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Income Inequality and Economic Growth:An Empirical Analysis of Kenya

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Despite the well-known potential benefits of equality of income in economic growth, the statistics for Kenya show that income is heavily skewed in favour of the rich and against the poor with the country's top 10% households controlling 42% of the total income while the bottom 10% controls less than 1%. The existing empirical evidence for the Kenyan economy does not shed light on whether there is a robust association between income inequality and growth over time. This paper provides an empirical investigation on the relationship between income inequality and economic growth and the hypothesis addressed was: inequality is harmful for growth. We contribute to the literature by employing an autoregressive distributed lag model using a time series date spanning from 1990–2015. The study found a significant positive but weak long run relationship between income inequality and growth. The short run was a strong positive relationship, which was significant at 1% level. This income inequality favours the rich, and therefore, to ensure fair distribution of wealth and a balanced growth, a policy goal should be equity in income distribution to reduce excessive income disparities. More research should be carried out on all other measures of inequality, to bring to light, which among them is more influential to GDP growth.

Keywords: GINI coefficient, ARDL estimation, income inequality, GDP growth, Kenya

1. Introduction

Why does a country like Kenya in different periods grow at such fluctuating different rates (Figure 1)? Can the growth trend be associated with the level of income inequality (Figure 2)? Or in short, is there a relationship between income inequality and economic growth? This question of income inequality and economic growth has been a major concern for social scientists and frustrated our political energies in Kenya for decades. Ever since Kenyan independency, the guise of equality of wealth and income has been the guiding motive of successive Kenyan governments. This has seen the introduction of such measures as free primary education, constituency development funds, and other sector-level reform initiatives to reduce income inequality, hence stimulate growth (Constitution of Kenya 2010, National Treasury 2015). However, statistics for Kenya show that income inequality is ever increasing and is heavily skewed in favour of the rich and against the poor, with the country's top 10% households controlling 42% of the total income while the bottom 10% controls less than 1% (SID 2004).

Figure 2 Trend of GDP growth in percentage

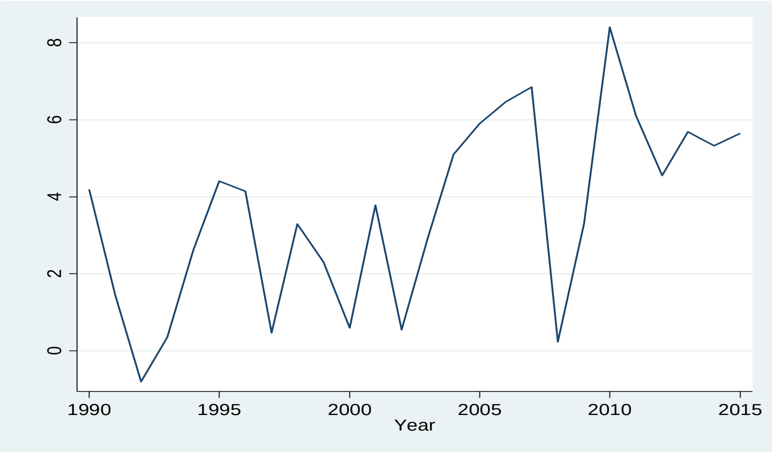
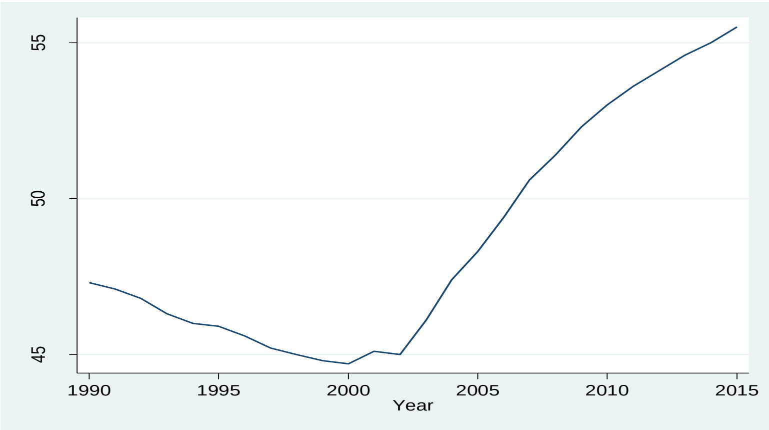


Figure 3 Trend in GINI Coefficient in percentage



Source: Own construction based on United Nations Development Programme (UNDP) and World Bank World Development Indicators (WDI) databases

On the effect of inequality on growth, a contradictory view has been gaining currency. Whereas the convectional textbook approach is that inequality is a good incentive for growth (Kuznets 1955), essentially insofar as it generates an incentive to work and invest more, or can trigger more investment, given that high-income groups tend to save and invest more. On the other hand, development economies have long expressed counter-arguments although not in a formalized way (Todaro 1992, Galor 2009). One of the main arguments by Cingano (2014) and Campos (2017) was that greater inequality can reduce the professional opportunities available to the most disadvantaged groups in society and therefore decrease social mobility, limiting the economy's growth potential. Similarly, greater inequality can also negatively affect growth if, for example, it encourages populist policies (Eisler 2016, Garcia and Arenas 2017) or leads to an excessive rise in credit, which ends up acting as a brake on growth (Morron 2017). While classical and neoclassical approaches have underlined a growth-promoting effect, modern perspectives highlight a potential growth-dampening impact of inequality on growth, the question of which of these effects are predominant depends strongly on the degree of income inequality already reached (Galor 2009). In this paper, as our empirical aim is to identify differentiated negative and/or positive effects income inequality has on Kenyan economic growth, we were, therefore, tempted to follow the position of the modern economists and summarize our tentative hypothesis in a simple statement: inequality is harmful for growth.

Before subjecting this hypothesis into empirical investigation, it would be prudent to provide some insight into various forms of inequalities associated with economic growth. Inequality is observed not only in incomes, but also in terms of social exclusion and the inability to access social services and socio-political rights by different population groups, genders and even races. According to Mount (2008) and Rugaber and Boak (2014), inequality can, therefore, be classified as, 1) Income inequality which measures the gap between the rich and the poor or people with similar background, status, qualifications but with different incomes, 2) Gender inequality as manifested in wages, discrimination, domination of positions of power and responsibility – it limits the extent to which women or men can make it to the top, 3) Opportunity inequality, which is measured in terms of ease of access to education, work, and housing, markets on the basis of race, ethnicity or gender, even across countries, and 4) Asset/wealth inequality, which measures the disparity not just in quantity but also in quality of natural resources, infrastructure, raw materials, and amount of human capital and assets. The focus of this article will be income inequality and its contribution to economic growth[1].

Why the focus on income inequality rather than some other measurable quantity? The reason is twofold: firstly, income as a proxy for economic welfare, and secondly, income as command over resources (Cowell 2007). In this article, income inequality is, therefore, defined as the degree to which distribution of economic welfare generated in an economy differs from that of equal shares among its inhabitants which means that one segment of the population has a disproportionately large share of income compared to other segments of that population (SID 2004). It may also entail comparison of certain attributes or well-being between two persons or a group of people and the differences in share of these attributes. However, the existing empirical evidence for the Kenyan economy does not shed light on whether there is a robust association between income inequality and growth over time. Therefore, this paper attempt to establish whether any relationship between income inequality and GDP growth really exists. In particular, our contribution is the use of autoregressive distributed lag to empirically assess whether and/or how inequality affects economic

[1]Note economic growth will be used interchangeably with GDP growth

growth. These results are crucially important for policy makers, as their challenge is to find out how, and not just if, inequality is affecting the process of economic growth. The remainder of the paper is organized as follows. Section II briefly reviews the theoretical foundation of income inequality on economic growth. This section also reviews some empirical literature on the relationship of income inequality and economic growth for Kenya and other parts of the world. Section III sets out the methodology, including the empirical model and database used in this study. Section IV displays the main results, which include tests result and empirical findings. Finally, section V concludes the paper.

2. Theoretical foundation of income inequality analysis

The most influential contribution in modern economic literature addressing explicitly the issue of economic inequality is grounded on the theoretical foundation developed by Kuznets (1955). Basing on empirical evidence, Kuznets maintains that inequality tends to rise in the early stages of economic development, as a consequence of industrialization, and then it declines in later stages, as capitalism matures. In this way income inequality presents the classical inverted-U shaped trend in time. Kuznets describes a positive relationship between income inequality and economic growth in the early phases of growth and a negative relationship in the later phases.

The research by Kuznets laid a significant foundation for studying the relationship between economic growth and income inequality. Beyond the theoretical sphere, many authors have attempted to provide empirical evidence of inequality's effects on economic growth although with contradictory findings. While some scholars found income inequality as negatively associated with growth in the long run (e.g. Alesina–Rodrik 1994, Perotti 1996, Panizza 2002, Nel 2003), other scholars found mixed results comparing income inequality and growth for developed and developing countries. For instance, Barro (2000) and Voitchovsky (2005) found a negative relationship between inequality and growth for poorer countries, but a positive relationship in the case of richer countries. However, this positive impact relies on panel data analysis and is either associated with short-term economic growth (Forbes 2000) or is dependent on national income (Barro 2000), on the initial income distribution itself (Chen 2003), on the profile of inequality (Voitchovsky 2005), or on the process of urbanization (Castells-Quintana–Royuela 2014).

In the stream of income inequality and GDP growth analysis, the critics of Kuznets' hypothesis question the nature of causality between the two variables, especially on the basis of empirical economic literature. The most relevant finding was that of Fields (2002) who observed that it is not economic growth per se which gives rise to economic inequality but it is the nature of economic growth which determines the development of inequality. In particular, Fields claimed that the effect of growth on inequality depends on the size and structure of the economy (which can be classified as a developed or developing economy).

In Kenya, there is scanty information in the literature on the relationship between income inequalities and economic growth. Most of the studies focus on explaining the contribution of income inequality on poverty levels experienced in the country. By way of example, Njuguna (2005) investigated the extent of poverty and the level of inequality in the Kenyan economy. The author compared changes in poverty and inequality between regions and their robustness using stochastic dominance analysis. The study used Welfare Monitoring Survey data spanning from 1994 and 1997 to shed some light on the intertemporal patterns of changes in welfare levels and distribution in Kenya across geographical and socio-economic groupings of policy interest. The author found that for a wide range of poverty lines, poverty and inequality increased in Kenya over the period. Along the same lines, a study by Suri et al. (2008) using time series data that ranged from 1997–2007 found that income inequality has been declining. The salient recommendation of these two studies was that poverty reduction requires economies to address inequality and economic structures – in addition to sustaining high levels of economic growth.

A more recent study by Gakuru and Mathenge (2012) followed the same line and seeks to highlight the levels of income inequality in Kenya and its implications on various policy options targeted at reducing poverty. The study applied the 2003 Kenyan SAM to develop a multiplier simulation model which tracks the linkages among the demand-driven shocks on economic growth, income generation, and consequently income distribution implications on different economic groups. The empirical results from the multiplier analyses show that due to high inequality in Kenya, stimulation of growth mainly benefit the richest urban household deciles, who own most of the factors of production. The authors recommended that Kenya will need to focus not only on economic growth, but also on inequality in order to effectively tackle poverty in the country.

The study of the impact of income inequality on the country's economic growth is highly relevant today. However, we were only able to discover one paper that tried to include income inequality proxies in the growth regression. This study was carried by Wanyagathi (2006) who used an ordinarily least squares estimation procedure to investigate the relationship between income inequality and economic growth using time series data spanning from 1950–2008. The author used control variables such as total expenditure on education, health, and population growth. Although this study did not consider the problems associated with time series data (the presence of multicollinearity, heteroscedasticy, autocorrelation etc.) the study provides some insight concerning the relationship between income inequality and growth. The author found that GINI coefficient, which is the measure of income inequality, to be negatively related to growth, which contradicts the Kuznets hypothesis. The author associated this to the social problems linked to inequality for the developing economy such as Kenya's, include corruption, civil wars, political instability and many issues.

Broadly speaking, as indicated in the reviewed literature, there is no single, universal mechanism behind the relationship between inequality and growth. Nevertheless, the reviewed literature has provided mechanisms supporting both possibilities, and the empirical literature attempting to discriminate between these mechanisms in the Kenyan situation has been largely inconclusive. Further, the econometric method employed in most studies was ordinary regression using OLS estimation technique, which does not take in account the problem associated with multicollinearity, heteroscedasticy, autocorrelation, or model specification among other things. Even if the results of the previous studies provide an important step in understanding the impact income inequality has on economic growth, given these problems, the findings of these studies can be considered preliminary in nature. Establishing a relationship between inequality and economic growth can be severely obstructed by inadequate econometric techniques. We tried to overcome this problem by applying autoregressive distributed lag (Nkoro–Uko 2016) model, specifically system ARDL, which improves the ability to handle endogeneity and avoids problems resulting from non-stationary time series data typically found in economic growth regressions. (Laurenceson–Chai 2003, Manyeki–Kotosz 2017). Further, the ARDL model was considered because it is flexible and combines both short run and long run effect into a single equation, which was the aim of the paper.

3. Methodological Framework and Data

The main objective of the research is to find out the relationship between inequality in income and growth of the economy in Kenya. Ultimately, in order to test our hypothesis that inequality is harmful to growth, we needed to optimize the model to capture both the short-run and long-run effects, and therefore this section continues with discussion of the empirical model and data applied.

3.1. Empirical model: ARDL Approach

Before specifying the model for use in this analysis we had to investigate whether the variables are stationary or not. The stationarity of the variables was examined to avoid the existence of spurious estimation results. Stationarity can be done in two ways; 1) KPSS test for stationarity that consider the null hypothesis H_0 that the series is stationary, and 2) unit root tests, such as the Dickey-Fuller test and its augmented version, the augmented Dickey–Fuller test (ADF) (Dickey and Fuller, 1979, 1981), or the Phillips–Perron test (PP) (*Phillips and Perron 1988)*, for which the null hypothesis H_0 is the opposite, that the series possesses a unit root and hence is not stationary. In this study, unit root test was adopted and both ADF and PP test conducted. Both ADF and PP tests the null hypothesis of a unit root in a time series sample. If a series is stationary without any differencing, it is said to be $I(0)$ or integrated of order 0. On the other hand, if a series is stationary after d-difference, it is said to be $I(d)$ or integrated of order d.

The second step involved is cointegration test. Several methods are available for conducting the cointegration test and the most commonly and widely used methods include the residual based Engle-Granger (1987) test, the maximum likelihood test based on Johansen (1991, 1998) and Johansen and Juselius (1990) tests. Due to the low power and other problems associated with these test methods, the OLS based autoregressive distributed lag (ARDL) approach to cointegration was adopted. The main advantage of ARDL modelling lies in its flexibility, in particular that it can be applied when the variables are of different order of integration (Pesaran–Pesaran 1997). Compared to other cointegration test approaches that require order of integration of the variables to be determined first which may lead to misclassification of variables as $I(0)$ or $I(1)$, a ARDL uses a bounds testing procedure to draw conclusive inference without knowing whether the variables are integrated of order zero ($I(0)$) or one ($I(1)$) (Pesaran et al. 2001). Another advantage of this approach is that the model takes sufficient numbers of lags to capture the data generating process in a general-to-specific modelling framework (Laurenceson–Chai 2003), and this accounts for the autocorrelation issue. Its popularity also stems from the fact that cointegration of nonstationary variables is equivalent to an error-correction (EC) process[2], and the ARDL model has a reparameterization in EC form (Engle and Granger 1987, Hassler and Wolters 2006). The EC integrates the short-run dynamics with the long-run equilibrium without losing long-run information, and the existence of a long-run cointegrating relationship can be tested based on the EC representation. In addition, it is also argued that using the ARDL approach avoids problems resulting from non-stationary time series data (Laurenceson–Chai 2003).

The existence of the long-run relation between the variables under investigation is tested by computing the Bound F or t statistic (bound test for cointegration) in order to establish a long run relationship among the variables. This bound for t-statistic is carried out on each of the variables as they stand as endogenous variables while others are assumed as exogenous variables. This approach is illustrated by using an ARDL (p,q) regression with an I(d) regressor as follows

$$GDPG_t = C_0 + \beta_1 GDPG_{t-1} + \cdots + \beta_p GDPG_{t-p} + \alpha_0 GINICoeff_t + \alpha_1 GINICoeff_{t_{t-1}} + \cdots + \alpha_q GINICoeff_{t_{t-q}} + \mu_t$$

or

$$GINICoeff_t = C_0 + \beta_1 GINICoeff_{t-1} + \cdots + \beta_p GINICoeff_{t-p} + \alpha_0 GDPG_t + \alpha_1 GDPG_{t-1} + \cdots + \alpha_q GDPG_{t-q} + \mu_t \qquad (1)$$

Where I =1,2,…T and $\mu_t \sim iid(0, \sigma^2)$, C_0 is the drift and $GINICoeff_t$ and $GDPG_t$ are the gross real GINI coefficient in percent and gross domestic product growth in percentage, respectively.

[2]A dynamic error correction model (ECM) can be derived from ARDL through a simple linear transformation (Banerjee et al. 1993)

The GINI coefficient is the measurement of the income distribution in a country. It is based on a scale from 0 to 100% with 0 being perfect equality and 100% representing perfect inequality. The $I(d)$ process can be generated by

$$GDPG_t = GDPG_{t-1} + \varepsilon_t \text{ Or } GINICoeff_t = GINICoeff_{t-1} + \varepsilon_t \tag{2}$$

Note u_t and $\varepsilon_t$are uncorrelated for all lags such that $GDPG_t$ or $GINICoeff_t$ is strictly exogenous with respect to u_t.ε_t is a general linear stationary process. In practice the ARDL ($p, q_1, q_2 \ldots\ldots q_k$) model for cointegration testing is expressed as;

$$\Delta GDPG_t = C_0 + \sum_{i=1}^{k} \beta_i \Delta GDPG_{t-i} + \sum_{j=0}^{k} \alpha_j \, \Delta GINICoeff_{t-j} + \delta_1 GDPG_{t-1} + \delta_2 GINICoeff_{t-1} + v_{1t}$$

or

$$\Delta GINICoeff_t = C_0 + \textstyle\sum_{i=1}^{p} \beta_i \Delta GINICoeff_{t-i} + \sum_{j=0}^{q} \alpha_j \, \Delta GDPG_{t-j} + \delta_1 GINICoeff_{t-1} + \delta_2 GDPG_{t-1} + v_{1t} \tag{3}$$

Here, k is the ARDL model maximum lag order and chosen by the user. The F-statistic is carried out on the joint null hypothesis that the coefficients of the lagged variables (δ_1, δ_2) are zero. The null of non-existence of the long-run relationship is defined by; H_0: $\delta_1 = \delta_2 = 0$ (null, i.e. the long run relationship does not exist) H_1: $\delta_1 \neq \delta_2 \neq 0$ (Alternative, i.e. the long run relationship exists). The model is "autoregressive", in the sense that $GDPG_t$ or $GINICoeff_t$ is "explained (in part) by lagged values of itself. Pesaran et al. (2001) provide lower and upper bounds for the asymptotic critical values depending on the number of regressors, their order of integration, and the deterministic model components based in F-test or t-test. Based on Pesaran et al. (2001), you fail to reject the null H_0^F or H_0^t respectively if the test statistic is closer to zero than the lower bound of the critical values, and reject the null H_0^F or H_0^t respectively if the test statistic is more than the extreme upper bound of the critical values. The existence of a (conditional) long-run relationship is confirmed if both null H_0^F or $H_0^t$are rejected. If a long run relationship exists between the underlying variables, while the hypothesis of no long run relations between the variables in the other equations cannot be rejected, then ARDL approach to cointegration can be applied. The optimal lag orders *p* and *q* (possibly different across regressors) can be obtained with proper model order selection criterion, e.g. the Akaike information criterion (AIC) or the Bayesian information criterion (BIC) or Hannan–Quinn Criterion (HQC). For this case, we adopted AIC criteria

Having confirmed that there exists a long-run relationship among variables, then the ARDL model can be reparameterization in conditional ECM form as follows;

$$\Delta GDPG_t = C_0 - \gamma(GDPG_{t-1} - \vartheta GINICoeff_{t-1}) + \sum_{i=1}^{p-1} \varphi_{GDGG_i} \Delta GDPG_{t-i} + \sum_{j=0}^{q-1} \varphi_{GINICoeff_i} \Delta LnGINICoeff_{t-j} + \mu_t \quad (4)$$

Where μ_t is a random "disturbance" term (white noise error term) and C_0, $GDPG_t$ and $GINICoeff$ are as defined earlier, with the speed-of-adjustment coefficient $\gamma = \sum_{j=1}^{p} \varphi_i$; and the long-run coefficients $\vartheta = \frac{\sum_{j=0}^{q} \beta_i}{\gamma}$.

Where φ_{LGDPG_i} and $\varphi_{GINICoeff_i}$ are the short-run dynamic coefficients of the model convergence to equilibrium. If the value of speed of adjustment is zero, it means that there is no long-run relationship. If it is between −1 and 0, there exists partial adjustment; a value smaller than −1 indicates that the model over-adjusts in the current period; a positive value implies that the system moves away from equilibrium in the long run (Oktayer–Oktayer 2013).

The model was further subjected to diagnostic and the stability tests to ascertain the appropriateness of the ARDL model. The diagnostic tests include a check for normality (Shapiro-Wilk W test for normal data: H_o: Normal), serial correlation (LM Test – Breusch–Godfrey LM test for autocorrelation: H_0: no serial correlation), the autoregressive conditional heteroscedasticity (ARCH Test - Breusch–Pagan / Cook–Weisberg test for heteroskedasticity: H_o: Constant variance), and finally the functional form of the model (Ramsey RESET test 1978) using powers of the fitted values: H_o: model has no omitted variables). In addition, the stability tests of ARDL model for long-run and short-run parameters was conducted by using the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares (CUSUM square) of recursive residuals.

3.2. Data

The study relied entirely on secondary data sources. Income inequality is measured by the GINI coefficient. The GINI coefficients data was obtained from the World Income Inequality Database (WIID) put together by the United Nations Development Programme (UNDP) and GDP growth data was sourced from World Bank World Development Indicators Database (WDID). The researcher collected annual time series data of the GINI coefficients and GDP growth for Kenya spanning from 1990 to 2015. We intended to use data from 1963 to 2017 but the main constraint encountered while collecting data for the model was with the amount of information available for the GINI coefficient used to measure income inequality and GDP growth. The GDP data between 1963 up to 2015 was available but beyond 2015 was not recorded while the GINI coefficients had a lot of gaps forcing us to use the shorter data series of between 1990–2015.

The paths and patterns of income inequality represented by GDP growth (Figure 1) and GINI coefficient (Figure 2) differ over time period. Figure 1 shows GDP growth fluctuating over time with a big drop recorded around 1992 (coinciding with the beginning of multiparty in Kenya) and 2007 (the post-election violence). Income inequality in percentage shows a declining trend up to 2000. From early 2002 onwards, the increase in income inequality became gradual (Figure 2) widening gap between rich and poor. Figure 2 also shows a great depression around 2000–2001 which can be associated with the transitions between two government regimes. The former Moi regime,was more of one party system of government compared to president Kibaki's regime, which was more inclusive and development oriented in that it created a favorable environment for investment. In this regard, the rich people with high propensity to save, expended their investment, thereby accumulating wealth that widened the gap between rich and poor to about 55%.

4. Results

The main objective of this article is to establish whether the current upsurge of income inequality in Kenya is growth- promoting or growth-dampening. Following the influential paper by Nelson and Plosser (1982) that provided statistical evidence of the presence of stochastic trends in many macroeconomic time series (like GNP, GINI coefficient, etc.), the first part of the empirical analysis focuses on testing the unit root and cointegration of the GINI coefficients and GDP series. The notion of unit/cointegration arose out of the concern about spurious or nonsensical regressions in time series. The second part involve the estimation of the ARLD model and the last part contain model diagnostic and stability tests.

4.1. Unit root test

This section investigates whether the income inequality measured using GINI coefficients and growth in GDP data has a unit root. The test was carried out in order to eliminate any possibility of spurious regressions and erroneous inferences. This involved determining the order of integration of the time series through unit root test. Accordingly, ADF and PP test were conducted at level and at different levels of difference and the results of the two are reported in Table 1 below. As indicated in the table, both tests, the ADF and PP test failed to reject the null hypothesis of unit root at level for GINI coefficients implying that the variables are non-stationary in level. But at second difference, null hypothesis is rejected implying that the variables become stationary at second difference. For GDP growth, the two tests confirm the present of unit root at level at 5% level of significance. However, since first and second order differencing in all cases eliminates the unit root of most of the variable under consideration, the maximum order of integration can be concluded to be $I(2)$.

Table 1 Summary result of Unit Root Test

Test	Variable	Level (I(0)) T-statistics	Level (I(0)) Lags	1st Difference (I(1)) T-statistics	1st Difference (I(1)) Lags	2nd Difference (I(2)) T-statistics	2nd Difference (I(2)) Lags
ADF	GDP Growth	–2.998** (0.0351)	0	–5.922*** (0.0000)	0	–	–
	GINI Coeff	2.055 (0.9987)	0	–1.580 (0.4938)	0	–6.333*** (0.0000)	0
Phillips-Perron	GDP Growth	–2.972** (0.0376)	3	–6.685*** (0.0000)	3	–	–
	GINI Coeff	0.969 (0.9939)	3	–1.407 (0.5791)	3	–6.473*** (0.0000)	3

Note: P-value at the parenthesis
Source: Own computation based on analysis

4.2. ARDL modelling approach to cointegration analysis

The next step was to examine the existence of cointegration. Since the variables are of different order of integration, we used ARDL modelling due to the fact that it can be applied when the variables are of different order of integration (Pesaran and Pesaran 1997).

The bounds test approach on the two variables has been used to examine long-run relationship between the variables. The maximum lag length of the variables in ARDL model, were selected using the AIC. Based on the result there is strong evidence of cointegration between GDP growth and GINI coefficients because the calculated F-statistic is 11.986, which is greater than the critical values of upper bound at 1% level of significance. The causality is a unidirectional relationship with GINI coefficient Granger cause GDP growth.

Table 2 Result of the cointegration test using ARDL Approach

Dependent variable			Independent variable		F-test Statistic		Cointegration	
GDP Growth			GINI Coeff		11.986****		YES	
GINI Coeff			GDP Growth		0.868		NO	
	*10% Sign. Level		**5% Sign. level		***2.5% Sign. level		****1% Sign. level	
K	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F_c	4.04	4.78	4.94	5.73	5.77	6.68	6.84	7.84

Source: Own computation based on analysis

4.3. Estimation of the model

Presented in table 3, are the result for the long run and short run coefficient. The result shows a weak positive long run relationship between GDP growth and GINI coefficients at 1% level of significant and a strong positive short run relationship between the two variables at 5% significant level which is against the hypothesis. Basing therefore on these results, a one percent point change in the level of inequality will result to an increase in GDP growth by 0.019percentage point in short run and by 0.003 percentage point in long run if appropriate policies that check on redistribution of income are put in place. Although the results confirm the Kuznets hypothesis that describes a positive relationship between income inequality and economic growth in the early phases of growth, which can be associated in this case with the short run, a negative relationship in the later phases means Kuznets hypothesis was contradicted. In addition, the result also contradicts the prediction of some of the theories about how inequality might impact growth in a non-linear way (Kuznets 1955). For our case, the short run and long run relationship is positive and linearly related. One of the possible causes for the differences in the result may be attributed to the data points used for GINI coefficients and GDP growth, model specification and the control variables being included in the estimation. While the author of this study used percent values and the ARDL model which uses lagged difference as instrument variables, most other scholar used absolute values and OLS regression, and include variables such as education, employment, health expenditures and population growth as control variables. This behavior can similarly be explained using some of the political economy and socio-political instability theories (e.g. Benhabib 2003), which suggest that while some inequality is unlikely to cause unrest and provides growth-enhancing incentives in short run, inequality can disrupt economic relations after it reaches some 'tipping point' by inviting political interference through rent-seeking behavior and appropriation. This paradigm was experienced recently in Kenya as a result of changes from the presidential system to a parliamentary system rather than the recommended establishment of a devolved governmental system.

ARDL model select instrument variables (lagged levels for first differences). The p-values indicate that the instrument variables are significant 1% or 5% level of significant, which is clear evidence of the absence of "instrument proliferation", which has been shown to lead to severe biases and weakened tests of instrument validity in the GMM model (Roodman 2009). The adjustment variable (ADJ_GDP Growth_ L1) provides the feedback and/or speed of adjustment from short-run to long-run equilibrium. There are two important things about this adjusted variable. Firstly, the coefficient should be significant, and secondly it must be negative, so that it provides further proof of stable long-run relationship (Shahbaz and Rahman 2010). The results of the short run model show that adjustment is very strong and negative as well as significant, thus we can rely on adjustment for short-run to converge to long run equilibrium. The R^2 value for two variable cases (GDP growth and GINI coefficient) is 0.74923981. The value implies that 74.9% variation in the GDP growth can be explained by the GINI coefficient while 25.1% is unexplained. The adjusted R^2 of 0.64893573 indicate good fit and correctness of the model specification.

Table 3 Estimated Long Run Statistic Using ARDL Approach

Models	Coefficient	Std. Error	t	P>|t|
Long run				
LR_GINI Coeff_L1	0.2990922***	0.0511981	5.84	0.000
Short run				
GDP Growth_LD	0.991758**	0.3416773	2.90	0.011
GDP Growth_L2D	0.440398*	0.2523159	1.75	0.101
GDP Growth_L3D	0.3736959*	0.1888455	1.98	0.066
GINI Coeff_D1	1.908839**	0.7052704	2.71	0.016
ADJ_GDP Growth_L1	–2.038949***	0.4310692	–4.73	0.000
_Cons	–22.83591***	7.7809530	–2.93	0.010
R-squared	0.74923981			
Adj R-squared	0.64893573			

* Statistically significant at 10% level; ** Statistically significant at 5% level;
*** Statistically significant at 1% level

Source: Own contribution based on analysis

4.4. Diagnostic tests

The model was further subjected to diagnostics to ascertain the appropriateness of the ARDL model in estimating the effect of GINI coefficients on GDP growth. The diagnostic tests involved checking for normality (Shapiro–Wilk W test for normal data), serial correlation (Breusch–Godfrey LM test), the autoregressive conditional heteroscedasticity (ARCH Test–Breusch–Pagan / Cook–Weisberg test), the functional form of the model for omitted variables (Ramsey RESET test), and Durbin–Watson d–statistic. Based on the results of different diagnostic tests, the statistics reported the ARDL model was fit to be used for the estimation purpose since the tests show that there is absence of autocorrelation, functional form misspecification, heteroscedasticity in the models, and the errors follow the normal distribution since the p-values in all test are greater than 0.05. For Durbin-Watson d-statistic test, a rule of thumb is that test statistic values in the range of 1.8 to 2.2 are relatively normal. Values outside of this range could be cause for concern. Field and Miles (2010) suggests that values under 1 or more than 3 are a definite cause for concern.

Table 5 Results of Diagnostic Tests at constant prices

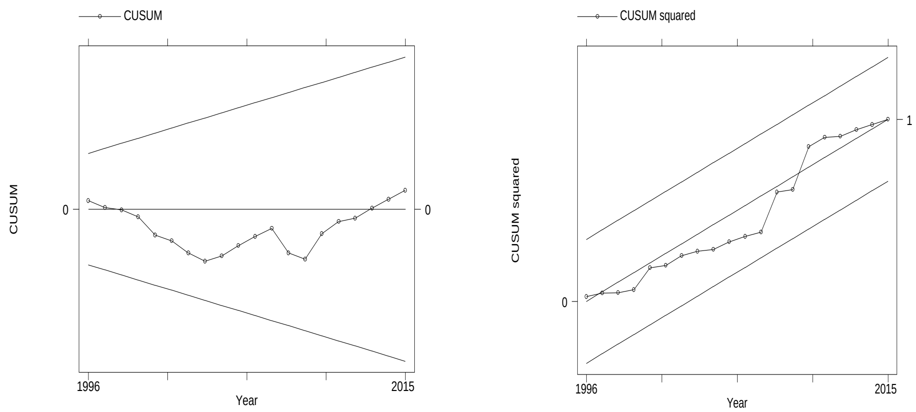
Test	**Statistic**	**Prob> chi2**
Shapiro–Wilk W test for normal data	0.98340	0.96045
LM test for autoregressive conditional heteroskedasticity (ARCH)	0.186	0.6661
RESET test	2.31	0.1283
Breusch–Pagan / Cook-Weisberg test for heteroskedasticity	2.24	0.1341
Breusch–Godfrey LM test for autocorrelation	0.559	0.4546
Durbin–Watson d–statistic	2.159444	

Source: Own computation

4.5.Model stability test

Assessment of model stability was done by plotting the CUSUM and CUSUM squares. The CUSUM test is based on the residuals from the recursive estimates, and based on this test, the null hypothesis implies that the statistic is drawn from a distribution called the CUSUM distribution developed by Page in 1954 (Grigg et al. 2003). If the calculated CUSUM statistics appear to be too large to have been drawn from the CUSUM distribution, we reject the null hypothesis (of model stability). The output will be a graph of the CUSUM statistics and bands representative of the bounds of the critical region for a test at the 5% significance level. In the figure below, the straight lines represent critical bounds at 5% significance level and since the plots of these two tests do not cross the critical value line, it implies that there is a stable long-run relationship between GDP growth and GINI coefficients.

Figure 3 Parameter Stability Test



Source: Own construction based on the analysis

5. Conclusion and policy recommendations

From the literature search, it is clear that the topic of income inequality has not been a major topic of discussion in Kenya, yet it is an important element in the process of economic growth. This paper focus on analyzing the relation between income inequality and GDP growth for the Kenyan economy. More precisely, the study focuses on investigation whether there is a relationship between income inequality and GDP growth. A GINI coefficient was used as a measure for income inequality. An Autoregressive-Distributed Lag (ARDL) model that combines long and short run into a single equation was applied. The ARDL approach was selected because of its flexibility and that it can be applied when the variables are of different order of integration. The ARDL model for GDP growth and GINI coefficients was fitted and a weak positive but significant long run relationship was found between the two variables. There was a strong positive short run relationship between GINI coefficient and GDP growth, and very strong and significant at 1% adjustment rate. The diagnosis and stability tests accepted the model as stable for predicting GDP growth.

Results emphasize the complexity of the relationships between income inequality and economic growth in Kenya data. In this matter, what is interesting is not whether inequality is harmful or beneficial for growth, since the finding are contradictory, but rather the magnitude of the relationship. Although the study found a positive effect of inequality on growth, for a balanced welfare, one policy goal should be equity in income distribution to reduce excessive income disparities. As suggested by Todaro (1997), a more equitable distribution of income can stimulate healthy economic expansion by acting as a powerful material and psychological incentive to widespread public participation in the development process. This endeavor as currently being realized in Kenyan economy through implementation of the Constitutional Development Fund (CDF), the Economic Stimulus Project, free primary education and free tuition in secondary schools, and recently, universal free medical care, should be encouraged and if possible enhanced, although the impact of these remain unknown.

This recent research has focused attention on the impact of income inequality on economic growth. More research should be carried out on all other measures of inequality, to bring it into light which among them is more influential on GDP growth.

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