

Income Inequality in Ethiopia: Do Macroeconomic Factors Matter?

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How to cite: Geddafa, T. (2026). Income Inequality in Ethiopia: Do Macroeconomic Factors Matter? *Revista Finanzas y Política Económica*, 18, 1-33. <https://doi.org/10.14718/revfinanzpolitecon.v18.2026.3>

Received: September 21, 2024
Evaluated: September 11, 2025
Approved: December 15, 2025

Research article


Abstract

This study identifies factors driving income inequality in Ethiopia from 1991 to 2022 using secondary data and an autoregressive distributed lag (ARDL) model. Long-run results show that education and foreign direct investment significantly reduce inequality. Conversely, inflation, real interest rates, trade openness, and population growth exacerbate it. Short-run findings indicate that government expenditure and trade openness negatively impact inequality, while unemployment and inflation have positive effects. Notably, inflation positively correlates with inequality in both periods by eroding real wages. The study recommends that the National Bank of Ethiopia pursue stable macroeconomic policies to curb inflation and that the government enhances access to education to boost productivity and reduce income disparities.

Keywords: ARDL model; income inequality; macroeconomic factor; time series; Ethiopia.

JEL Classification: D63; O15; E25; I24; F63

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Desigualdad de ingresos en Etiopía: ¿Importan los factores macroeconómicos?

Resumen

Este estudio identifica los factores determinantes de la desigualdad de ingresos en Etiopía entre 1991 y 2022 mediante datos secundarios y un modelo de rezagos distribuidos autorregresivos (ARDL). Los resultados de largo plazo muestran que la educación y la inversión extranjera directa reducen significativamente la desigualdad, mientras que la inflación, las tasas de interés, la apertura comercial y el crecimiento poblacional la aumentan. A corto plazo, el gasto público y la apertura comercial impactan negativamente, mientras que el desempleo y la inflación inciden positivamente. La inflación se correlaciona positivamente con la desigualdad al erosionar los salarios reales. Se recomienda implementar políticas macroeconómicas estables para controlar la inflación y ampliar el acceso educativo para mitigar las disparidades.

Palabras clave: Modelo ARDL; desigualdad de ingresos; factor macroeconómico; serie de tiempo; Etiopía.



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INTRODUCTION

The structure and transformation of Ethiopia's economy play a critical role in shaping income distribution across the country. Over the past three decades, Ethiopia has experienced notable economic growth, largely driven by public investment, agricultural-led development, and recent industrialization efforts (World Bank, 2020). However, the benefits of this growth have not been evenly distributed. The rural-urban divide, the dominance of low-productivity agriculture, and limited access to education and infrastructure have contributed to persistent income inequality (UNDP, 2022). Furthermore, trade liberalization and market reforms, while fostering growth, may have disproportionately benefited certain regions and income groups, thus influencing inequality trends (African Development Bank [ADB], 2021). Understanding how macroeconomic factors interact with Ethiopia's unique economic landscape is therefore essential in analyzing income inequality dynamics.

Income inequality remains a barrier to inclusive economic progress, social development, and environmental sustainability in the modern world (Odusola, 2019). This chronic and pressing issue requires careful intervention through proper policies (Esaku, 2021). Income inequality is worsening across sub-Saharan Africa, including Ethiopia (Uwajumogu et al., 2023). In addition, inequality in urban areas is more severe than in rural areas (Haile & Asfaw, 2018). Income inequality refers to the distribution of economic variables among individuals within a group, among groups within a population, or among countries (Fuentes-Nieva & Galasso, 2014).

There are three main types of economic inequalities. These include income, wage, and wealth inequalities. The first is income inequality, the degree to which income is unevenly distributed within a group. Income is not just money received as salary but also from employment (wages, salaries, bonuses, etc.), investments (interest from accounts, savings, dividends from shares, state benefits, pensions, and rent), and other sources. The word income refers to "the amount of money that a person, region, country, etc., earned by investing money, doing business, etc." Inequality is defined as "something unjust, the state of being unjust." Income inequality refers to "the unfair or unequal distribution of money, investment income, business income" (Polacko, 2021). Rising inequality leads to high social costs, such as increased violence and criminal activity, worse health outcomes (Alvarado et al., 2021), poor

environmental quality (Hailemariam et al., 2021), lower economic growth (Brueckner & Lederman, 2018), and reduced consumption (Akpa et al., 2024). Global inequality has never been as severe since the 19th century. Milanovic (1998), one of the world's leading experts on global income inequality, says that although inequality is getting worse in countries, it is recovering globally.

Africa has the world's most unequal economy (Hakura et al., 2016). The upper bound of the continent's Gini coefficient range is more significant than that of the developing world. The average Gini coefficient in Africa is 0.43, which is 1.1 times that of the rest of the developing world (0.39). This demonstrates the high level of income inequality in Africa. Furthermore, according to Mbroh (2021), Sub-Saharan African countries rank second worldwide in income inequality, just after Latin America and the Caribbean. Ethiopia's economy is among the fastest-growing in the world, with its GDP expanding by 10.5 % annually since 2005 (Wolde et al., 2022). The country aims to become a middle-income nation by 2025 (Ministry of Finance and Economic Cooperation [MOFEC], 2018), making it an intriguing case study. Since the early 1990s, Ethiopia has maintained low levels of income inequality. It is among the least unequal countries in the world, with a Gini coefficient of 0.30 (MOFEC, 2018; World Bank, 2018). Despite this growth, the Gini coefficient continued to rise, reaching 0.37 in 2020, 0.38 in 2021, and 0.39 in 2022. Economic growth is adversely affected by high levels of income inequality (Belfield et al., 2017). Growing wealth inequality is anticipated to slow economic growth and increase poverty.

However, few Ethiopian researchers have studied this topic. Most of these studies (Abate & Wendimnew Sitotaw, 2024; Geda & Yimer, 2014; Haile & Asfaw, 2018; Hordofa, 2023) have examined the links among economic growth, poverty, and inequality. Other studies have focused on the relationship between income inequality and economic development (Girma & Shete, 2018; Wogari, 2021; Wolde et al., 2022). Only one published study (Belay, 2020) examined the patterns and factors influencing income inequality in Ethiopia between 1988 and 2018. However, it omitted crucial factors such as the actual interest rate, government spending, the inflation rate, and population growth rate, all of which are significant contributors to income inequality. Therefore, a thorough analysis of these variables and their trends is required, using the period from 1991 to 2022 and the unique macro variables that still need to be studied. This study fills the knowledge gap and provides recent insights by investigating the factors affecting income inequality

in Ethiopia using appropriate analytical methods. Understanding the factors that influence income inequality is essential for shaping a country's domestic economic policies and enacting political reforms. This is crucial because policies aimed at economic growth can significantly affect income distribution, potentially exacerbating income inequality.

LITERATURE REVIEW

Concept of Income Inequality in Developing Economies

Inequality is the degree to which the distribution of economic welfare generated in an economy differs from that of equal shares among its nations (Todaro & Smith, 2015). According to Gehring and Kulkarni (2006), income equality is the equal distribution of total income among the population. In a nation with perfect income equality, each individual has an equal share of total income. This is the opposite of perfect income inequality, in which one individual receives all the income. But neither of these extreme situations exists in any national economy.

According to Ray (1998) and Todaro and Smith (2015), measures of income distribution for both analytical and quantitative purposes are as follows:

Range: It is given by the difference in the income of the richest and the poorest individuals, divided by the mean to express it independently of the units in which income is measured (Todaro & Smith, 2015). Thus, the range R is given by Equation 1:

$$R = \frac{1}{\mu} y_m - y_1 \quad (1)$$

Where R stands for range, y_m for the income of the richest, y_1 for the income of the poorest individuals, and μ represents the mean (average) income of the population. This is a rather crude measure. It pays no attention whatsoever to people between the richest and the poorest on the income scale. It is a useful measurement when detailed information on income distribution is missing.

Kuznets ratio: Simon Kuznets introduced these ratios in his pioneering study of income distributions in developed and developing countries (Ray, 1998). These ratios refer to the share of income owned by the poorest 20 or 40 % of the population, or by the

richest 10 %, or more commonly to the ratio of the shares of income of the richest x % to the poorest y %, where x and y stand for numbers such as 10,20 or 40. The ratios are essentially “pieces” of the Lorenz curve and, like the range, serve as a useful shorthand when detailed income distribution data are missing (Todaro & Smith, 2015).

Mean absolute deviation: This is the first measure that uses the entire income distribution. The idea is simple: inequality is proportional to distance from the mean income (Todaro & Smith, 2015). Therefore, simply take all income distances from the average deviation as a fraction of total income. This means that the mean absolute deviation, M , is defined as shown in Equation 2.

$$M = \frac{1}{\mu n} \sum_{i=j}^m n_j / y_j - \mu \quad (2)$$

Where the notations stand for the absolute value (neglecting negative signs), and M is a measure of inequality that takes into account the overall income distribution. Then a regressive income transfer from y_j to y_k certainly raises inequality as measured by M .

The Kuznets curve is among the earliest attempts to describe trends in income inequality. Kuznets found that inequality in the US peaked in the 1890s, stayed constant for a few decades, and then declined after the 1920s (Alderson & Nielsen, 2002). According to several economists, a clear trajectory of a new political economy paradigm emerged after 1980 in the USA and Europe, which underlies the worsening of income distribution. This paradigm is shaped by specific and flawed economic policies.

Palley (2012) sees three moments shaping the new model: the first was the growth model adopted after 1980, which relied on debt and asset-price inflation to fuel growth rather than wages. The second flaw was the model of globalization that created an economic gash. The third was financial deregulation and the house price bubble, which kept the economy going by making ever more credit available. In this context, while income distribution worsened and debt accumulated, the economy needed larger speculative bubbles to grow. Finally, these bubbles started to burst with the housing sector crash in 2007.

According to Lorenz (1905), income inequality is a graphical representation of the distribution of income or of wealth. It was developed by Max O. Lorenz to

represent the inequality of wealth distribution. The curve is a graph showing the proportion of overall income or wealth assumed by the bottom x % of the people. It is often used to represent income distribution, showing, for the bottom x % of households, what percentage (y %) of total income they receive. The percentage of households is plotted on the x -axis, and the percentage of income on the y -axis. It can also be used to show the distribution of assets. In this context, many economists consider it a measure of social inequality (Caballero Urdiales, 2011; Gutiérrez Cruz, 2017). If all individuals are the same size, the Lorenz curve is a straight diagonal line, called the line of equality. If there is any inequality, it can be summarized by the Gini coefficient (also called the Gini ratio), which is the ratio between the area enclosed by the line of equality and the Lorenz curve, and the total triangular area under the line of equality.

For Gini (1912), income inequality is measured by the extent to which the Lorenz curve departs from the line of equality. It is defined as a ratio with values between 0 and 1: the numerator is the area between the Lorenz curve of the distribution and the uniform distribution line; the denominator is the area under the uniform distribution line. The Gini coefficient is often used to measure income inequality. Here, 0 corresponds to perfect income inequality (everyone has the same income) and 1 corresponds to perfect income equality (i.e., one person has all the income, while everyone else has zero income) (Gini, 1912). The Gini coefficient can also be used to measure wealth inequality. It is also commonly used to measure the discriminatory power of rating systems in credit risk management. The Gini Index is the Gini coefficient expressed as a percentage and equals the Gini coefficient multiplied by 100. The Gini coefficient is equal to half of the relative mean difference (Gini, 1912).

Income Inequality and Macroeconomic Variables

A large body of literature has examined income inequality. The existing empirical literature identifies several factors as key causes of income inequality, such as increases in household debt (Iacoviello, 2008), innovation and technology (Acemoglu, 2003; Jones & Kim, 2018), trade openness and globalization (Jaumotte et al., 2013), and monetary policy (Furceri et al., 2018).

Different studies propose many factors that influence income inequality in both developing and developed countries. The direction of these influences, however, is often unclear: whether a higher value of a given factor leads to higher or lower

inequality depends on the characteristics of the economic system in question. **Kaasa (2003)** classified factors affecting inequality into five groups: economic growth and a country's overall development level; macroeconomic factors; demographic factors; political factors; and historical, cultural, and natural factors.

Kuznets (1955) describes a positive relationship between income inequality and economic growth in the early phases of growth and a negative relationship in the later phases. He held the manufacturing sector as the main driver of economic growth. The intra-sectoral distribution of income is necessarily wider in the urban (manufacturing) sector than in the rural (agricultural) sector, and a mass shift in the population from a sector with low inequality to the one with greater inequality increases the weight of the unequal sector, thus rising overall inequality (**Kuznets, 1955**).

Bigsten and Abebe (2006) attempted to decompose the determinants of income inequality in Ethiopia using a household-level regression model of consumption expenditure. The result indicated that in rural areas, a large part of the variation in income inequality could be explained by differences in village-level characteristics and other unobserved factors. In urban areas, significant factors in determining inequality included household characteristics such as the head of household's occupation and educational level, as well as unobserved characteristics.

Ncube and Hausken (2013) assessed inequality, economic growth, and poverty in the Middle East and North Africa (MENA) and presented patterns of inequality, growth, and poverty in the MENA region using cross-sectional time-series data for MENA countries for the period 1985–2009. They investigated the effect of income inequality on key societal development, namely, economic growth and poverty, in the region. The empirical results show that income inequality reduces economic growth and increases poverty in the region. Apart from income inequality, other factors that increase poverty in the region include foreign direct investment, population growth, inflation, and the attainment of only primary education. Poverty-reducing variables in the region include domestic investment, trade openness, exchange rate, income per capita, and oil rents as a percentage of GDP.

Education is very important for economic growth; however, gender-based educational inequality also influences the economy. Gender inequality in education can result in slow economic growth, thus creating a poverty trap. It is suggested

that a large gap between males and females may indicate backwardness and be associated with lower economic growth, which can explain economic inequality between countries. In addition, labor market success is linked to schooling achievement; the consequences of widening disparities in schooling are likely to be further increases in earnings inequality. By increasing labor force efficiency, education creates better conditions for good governance, improved health, and greater equality (Amin et al., 2024).

A simple Heckscher-Ohlin model says that countries export the factors (in goods bundles) for which they are relatively well endowed (Castillo et al., 2005; Nielsen & Alderson, 1997). This increases the demand for their abundant factors and, through that, raises the relative prices of these factors. In general, developed countries can be said to be well endowed with capital, and developing countries with unskilled labor. From this theoretical standpoint, we can predict that openness would benefit unskilled labor in developing countries and capital owners in developed countries if more factors of production and more countries are included, as comparative advantage becomes more complicated. Depending on the distribution of factors of production across countries, we may formulate different hypotheses in this setting (Satheesh & Kumar, 2022).

RESEARCH METHODOLOGY

Research Design

The study employed a quantitative research approach owing to the nature of time-series analysis and the use of numerical variables. This study employed both descriptive and econometric research designs to achieve its objectives. A descriptive research design elaborated on the variable nature of the phenomenon, while an econometric research design identified macroeconomic factors that influence income inequality.

Data Types and Sources

This study used annual time-series data from 1991 to 2022. Secondary data sources include the World Income Inequality Database (WIID) for the Gini index and the National Bank of Ethiopia for other explanatory variables.

Method of Data Analysis

This study analyzed income inequality trends in Ethiopia using statistical measures, such as the mean, median, maximum, minimum, standard deviation, skewness, and kurtosis.

Econometric Analysis

The study employed an autoregressive distributed lag (ARDL) model in EViews version 12 to analyze the relationship between the dependent and independent variables.

Specification and Justification for ARDL Bounds Test

Theoretical models, such as Keynesian, neoclassical, and neoliberal theories, are, by themselves, insufficient to fully identify the factors influencing income inequality. To investigate the causes of income disparities in Ethiopia, this study employs the ARDL bounds testing strategy created by [Pesaran et al. \(2001\)](#). Compared to other cointegration techniques, such as those of [Engle and Granger \(1987\)](#) and [Johansen and Juselius \(1990\)](#), the ARDL bounds testing approach has advantages. First, according to [Pesaran et al. \(2001\)](#), the variables in the model need not be integrated in the same order. Instead, they can combine I(0) and I(1). Second, it reduces endogeneity and serial correlation. Third, even with small sample sizes, it yields trustworthy results. Fourth, the model's long- and short-run parameters are estimated simultaneously using the ARDL bound test approach. Fifth, cointegrating vector(s) can be identified using the ARDL approach. The ARDL model of a cointegrating vector is re-parameterized into an Error Correction Model (ECM) upon identification of the cointegrating vector. Thus, the frameworks of [Karagoz and Ergun \(2010\)](#), [Maluleke et al. \(2023\)](#), and [Ngoma et al. \(2021\)](#) are followed in the empirical model used to investigate factors influencing income inequality. In the ARDL model, the variables were formulated as shown in [Equation 3](#):

$$GINI_t = f(EDUC, FDI, GE, INF, IR, POPN, TRADE, UNEMP) \quad (3)$$

Where $GINI_t$ is the Gini coefficient of income inequality, EDUC is education, GE is government expenditure, INF is the inflation rate, IR is the real interest rate, POPN is the population growth rate, TRADE is trade openness, and UEMP is the unemployment rate.

Therefore, the ARDL model specified for this study is as follows (Equation 4):

$$\begin{aligned} \Delta \ln \text{GINI}_t = & \alpha_0 \sum_{i=1}^n \alpha_{1i} \Delta \ln \text{GINI}_{t-i} + \alpha_0 + \sum_{i=0}^n \alpha_{2i} \Delta \ln \text{EDUC}_{t-i} + \sum_{i=0}^n \alpha_{3i} \Delta \ln \text{FDI}_{t-i} + \sum_{i=0}^n \alpha_{4i} \Delta \ln \text{GE}_{t-i} \\ & + \sum_{i=0}^n \alpha_{5i} \Delta \ln \text{INF}_{t-i} + \sum_{i=0}^n \alpha_{6i} \Delta \ln \text{IR}_{t-i} + \sum_{i=0}^n \alpha_{7i} \Delta \ln \text{POP}_N_{t-i} + \sum_{i=0}^n \alpha_{8i} \Delta \ln \text{TRADE}_{t-i} \\ & + \sum_{i=1}^n \alpha_{9i} \Delta \ln \text{UNEMP}_{t-i} + \beta_1 \ln \text{GINI}_{t-1} + \beta_2 \ln \text{EDUC}_{t-1} + \beta_3 \ln \text{FDI}_{t-1} + \beta_4 \ln \text{GE}_{t-1} + \\ & \beta_5 \ln \text{INF}_{t-1} + \beta_6 \ln \text{IR}_{t-1} + \beta_7 \ln \text{POP}_N_{t-1} + \beta_8 \ln \text{TRADE}_{t-1} + \beta_9 \ln \text{UNEMP}_{t-1} + \mu_{1t} \quad (4) \end{aligned}$$

Where $\ln \text{GINI}$ is the log (natural logarithm) of income inequalities, which is measured by the Gini coefficient; $\ln \text{EDUC}$ is the log of education; $\ln \text{FDI}$ is the log of foreign direct investment; $\ln \text{GE}$ is the log of total government expenditure; $\ln \text{INF}$ is the log of annual inflation rate; $\ln \text{IR}$ is the log of real interest rate; $\ln \text{GE}$ is the log of total government expenditure; $\ln \text{POP}_N$ is the log of population growth rate; $\ln \text{TRADE}$ is the log of trade openness; $\ln \text{UNEMP}$ is the log of unemployment rate; Δ is the first difference of a variable; μ_{1t} is the error term; α_0 is a constant term; β is the respective coefficient; and n is the lag length.

The ECM of the ARDL model is expressed as follows (Equation 5):

$$\begin{aligned} \Delta \ln \text{GINI}_t = & \alpha_0 \sum_{i=1}^n \alpha_{1i} \Delta \ln \text{GINI}_{t-i} + \sum_{i=0}^n \alpha_{2i} \Delta \ln \text{EDUC}_{t-i} + \sum_{i=0}^n \alpha_{3i} \Delta \ln \text{FDI}_{t-i} + \\ & \sum_{i=0}^n \alpha_{4i} \Delta \ln \text{GE}_{t-i} + \sum_{i=0}^n \alpha_{5i} \Delta \ln \text{INF}_{t-i} + \sum_{i=0}^n \alpha_{6i} \Delta \ln \text{IR}_{t-i} + \sum_{i=0}^n \alpha_{7i} \Delta \ln \text{POP}_N_{t-i} \\ & + \sum_{i=0}^n \alpha_{8i} \Delta \ln \text{TRADE}_{t-i} + \sum_{i=1}^n \alpha_{9i} \Delta \ln \text{UNEMP}_{t-i} + \theta_1 \text{ECM}_{t-1} + \mu_t \quad (5) \end{aligned}$$

Where ECM_{t-1} is the error correction term lagged once, and θ is used to measure the speed of adjustment toward long-run equilibrium following a short-run shock.

Estimation Procedures of Diagnostic Tests

This study was conducted in several steps to ensure the data were suitable for the ARDL model. These include pre-estimation tests, such as unit root and cointegration testing, determination of the maximum lag length, and post-estimation tests encompassing stability, normality, autocorrelation, heteroscedasticity, multicollinearity, and model misspecification. The key structural breaks—such as the Ethiopian political transition in the early 1990s, the Ethio-Eritrean war, economic reforms post-2018,

the 2005 election crisis, and the recent conflict period—may influence the data and estimation results.

Selected Variables

Income inequality is the dependent variable in this study. The Gini coefficient quantifies the degree of inequality in a country's income distribution. According to [Gradín et al. \(2021\)](#), it ranges from 0 (perfect equality, where every household earns the same amount of money) to 1 (perfect inequality, where a single household earns all the income and the rest earn nothing). The selection of the primary explanatory variables, including trade openness, unemployment rate, inflation rate, population growth rate, education, real interest rate, foreign direct investment, and government expenditure, was based on the researcher's observation and prediction of the need for variables in Ethiopia's situation as well as a review of the pertinent literature that already existed (by understanding the effect of variables). The optimal lag length was selected using the Akaike Information Criterion (AIC), which has been validated in most empirical studies for data from smaller sample sizes, and the maximum lag was determined based on the annual nature of the data and model stability.

RESULTS AND DISCUSSION

Descriptive Statistics Results

The mean Gini coefficient across the study periods was 34.35, with a standard deviation of 4.27, indicating less variation in income inequality in Ethiopia and across the study years. The maximum and minimum values were 44.60 and 29.00, respectively ([Table 1](#)). The mean education value for income inequality during the study period is about 61.29, and the standard deviation is 27.39, indicating that more than half of the population was enrolled in primary education ([Table 1](#)). The mean value of Foreign Direct Investment (FDI) for income inequality during the study period is about 2.41, and the standard deviation is 1.80, suggesting a high inflow of FDI that can reduce income inequality by creating employment and transferring advanced technology. The maximum and minimum values were 5.58 and 0.01, respectively ([Table 1](#)). The mean annual inflation rate for income inequality during the study period is about 12.10, and the standard deviation is 12.07, suggesting that high inflation can widen

the income gap between the rich and the poor (Table 1). The mean population growth rate for income inequality during the study period is about 2.97 per woman, with a standard deviation of 0.31, indicating a high fertility rate per woman per year in Ethiopia that can widen the income gap between people (Table 1).

Table 1.

Summary of Descriptive Statistics of the Study Variables

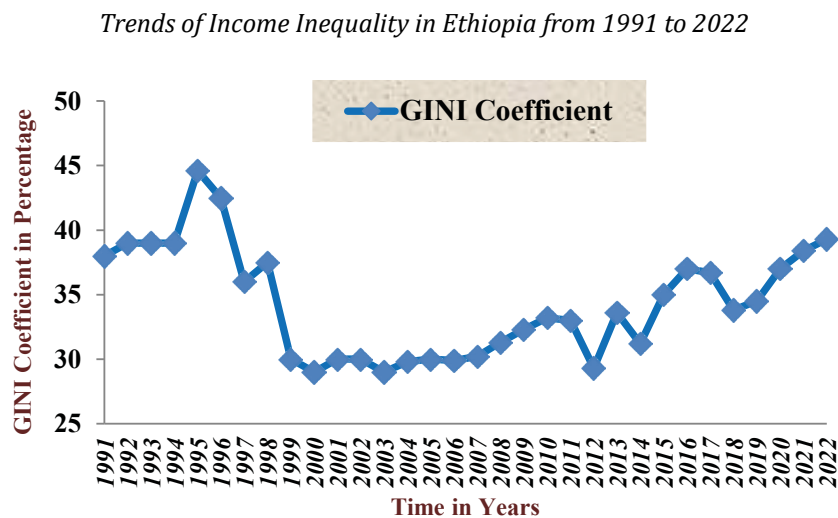
	GINI	EDUC	FDI	INFL	POPN	INT	GE	TRADE	UNEMP
Mean	34.35	61.29	2.41	12.10	2.97	12.19	17.33	4.92	3.03
Median	33.70	67.54	2.45	9.77	2.89	11.94	17.48	4.94	3.00
Max.	44.60	106.76	5.58	44.35	4.15	15.50	23.15	5.84	5.11
Min.	29.00	19.18	0.01	8.48	2.57	6.80	12.35	4.54	2.25
Std. Dev.	4.27	27.39	1.80	12.07	0.31	2.02	2.76	0.27	0.65
Skewness	0.48	0.07	0.14	0.82	1.82	0.81	0.26	1.16	1.14
Kurtosis	2.31	1.65	1.74	3.49	7.31	4.10	2.95	5.47	4.45
Observations	32	32	32	32	32	32	32	32	32

Source: Own computation using Eviews-12 (2023)

Trends of Income Inequality in Ethiopia

Income distribution in developing countries such as Ethiopia has been highly unequal, even exceeding the national average, with a Lorenz curve far from the equality line and a Gini coefficient of 0.39 (Debebe & Zekarias, 2020). According to the Gini coefficient, income inequality in Ethiopia peaked in 1995 at 44.6 %. This indicates a significant wealth gap, with the richest holding 44.6 % of the total wealth, leaving only 55.4 % for the rest of the population. The Gini coefficient data indicate a rising trend, increasing from 38 % in 1991 to 39 % in 1992 through 1994, as depicted in Figure 1. From 1991 to 2022, fluctuations in income inequality were observed annually. The Gini coefficient reached a minimum of 29 % in both 2000 and 2003 and a maximum of 44 % in 1995 (Figure 1). The significant decline occurs after 1996, reaching a low point around 1999–2000. This drop may reflect economic adjustments following the transition from the Derg regime to a market-oriented system, as well as the initial impacts of poverty-reduction and rural-development programs. The subsequent gradual rise in inequality after 2005 may be linked to urbanization, trade expansion, and the uneven distribution of economic gains.

Figure 1.



Source: Own computation from various years' reports of WBI data (2022)

Econometric Analysis Results

Results of Pre-estimation Diagnostic Tests

Unit Root Test Results

Given the non-constant nature of most financial time series, it is imperative to conduct unit root tests to assess their properties (Awe & Gil-Alana, 2019). The first step before beginning an empirical analysis is to test for the stationarity of the variables included in the study. This study uses the Augmented Dickey-Fuller (ADF) test to check for stationarity. ADF (Leybourne, 1995) employs a negative value in its statistics. The stronger the rejection of the hypothesis, the more negative the indication. The results show that, when taken at the first difference, across the constant, trend, and intercept tests, the ADF test statistics exceeded the critical values at the 5% significance level (Table 2). The implication is that all variables are stationary at first differences; therefore, the analysis can proceed as a cointegration test using the ARDL bounds testing approach.

Table 2.

Variables	Level				First difference			
	Intercept (constant)		Trend and intercept		Intercept (constant)		Trend and intercept	
	ADF	<i>t</i> critical value at 5 %	ADF	<i>t</i> critical value at 5 %	ADF	<i>t</i> critical value at 5 %	ADF	<i>t</i> critical value at 5 %
	<i>t</i> -statistics		<i>t</i> -statistics		<i>t</i> -statistics		<i>t</i> -statistics	
LNEDUC	0.528283	-2.960411	-3.697282	-3.562882	-6.368472	-2.963972	-6.318218	-3.568379
LNFDI	-1.018608	-2.967767	-4.040408	-3.562882	-7.345563	-2.967767	-7.344297	-3.221728
LNGE	-2.520202	-2.960411	-2.802039	-3.562882	-6.371518	-2.963972	-6.268250	-3.568379
LNGINI	-5.485312	-2.960411	-5.814785	-3.562882	-5.40163	-2.971853	-5.318601	-3.580622
LNINF	-5.255748	-2.960411	-5.667737	-3.562882	-4.613988	-2.971853	-4.447521	-3.580622
LNIR	-3.892377	-2.960411	-3.759441	-3.562882	-5.962512	-2.963972	-6.108354	-3.568379
LNPOPN	0.182539	-2.960411	-2.156663	-3.562882	-3.831821	-2.963972	-3.814220	-3.568379
LNTRADE	-2.502533	-2.960411	-2.621774	-3.562882	-9.803211	-2.963972	-11.07610	-3.568379
LNUNEMP	-1.752462	-2.960411	-1.628281	-3.562882	-7.023992	-2.963972	-7.043186	-3.568379

Note. The optimal number of lags was determined by the AIC, with a maximum lag of 2 chosen.

Source: Own computation based on E-views 12 output (2023)

Optimum Lag Selection

Because the cointegration test depends on the number of lags in the ARDL model, it is typically preceded by a test of optimal lag length selection. Various tests can be used to determine the appropriate lag length. These are the Log Likelihood (LL), the AIC, the Schwarz information criterion (SIC), and the Hannan-Quinn information criterion (HIC). The AIC, validated in most empirical studies owing to its application for the data from smaller sample sizes, was used to determine the maximum lag length for this investigation. The values indicated by an asterisk (*) show that the lag order is selected by the criterion at a 5 % significance level. As indicated in Table 3 below, the optimal lag length of the variables in this study became 2. The lag order with many asterisks is more optimal than a few asterisks (Pesaran et al., 2001).

Table 3.

Optimal Lag Length Selection Criterion						
Lag	LogL	LR	FPE	AIC	SC	HQ
Zero	-376.3055	NA	1.157618	25.68704	26.10739	25.82151
One	-219.0978	209.6103	0.009131	20.60652	24.81011	21.95128
Two	-45.56819	127.2550*	0.000116*	314.43788*	22.42470*	16.99293*

Note. * is the lag order selected by the criterion, LR is the sequential modified LR test statistic (each test at the 5 % level), FPE is the final prediction error, AIC is the Akaike information criterion, SC is the Schwarz information criterion, and HQ is the Hannan-Quinn information criterion.

Source: Own computation using Eviews-12 (2023)

Bound Tests for Cointegration

There is a long-run relationship among all variables when their F -statistics exceed the upper-bound critical value at the 5 % level (Pesaran et al., 2001). Accordingly, the computed F -statistic of 21.09490 exceeds the upper critical value of 3.15 at the 5 % significance level (Table 4). This indicates that the variables were cointegrated. Therefore, this study rejects the null hypothesis of no cointegration and finds a long-run equilibrium relationship between income inequality and the explanatory variables.

Table 4.

<i>Bound Test result for Cointegration Analysis</i>			
Critical value	Lower bound value, I(0)	Upper bound value, I(1)	
1 %	2.62	3.77	
5 %	2.11	3.15	
10 %	1.85	2.85	
Model	F -statistic	Cointegration status	
LNGINI/Y (LNEDUC, LNFDI, LNGE, LNINF, LNIR, LNPOPN, LNTRADE and LNUNEMP)	21.09490** K = 8	Cointegrated	

Note. ** denotes statistical significance at 5 % level.

Source: Own computation using E-views 12 (2023)

Results of Post-Estimation Diagnostic Test

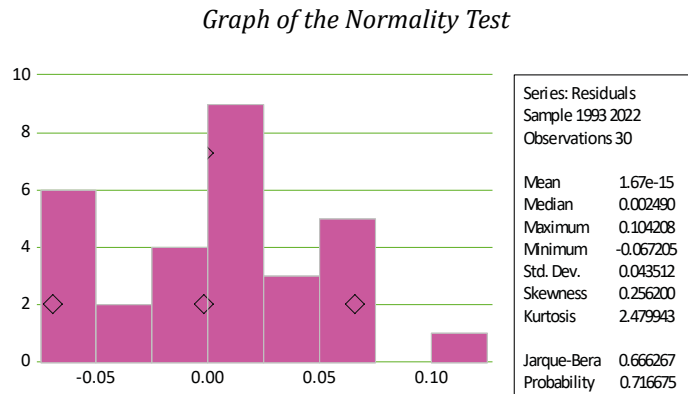
Normality Test

This study used the Jarque-Bera test to assess data normality, as it has been shown in most empirical studies to be superior to other tests. The graph shows that the results for Prob Chi = 0.716675 are greater than $\alpha = 5\%$ (0.05). Because the histogram is bell-shaped and the JB statistic is insignificant, the P -value at the bottom of the normality test should be $> 5\%$; it is more significant than average (Figure 2). Thus, the null hypothesis (H_0 = error terms are normally distributed) is accepted.

Model Misspecification Test

The Ramsey RESET test was used to test the misspecification. The Ramsey regression specification error test was used to identify variables that were significant but not included in the model. It checks whether the model is correctly specified (Kristensen, 2007). The test reports that the p -values of the t -statistic, F -statistic, and likelihood ratio were more significant than the 5 % significance level (0.7032, 0.7032, and 0.4138 $> \alpha = 5\%$ or 0.05, respectively) (Table 5). Therefore, the test concludes that the model is free from misspecification.

Figure 2.



Source: Own elaboration

Table 5.

Ramsey RESET Test

	Value	Df	Probability
<i>t</i> -statistic	0.396956	7	0.7032
<i>F</i> -statistic	0.157574	(1,7)	0.7032
Likelihood ratio	0.667828	1	0.4138

Source: Own computation using Eviews-12 (2023)

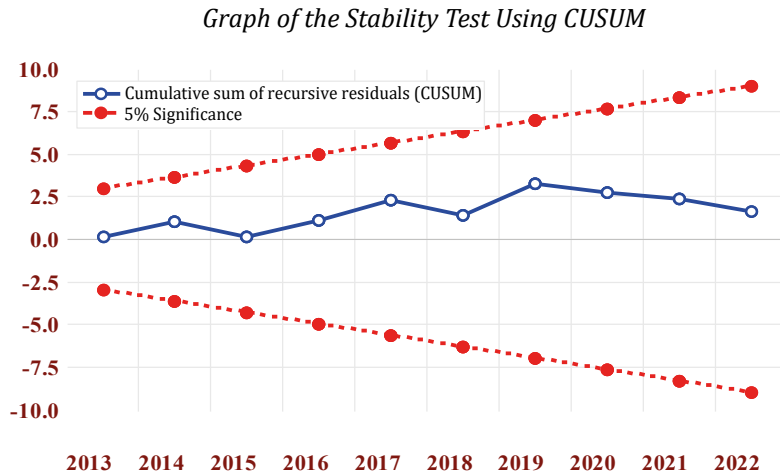
Stability Test

The cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMQ) were calculated to determine whether the model parameters were stable. The blue line on the graph should lie between the two red lines to indicate stable data. The CUSUM and CUSUMQ results in Figures 3 and 4 suggest that the estimated model was stable. The study failed to reject the null hypothesis (H_0 = the model is stable at all conventional significance levels).

Auto-Correlation Test

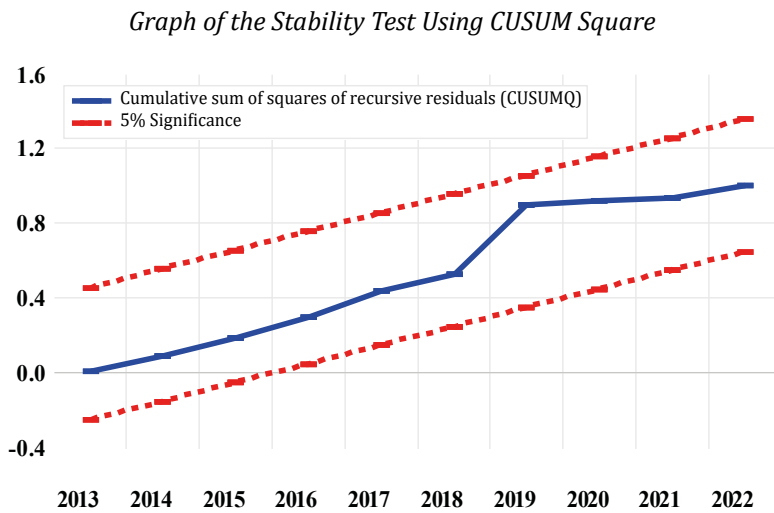
To test this assumption, the Breusch-Godfrey serial correlation LM test was used to check for autocorrelation. The test reports that the *p*-value of the *F*-statistic and *R*-squared should be more significant than the 5 % significance level (0.8487 and 0.7065 > α = 5 % or 0.05), respectively (Table 6). Both the *F*-statistic and

Figure 3.



Source: Own elaboration

Figure 4.



Source: Own elaboration

R-squared results were insignificant. In this case, the null hypothesis ($H_0 = \text{no autocorrelation}$) is accepted in both versions of the test.

Table 6.

Breusch-Godfrey Serial Correlation LM Test

F-statistic	0.165956	Prob.F(2,14)	0.8487
Observed R-squared	0.694769	Prob.chi-square(2)	0.7065

Source: Own computation using Eviews-12 (2023)

Heteroskedasticity Test

The homoscedasticity assumption states that the variance of the error term is constant, σ^2 . This is known as the homoscedasticity assumption. If the errors do not have constant variance, they are considered heteroskedastic (Brooks, 2008). This study used both the Breusch-Pagan-Godfrey test and ARCH to check for heteroskedasticity. The *F*-statistics and Chi-square results showed no evidence of heteroskedasticity, as the *P*-values were greater than 0.05 (Tables 7 and 8). In this case, the study fails to reject the null hypothesis of constant variance (homoscedasticity) and concludes that heteroskedasticity is absent in the data.

Table 7.

Heteroskedasticity Test Using the Breusch-Pagan-Godfrey Test

F-statistic	0.843266	Prob.F(22,7)	0.6492
Observed R-squared	21.78142	Prob.chi-square(22)	0.4730
Scaled explained SS	0.877515	Prob.chi-square(22)	1.0000

Source: Own computation using Eviews-12 (2023)

Table 8.

Heteroskedasticity Test Using ARCH

F-statistic	0.536669	Prob.F(2,25)	0.5913
Observed R-squared	1.152651	Prob.chi-square(2)	0.5620

Source: Own computation using Eviews-12 (2023)

Multicollinearity Test

In this study, variance inflation factors (VIFs) were used to assess multicollinearity among independent variables. VIFs are one of the tools used to measure collinearity among factors (Daoud, 2017). According to Hailer et al. (2006), multicollinearity is

corrected when the centered VIF is lower than the uncentered VIF. In this study, all centered VIF values are lower than the uncentered VIF values, which fail to reject the null hypothesis (no multicollinearity) (Table 9).

Table 9.

Multicollinearity Test Result

Variable	Coefficient variance	Uncentered VIF	Centered VIF
LNGINI (-1)	0.016594	761.7806	19.05964
LNGINI (-2)	0.011984	550.0272	13.75741
LNEDUC	0.000165	2978.289	439.6674
LNEDUC (-1)	0.000128	2132.281	330.2797
LNFDI	0.1.70E-05	16.89992	8.523813
LNFDI (-1)	1.19E-05	10.51229	5.339622
LNFDI (-2)	1.69E-05	13.62508	7.000899
LNGE	0.000898	32.81688	10.10157
LNGE (-1)	0.000496	17.09372	5.824645
LNINF	0.001506	72.31170	2.242198
LNINF (-1)	0.015932	764.8512	23.71400
LNIR	0.001526	896.2493	10.92979
LNIR (-1)	0.001220	701.4737	13.30072
LNIR (-2)	0.000638	358.9835	9.200175
LNPOPN	0.030378	972.1120	27.72620
LNPOPN (-1)	0.380468	13000.07	132.2237
LNTRADE	0.176150	16073.90	2764730
LNTRADE (-1)	0.260819	24121.02	70.66358
LNUNEMP	0.003893	143.4375	6.556872
LNUNEMP (-1)	0.003924	141.0260	6.105307
LNUNEMP (-2)	0.005752	201.9614	8.290018
C	5.931505	22686.51	NA

Source: Own computation using Eviews-12 (2023)

Estimation Results of Long-Run ARDL Bounds Test

This study used a long-run form and a bound test to examine the variables' long-run effects. All variables used in the ARDL model were converted to natural logarithms (ln). The results of the ARDL bound test indicate that six variables have long-run relationships with income inequalities, as follows:

First, education, measured by the net primary school enrollment rate, has a negative and highly significant effect on income inequality in the long run at the 1 %

significance level, consistent with the prior expectation. This means keeping other things constant: with a 1 % increase in the number of children enrolled in primary school, there will be a 2.100361 % decrease in income inequality in the long run (Table 10). The finding was consistent with the findings of Jakiel (2016), Sharma et al. (2014), and Zegeye (2023). They found that education can reduce income inequality because the literate are eager to access information and use it to share resources more equitably. The findings were contradicted by Abate (2019), Baye (2015), Dharmadasa (2023), Mengesha (2019), and Wolde et al. (2022), who found that education positively correlated with income inequality. This implies that having a higher education qualification increases one's income so drastically that it widens the income gap in the population. This contradiction can be attributed to differences in variables, samples, estimation techniques, and periods across studies.

Second, FDI had a significant negative effect on income inequality at the 5 % significance level, consistent with prior expectations. Other things remain the same: the Gini coefficient decreases by 0.015858 points for every one-unit increase in FDI (Table 10). The inflow of FDI can result in employment creation, the transfer of advanced technology, and the development of management skills, thereby increasing productivity and reducing the income gap. These results are consistent with those of McLaren and Yoo (2017) and Yuldashev et al. (2023), but conflict with those of Balthazaar (2023) and Rivera and Castro (2013), who discovered a favorable correlation between FDI and income inequality. FDI raises wage inequality by boosting the wages of skilled workers more than those of less-skilled workers.

Third, the annual inflation rate has a positive and highly significant effect on income inequality at the 1 % level of significance, which is parallel with the prior expectation. Holding other variables constant, a 1 % increase in annual inflation is associated with a 0.779284 % increase in income inequality (Table 10). A high and rising inflation rate indicates macroeconomic instability, causing an unexpected decline in aggregate demand due to uncertainty, leading to excess demand and depressed production (Akpalu, 2006). This finding aligns with those of Molla et al. (2022) and Odusanya (2023), who found that inflation widens the income gap. Maestri and Roventini (2012) and Siami-Namini and Hudson (2019) disputed the findings, arguing that inflation reduces income disparity. This is because inflation lowers the average wealth of the population, which can impact income inequality.

Fourth, the real interest rate has a significantly positive effect on income inequalities at a 5 % significance level, in line with the prior expectation. This result

indicates that, holding all other explanatory variables constant, a 1 % decrease in the interest rate is associated with a 0.054429 % decline in income inequality (Table 10). Increases in interest rates would reduce aggregate demand, slow growth, and thereby decrease real wages. Lower- and middle-income groups are more affected by falling real wages, upper-income groups benefit from increased returns on their financial assets, and lower- and middle-class consumption relies heavily on earnings (Areosa & Areosa, 2016). The findings agreed with those of Areosa and Areosa (2016), Hailemariam et al. (2021), and Wolde et al. (2022).

Fifth, the population growth rate has a significantly positive effect on income inequalities at a 1 % significance level, in line with the prior expectation. This result indicates that, holding all other explanatory variables constant, a 1 % decrease in population growth is associated with a 2.850207 % decline in income inequality (Table 10). In developing countries like Ethiopia, populations that live below the poverty line have a higher fertility rate, which makes them more vulnerable to poverty and widens the income gap. The findings were consistent with those of Kuznets (2019), Odusanya (2023), and Wolde et al. (2022). However, Dharmadasa (2023) challenged the conclusions, finding that as the population grows, the total labor force (working-age population) increases and, as a result, economic activity rises, potentially narrowing income disparities.

Sixth, trade openness has a positive and highly significant effect on income inequality at the 1 % significance level, contrary to prior expectations. This conclusion shows that, provided all other explanatory variables remain constant, a 1 % increase in trade openness is associated with a 0.038660 % increase in income inequality (Table 10). Trade openness exacerbates economic disparities because developing countries' incomes are subject to external shocks. Exposure to international markets without sufficient structural reforms can increase inequality due to sectoral dislocation and wage polarization. Unlike in many Asian or Latin American contexts, where trade liberalization led to job creation in labor-intensive sectors, in Ethiopia, it has often favored capital-intensive or import-driven sectors, exacerbating inequality (Bigsten et al, 2007). This outcome was consistent with the findings of Wolde et al. (2022). However, the conclusions were refuted by the findings of Belay (2020), Dharmadasa (2023), Dorn et al. (2022), Sisay et al. (2024), and Xu et al. (2021), who found that trade openness narrowed income differences.

Table 10.

Results of Estimated Long-Run Coefficients

ARDL (ARDL (1, 2, 2, 2, 2, 1, 2, 1, 2) selected based on Akaike Information Criterion (AIC) = level equation) Dependent variable: LNGINI

Variable	Coefficient	Std. error	t-statistics	P-value
LNEDUC	-2.100361	0.309931	-6.776864	0.0003***
LNFDI	-0.015858	0.005409	-2.931686	0.0220**
LNGE	0.039998	0.022168	1.804309	0.1142
LNINF	0.779284	0.086009	9.060464	0.0000***
LNIR	0.054429	0.022204	2.451332	0.0440**
LNPOP	2.850207	0.577367	4.936562	0.0017***
LNTRADE	0.038660	0.007112	5.435842	0.0010***
LNUNEMP	0.068642	0.068231	1.006023	0.3479
C	-0.653719	1.557420	-0.419744	0.6873

Note. ** significant at 5 %; *** significant at 1 %

Source: Own computation using Eviews-12 (2023)

Estimation Results of Short-Run ARDL Bounds Test

Table 11 presents the short-run error-correction terms. The ECM is a non-spurious regression model, as indicated by the *R*-squared and Durbin-Watson statistics. The *R*² value implies that 99.46 % (0.994613) of variations in income inequalities can be explained by variations in the independent variables considered. Therefore, the short-run model's goodness-of-fit was robust. In this test, explanatory variables such as government expenditure and trade openness were found to have significant, adverse effects on income inequality. The real interest rate, population growth rate, unemployment rate, and inflation rate were found positively and significantly impact income inequality (Table 11).

In the short term, total government expenditure negatively and significantly influences income inequality at the 1 % significance level, contradicting previous expectations. This means that if all other explanatory variables remain constant when government spending rises by one percent, income inequality falls by 0.012480 % (Table 11). This suggests that the more funds the government commits to infrastructure, the smaller the gap between the rich and the poor. Low-income groups should benefit more from subsidies, grants, and social help than middle- or high-income groups. As a result, an increase in the proportion of social aid and subsidy grant expenditures is required to significantly lower inequality in Ethiopia. These results are

consistent with the findings of [Alamanda \(2021\)](#), [Dharmadasa \(2023\)](#), [Hailemariam et al. \(2021\)](#), and [Kim and Samarasekara \(2023\)](#). This conclusion contradicts the findings of [Molla et al. \(2022\)](#) and [Rhee and Kim \(2018\)](#), who discovered that some segments of the population benefit less than others due to political considerations and physical location (remote rural areas).

For the unemployment rate, there will be a 0.296072 % increase in income inequality ([Table 11](#)). This suggests that unemployment reduces income inequality by narrowing labor demand and the market. This finding is consistent with the results of [Belay \(2020\)](#) and [Mengesha \(2019\)](#). However, this contradicts the results of [Haini et al. \(2023\)](#), who found that unemployment reduces the income difference. The annual inflation rate favors income inequality at the 1 % significance threshold, consistent with previous expectations. Holding all other variables fixed, a 1 % increase in annual inflation will result in a 0.855433 % increase in income disparity ([Table 11](#)). In Ethiopia, inflation disproportionately affects lower-income households, as they spend a higher share of their income on food and non-durable goods, contributing to increased inequality. Poor households in Ethiopia spend most of their income on basic necessities such as food, rent, and transportation. When prices rise, their real income declines, reducing their standard of living more sharply than for wealthier households, who spend a smaller share of their income on basics. These findings are consistent with those reported by [Areosa and Areosa \(2016\)](#), [Auclert \(2016\)](#), [Maraşlı \(2018\)](#), and [Wolde et al. \(2022\)](#).

The rate of population expansion has a significantly positive effect on income inequality at the 1 % significance level, which is consistent with previous expectations. This conclusion shows that, if all other explanatory variables remain constant, income inequality increases by 1 %, and population growth rises by 0.175831 % ([Table 11](#)). These findings are consistent with those of [Maestri and Roventini \(2012\)](#) and [Siami-Namini and Hudson \(2019\)](#). Trade openness has a negative, highly significant effect on income inequality at the 1 % significance level, contradicting previous expectations. This conclusion shows that, holding all other explanatory variables constant, a 1 % decline in trade openness raises income inequality by 2.076610 % ([Table 11](#)). This implies, in the short run, that trade may improve income distribution by creating jobs and enabling access to cheaper imports.

Table 11.

Results of Estimated Short-Run Coefficients (Error Correction Form)

ARDL (2, 1, 2, 1, 1, 2, 2, 1, 2) selected based on Akaike Information Criterion (AIC)			Dependent Variable D (LNGINI)	
Variable	Coefficient	Std. error	t-statistics	P-value
D(LNEDUC)	-0.000963	0.002959	-0.325549	0.7543
D(LNGE)	-0.012480	0.001234	-10.11613	0.000***
D(LNFDI)	-0.010283	0.008396	-1.224855	0.2602
D(LNINF)	0.855433	0.016540	51.71962	0.0000***
D(LNIR)	0.220855	0.030187	7.316151	0.0000***
D(LNPOP)	0.175831	0.034458	5.102742	0.0014***
D(LNTRADE)	-2.076610	0.135442	-15.33208	0.0000***
D(LNUNEMP)	0.296072	0.027811	10.64580	0.0000***
CointEq(-1)*	-1.580837	0.071993	-21.95835	0.0000***
R-squared	0.997028	Log likelihood		51.98191
Adjusted R²	0.994613	Durbin-Watson stat		2.745450
S of regression	0.058580			

Note. *** denotes statistical significance at 1 % level.

Source: Own computation using Eviews-12 (2023)

CONCLUSION AND RECOMMENDATION

This study empirically examines the factors affecting income inequality in Ethiopia from 1991 to 2022. The long-run results show that education and foreign direct investment are negatively associated with income inequality and significantly affect it, whereas inflation, real interest rates, trade openness, and population growth rates are positively associated with income inequality. Government spending and the unemployment rate were positively correlated, but neither affected income inequality. The short-run results show that government spending and trade openness are negatively associated and significantly affect income inequality. The real interest, population growth, unemployment, and inflation rates all had substantial and beneficial impacts on income inequality. Foreign direct investment and education were negatively associated, but neither affected income inequality in the near term. The study concludes that most of the identified explanatory variables significantly affect income inequality in Ethiopia.

Based on these findings, the study suggests that rising inflation reduces workers' real wages, particularly those with lower earnings. This scenario widens the

divide between the rich and poor, lowering their standard of living. Consequently, the Ethiopian government should raise wages for low-income workers. Given that education has a significant long-term impact on reducing income inequality, policymakers and the government should aim to promote access to education to boost individual productivity and help people find better-paying jobs. Primary and secondary education are the most important levels for reducing income inequality because they provide broad access to skills and opportunities for the poor.

Although trade openness can stimulate economic growth, in Ethiopia, it has been associated with rising income inequality. To address this, the government should promote industrialization and provide strong support to small and medium enterprises (SMEs), particularly in the agriculture and manufacturing sectors. Enhancing the competitiveness of these sectors in international markets will enable rural populations and low-income groups to share more equitably in the gains from trade. Most explanatory variables were significant in explaining income inequality in Ethiopia. This analysis focused on the primary variables over a few years (1991–2022) rather than incorporating all the precise components of the explanatory variables that drive income disparities in Ethiopia. This study can be used as a benchmark for future research; thus, the researcher suggests that any future study should extend the study period (to more than 32 years) and include new variables that were not included in this study due to a lack of recorded data at the country level.

ACKNOWLEDGMENTS

I would like to thank the National Bank of Ethiopia and the World Income Inequality Database for providing me with the necessary data and information.

COMPETING INTERESTS

The author has no competing or conflicting interests to declare.

FUNDING

The author received no specific funding for this work.

DATA AVAILABILITY

The raw data that support the findings of this study are available upon request from the corresponding author.

AI USAGE

In preparing this manuscript, AI tools, specifically ChatGPT (GPT-5-mini), were used to assist with literature searches, summarization, and formatting guidance. All ideas, analyses, interpretations, and conclusions presented in this work are solely those of the author. The AI tool did not generate original content, perform data analysis, or influence the substantive academic arguments of the manuscript.

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