*	1.033132 (0.4128)	2.391958 (0.1086)	3.517804 (0.0490)	-------	3.961069 (0.0283)	7.784014 (0.0025)	None
LnEXD	*e*	6.865831 (0.0001)	5.656562 (0.0085)	7.757029 (0.0049)	5.476741 (0.0064)	--------	5.949452 (0.0070)	A to e
LnPOP	*f*	7.55 (0.9932)	7.247822 (0.0154)	2.820854 (0.0701)	12.53645 (0.0001)	3.953521 (0.0262)	----------	None

Source: E-views-v-10

For foreign direct investment, the logarithmic correlation is unidirectional with the unemployment rate, while the F-statistic for inflation is 3.312775, which is greater than the critical value of (0.0444) at 95% significance level. In other words, the inflation rate predicts unemployment, which is in line with the findings of the study (Asif and Aurangzeb, 2013). In this study, we found that unemployment is not significantly caused by inflation, but inflation causes unemployment. Other study also showed that there is no causality running between inflation and unemployment in the short run (Anup, 2017). A grangers test with an F-statistic of 3.539446 is greater than the critical value of (0.0365) at 95% standard significance level. This indicates that FDI granger causes unemployment. The results are similar to those from Adam and Miroslawa (2011).Furthermore, the findings indicate a nonsignificant granger causal relationship between unemployment and foreign direct investment.

An F-statistic of 4.459322 was calculated for the third Grangers test, which is greater than the critical value of (0.0173) at 95% significance level. This implies unemployment grangers cause RGDP. However, the overturn is not true. But the reverse is not true and it is consistent with the study of (Fouzeia et al., 2015). In the fourth granger test, the F-statistic for the unemployment granger is 6.865831 which is significantly greater than the significance threshold of (0.0001). This suggests that unemployment granger causes EXD. In other words, unemployment predicts external debt. Unemployment can lead to financial crisis and a decline in a nation's purchasing power, which can result in poverty followed by increasing debt. These results indicate that there is no significant granger causality from external debt to unemployment.As a final note, POP Granger cause unemployment, but the reverse is not true.

4.6. Granger Long Run Causality Tests

Table 5: Results of long run granger causality

Dependent Variable	Independent Variable					
	D(LnUNR)	D(LnRGDP)	D(LnINFR)	D(LnFDI)	D(LnEXD)	D(LnPOP)
	Coefficient of ECM(t-1)		ECM (t- Value)		Probability	
D(LnUNR)	-1.266859		-7.775125		0.0000	
D(LnRGDP)	-1.126292		-10.49189		0.0000	
D(LnINFR)	-1.304447		-7.897164		0.0000	
D(LnFDI)	-1.532703		-7.092909		0.0000	
D(LnEXD)	-0.257428		-7.731363		0.0000	
D(LnPOP)	-0.145504		-7.980380		0.0000	

Source: E-views-v-10

The outcomes show that there's a bidirectional causality between unemployment and the macroeconomic variables.It has been observed that unemployment causes inflation, external debt, GDP growth, population growth, and foreign direct investment in Ethiopia, and the reverse is also true. A regression analysis shows that long-run coefficients of unemployment rate, real GDP, inflation rate, foreign direct investment, external debt, and population growth are negative and statistically significant at a one percent level.

Stamatiou and Dritsakis (2015) argue that unemployment has a bidirectional relationship with real gross domestic product in the long run.Therefore, a change in unemployment rate affects economic growth as well as a change in economic growth level affecting unemployment. There is a bi-directional causal relationship between inflation rate and unemployment. The observation from the above table suggests that changes in inflation rate affect unemployment, which ultimately affects monetary policy. The change in unemployment rate has the same effect on inflation, which prompts the monetary authorities to change their monetary policy approach.

The other explanation is that unemployment has a critical influence on population growth and that population growth also has a critical impact on unemployment at the same time.FDI and unemployment are also bidirectional; a change in unemployment rate has an effect on FDI, and a change in FDI affects unemployment in the country. It is consistent from the study of(Safet et al., 2015).Finally, there is bidirectional causality between external debt and unemployment; this implies that when external debt changes, unemployment changes as well, and vice versa.

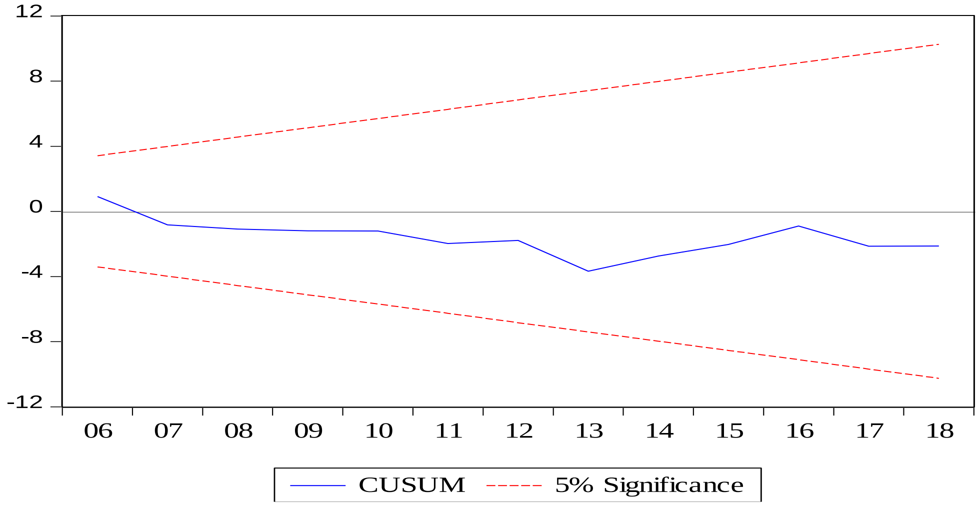
4.7. Diagnostic Test

Table 6: Diagnostic test of model and residuals

Normality Test			
Skewness (-0.653714)	Kurtosis (3.188191)	Jarque-Bera (2.326375)	Probability (0.312489)
Ramsey's RESET test			
t-statistic (1.239056)	df(12)	Probability (0.2390)	
F-statistic (1.535260)	df(1, 12)	Probability (0.2390)	

Heteroscedasticity (Breusch–Pagan test statistics)	
F-statistic (0.521975)	Prob. F(18,13) = 0.9000
Breusch-Godfrey Serial Correlation LM Test	
F-statistic (1.107776)	Prob. F(2,11) = 0.3645

Source: E-views-v-10



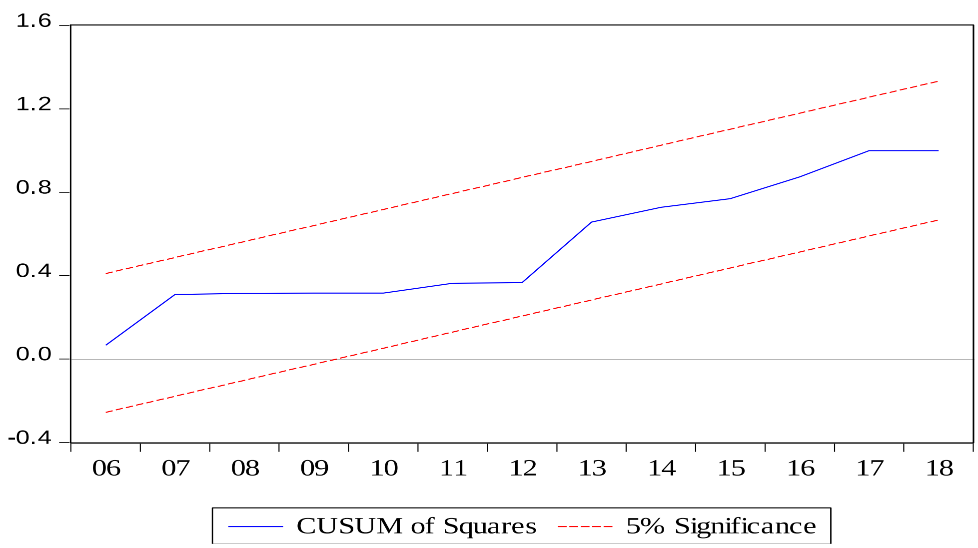


Figure 4.1. Stability test

Source: E-views-v-10

If the p-value is greater than the 5% significance level, then we can conclude that there is no heteroscedasticity, autocorrelation, and Ramsey's RESET test problem. The plotted values of CUMSUM and CUMSUMSQ remain within the straight lines, which supports the null hypothesis of a correct specification.It can be seen from the graph below that the actual and fitted values are almost identical, which indicates the ARDL model is robust.

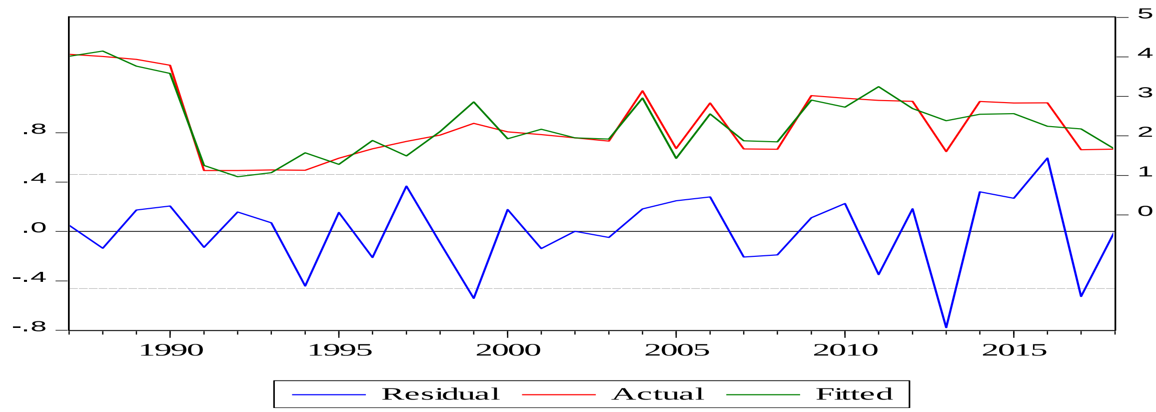


Figure 4.2. ARDL Model Robustness

Source: E-views-v-10

5. Conclusion

The bounds testing approach demonstrates that there is a long-run relationship between the unemployment rate and real gross domestic product, foreign direct investment, population growth, inflation rate, and external debt. According to the bounds testing approach, the unemployment rate has a long-run relationship with real gross domestic product, foreign direct investment, population growth, inflation rate, and external debt. Further, except for population growth, all of the macroeconomic variables have a short-run impact on unemployment. This study performed diagnostic checks. The results show that there is no serial correlation, no conditional heteroscedasticity, and no specification error and there is a normal distribution in the ARDL model. The CUSUM and CUSUMSQ statistics are well within the 5% critical bounds implying that short-run and long-run coefficients in the ARDL models are stable.The findings of the VECM estimates indicate that short-run unidirectional causality runs from foreign direct investment and inflation to unemployment. Again short-run unidirectional causality runs from unemployment to real gross domestic product and external debt. In the long run, the results provide evidence that macroeconomic variables such as inflation rate, population growth, real gross domestic product, foreign direct investment, and external debt, granger cause unemployment. In the long run, unemployment also causes the above-listed macroeconomic variables.

6. Recommendation

Hence, taking note of the points below would support the process of maintaining a stable unemployment rate; and hence, the well-being of the general macroeconomic environment in Ethiopia. For the unemployment rate in the country to be reduced, policymakers must address all of the major macroeconomic determinants of unemployment - population growth, foreign direct investment, real gross domestic product, inflation rate, and external debt.

The government should also consolidate the existing entrepreneurship activity and attract new entrepreneurs in order to create more employment and absorb a large pool of unemployed people. Those conditions help the government to reduce unemployment which comes from high population growth.

Government should encourage foreign investors to invest as soon as they enter the country in order to lower unemployment rates. Additionally, it should make the country more attractive to all citizens regardless of their education or profession.

Any action of the government to decrease unemployment may ultimately result in inflation. In order to overcome this problem, the government should increase the level of aggregate supply.

The government should borrow debt for only productive purposes and projects to reduce high unemployment. They also help the government to be free from external debt by increasing the productivity of its labor force and by repaying the loan within a reasonable timeframe. Otherwise, the huge external debt would throw the economy into a series of economic problems, and then high unemployment. The study recommends that the external debt stock should be effectively managed. Furthermore, the government should avoid dalliances with projects.

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