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Determinants of Income Inequality in Ethiopia

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Abstract:

Purpose: *The main objective of this study is to analyze determinants of income inequality in Ethiopia from (1988 to 2018).*
Design/methodology/approach: *This study used quantitative research approach and an explanatory research design in order to achieve its objectives. The method of analysis was econometrics analysis. This paper used Autoregressive Distributed Lag (ARDL) and Error Correction Model (ECM) in order to investigate the long-run and short run relationship between the dependent variable (income inequality) and its determinants. To test stationary Augmented Dickey –Fuller (ADF) test and Phillpes Perron (PP) test were used. The error correction coefficient, estimated at -0.84277 is highly significant, has the correct negative sign, and imply a very high speed of adjustment to equilibrium.*
Findings: *According to the econometrics analysis, real GDP per capita and unemployment rate are the main determinants of income inequality for Ethiopia based on ARDL model estimation result, R-squared is 0.7568. This implies that 75.68 % of the income inequality function is explained by the selected explanatory variables. If the value of R-Squared is higher, that model is the greatest the goodness of fit. Therefore, is the R-Squared in the regression model reveals that there is good fitness of value for a given result. The overall model is statistically significant because of P (F- Statistics) is 0.0009, which is less than 5% percent.*
Practical implications: *According to the research, the paper gives some policy recommendations. The government or other responsible bodies should focus on the country's growth and development, decreasing unemployment rate, inflation rate, the expansion of education access and the support of the social state.*
Originality value: *This is an original research for the state of Ethiopia. The use of specific econometric techniques, ARDL, ECM, VIF, make this research unique.*

Keywords: *Economic growth, income inequality, ARDL, ECM, VIF, Ethiopia.*

JEL codes: *E50, E58.*

Paper type: *Research article.*

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1. Introduction

Economic inequality is most obviously shown by people's different positions within the economic distribution - income, pay, and wealth (The Equality Trust 2012-2016). There are three main types of economic inequality. Such as income inequality, pay inequality, wealth inequality. The first one is income inequality which is the extent to which income is distributed unevenly in a group of people. Income is not just the money received through pay, but all the money received from employment (wages, salaries, bonuses etc.), investments, such as interest on savings accounts and dividends from shares of stock, savings, state benefits, pensions (state, personal, company) and rent.

The second one is pay inequality. Pay refers to payment from employment only. This can be on an hourly, monthly or annual basis, is typically paid weekly or monthly and may also include bonuses. Pay inequality therefore describes the difference between people's pay and this may be within one company or across all pay received. The last one is wealth inequality. Wealth refers to the total amount of assets of an individual or household. This may include financial assets, such as bonds and stocks, property and private pension rights. Wealth inequality therefore refers to the unequal distribution of assets in a group of people, (The Equality Trust 2012-2015). There are a number of factors that drive income inequality, such as technological change, change in labor market institutions, redistributive policy, education and other social, economic, political and demographical factors.

Technology has led to improvements in productivity and well-being by leaps and bounds, but has also played a central role in driving up the skill premium resulting in increased labor inequality. This is because technological changes can disproportionately raise the demand for capital and skilled labor over law – skilled and unskilled labor by eliminating many jobs through automation or upgrading the skill level required to attaining or keeping those jobs (Card and Dinardo, 2012; Acemoglu, 1998). Education can play an important role in reducing income inequality, or it determines occupational choice, access to jobs, and the level of pay, and plays a pivotal role or ability and productivity in the job market. The distribution of income will be unfair when education is not well address to the people. Income inequality influences the macroeconomic and social activities indifferent ways.

According to previous IMF studies, income inequality (which is measured by GINI coefficient) negatively affect growth and its sustainability (Beerg and Ostry, 2014). By depriving the ability of lower – income households to stay healthy and accumulate physical and human capital higher inequality lowers growth of the country (Galor and Moav, 2014). For example, it leads to under-investment in education as poor children ends up in lower quality schools and are less able to go to college. Because of this, labor productivity could be lower than it would have been in more equitable world (Stiglitz, 2012). Many empirical and theoretical studies indicates that the rising influence of the rich and stagnant incomes of the poor and the middle class have a causal effect on crises, and thus directly hurts short and long term growth. Similarly, higher inequality in advanced economies is associated with the global financial crisis.

This global imbalance can be challenged for macroeconomic and financial stability and thus growth (Kumholf, 2013). Extreme inequality can be associated with conflict by damaging trust and social cohesion. Conflicts may arise from the management of common resources. In other words, inequality affects the economies of conflict by intensifying the power of a certain group and then reducing the opportunity costs of initiating and joining a violent conflict (Lichbach, 1989).

2. Research Methodologies

2.1 Research Approach and Design

The research has used a quantitative research approach to analyse determinants of income inequality in the case of Ethiopia. Furthermore, the study was employing an explanatory research design in order to achieve its objectives. It is the most appropriate design for identifying the relationships between income inequality and its determinants by using macro variables.

2.2 Econometric Model Specification

There are a lot of factors that affect income inequality. Such factors have been studied by many researchers from different countries. Because of differences in the levels of economic development and characteristics of the economic system, the determinants of income inequality are not the same from one country to another even within the country. The most common determinants are GDP per capita, the technological progress, financial development, openness to trade, education, unemployment, inflation, urbanization, structure of the economy, government expenditure, external debit and financial aid, foreign reserves and exchange rate, growth of population, privatization and level of tax rates. In fact there are many determinants, this paper select five of them based on their relevance for developing countries like Ethiopia.

With this framework the mathematically relationship between income inequality and its major macroeconomic determinant are expressed as follows:

$$GINI = f\ (Y_t^2,\ PSER_t\ TO_t\ ,UEMR_t,\ \ INF_t) \tag{1}$$

Whereas $GINI_t$ – Income Inequality, Y_t^2 - Real GDP per capita squared according to many studies on the same study area, there is a non-liner relationship between income inequality and economic growth (like Kuznets). Based on this, this paper expects a non-liner relationship between them and economic growth of Ethiopia is not reach at maximum. So, it takes the squared real GDP per capita variable. $PSER_t$-

education, TO_t Degree of Tread Openness, UEMRt Unemployment rate and INF_t the inflation rate. Thus, an explicit estimable econometric model is formulated as follows**:**

$$LnGini=\beta_0+\beta_1 lnY^2_t+\beta_2 lnPSER_t+\beta_3 lnTO_t+\beta_4 lnUEMR_t+\beta_3 lnINF_t+e_t \qquad (2)$$

Researcher transformed all the variables into Log data to convert nonlinear to linear and avoid hetroscedasticity (Gujarati, 2004) and to show elasticity of the variables. Where all variables are defending previously except e_t which is the white noise process/marginal errors and t, time. Log transformation can reduce the problem of heteroscedasticity because it compresses the scale in which the variables are measured; thereby reducing a tenfold difference between two values to a twofold difference (Gujarati, 2004). It is important to note that the model is a multiplicative one where all parameters (coefficients) represent constant Elasticties.

2.2.1 Model

For time series data we have three main types of models, Vector Error Correction model (VECM), Auto Regressive Distributed Lag model (ARDLM) and Vector Auto Regressive model (VAR). All the variables in a VAR model are endogenous, there is no exogenous variable. Based on available data, this research has used one of the above models. Research has chosen the correct model after testing data. The variables were integrated of different order, that is a model having combination of variable with I(0) and I(1) order of integration, due to this reason this research has used ARDL model. ARDL model uses a combination of endogenous and exogenous variables, unlike a VAR model which is strictly for endogenous variables, from the bound test of the results.

Because the variables are integrated of different order, that is a model having combination of variable with I(0) and I(1) order of integration, which are not integrated of order two and co-integrated, this research has applied both long run (ARDL) and short run (VECM) models. ARDL model is relatively more efficient in the case of small and finite sample data sizes. According to Gujarati (2004), the ARDL modeling of unrestricted error correction model using Ordinary Least Square (OLS) can be represented as follows:

$$\Delta Yt=\beta_{0+}\sum_{i=1}^{P}\beta 1\Delta X_t+\sum_{i=1}^{P}\beta 2\Delta Xt-1+\beta 3\Delta Xt-1+\beta 41Xt-1+\beta 5Xt-1+ut \quad \dots\dots(3)$$

Where Δ denotes for first difference operation, Yt is for a vector of dependent variables, X_t is a vector of independent variables, p is optimal lag length, u_t is the residual term which is assumed to be white noise.

In order to test the existence of long-term relationship among the variables, the following equation will estimate by applying OLS.

Δ***GINt***$=$

$$\sum_{i=1}^{p}\beta 1\Delta ln\, Y^2 t-1+\sum_{i=0}^{p}\beta 2\Delta lnP\, SEPt-1+\sum_{i=0}^{p}\beta 3\Delta ln\, TOt-1\sum_{i=0}^{p}\beta 4\Delta lnUNEMt-1+\sum_{i}^{p}\beta 5lnINFt-1+u\,t\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Whereas $GINI_t$- Income Inequality Y_t^2-Real GDP per capita squared, $PSER_t$-education, TO_t-Degree of Tread Openness, $UEMR_t$ -Unemployment Rate and General inflation rate-INFt, ut is the residual term, which is assumed to be white noise, p is the optimal lag length and ln is natural logarithm. To test the significance of lagged level of the variables under consideration, the appropriate statistic is F or Wald test as Pesaranet *et al.* (2001) proposed for bound test approach was applied. The bounds test is mainly based on the joint Wald test or F- test which its asymptotic distribution is non-standard under the null hypothesis of no co-integration. The null hypothesis for no co-integration in the long-run among the variables in equation (4) is:

Ho $=\theta_o=\theta_1=\theta_2=\theta_3=\theta_4=\theta_5=0$ (meaning no long run relationship among the variables)

against the alternative one: $H_1\#\theta_o\#\theta_1\#\ \theta_2\ \#\ \theta_3\ \#\ \theta_4\#\ \theta_5\#\ 0$

The F-test has no standard distribution which depends on (i) whether the variables include in the model are I(0), or I(1), (ii) the numbers of regressors, and (iii) whether the model contains an intercept and/or a trend (Nara yan, 2008).

According to Gujarati (2004), there are two sets of critical value bounds for all classifications of regressors' namely upper critical bound value and lower critical bound value. The critical values for I(1) series are referred to as upper bound critical values, while the critical values for I(0) series are referred to as lower bound critical values. If the calculated F statistic is greater than the upper bound critical values, we reject the null hypothesis of no long run relationship among the variables. If the calculated F statistic is less than the lower bound critical values, we can't reject the null hypothesis rather accept the null hypothesis of no co integration among the variables.

However, if the calculated F statistic is between the upper and lower bound critical values, inference is inconclusive and we need to have knowledge on the order of integration of underling variables before we made conclusive inference (Gujarati, 2004). However, in this study we are not going to follow the bound critical value developed by Pesaran because of the computed critical values are based on large sample size (500 and more). Rather, a relatively small sample size in this study of 31 years observations, the research has used the critical values which are gotten from Eview's results.

$$lnGINIt \quad \beta o+\sum_{i=1}^{p} \beta olnGINIt-1+\sum_{i=0}^{p} \beta 1lnY^2t-1+\sum_{i=0}^{p} \beta\, 2lnTOt-1+ \sum_{i=0}^{p} \beta 3lnUNEMt-1+\sum_{i=0}^{p} \beta\, 4INFt-1+ \quad \sum_{i=0}^{p} \beta 5lnPsert- 1+\ \varepsilon t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5$$

In equation 5 all variables are as previously defined. The orders of the lags in the ARDL Model is selected by the Akaike Information Criterion (AIC). Researcher was use the Akaike Information Criterion (AIC) in lag selection because of its advantages for small sample size (Tsadkan, 2017). Determination of the optimal lag length is two, so it is crucial in ARDL model, because of it helps us to address the issue of over parameterizations and to save the degree of freedom (Taban, 2010) as cited in Tsadkan (2013). For annual data, Pesaran and Shin (1999) recommend choosing a maximum of 2 lags. From this, the lag length that minimizes Akaike Information Criterion (AIC) is selected.

$$YECTt = lnGINI-(\beta o \ +\sum_{i=1}^{p} \beta olnGINIt-1 \quad \sum_{i=0}^{p} \beta 1lnY^2t-1 \quad + \sum_{i=0}^{p} \beta 2lnPSEPt-1+\beta 3lnTOt-1\beta 4lnUNEMt-\ 1+\beta 5INFt- 1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6\ )$$

Here Δ is the first difference operator; β’s are the coefficients relating to the short -run dynamics of the model's convergence to equilibrium, and Y measures the speed of adjustment.

2.2.2 Description of variables

The dependent variable is income inequality. There are many types of measurements that measures income inequality in the global, country and regional level. Gini coefficient is the most common or popular measures of income inequality in the world. The model includes five explanatory variables. One of the independent variable is economic growth. This variable is measured by real GDP per capita. GDP per capital is growth domestic products divided by midyear population.

According to many studies on the same study area, there is a non-liner relationship between income inequality and economic growth (like Kuznets). Based on this, this paper expects a non-liner relationship between them. So, it takes the squared real GDP per capita variable. For the case of Ethiopia, it expects a positive relationship between them. Second independent variable of this study is education. When we take education for the purpose of this study, it can be measured by many measurements. Primary school enrollment rate is the most common measurement of the country’s education level.

Net primary school enrollment rate is defined as the number of children enrolled in primary school that belongs to the age group that officially corresponds to primary schooling, divided by the total population of the same age group. Education creates a high wage for those with good education, and then it leads to higher competition in the labor market. Thus, uneducated people will be unemployed and they cannot generate income. Finally, the income gap between the educated and uneducated people increased. Therefore, net primary school enrollment rate expected to affect income inequality negatively. Third independent variable of this study is trade openness. Trade openness is a measure of economic policies that either restrict or invite trade between countries. It can be calculated as the simple average of total trade (i.e., the sum of exports and imports of goods and services) relative to GDP.

According to Hecksher- Ohlin model, developing countries are thought to have more unskilled labor relative to skilled labor (and/or relative to capital) is assumed to be unequally distributed across the population and the increase in the relative demand for skilled labor (capital) in developed countries as a result of trade the distribution of income between rich and poor are not equal. But, within one developing country trade is used to efficiently utilizing the hidden resource and the poors' with unskilled labor start generate a better income.

So, it is expected to get a negative relationship between income inequality and trade openness. The fourth independent variable of this study is unemployment Rate. Unemployment occurs when people who are without work are actively seeking work. The most frequently used measure of unemployment is the unemployment rate. The unemployment rate is a measure of the prevalence of unemployment and it is calculated as a percentage by dividing the number of unemployed individuals by all individuals currently in the labor force. The rise in unemployment rate results high dependency ratio and lower per capita GDP.

In one family, if the number of unemployed members is larger than the employed, the overall income of that family will be lower when we compare it with the family with most of the family members employed. As a result, the gap between the rich with a job (employed) and the poor without job (unemployed) widen with increased unemployment rate. So, it is expected to get a positive relationship between income inequality and unemployment rate. The least independent variable of this study is general inflation (INF), inflation is defined as an increase in the overall price level in a country and measured in percent (CPI).

Therefore to analyze its effect on income inequality, it is the other interest of the researcher, which is included in this study as independent variable. The coefficient of this variable would be expected a positive sign. Inflation is measured in percent (CPI). Inflation reduces the purchasing power of individual as a result of the demand of goods produced by individuals will significantly increase. This implies that income inequality is increased. Therefore, positive sign is expecting for the estimated coefficient of the inflation variable in the regression result.

2.3 Methods of Data Analysis

The study has used econometric methods of data analysis. To analyze statistical data standard econometric techniques would apply to analyze the major determinants of income inequality under the study period. In the econometric part of this research has used the following multivariate models i.e., Auto Regressive Distributed Lag model (ARDL) and Vector Error Correction nofel (VEC). Finally, Eview 10.0 versions have been used as statistical software package for the entire analysis of this study.

3. Data Analysis and Interpretation

3.1 Unit Root Test Analysis

In order to determine the degree of integration, a unit root test is carried out using the standard Augmented Dickey-Fuller (ADF) and Phillips-Person test statistic (PP). Moreover in applying ARDL model all the variables entered in the regression should not be integrated of order two. To check these conditions, unit root test is conducted before any sort of action taken. Even though the ARDL framework does not require per-testing variables to be done, the unit root test could convenience us whether or not the ARDL model should be used. The result in Table 1 shows that there is a mixture of I(0) and I(1) but not any order two.

Table 1. *Unit root test (Augmented Dickey-Fuller test*

	Augmented Dickey-Fuller test statistics (ADF-Test)					
Variables	**With Intercept**			**Trend and Intercept**		
	At Level	At first difference	Order [ ]	At Level	At first difference	Order **( )**
Gini Coefficient(LGini)	-1.79	-6.177	I[0]at1,5 and 10 %	-1.86	-6.088	I[0]at1,5 and 10 %
GDP Per Capital (LY)	0.747	3.11	I[0] at 1, 5 and 10 %	-1.581	-3.085	I[0]at1,5 and 10 %
Net Primary School Enrollment Rate(LPSER)	-0.1144	-4.248	I[0] at1, 5 and 10 %	-2.07	-4.1257	I[0] at1, 5 and 10 %
Unemployment Rate (LUEMR)	-1.680	-4.422	I[0] at1, 5 and 10 %	-3.83	-2.895	I[1]at1,5 and 10 %
Inflation Rate (LINFR)	-1.887	-7.598	I[0] at1, 5 and 10 %	-3.35	-3.083	I[1]at1,5 and 10 %
Trade Openness(LTO)	-3.48	-2.065	I[1] at 1, 5 and 10 %	-2.546	-3.2205	I[0]at1,5 and 10 %
MacKinnon (1996) with constant, no trend Test critical values:1% level = -3.67 5% level = -2.96 10% level = -2.62 **Note:** If absolute value of t- Statistics is less than Test of critical values then the data is stationery or if probability is greater than 5% then data is stationary **i.e** we accept null hypothesis				with constant and trend Test critical values: 1% level = -4.2967 5% level = -3.5683 10% level = -3.2183 **Note:** If absolute value of t- Statistics is less than Test of critical values then the data is stationery or if probability is greater than 5% then data is stationary **i.e** we accept null hypothesis		

Source: *Eview 10.0 results.*

As we have seen form Table 1, Gini coefficient, real GDP per capital, primary school of enrolment rate, inflation rate, and unemployment rate are integrated of order zero I(0), while trade openness is integrated of order one I(1). Meaning Gini coefficient, real GDP per capital, primary school of enrolment rate, inflation rate and unemployment rate are stationary in level where as trade openness is stationary in first difference (with intercept). However, with trend and intercept, except unemployment rate and inflation rate, all the variables are stationary in level.

Table 2. *Unit root test (Phillips-Perron test statistic test)*

	Phillips-Perron test statistic (PP Test)					
Variables	**With Intercept**			**Trend and Intercept**		
	At Level	At first difference	Order [ ]	At Level	At first difference	Order [ ]
Gini Cofficient (LGINI)	-1.83	-6.165	I[0]at1,5 and 10 %	-1.98	-6.0844	I[0]at1,5 and 10 %
GDP per Capital (LY)	11.09	0.516	I[1] at 1, 5 and 10 %	6.32	-1.789	I[1]at1,5 and 10 %
Net Primary School Enrollment rate (LPSER)	-0.2722	-4.25	I[0] at1, 5 and 10 %	-2.08	-4.134	I[0] at1, 5 and 10 %
Unemployment Rate (LUEMR)	-1.517	-7.09	I[0] at1, 5 and 10 %	-3.624	-2.923	I[1]at1,5 and 10 %
Inflation Rate (LINFR)	-1.887	-7.598	I[0] at1, 5 and 10 %	3.082	-3.783	I[0]at1,5 and 10 %
Trade Openness (LTO)	-1.338	-4.894	I[0] at 1, 5 and 10 %	-0.496	-4.91949	I[0]at1,5 and 10 %
MacKinnon (1996) with constant, no trend Test critical values:1% level = -3.679 5% level = -2.967 10% level = -2.622 **Note:** If absolute value of t - Statistics is less than Test of critical values then the data is stationery or if probability is greater than 5% then data is stationary **i.e** we accept null hypothesis.				with constant and trend Test critical values:1% level = --4.31 5% level = -3.57 10% level = -3.22 **Note:** If absolute value of t - Statistics is less than Test of critical values then the data is stationery or if probability is greater than 5% then data is stationary **i.e** we accept null hypothesis.		

Source: *Eview 10.0 results.*

Similarly, the PP test shows that there is a mixture of integration order zero and order one. That is, Gini coefficient, primary school of enrollment rate, unemployment rate , inflation rate and trade openness are stationary in level while real GDP per capital is e stationary in first difference (with intercept only). However, except unemployment rate and real GDP per capital all the variables are stationary at level with intercept and trend. Form Tables 2 and 3 we can conclude that none of the variables entered in the regression are of order two, which are not desired in applying ARDL model. So, ARDL cointegration technique proposed by Pesaran *et al.* (2001) is the most appropriate method for estimation or to check the long run relationship among the variables.

3.2 Model Stability and Diagnostic Test

To check the verifiability of the estimated long run model, some diagnostic tests are undertaken. Priority in doing any analysis, the researcher required to check the standard property of the model. In this study the researcher carried a number of model stability and diagnostic checking, which includes Functional form (Ramsey's RESET) test Normality (Jaque-Bera test), Multicolinearity (Variance Inflation Factor test), Autocorrelation test (Durbin-Watson test) and Hetroscedasticity (Breusch-Pagan-Godfrey test).

In addition to the above diagnostic tests, the stability of long run estimates has been tested by applying the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ) test. Such tests are recommended by Pesaran *et al.* (2001). In order to reject or accept the null hypothesis, we can decide by looking the p-values associated with the test statistics. That is the null hypothesis is rejected when the p-value are smaller than the standard significance level (i.e., 5%).

3.2.1 Test of Multicolinearity

Multicolinearity refers to the condition that variables are correlated and its presence affects the features of the sample. The classical linear regression models assume that there is no multicollearnity among the explanatory variables. If perfect multicolinearity exists, the regression coefficient of the explanatory variable are indeterminated and the standard errors are infinite and cannot be estimated with accuracy. In order to test multicolinearty, this study used the Variance Inflation Factor (VIF). The larger the mean value of VIF, the more multicollinearity occurred. As the rule, if the mean of VIF is greater than 5 (VIF>5), that variable is highly collinear between the explanatory variables (Gujarati, 2004).

Table 3. *VIF test for Multicolinearity*

Variables	**VIF**	**1/VIF**
Constant	11.49	0.0870
GDP per capital (LY)	7.56	0.1323
Net PrimarySchool Enrollment Rate (LPSER)	2.74	0.3651
Unemployment rate (LUEMR)	2.0	0.4897
Inflation rate (LINF)	1.12	0.8890
Trade Openness (LTO)	1.38	0.7270
Mean of VIF		**4.39**

Source: *Eview 10.0 results.*

From the above Table 3 the mean of VIF shows that there is no problem of multicollinearty or linear relationship between a given explanatory variables. If the mean value of VIF is greater than 5, then we would say that there is multicolinearity. However, it is far less than 5 there is no problem of multicollinearity (Gujarati, 2004).

3.2.2 Functional form (Ramsey RESET test)

Ramsey RESET test stands for regression specification error test and was proposed by Ramsey (1969). The Ramsey Regression Equation Specification Error Test (RESET) is a general specification test for the linear regression model. More specifically, it tests whether non-linear combinations of the fitted values help to explain the response variable. The intuition behind the test is that if non-linear combinations of the explanatory variables have any power in explaining the response variable, the model is misspecified in the sense that the data generating process might be better approximated by a polynomial or another non-linear functional form so, when we test the specification of the functional form the following result has obtained (Table 4).

Table 4. *Functional form (Ramsey RESET Test)*

	Value	Df	Probability
t- statistics	1.8326	24	0.0724
F- statistics	3.3584	(1,24)	0.0724
Likelihood ratio	3.4995	1	0.0614
Note: *Decision criteria of RESET test ,if t-statistics ,F- statistics and likelihood ratio are not significant since the probability value are greater than 0.05. It means the estimated model is free from specification errors.*			

Source: *Eview's 10.0 results.*

We could not reject the null hypothesis using the Ramsey's RESET test, which tests whether the model suffers from omitted variable bias or not. As the test result indicates above we cannot reject the Ramsey's test, which means that the model is correctly specified.

3.2.3 Test of Heteroscedasticity

To test Heteroscedasticity, the Breusch-Pagen-Godfrey test is used. The result shows the following; as an important assumption of the classical linear regression model is that the disturbance μ_i appearing in the population regression function is homoskedastic. They all have the same variance but when there exists an outlying observation in relation to the observation in the sample the assumption of constant variance is violated. This violation refers to as hetroscedastisticity which leads to estimator to be inefficient and, estimated variance to be biased.

Table 5. *Test of Heteroscedasticity*

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.4783	Prob. F(8,20)	0.8571
Obs*R-squared	4.6580	Prob. Chi-Square(2)	0.7934
Scaled explained SS	3.1214	Prob. Chi-Square(8)	0.9265

Source: *Eview 10.0 results.*

As we have seen from the above Table 5, we can reject the alternative hypothesis at 5% significant level due to its p-value associated with the test statistics which are greater than the value for the standard significance level (i.e., 0.7934> 0.05). From the above result the probability of chi^2>5% level of significance leads to the acceptance of the null hypothesis, so, the error term is not heteroscedastic that means there is the problem of homoscedasticity.

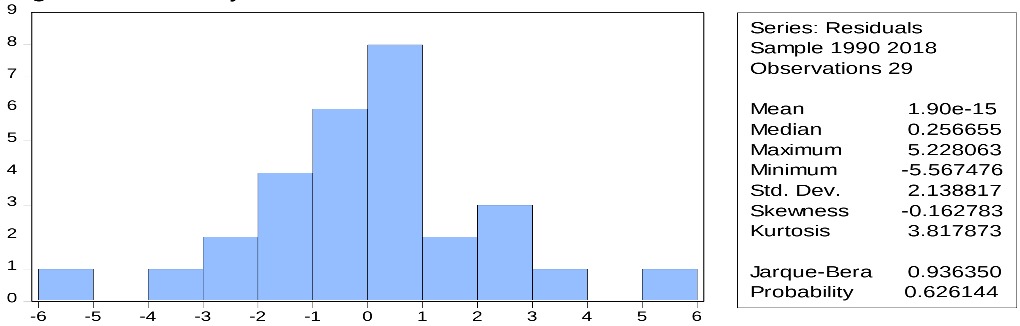
3.2.4 Tests for Autocorrelation

The disturbance term of any observation is not influenced by the disturbance term of any other observation. However, if there is such dependence there is autocorrelation. The simplest and widely used model is one where the error term μ_t and μ_{t-1} have correlation p. For this model one can test the hypothesis about p based on estimated correlation coefficient between the residuals. A common used statistic for this purpose is the Durbin-Watson (DW) denoted by DW. When the DW statistic is zero DW=0, there is a series of positive autocorrelation. When the Durbin-Watson statistic (DW) = (1.5<DW<2.5), there is no autocorrelation problem. If the DW is close to 4, there is a series of negative autocorrelation. In addition to this, to test correlation R statistic can be used. If R statistic is greater than the Durbin-Watson statistic, there is a series problem of autocorrelation. From the regression result DW=1.98 it is found between 1.5 and 2.5 (1.5<1.98<2.5) so, there is no problem of autocorrelation.

3.2.4 Test for Normality

The model assumes that the random variable u is normally distributed. Symbolically, $u \sim N(0, \delta^2 U)$, which reads as, u is normally distributed around zero mean and constant variance $\delta^2 u$. This means that small values of u's have a higher probability to be observed than large values. This assumption is necessary for constructing confidence intervals. If the assumption of normality is violated, the estimates of parameters are still unbiased but the statistical reliability by the classical tests of significance of the parameters cannot be assessed because these tests are based on the assumption of normal distribution of the u's. The null hypothesis is that it has normal distribution against the alternative hypothesis that the u's are not normally distributed.

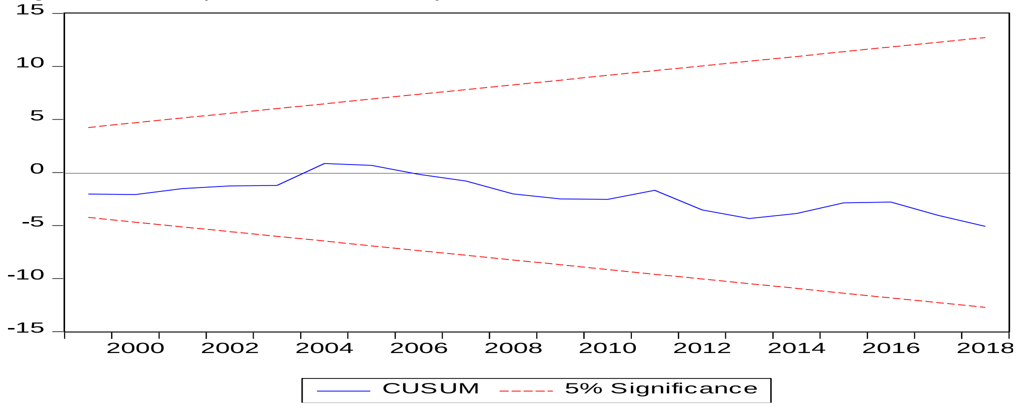
Figure 1. *Normality Test*



Source: *Eviews 10.0 results.*

As the result indicates that we could not reject the null hypothesis which says that the residuals are normally distributed, for the reason that the p-value associated with the Jaque-Berra normality test is larger than the standard significance level (i.e., 0.937>0.05), then the error term is normally distributed. Moreover, the stability of the model for long run and short run relationship is detected by using the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ) tests (Figure 2 and 3 respectively). The test finds serious parameter instability if the cumulative sum goes outside the area (never returns back) between the two critical lines.

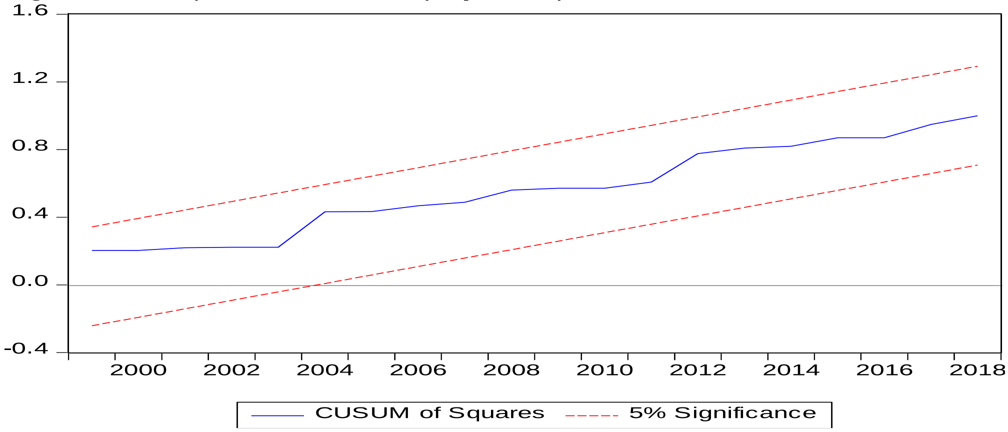
Figure 2. *Plot of Cumulative Sum of Recursive Residuals*



Source: *Eview's 10.0 results.*

The straight lines represent critical bounds at 5% significance level. As can be seen from the above figure, the plot of CUSUM test did not cross the critical limits. So, we can conclude that long run estimates are stable.

Figure 3. *Plot of Cumulative Sum of Squares of Recursive Residuals*



Source: *Eview's 10.0 results.*

The straight lines represent critical bounds at 5% significance level. As can be seen from the first figure, the plot of CUSUM test did not cross the critical limits. Similarly, the CUSUM of squares test shows that the graph does not cross the lower and upper critical limits. So, we can conclude that long run estimates are stable and there is no any structural break during the study period.

In addition to the model stability, 75.6 percent of the model has been explained by the regressors. Hence the results of the estimated model are reliable and efficient.

3.3 Long Run ARDL Bounds Tests for Co-integration

Since the researcher determined the stationary nature of the variables, the next task is the bounds test approach of co-integration by estimating the ARDL model specified in equation (3.5) using the appropriate lag-length selection criterion. According to Pesaran and Shine (1999), as cited in Narayan (2004) for the annual data are recommended to choose a maximum of two lag lengths. From this, a lag length that minimize AIC is 2. In addition to this, researcher have also used AIC to determine the optimal lag because it is a better choice for smaller sample size data as this study.

Apart from this, AIC found to produce the least probability of under estimation among all criteria available (Liew*et al.*, 2004) as cited in Tsadkan (2014). As we discus in the third part of this study, the F-test through the Wald-test (bound test) is performed to check the joint significance of the coefficients specified in equation (5). The Wald test is conducted by imposing restrictions on the estimated long-run coefficients of Gini coefficient, real GDP per capital, primary school of enrollment rate, unemployment rate, trade openness and inflation rate. The computed F-statistic value is compared with the lower bound and upper bound critical values provided by Eview's 10.0 results (Table 6).

Table 6. *F-Bounds test*

F-Bounds test statistics value	**Lag length**	**Critical value**	**Lower Bound Or I(0)**	**Upper Bound Or I(1)**
6.100904	2	1 percent	3.06	4.15
		5 percent	2.39	3.38
		10 percent	2.08	3

Note : *Decision criteria for Bounds test , If the calculated F-statistics is greater than the critical values for upper bound I(1), than we can conclude that there is co integration. That is along run relationship. Reject the null hypothesis. Estimate the long run model which is the error correlation model (ECM).*
If the calculated F- statistics is lower than the critical value for lower bound I(0), then we conclude that there is no co-integration, hence no long run relationship. Do not reject the null hypothesis. Estimate the short run model which is Autoregressive Distribute Lag (ARDL) model.
If the F-statistics falls between the lower bound I(0) and the upper bound I(1).the test is considered inclusive.

Source: *Eviews 10.0 results.*

As it is depicted in Table 6 above, with an intercept and trend, the calculated F statistics (6.100904) is higher than the upper bound critical values at 1%, 5%, and 10% level of significance. This implies that the null hypothesis of no long-run relationship is rejected; rather accept the alternative hypothesis (there is long-run relationship) based on the above critical values at 1%, 5%, and 10% level of significance. Therefore, there is co integration relationship among the variables in the long run. Then the researcher must estimate the short run model which is the Error Correlation Model (ECM).

3.4 ARDL Model Estimation

After confirming the existence of long-run co-integration relationship among the variables, the next step is running the appropriate ARDL model to find out the long run coefficients and ECM model to find out short-run coefficients, which are reported in Table 7 below.

Table 7. *Estimated long run Coefficients*

Dependent variable is Gini Coefficient			
Regressors	**Coefficient**	**Standard Error**	**T- Ratio [Prob]**
GDP Per Capital [LY]	0.2998***	0.0780	3.8435[0.0001]
Net Primary School enrollment rate [LPSER]	-0.0840***	0.0230	-3.6521[0.0013]
Unemployment rate [LUEMR]	0.2579*	0.0696	3.7054[0.0116]
Inflation rate [LINFR]	0.0830	0.0567	1.4638[0.1590]

Trade openness [LTO]	-0.1291	0.1973	-0.6538[0.5201]
Constant [C]	0.0103***	0.0015	6.8666[0.0000]
R-Squared =0.7560 Adjusted R- Squared =0.6590 Durbin –Watson statistics =1.9819 P (F- Statistics) =0.0009 ***Note:*** *Decision criteria for significance , If the Absolut value of t- ratio or t-critical is greater than t- statistics , for some chosen level of significance(Usually 1%, 5% or 10%) then the null hypothesis is can be rejected and variables are significant .*			

Source: *Eview's 10.0 results*

From the previous section the model has the following specification:

$$LnGini = \beta_o + \beta_1 \ln Yt^2 + \beta_2 \ln Pser_t + \beta_3 \ln To_t + \beta_4 \ln Uemr_t + \beta_5 \ln Ifr_{t} + ei$$

From the above ARDL estimation result the following regression model is obtained:

$$\begin{array}{lllllll} Gini = 0.0103 & + 0.2998Yt^2 & - 0.084Psert & - 0.1291Tot & + 0.2579Uemr & + 0.0830Infr_t \\ SE = (0.0015) & (0.0780) & (0.0230) & (0.1973) & (0.0696) & (0.0567) \\ t = (6.6500) & (3.7452) & (-3.4525.) & (-0.7546) & (3.6018) & (1.8731) \end{array}$$

But the researcher has put only the significant variables as follows:

$$\begin{array}{lllll} LNGini = 0.0103 & + 0.2998Yt^2 & + 0.2579Uemr_t & - 0.0840Pser_t \\ SE = (0.0015) & (0.0780) & (0.0696) & (0.0230) \\ t = (6.6500) & (3.7062) & (3.6018) & (-3.4525) \end{array}$$

3.4.1 Interpretation of the ARDL model estimation coefficients

As the ARDL model estimation shows, all the variables have a sign as expected by the theory. Real GDP per capita, unemployment rate, inflation rate and constant term have a positive sign. When the variables' unit increased the GINI coefficient also increased, and vice versa. On the other hand, primary school enrollment rate and trade openness have negative signs. This means, when these variables increased the GINI coefficient decreased, it changes in the opposite direction.

As we have discussed in the theoretical and empirical literature review, real GDP per capita, unemployment rate, and inflation rate have positive impact on income inequality while primary school enrollment rate and trade openness have an inverse impact on income inequality. As the ARDL model estimated result of the above Table 7 shows, unemployment rate have a positive impact on income inequality and is statistically significant at 10% percent level of significance. Holding other things constant, the GINI coefficient will be increased by 0.2579 when unemployment rate increased by 1%. The real GDP per capita coefficient, which is 0.2998, has a positive value and it is statistically significant at 1%, 5% and 10% percent significant levels.

Holding other variables constant, the GINI coefficient will be increased by 0.2998, when the real GDP per capita increased by 1birr. This result supports the Kuznets hypothesis. This hypothesis says that in the initial stages of development income inequality and real GDP per capita increases in the same direction. After achieving maximum stages of economic growth income inequality reaches its maximum point and starts to decline with a high economic growth. Ethiopia is one of the least developed countries. Then, based on this hypothesis the result gets a positive relationship between these variables.

Finally, the results of the paper show that the Kuznets hypothesis is applicable for Ethiopia. The thread significant variable is primary school enrollment rate. The coefficient of primary school enrollment rate, which is 0.0840, has a negative sign and it is statistically significant at 1%, 5%, and 10% level of significance. Other things remains constant, if the proportion of the number of children enrolled in primary school that belongs to the age group that officially corresponds to primary schooling to the total population of the same age group increased by 1%, the GINI coefficient will decrease by 0.0840. R-squared is 0.7568, this implies that 75.68% of the income inequality function is explained by the selected explanatory variables.

In other words, 75.68 % of variation of the dependent variable is due to the variation of the independent variables which have been included in the model and the remaining variation 24.32% is explained by the variables which are not included in the model. If the value of R-Squared is higher, than model is the greatest the goodness of fit. There for, is R-Squared in the regression model reveals that there is good fitness of value for a given result. The overall model is statistically significant because of P (F-Statistics) is 0.0009, which is less than 5% percent. Real GDP per capital and unemployment rate are the main factors that determine the income inequality this because of coefficient is high and also statistically significant and the result support kunzites hypothesis.

3.5 Short-Run Error Correction Model (ECM)

After the acceptance of long-run coefficients of the growth equation, the short-run ECM model is estimated. The error correction term (ECM), as we have presented before, indicates the speed of adjustment to restore equilibrium in the dynamic model. It is a one lagged period residual obtained from the estimated dynamic long run model. The coefficient of the error correction term indicates how quickly variables converge to equilibrium. In the short run there may be disequilibrium even if there is a long-term equilibrium relationship between the dependent variable and the independent variables which means that there is co-integration.

In order to correct this disequilibrium and to determine the short run relationship between variables the researcher has used the Vector Error Correction Model because data is co-integrated. The dynamic short run equilibrium is obtained by regressing the first difference of the dependent variable with the first difference of the explanatory variable with one period lagged error term to capture the adjustment towards the long run equilibrium. The coefficient of the error correction term indicates how quickly variables converge to equilibrium. Moreover, it should have a negative sign and are statistically significant at a standard significant level (i.e., p-value should be less than 0.05).

Table 8. *Error Correction Representation for the Selected ARDL*

Dependent variable is First Difference of Gini coefficient [DLGini]			
Regressors	**Coefficient**	**Standard Error**	**T-Ratio [Prob]**
Difference of Constant [DCONS]	1.9414***	1.0902	-1.78067[0.000]
The Error Correlation Coefficient [ECM-1)]	-0.8427**	0.4232	- 1.9912[0.008]
Difference of GDP Per Capital [D(LNY)]	0.0033***	0.0016	2.0625 [0.003]
Difference of Unemployment Rate [D(LNUEM)]	2.3549	1.2256	-1.9214[0.569]
Difference of Net Primary School Enrollment rate [D(LNPSER)]	-0.1083**	0.1603	-0.6756[0.056]
Difference of Trade Openness [D(LNTO)]	-0.1974	0.1825	-1.0816[0.281]
Difference of Inflation rate [D(LNINFR)]	0.0138**	0.0415	-0.3325[0.047]
R-Squared = 0.6647		Adjusted R Squared =0.6227	
Durbin –Watson statistics = 2.0800		P (F- Statistics) =0.0032	

Source: *Eview's 10.0 results *, **, *** indicate significance at the level 10%, 5% and 1%, respectively.*

From the above Table 8, similar to the log run result, real GDP per capital, unemployment rate, and inflation rate have positive impact on income inequality. Net primary school enrollment rate and trade openness have negative impact on income inequality in Ethiopia. The short run impact of unemployment rate on income inequality in Ethiopia is positive but insignificant. The error correction coefficient, estimated at -0.8427 is highly significant, has the correct negative sign, and implies a very high speed of adjustment to equilibrium. According to Bannerjee *et al*. (2003) as cited in Kidanemarim (2014), the highly significant error correction term further confirms the existence of a stable long-run relationship.

Moreover, the coefficient of the error term (ECM-1) implies that the deviation from long run equilibrium level of income inequality in the current period is corrected by 84.27% in the next period to bring back equilibrium when there is a shock to a steady state relationship. The short run coefficients of real GDP per capita indicate a positive and significant effect on income inequality, at 1%, 5% and 10% significance level. That is when real GDP per capita increased by one unit or one birr, income inequality is increase by 0.0033.

As one can understand from the above Tables (4-7) and (5-8) trade openness is not significantly affecting income inequality during the study period, despite their relationship which is negative both in the short run and in the long run. From this we can understand that under the study period, both in the long run and in the short run, trade openness, does not have significant effect on income inequality. Unlike the long run, the inflation rate variable significantly affects income inequality in the short run at 5% and 10% significance level. Even though, the sign is positive.

The constant term is positive, which is 1.9414. This indicates, if all variables are zero at the same time, the GINI coefficient becomes 1.9414. The short run R-squared is 0.6647. This implies that real GDP per capita, net primary school enrollment rate, unemployment rate, trade openness and inflation rate explained 66.47% of the variation on GINI coefficient. The overall model is statistically significant in the short run because of P (F-tatistics) is 0.0032, which is less than 5%. As the result indicates, the error correction term is statistically significant. Therefore, there is adjustment in the short run.

4. Conclusion and Recommendations

4.1 Conclusion

The main objective of this study is to analyze the determinants of the income inequality by using macro variables during the specified period. All determinants have a sign as expected by this paper based on the theoretical framework. To determine the long run and short run relationships among the variables, Autoregressive Distributed Lag (ARDL) and ECM model were applied. Before applying the ARDL model, all the variables are tested for their time series properties (stationarity properties) using the ADF and PP tests. As a result, GINI coefficient, real GDP per capita, primary school of enrolment rate, inflation rate and unemployment rate are stationary in all levels, where trade openness is stationary in first difference level (with intercept).

However, with trend and intercept, except unemployment rate and inflation rate, all variables are stationary in level I(0). Next to testing for time series property, the model stability has done by testing the diagonal testing techniques. The result revealed that, no functional form problem (the model is correctly specified), the residual is normally distributed, no multicolinearity, no autocorrelation and heteroscedasticity problem. The dependent variable, income inequality, was regressed against five explanatory variables. As discussed above, this study applied the methodological approach called ARDL model also known as bound test approach.

As the results indicted the calculated F-statistic is greater than the critical values for upper bound I(1), then we can conclude that there is co-integration. That is along run relationship between income inequality and its determinants (real GDP per capita, school of enrollment rate, unemployment rate, trade openness and inflation rate in long run during the study). As we have discussed in the theoretical and empirical literature parts, real GDP per capita, unemployment rate, and inflation rate have positive impact on income inequality while primary school enrollment rate and trade openness have an inverse impact on income inequality.

In the long run unemployment rate, has a positive impact on income inequality and is statistically significant at 10% significance level. The empirical result showed that unemployment rate, inflation rate and real GDP per capita are found to have positive impact on income inequality during the study period. Unemployment rate have a positive impact on income inequality and statistically significant at 10% significance level. A one percent increase in unemployment rate results in 0.2580 and 2.3550 percent increase in income inequality in long run and short run, respectively.

Likewise, a one percent increase in real GDP per capita will result in 0.2998 and 0.0035 percent increase in real GDP in long run and short run, respectively. According to the results, economic growth measured by real GDP per capita and unemployment rate are the major determinants of income inequality. In the long run, a coefficient of real GDP per capita is 0.2998, it is also statistically significant and it affects it positively as expected. In the short run, like in the long run it has a positive effect.

Ethiopia is at initial level of economic development, so according to Kuznets hypothesis it is expecting to have a positive relationship between them. Therefore, the result supports Kuznets hypothesis. Primary school enrollment rate and trade openness have also negative impact in income inequality during the study period in both long run and short run. A one percent increase in primary school enrollment rate will result in 0.0840 and 0.1083 percent decline in income inequality in long run and short run, respectively. It is statistically significant at 1%, 5% and 10% level of significant in the long run and it is statistically significant at 10% level of significance in the short run.

However, the study found out that trade openness has statistically insignificant impact on income inequality with negative sign in both long run and short run. Inflation rate has statistically insignificant impact on income inequality in the long run but it has statistically significant impact on income inequality in the short run at 10% level of significance.

4.2 Recommendations

Based on the finding of this study the following recommendations are forwarded.

- Though inflation is one serious problem in income inequality, the federal government should work to reduce the inflation rate if possible; otherwise, it should sustain the existing inflation rate by financing the budget deficit from non-inflationary sources and implementation of price stabilization program by subsiding basic food items and by controlling money supply.
- Education creates high wages for those with good education, and then it leads to higher competition in the labor market. Thus, uneducated people will be unemployed and they cannot generate income, therefore, educational level has negative influence on income inequality. This clearly indicates that when education increases income inequality is decreased, so to reduce income inequality, responsible body gives more attention for expansion of education and the responsible bodies should provide more equal access to basic education (by spending on public education that benefits the poor) to reduce inequality by facilitating the accumulation of human capital and making educational opportunities less dependent on socio economic circumstances and has to provide better job related training and education for low-skilled workers (on-the job-training).
- As the paper results indicate, real GDP per capita had positively and a highly significant effect on income inequality of the country. Based on Kuznets hypothesis after some high economic development level the relationship changes inversely (when the economy grows the income gap diminish). So, to reduce income inequality the country must grow very fast to reach that high economic development level. In order to grow very fast, the government should implement some policies like, pro-poor growth strategy to attract the participation of all people for the benefits of growth, well-targeted income support policies and policies that encourage innovations, skill-intensive production techniques, and formulate a better market that initiate competition, technology diffusion and create a good chain to products' movement.
- When the unemployment rate decreased the income gap also decreased. If the country aims at decreasing income inequality the government should, create accessible, productive and rewarding jobs, facilitate and encourage access to employment by formulating a policy that reduces market imperfection and institutional failure. For instance, minimum wage, spending on well-designed active labor market policies aimed at supporting job searching people, reducing the gap in employment protection like permanent and temporary workers, legalizing informal workers by giving some training and expanding formal sectarian employments by reducing tax, financial and regulatory constraints.
- This research can be used as a bench mark for further researches, therefore, anyone who are interested can assess the effect through adding additional variables which could be considered as a determinant of income inequality.

Further studies should be conducted with a wider coverage as this study only confined 31 years data.

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