The Dynamic Nexus between Macroeconomic Factors and Income Inequality: Evidence from Lower-Middle-Income Countries

Mohsen Ayyash[1] | *Universiti Sains Malaysia, Penang, Malaysia*
Mohammed Fuqaha[2] | *Birzeit University, Ramallah, Palestine*

Received 17.10.2024 (revision received 30.12.2024), **Accepted** (reviewed) 22.2.2025, **Published** 12.12.2025

Abstract

Income inequality has been a persistent challenge for policymakers worldwide, especially in developing economies. This study aims to explore the dynamics of income inequality in lower-middle-income economies by analyzing the long-run impact of critical macroeconomic factors. Utilizing annual panel data for 18 lower-middle-income countries from 1996 to 2018, the study employs the Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS). Furthermore, the Pooled Mean Group (PMG) estimator is utilized to validate coefficient estimation. The findings suggest a significant nonlinear linkage between economic growth and income inequality and confirm the Kuznets Curve Hypothesis (KCH) in the selected panel. The findings also substantiate significant long-run positive effects of inflation, trade, and unemployment on income inequality. However, the long-run impact of gross capital formation (GCF) is insignificant. The insights gained from this study could inform policymaking to foster inclusive economic growth and reduce income disparities within lower-middle-income economies.

Keywords	***DOI***	***JEL code***
Income inequality, macroeconomic factors, lower-middle-income countries, dynamic panel models	*https://doi.org/10.54694/stat.2024.67*	*C33, D33, D63*

INTRODUCTION

Income inequality is an indicator that quantifies the degree to which income is evenly distributed among individuals within a given population. A more uneven income distribution indicates higher income

[1] School of Mathematical Sciences, Universiti Sains Malaysia, 11800 USM Penang, Malaysia. Corresponding author: e-mail: ayash.mohsen@gmail.com, phone: (+60)46574488. ORCID: <https://orcid.org/0000-0002-5618-6313>.
[2] Faculty of Graduate Studies and Research, Birzeit University, Ramallah, Palestine. E-mail: mohammedfuqaha27@gmail.com.

inequality, while a more even distribution reflects lower income inequality (OECD, 2023). Income inequality poses significant global challenges that hinder development across developed and developing regions. Addressing income inequality is important for promoting social justice and sustainable economic development. As such, it remains a critical concern on the agenda of international organizations and policymakers dedicated to promoting inclusive and equitable development. For instance, the United Nations (UN) has made addressing inequality within and between nations a key focus of its 17 Sustainable Development Goals (SDGs) (UN, 2015).

Over the past two decades, the global economy has undergone notable transformations, including robust economic growth, greater trade integration, and significant capital accumulation. However, these changes have not been translated into equitable benefits for all population segments, particularly in underdeveloped and low-income countries (IMF, 2023). Therefore, lowering income inequality is essential for stabilizing the economy and achieving sustainable development.

The existing literature concerning the dynamics of income inequality and its macroeconomic drivers has yielded mixed findings across various countries and regions (Batuo et al., 2022; Berisha et al., 2018; Deyshappriya et al., 2017; Taresh et al., 2021; Zandi et al., 2022). The direction and magnitude of macroeconomic influences often vary depending on various aspects, including the country's stage of development, income levels, periods, and methodologies applied (Adams and Klobodu, 2019; Batuo et al., 2022; Shahbaz, 2010; Siami-Namini and Hudson, 2019; Zheng et al., 2023). Economic growth, for example, is often regarded as a double-edged sword: while it can reduce poverty, it may also exacerbate income inequality if the resulting wealth is distributed unevenly (Cerra et al., 2021; Lim and Sek, 2014). The pioneering work of Kuznets (1955) revealed controversial findings, indicating that income distribution is more equitable in developed and industrialized economies compared to developing or agrarian countries.

Inflation can diminish purchasing power, often disproportionately affecting lower-income households and exacerbating income (Nantob, 2015; Zheng et al., 2023). While fostering economic growth, trade openness can generate uneven benefits across regions and sectors, further contributing to disparities in income distribution (Dorn et al., 2022). Unemployment can also exacerbate income inequality due to job losses and a lack of economic opportunities (Nayyar, 2014). However, this effect can be mitigated by better institutional quality that can provide more opportunities and support for the unemployed (Law and Soon, 2020). Furthermore, Gross capital formation (GCF), which reflects the investment levels, can stimulate economic activities within and between countries. However, without policies that promote more inclusive wealth distribution, the benefits may disproportionately flow to wealthier segments of the population (Piketty, 2014).

While extensive research has examined how macroeconomic factors affect income inequality in different countries, there is a lack of studies exploring the dynamic effects of these factors collectively, especially in lower-middle-income countries. Furthermore, the latest Sustainable Development Report 2024 highlights that most lower-middle-income economies continue to face significant and persistent challenges in achieving reduced inequalities (Sachs et al., 2024). Given the diverse economic landscapes in these economies, a deeper look at the dynamic relationship between income inequality and key macroeconomic indicators is essential for policymakers seeking to promote equitable societies and inclusive growth. Therefore, the main purpose of this study is to deepen the existing body of research by analyzing the dynamic impacts of five key macroeconomic factors on income inequality in 18 lower-middle-income countries from 1996 to 2018. More specifically, this research seeks to verify the KCH's validity and examine the dynamic effects of inflation, GCF, trade, and unemployment on income inequality.

1 LITERATURE REVIEW

Income inequality is perhaps one of the most significant macroeconomic issues that continuously attract the attention of policymakers, especially in underdeveloped and emerging economies. It is reflected in various economic dimensions, such as earnings, wages, consumption, expenditure, and income (Goodman and Oldfield, 2004). The theoretical background of income inequality is rooted in classical economic theories, which regarded income inequality as a natural consequence of a free market system (Ricardo, 1817; Smith, 1776). In light of this, Marx (1867) viewed the capitalist system as exploitative, potentially widening the inequality gap, while John Mill advocated for societal intervention to moderate the excesses of capitalism and ensure a fairer income distribution through taxes and social welfare – principles that later formed the basis of welfare economics (Bowden, 2020; Mill, 1982). From a modern theoretical perspective, human capital theory posits that investment in education, skill development, and training is a solution to reducing income disparity (Mincer, 1974; Psacharopoulos and Patrinos, 2018). Recently, proponents of the capability approach have argued that enhancing individuals' capabilities through education and health investments improves economic outcomes and fosters a more equitable distribution of opportunities and resources in society (Nussbaum, 2000; Sen, 1999). Meanwhile, Kuznets (1955) hypothesized an inverted U-shaped linkage between economic growth and income inequality. According to his hypothesis, income distribution initially becomes more unequal during the early stages of the development process, reaching a peak before eventually showing a trend toward becoming more equal as per capita income rises; income inequality begins to decline as wealth becomes more evenly distributed.

The extant literature has widely scrutinized how economic growth impacts income inequality. Some researchers have analyzed this relationship through the prism of validating the KCH. In contrast, others have delved into the traditional framework by examining the individual impact of economic growth on income distribution. Using panel data from 33 Asian countries from 1990 to 2013, Deyshappriya (2017) employed the Generalized Method of Moments (GMM) and identified compelling evidence supporting the KCH. Additionally, Batuo et al. (2022) examined the validity of KCH and other macroeconomic factors by employing static and dynamic panel models for 52 African countries from 1980 to 2017. The countries were divided into four cups concerning income levels. Their findings revealed compelling evidence on the validity of KCH in the least-developed countries, while they found positive and non-linear U-shaped linkage in higher-income countries. Two studies conducted in Indonesia have applied several panel data models indicating that KCH holds in Indonesian provinces (Muryani et al., 2021; Taresh et al., 2020). However, some studies indicated that KCH does not hold but showed a positive linkage between them (Adams and Klobodu, 2019; Berisha et al., 2020). Nonetheless, Asogwa et al. (2022) employed GMM models on a panel of 28 African countries from 2001 to 2016 and demonstrated that this dynamic linkage is insignificant. In Pakistan, Shahbaz (2010) went beyond these relationships. He confirmed that not only did the KCF hold, but also an S-shaped relationship, determined by applying an autoregressive distributed lag (ARDL) model from 1970 to 2005.

As for inflation and income inequality dynamics, economic theory suggests that inflation can affect income inequality negatively and positively. As for the positive effect, inflation diminishes individuals' purchasing power and the real values of their unindexed assets, pensions, and social transfers, thereby disproportionately impacting people with lower income (Balcilar et al., 2018; Glawe and Wagner, 2024; Wolff, 2023). It also distorts income distribution by favoring profit earners over wage earners (Nantob, 2015; Siami-Namini and Hudson, 2019). On the negative side, conversely, inflation may reduce the real value of debt, easing the burden on borrowers, who are typically lower-income individuals, taxing the wealthy, and reducing income from assets (Bulíř, 2001; Monnin, 2014; Romer and Romer, 1998; Zheng et al., 2023). Empirical research has shown either negative or positive effects and, in some cases, a nonlinear impact. For example, Galli and van der Hoeven (2001) found that inflation directly impacted income inequality in a sample of 15 OECD countries. Berisha et al. (2023) revealed a negative effect of inflation on income inequality, which intensifies at higher inequality levels. Moreover, Zhang and Ben

Naceur (2019) showed that inflation negatively impacted income inequality in low-income countries. This negative effect was also supported by El Herradi et al. (2023) in 14 OECD economies and Göcen (2024) in 58 countries. However, Albanesi (2007) and Thalassinos et al. (2012) found that inflation positively affected income inequality. Brei et al. (2023) and Zandi et al. (2022) also indicated that inflation positively affected income inequality in high-income countries and Asian developing economies, respectively. Law and Soon (2020) used the GMM panel models from 65 developed and emerging economies from 1987 to 2014 and demonstrated that higher income inequality was positively linked with inflation across both the developed and developing countries. However, this effect is significantly moderated by better institutional quality. Nantob (2015) applied the GMM econometric models utilizing annual panel data from 2001 to 2012 from 45 developing nations and identified that income inequality was nonlinearly linked with inflation and exhibited an inverted U-shaped pattern. The study showed that GDP per capita, political instability, and trade openness significantly mediated this dynamic nexus. Balcilar et al. (2018) identified a nonlinear relationship with a 3% inflation threshold in the US. When inflation exceeds this threshold, it positively influences income inequality, while inflation below this level has a negative effect on income inequality. Likewise, a recent study conducted by Glawe and Wagner (2024) employed dynamic panel threshold models on a sample of 101 economies. It revealed that income inequality increased when inflation exceeds a 6% threshold, while at lower inflation levels, the dynamic relationship was insignificant. A study by Siami-Namini and Hudson (2019) highlighted that inflation effects on income inequality varied depending on the stage of development. They identified an inverted U-shaped link in developing economies and a U-shaped connection in developed countries. In contrast, a recent study by Zheng et al. (2023) suggested that this relationship can be either negative, positive, or U-shaped. This variation depends on the relative prominence of wealth disparities versus skill gaps and how the proportion of interest income to labor income reacts to inflationary pressures. Meniago and Asongu (2018) suggested that inflation could disproportionately impact lower-income groups more adversely than higher-income groups, exacerbating income inequality. This indicates that inflation's impact on income distribution may widen the gap between different socioeconomic groups.

Meanwhile, the literature did not extensively discuss the dynamic effects of other macroeconomic factors, including the GCF, trade, and unemployment. Most previous research has included these variables to control the income inequality equation, whereby empirical findings showed mixed results. Empirical analysis in Asian countries demonstrated that higher income inequality was significantly associated with higher levels of political instability, trade, unemployment, and inflation (Deyshappriya, 2017). In the same way, Zandi et al. (2022) employed a random effect model (REM) and GMM utilizing data from developing Asian countries. They demonstrated that income inequality and unemployment were positively linked. However, Heer and Süssmuth (2003) employed a traditional linear regression model in the US economy. They found no significant linkage between unemployment and income inequality, while applying the error correction model revealed a positive linkage between them. Law and Soon (2020) investigated the dynamics of inflation and income inequality and revealed positive effects of trade openness and foreign direct investment on income inequality but not for unemployment as controlling variables. Using the system GMM panel model for a penal of 58 economies from 2012 to 2018, Göcen (2024) revealed negative effects of per capita GDP and trade openness while unemployment weekly and positively impacted income inequality.

Given the mixed results discussed above and the lack of studies that have examined the dynamic impacts of key macroeconomic indicators like GCF, inflation, per capita GDP, unemployment, and trade collectively, there is a need to explore how these factors influence the dynamics of income inequality. Furthermore, there is a shortage of research examining these dynamic relationships within developing countries, especially in lower-middle-income economies. Therefore, the current research will contribute to the current body of knowledge by exploring the dynamic relationships between income inequality and these macroeconomic indicators in a group of economies classified as lower-middle-income nations.

2 METHODOLOGY AND DATA

This section outlines the methodological framework guiding our econometric study. It presents the econometric model, the data, and the estimation process.

2.1 Econometric specifications

This study intends to estimate the following income inequality equation:

$$\begin{aligned} Ln(GINI)_{it} &= \beta_0 + \beta_1 Ln(GDPPC)_{it} + \beta_2 \left(Ln(GDPPC_{it}\right)^2 + \beta_3 INF_{it} + \beta_4 GCF_{it} + \beta_5 UNEM_{it} \\ &+ \beta_6 TRADE_{it} + \varepsilon_{it}, \end{aligned} \tag{1}$$

where i refers to countries, and t denotes the period. $Ln(GINI)_{it}$ is the natural logarithm of the Gini index, which represents the dependent variable of this study. The parameters, β_1, β_2, β_3, θ_4, β_5 and β_6 capture the effects of GDP per capita ($Ln(GDPPC)_{it}$), the squared term of GDP per capita (($Ln(GDPPC_{it})^2$), inflation (INF_{it}), GCF (GCF_{it}), unemployment rate ($UNEM_{it}$), trade ($TRADE_{it}$). β_0 denotes a scaler that captures the intercept of the income equation, and the error terms are represented by ε_{it}.

2.2 Data sources

This study employs annual panel data from 1996 to 2018 for lower-middle-income economies, driven by the significant economic and social challenges these countries have confronted. These challenges include efforts to address income inequality and make progress toward reducing disparities, as emphasized by SDG10 (Sachs et al., 2024). The study sample includes 18 lower-middle-income countries from 1996 to 2018, as displayed in Table A1 in the Appendix. The selection of this specific set of 18 lower-middle-income economies was primarily driven by the availability and completeness of the data required for the analysis, particularly the Gini index. While other countries are classified as lower-middle-income by the World Bank, they could not be included in this study due to missing data on key variables. Moreover, extending the study period would have resulted in increased missing data. Therefore, the analysis was limited to the 1996–2018 period to maximize the available data and include as many countries as possible.

The variables used in this study and their sources are shown in Table A2 in the Appendix. In line with the literature, the study utilized the Gini index based on disposable income, extracted from the Standardized World Income Inequality Database (version 9.7), as a proxy measure for income inequality (Solt, 2020). It is expressed in percentage and takes possible values between 0 and 100%. A Gini index value approaching zero indicates less income inequality and more equitable societies, while a value approaching 100% exhibits higher income inequality. The World Bank Development Indicators (WDI) database was the primary source of the five key macroeconomic predictors over the study period. These include per capita GDP adjusted for 2015 prices, GCF as a percentage of GDP, inflation rate based on the consumer price index, unemployment rate calculated based on the International Labor Organization (ILO) estimates, and trade openness calculated as the ratio of net exports and imports to GDP. Furthermore, Table 1 displays the descriptive statistics of the study variables.

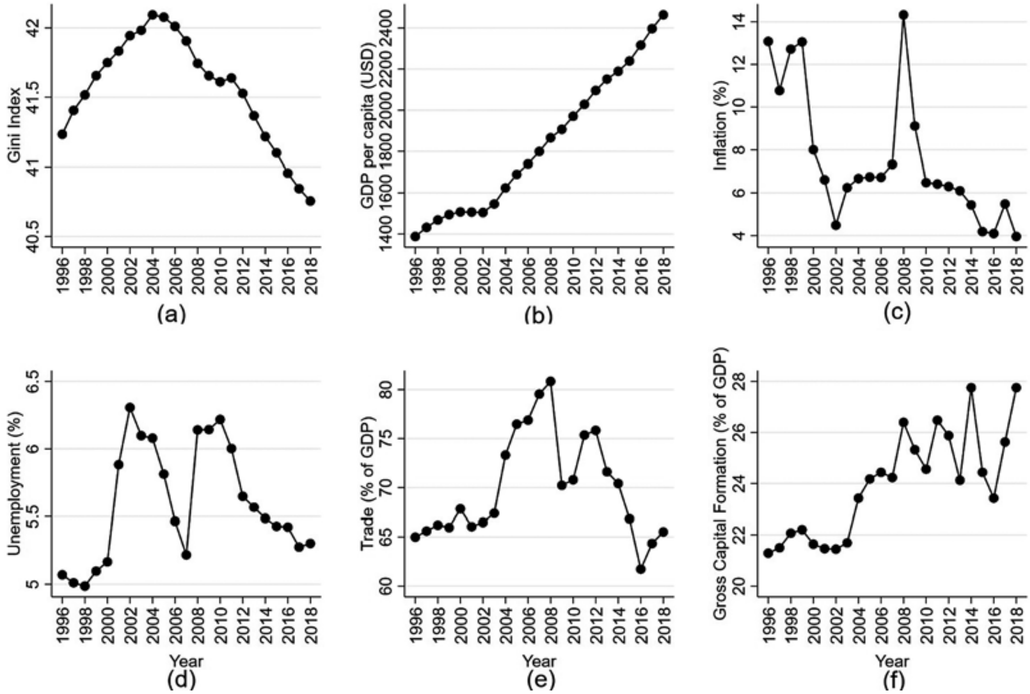
To gain more insight into the dataset, the study provided time series plots for the study variables by averaging the data for each year across all countries. Figure 1(a) shows a time series plot of the annual average Gini index for the entire sample, which indicates that income inequality, on average, increased from 1996 to 2005 and then decreased slightly until 2018. However, the average levels of income inequality across the 18 lower-middle-income economies remained high over the study period.

Table 1 Descriptive statistics for countries and the entire sample

Variable	Gini Index		GDPPC		INF		UNEM		TRADE		GCF		Obs.
	Mean (SD)	Range (Max-Min)	Mean (SD)	Range (Max-Min)	Mean (SD)	Range (Max-Min)	Mean (SD)	Range (Max-Min)	Mean (SD)	Range (Max-Min)	Mean (SD)	Range (Max-Min)	
Bangladesh	32.79 (0.77)	33.5–31.6	903.20 (272.01)	1 460.81–575.04	6.24 (2.29)	11.40–2.01	3.90 (0.66)	5.00–2.51	35.17 (7.42)	48.11–26.08	26.12 (2.93)	31.82–20.73	23
Bolivia	48.83 (4.79)	54.5–40.8	2 403.48 (421.52)	3 219.20–1 912.00	5.16 (3.34)	14.01–0.93	2.62 (0.46)	3.66–2.02	63.64 (14.28)	85.26–44.17	17.73 (3.15)	23.61–11.02	23
Cote d'Ivoire	51.63 (2.08)	53.9–47.2	1 736.45 (205.99)	2 168.91–1 507.09	2.42 (1.65)	6.31–0.36	4.97 (1.54)	7.22–1.90	57.29 (6.55)	70.30–46.04	17.56 (3.87)	23.39–12.02	23
Egypt	39.85 (0.66)	41.4–38.9	2 926.87 (449.27)	3 635.42–2 181.25	9.14 (6.15)	29.51–2.27	10.32 (1.75)	13.15–7.95	46.85 (10.68)	71.68–30.25	17.97 (2.37)	22.39–13.64	23
Ghana	42.13 (1.02)	43.5–40.2	1 323.47 (319.66)	1 899.81–951.92	18.22 (11.34)	46.56–4.87	6.11 (2.30)	10.4–2.17	81.39 (15.76)	116.05–60.76	21.77 (4.81)	29.00–12.81	23
Honduras	50.47 (2.39)	53.1–46.4	2 015.77 (228.99)	2 423.28–1 693.72	8.43 (5.19)	23.84–2.72	4.61 (1.17)	7.08–3.16	118.28 (11.73)	136.49–96.91	26.71 (3.85)	36.07–20.60	23
India	44.22 (1.59)	47.2–41.4	1 122.44 (381.48)	1 891.14–651.96	6.68 (2.98)	13.23–3.33	8.06 (0.42)	8.70–7.15	39.41 (11.37)	55.79–21.93	33.21 (5.41)	41.95–22.76	23
Jordan	37.48 (0.68)	38.7–36.8	4 176.60 (496.86)	4 920.87–3 477.17	3.37 (3.13)	13.97–(–0.88)	14.01 (1.63)	18.26–11.90	116.14 (17.47)	146.91–87.96	26.97 (4.88)	36.05–20.10	23
Kenya	45.16 (1.33)	47.1–43.0	1 318.13 (134.73)	1 604.80–1 165.17	9.01 (4.85)	26.24–1.96	2.88 (0.35)	4.28–2.65	50.58 (8.06)	64.48–34.41	18.99 (2.73)	24.95–15.00	23
Kyrgyzstan	34.63 (1.40)	36.9–32.4	903.73 (180.77)	1 197.61–619.96	10.54 (10.07)	37.03–0.39	2.56 (0.67)	3.67–1.51	108.97 (22.33)	146.11–73.75	25.29 (7.80)	36.76–11.83	23
Laos	35.93 (0.69)	37.0–35.0	1 433.35 (537.33)	2 467.96–782.96	16.80 (30.08)	125.27–0.14	1.83 (0.71)	3.27–0.71	78.55 (11.36)	99.06–60.57	26.07 (7.98)	34.06–12.95	23
Pakistan	34.43 (0.20)	34.7–34.1	1 243.75 (173.99)	1 612.84–1 033.88	7.68 (4.35)	20.29–2.53	1.34 (1.25)	4.08–0.40	29.61 (4.62)	38.33–21.46	16.39 (1.25)	19.00–14.63	23
Palestinian Territories	38.97 (1.36)	41.3–37.2	2 756.25 (491.80)	3 483.10–1 836.97	3.48 (2.60)	9.89–(–0.22)	19.38 (5.39)	27.47–10.35	78.04 (9.64)	96.35–65.42	26.14 (6.59)	42.88–16.66	23
Philippines	41.60 (1.03)	42.8–39.4	2 331.62 (517.86)	3 439.10–1 776.98	4.46 (2.14)	9.23–0.67	3.49 (0.42)	4.05–2.34	71.87 (10.91)	87.57–55.82	20.30 (3.08)	27.15–15.68	23
Senegal	41.23 (0.56)	42.2–40.6	1 145.18 (98.75)	1 384.64–980.77	1.57 (2.03)	7.35–(–2.25)	3.38 (1.13)	6.76–2.65	54.49 (5.02)	62.76–46.27	23.44 (3.80)	32.65–15.85	23
Sri Lanka	47.57 (1.16)	48.5–44.8	2 822.91 (916.81)	4 495.71–1 674.00	8.48 (4.91)	22.56–2.14	6.54 (2.32)	11.35–3.88	64.01 (15.24)	88.64–46.47	28.16 (4.85)	39.73–22.00	23
Tanzania	44.06 (0.92)	45.3–42.4	733.19 (162.48)	1 012.50–519.06	8.45 (4.56)	20.98–3.49	2.93 (0.42)	3.47–2.13	37.99 (9.73)	56.17–23.99	27.59 (8.83)	38.38–10.26	23
Vietnam	37.07 (0.32)	37.6–36.4	1 830.09 (638.28)	3 090.77–975.07	6.30 (5.52)	23.12–(–1.71)	1.88 (0.52)	2.87–1.00	127.90 (20.83)	164.66–92.71	32.53 (3.23)	39.57–27.63	23
Total	**41.56 (5.76)**	**54.5–31.6**	**1 840.36 (977.34)**	**4 920.87–519.06**	**7.58 (9.56)**	**125.27–(–2.25)**	**5.60 (4.92)**	**27.47–0.40**	**70.01 (32.20)**	**164.66–21.46**	**24.05 (6.93)**	**42.88–10.26**	**414**

Note: SD – standard deviation, obs. – number of observations.
Source: Own construction

Figures 1(a)–(f) Trends in the mean values of key study variables from 1996 to 2018



Source: Own construction based on WDI (World Development Indicators) and WIID (World Income Inequality Database)

As depicted in Figure 1(b), GDP per capita exhibited a steady upward trend throughout the study period from 1996 to 2018, suggesting overall economic growth and development within the lower-middle-income countries examined in this analysis.

As shown in Figure 1(c), the time series of inflation rates across the entire sample provides insights into the average inflation values. We observed that inflation, on average, followed a downward trend from 1996 to 2002. Furthermore, an increasing trend was observed from 2003 until 2008, culminating in a peak in 2008 due to the global economic crisis. From 2009 to 2018, inflation rates, on average, exhibited a declining trend.

Figure 1(d) presents a time series plot of unemployment for the entire sample. On average, the unemployment rate exhibited cyclical behavior over the study period. On average, from 1996 to 2002, we observed a decreasing trend in unemployment, suggesting improvements in labor market conditions during this period. However, this positive trajectory was followed by an upward trend between 2003 and 2011, driven by the consequences of the Great Recession in 2008–2009 that adversely affected labor markets worldwide. Subsequently, from 2012 to 2018, the unemployment rate resumed declining, reflecting a recovery phase as economies stabilized and labor markets strengthened.

Figure 1(e) illustrates a time series plot of trade for the entire sample. As shown, trade exhibited a steady upward trend from 1996 to 2008. This was followed by a reversal in the trend across the entire sample from 2009 to 2016 before returning to an increasing trajectory from 2017 to 2018.

Finally, Figure 1(f) displays the time series plot of the average GCF of the monitored economies. On average, GCF as a percentage of GDP experienced a steady rise over the period 1996–2008. However, it exhibited volatility from 2009 to 2016 and then returned to increase from 2017 to 2018. The trend suggests a long-term increase in investment levels as a share of GDP, though interrupted by periods of economic instability and fluctuations.

2.3 Estimation procedure

After collecting the data and confirming the absence of missing values, we conducted preliminary checks on all variables included in this study. Stationarity was assessed using both the Im-Pesaran-Shin (2003) and Phillips-Perron (1988) tests. Results indicated that all variables were stationary at their first difference, demonstrating an integration order of one I(1), as illustrated in Table A3 in the Appendix. Furthermore, residual cointegration tests were employed by Kao (1999) and Pedroni (1999) to investigate whether the study variables are cointegrated. The findings of both tests revealed that the null hypothesis of no cointegration among variables was rejected, and we concluded that a long-run equilibrium relationship existed among the variables in our panel (Table A4). Additionally, the study identified no multicollinearity among the independent predictors by examining the correlation matrix (Table A5).

For estimating the long-run coefficients while addressing issues of endogeneity and serial autocorrelation, the study employed FMOLS and DOLS econometric models (Phillips and Hansen, 1990; Stock and Watson, 1993). These methods were utilized for their appropriateness in panel data analysis and their ability to provide reliable estimates of the relationships among the variables, particularly in the context of cointegrated nonstationary time series data, allowing for robust estimation of the long-run effects of macroeconomic factors on income inequality. Kao and Chiang (2000) suggested that DOLS performs better than FMOLS in homogeneous and heterogeneous panels, regardless of sample size. A key distinction between these methods is that FMOLS involves non-parametric adjustments of the regressors, whereas DOLS uses parametric adjustments.

For the panel regression model presented by Formula (1), the FMOLS estimator is given by:

$$\hat{\beta}_{FMOLS} = \left[\sum_{i=1}^{N} \sum_{t=1}^{T} \left(X_{it} - \bar{X}_{it} \right) \right]^{-1} \left[\sum_{i=1}^{N} \sum_{t=1}^{T} \left(X_{it} - \bar{X}_{i} \right) \left(y_{it} - \bar{y}_{i} + \Delta_{it} \right) \right], \tag{2}$$

where $i = 1, ..., N$, and $t = 1, ..., T$ denote the cross-sections and periods, respectively. X_{it} denotes the vector of independent variables, and $\bar{X}_i$ are the means of X_{it}. y_{it} represents the dependent variable, and $\bar{y}_i$ its average. Δ_{it} is the correction term for serial autocorrelation and potential endogeneity. Meanwhile, DOLS includes leads and lags of the differenced predictors to account for endogeneity and serial correlation. The DOLS estimator is given by:

$$\hat{\beta}_{DOLS} = \left[\sum_{i=1}^{N} \sum_{t=1}^{T} Z_{it}^{'} Z_{it} \right]^{-1} \left[\sum_{i=1}^{N} \sum_{t=1}^{T} Z_{it}^{'} y_{it} \right], \tag{3}$$

where Z_{it} represents the augmented regression matrix $(X_{it}, \Delta X_{it+q}, ..., \Delta X_{it-q})'$ such that ΔX_{it+q} and ΔX_{it-q} are leads and lags of the first differences of the regressors X_{it}.

Both FMOLS and DOLS estimators produce t-statistics and corresponding p-values, which are used to assess the statistical significance of the estimated coefficients. As reported in the econometric literature, the statistical significance of the estimated parameters is assessed at the 1%, 5%, and 10% levels, indicating highly, moderately, and weakly significant effects, respectively, for rejecting the null hypothesis of no long-run effect.

2.4 Robustness check

To validate the estimated long-run coefficients, the current study employs mean group (MG) and pooled mean group estimators (Pesaran and Smith, 1995). The MG and PMG estimators are estimated using the ARDL modelling approach, which estimates both the long-run and the short-run effects. The PMG and MG methods differ in how they address estimator heterogeneity. In PMG, homogeneity is assumed only in the long-run relationship, but short-run coefficients and error variances vary across groups. In MG, meanwhile, both short-run and long-run coefficients differ across groups, making it more flexible in accounting for heterogeneity in panel data models. Pesaran et al. (1999) demonstrated that when the long-run homogeneity is presumed, the MG estimator becomes less efficient than the PMG estimator. However, the study focuses only on long-run estimates to compare with FMOLS and DOLS, as the latter estimators do not have short-run estimates.

The Hausman test assesses the efficiency and consistency of different estimators and whether their long-run coefficients exhibit homogeneity across groups, guiding which estimator best fits the data. The test examines the null hypothesis that states that the MG estimator yields results similar to the PMG. Upon rejecting the null hypothesis, it can be concluded that the MG estimator is more efficient and reliable than the PMG (p-value < 0.05). Otherwise, the PMG estimator is preferred (Hausman, 1978). The test statistic of this test can be calculated using the following formula:

$$H = \left[\hat{\gamma}_e - \hat{\gamma}_c\right]' \left[Var\left(\hat{\gamma}_e\right) - Var\left(\hat{\gamma}_c\right)\right]^{-1} \left[\hat{\gamma}_e - \hat{\gamma}_c\right], \tag{4}$$

where the estimator $\hat{\gamma}_e$ represents the value under the assumption of the null hypothesis (i.e., PMG), $\hat{\gamma}_c$ denotes the alternative estimator under the alternative hypothesis (MG), and $Var(\hat{\gamma}_e)$ and $Var(\hat{\gamma}_c)$ are the variance-covariance matrices of the two estimators.

3 RESULTS AND DISCUSSION

Table 2 shows the results obtained from FMOLS and DOLS estimation methods, which aimed to elucidate the nuanced long-term relationships among the variables examined in this study. Both FMOLS and DOLS estimators converge to reveal remarkable similarity and consistent estimates of the long-run parameters. The adjusted R-squared values were 73.8% for the FMOLS model and 80.2% for the DOLS model, demonstrating a good fit for the data.

Table 2 Long-run estimated parameters using FMOLS and DOLS

Variable	FMOLS				DOLS			
	Coefficient	S.E.	t-statistic	p-value	Coefficient	S.E.	t-statistic	p-value
Ln(GDPPC)	0.971***	0.027	36.118	0.000	1.076***	0.063	17.056	0.000
Ln(GDPPC)^2	–0.061***	0.004	–17.505	0.000	–0.072***	0.009	–7.198	0.000
INF	0.198***	0.025	7.965	0.000	0.189***	0.036	5.254	0.000
UNEM	0.249***	0.021	11.857	0.000	0.236***	0.042	5.619	0.000
TRADE	0.281***	0.064	4.413	0.000	0.269***	0.059	4.559	0.000
GCF	–0.001	0.002	–0.500	0.617	–0.005	0.004	–1.251	0.422
R-Squared	0.764				0.826			
Adjusted R-Squared	0.738				0.802			

Notes: *, **, and ***denote rejection of the null hypothesis of no long-run effect at the 10, 5, and 1% significance levels, respectively.
Source: Own construction

The empirical analysis reveals that the long-run effects of GDPPC and its quadratic term are statistically significant, validated by a 1% significance level using both estimators. Specifically, using the FMOLS estimator, the estimated long-run coefficients of Ln(GDPPC) and its quadratic term are 0.971 and –0.061, respectively. Likewise, the DOLS estimation demonstrates that the coefficients of Ln(GDPPC) and its squared term are 1.076 and –0.072, respectively. The positive and negative coefficients of Ln(GDPPC) and its squared term, respectively, demonstrate the nonlinear inverted U-shaped relationship between economic growth and income inequality within the studied lower-middle-income countries, which confirms the validity of the KCH in these economies. This suggests that, in lower-middle-income economies, income inequality initially rises with increasing GDP per capita but starts to decline once GDP per capita exceeds a specific threshold. Our empirical results are similar to several previous findings, including Deyshappriya (2017) for Asian economies, Muryani et al. (2021) and Taresh et al. (2020) for Indonesian provinces, Younsi and Bechtini (2020) for BRICS economies, and Younsi et al. (2022) for Asian and South African nations. The current results are also congruent with those of Batuo et al. (2022) for underdeveloped economies but contradict their findings for developed countries. In contrast, our results are dissimilar to the findings of Asogwa et al. (2022), who invalidate the KCH and did not even find any significant effect of per capita GDP on income inequality in their panel of 28 African economies.

The FMOLS and DOLS estimators reveal a substantial and positive relationship between inflation and income inequality, which is statistically significant at the 1% significance level. This indicates that higher inflation exacerbates income inequality within the studied economies. According to FMOLS analysis, a 1% increase in inflation corresponds to a 0.198% increase in income inequality. Similarly, the DOLS model indicates that a 1% increase in inflation leads to a 0.189% increase in income inequality in lower-middle-income economies. Our results align with several previous studies that suggest inflation exacerbates income inequality (Albanesi, 2007; Balcilar et al., 2018; Brei et al., 2023; Deyshappriya, 2017; Law and Soon, 2020; Nantob, 2015; Thalassinos et al., 2012; Younsi and Bechtini, 2020; Younsi et al., 2022; Zandi et al., 2022). The current finding is also consistent with the study by Clarke et al. (2006), which suggests that inflationary instability disproportionately affects the poor and middle class compared to the wealthy. The latter group benefits from greater access to financial tools that help diminish inflation's impact. Thus, this study confirms that inflation diminishes purchasing power for lower-income households and disrupts income distribution (Balcilar et al., 2018; Nantob, 2015). However, this study contradicts those that found a negative effect of inflation on income inequality (Berisha et al., 2023; Bulíř, 2001; El Herradi et al., 2023; Göcen, 2024; Monnin, 2014; Romer and Romer, 1998; Zhang and Ben Naceur, 2019).

The current analysis also reveals that both the FMOLS and DOLS models indicate that unemployment positively influences income inequality, highlighting the increasing impact on income inequality in the studied group of lower-middle-income countries, evidenced by a 1% significance level. According to the FMOLS estimation, a 1% increase in the unemployment rate corresponds to a 0.249% increase in income inequality. Similarly, the DOLS analysis indicates that a 1% rise in the unemployment rate leads to a 0.236% increase in income inequality within lower-middle-income countries. This empirical finding is congruent with several previous findings (Deyshappriya, 2017; Heer and Süssmuth, 2003; Zandi et al., 2022). In the meantime, Göcen (2024) and Monnin (2014) demonstrated a week of positive impact of unemployment on income inequality. The findings of Law and Soon (2020), who found no significant linkage between income inequality and unemployment, were dissimilar to our results.

The empirical findings of both FMOLS and DOLS reveal that trade significantly and positively impacts income inequality at a 1% level of significance within the group of lower-middle-income countries analyzed in the current investigation. The FMOLS estimation shows that a 1% rise in trade is associated with a 0.281% increase in income inequality. The DOLS estimation mirrors this finding, indicating that a 1% increase in trade is linked to a 0.269% rise in income inequality. Our results are congruent with the findings of Adams and Klobodu (2019), Deyshappriya (2017), and Law and Soon (2020). The results do not strongly support the notion that trade openness reduces income inequality in underdeveloped economies, which often have a larger proportion of human resources and primary education than developed economies (Topalova, 2007). Meanwhile, Gourdon et al. (2008) highlighted that trade openness had an increasing effect in high-income countries while decreasing in low-income countries. A comparative study by Yang and Greaney (2017) suggested mixed results, showing that trade openness reduces income inequality in Japan and the US, increases it in China, and has no impact in South Korea. Göcen (2024) showed that trade openness negatively influences income inequality, which contradicts our results.

Finally, this study finds no statistically significant effect of GCF on income inequality in the long run, as indicated by the FMOLS and DOLS estimators. The results suggest that higher investment levels as a share of GDP are not associated with a reduction in income inequality in the long-run for the group of lower-middle-income countries examined. This finding aligns with the results of Deyshappriya (2017) in a study of 33 Asian economies. However, our results differ from previous findings (Alesina and Perotti, 1996; Batuo et al., 2022). For example, Batuo et al. (2022) found a robust negative effect of investment measured by GCF in a sample of 52 African countries regardless of their income. The lack of a significant long-term relationship between GCF and income inequality suggests that simply increasing investment may not address income disparities in these economies.

3.1 Results of robustness check

The estimation results of MG and PMG models are shown in Table 3. The insignificant results of the Hausman test (H = 9.891, p-value = 0.129) demonstrate that the PMG estimator is more efficient than the MG estimator for the current dataset. Consequently, the long-run coefficients estimated using the PMG method are compared with those obtained from FMOLS and DOLS. The findings of the PMG-ARDL estimator align closely with those derived from FMOLS and DOLS methods, further confirming the robustness of the study's findings. The consistency observed across the FMOLS, DOLS, and PMG-ARDL estimators highlighted the reliability of the long-run relationships between macroeconomic variables and income inequality in lower-middle-income countries.

Table 3 Estimated long-run coefficients using MG and PMG estimators

Variable	PMG				MG			
	Coefficient	S.E.	t-statistic	p-value	Coefficient	S.E.	t-statistic	p-value
Ln(GDPPC)	1.494***	0.270	5.533	0.000	1.330***	0.260	5.115	0.000
Ln(GDPPC)^2	–0.100***	0.017	–5.882	0.000	–0.095***	0.015	–6.333	0.000
INF	0.154***	0.056	2.750	0.006	0.135*	0.072	1.875	0.062
UNEM	0.225**	0.102	2.206	0.026	0.306	0.227	1.348	0.178
TRADE	0.381***	0.049	7.776	0.000	0.423**	0.198	2.137	0.033
GCF	–0.003	0.004	–0.754	0.451	0.008	0.007	1.143	0.254

Note: Hausman test (H) = 9.891, p-value = 0.129.
Source: Own construction

The PMG estimation results show that the long-run coefficients for the logarithm of GDP per capita and its squared term are 1.494 and –0.100, respectively, both significant at the 1% level. These findings further validate the KCH within the examined lower-middle-income nations. Additionally, the positive long-run coefficient of 0.154 for inflation suggests that a 1% increase in the inflation rate leads to a 0.154% rise in income inequality, also significant at the 1% level. The analysis also indicates a positive long-run impact of unemployment on income inequality, with a coefficient of 0.225, significant at the 5% level. This implies that a 1% increase in the unemployment rate results in a 0.225% increase in income inequality.

Furthermore, the results demonstrate a statistically significant positive long-run relationship between trade openness and income inequality at the 1% significance level. Specifically, a 1% increase in trade leads to a 0.381% rise in income inequality within the analyzed lower-middle-income countries. However, the PMG analysis shows no statistically significant long-run impact of GCF on income inequality in the examined lower-middle-income economies.

CONCLUSION AND POLICY IMPLICATIONS

The current study investigated the dynamics of income inequality by focusing on the impact of macroeconomic factors on income inequality in 18 selected lower-middle-income economies covering the period from 1996 to 2018. The FMOLS and DOLS models were applied to estimate the long-run relationships among study variables. The PMG-ARDL model was employed to validate the robustness of the estimated relationships in the long run. The results of this study provided compelling evidence that the KCH holds for the examined lower-middle-income economies. This study also demonstrated that inflation, trade, and unemployment significantly exacerbate income inequality. However, the long-run effect of GCF was insignificant. The novelty of this study resides in its comprehensive examination of the macroeconomic contributing factors to income inequality in the examined lower-middle-income economies using advanced panel time-series techniques. Furthermore, the findings of this study can inform policymakers and governments in these nations how to develop more effective strategies and initiatives for reducing income inequality and fostering inclusive economic growth. This aligns directly with the SDGs provided in the UN Agenda for 2030, particularly SDG 10, which aims to achieve reduced inequality within and among nations. Finally, by providing evidence-based policy recommendations for addressing the macroeconomic influences on income inequality, this study can significantly contribute to achieving this global goal.

A key policy implication of this study is the critical need to reduce income inequality within lower-middle-income countries. Policymakers should carefully consider the distributional consequences of macroeconomic policies and integrate equity concerns into their decision-making process. Specifically, policymakers should prioritize investing in human capital, promote progressive taxation, enhance social safety nets, and ensure equal resource access and trade practices. Implementing effective monetary policies that maintain low and stable inflation can bolster the purchasing power of lower and middle-class households, ultimately narrowing income disparities. It is crucial to implement price stabilization programs for essential goods and services to protect vulnerable populations from the detrimental effects of inflation. Moreover, policies to lower unemployment rates should be implemented through job creation initiatives, vocational training programs, and fair wage policies, thereby strengthening labor market resilience. Our study highlights the need for policymakers to adopt a more holistic approach, combining these issues with redistributive policies and skill development to narrow income disparities.

References

ADAMS, S., KLOBODU, E. K. M. (2019). Urbanization, Economic Structure, Political Regime, and Income Inequality [online]. *Social Indicators Research*, 142: 971–995. <https://doi.org/10.1007/s11205-018-1959-3>

ALBANESI, S. (2007). Inflation and Inequality [online]. *Journal of monetary Economics*, 54(4): 1088–1114. <https://doi.org/10.1016/j.jmoneco.2006.02.009>.

ASOGWA, F. O., ONYEKE, Q. O., KUMA, P. M., ARAZUE, W. O., NKALU, C. N. (2022). Do Macroeconomic Indicators Determine Income Inequality in Selected African Countries? [online]. *Journal of Public Affairs*, 22(4): 1472–3891. <https://doi.org/10.1002/pa.2560>.

BALCILAR, M., CHANG, S., GUPTA, R., MILLER, S. M. (2018). The Relationship between the Inflation Rate and Inequality across US States: a Semiparametric Approach [online]. *Quality & Quantity*, 52: 2413–2425. <https://dx.doi.org/10.2139/ssrn.2926546>.

BATUO, M. E., KARARACH, G., MALKI, I. (2022). The Dynamics of Income Inequality in Africa: an Empirical Investigation on the Role of Macroeconomic and Institutional Forces [online]. *World Development*, 157: 105939. <https://doi.org/10.1016/j.worlddev.2022.105939>.

BERISHA, E., GUPTA, R., MESZAROS, J. (2020). The Impact of Macroeconomic Factors on Income Inequality: Evidence from the Brics [online]. *Economic Modelling*, 91: 559–567. <https://doi.org/10.1016/j.econmod.2019.12.007>.

BOWDEN, B. (2020). Economic Foundations: Adam Smith and the Classical School of Economics. In: BOWDEN, B., MULDOON, J., GOULD, A. M., MCMURRRAY, A. J. (eds.). *The Palgrave Handbook of Management History*, Springer International Publishing.

BREI, M., FERRI, G., GAMBACORTA, L. (2023). Financial structure and income inequality [online]. *Journal of International Money and Finance*, 131. <https://doi.org/10.1016/j.jimonfin.2023.102807>.

BULÍŘ, A. (2001). Income Inequality: Does Inflation Matter? *IMF Staff Papers*, 48(1): 139–159.

CERRA, V., LAMA, R., LOAYZA, N. (2021). *Links Between Growth, Inequality, and Poverty: a Survey*. International Monetary Fund.

CLARKE, G. R. G., XU, L. C., ZOU, H.-F. (2006). Finance and Income Inequality: What Do the Data Tell Us? [online]. *Southern Economic Journal*, 72(3): 578–596. <https://doi.org/10.2307/20111834>.

DEYSHAPPRIYA, N. P. R. (2017). Impact of Macroeconomic Factors on Income Inequality and Income Distribution in Asian Countries. *Adbi Working Paper*, 696.

DORN, F., FUEST, C., POTRAFKE, N. (2022). Trade Openness and Income Inequality: New Empirical Evidence [online]. *Economic Inquiry*, 60(1): 202–223. <https://doi.org/10.1111/ecin.13018>.

EL HERRADI, M., HAAN J., LEROY, A. (2023). Inflation and the Income Share of the Rich: Evidence for 14 OECD Countries [online]. *Review of Income and Wealth*, 69(1): 170–194. <https://doi.org/10.1111/roiw.12580>.

GALLI, R., VAN DER HOEVEN, R. (2001). Is Inflation Bad for Income Inequality: the Importance of the Initial Rate of Inflation. *ILO Paper*, 29.

GLAWE, L., WAGNER, H. (2024). Inflation and Inequality: New Evidence from a Dynamic Panel Threshold Analysis [online]. *International Economics and Economic Policy*, 21(2): 297–309. <https://doi.org/10.1007/s10368-023-00580-x>.

GÖCEN, S. (2024). Inflation and Income Inequality Linkages: Do Institutions Matter? [online]. *Applied Economics*, 56(48): 5713–5726. <https://doi.org/10.1080/00036846.2023.2257933>.

GOODMAN, A., OLFIELD, Z. (2004). *Permanent Differences? Income and Expenditure Inequality in the 1990s and 2000s*. IFS Report, R66.

GOURDON, J., MAYSTRE, N., DE MELO, J. (2008). Openness, Inequality and Poverty: Endowments Matter [online]. *The Journal of International Trade & Economic Development*, 17(3): 343–378. <https://doi.org/10.1080/09638190802136978>.

HAUSMAN, J. A. (1978). Specification Tests in Econometrics [online]. *Econometrica: Journal of the Econometric Society*, 1251-1271. <https://doi.org/10.2307/1913827>.

HEER, B., SÜSSMUTH B. (2003). Cold Progression and Its Effects on Income Distribution. *CESIFO Working Paper*, 951.

IM, K. S., PESARAN, M. H., SHIN, Y. (2003). Testing For Unit Roots in Heterogeneous Panels [online]. *Journal of Econometrics*, 115(1): 53–74. <https://doi.org/10.1016/S0304-4076(03)00092-7>.

IMF. (2023). *World Economic Outlook: a Rocky Recovery* [online]. Washington, DC. <https://www.imf.org/en/Publications/WEO/Issues/2023/04/11/world-economic-outlook-april-2023>.

KAO, C. (1999). Spurious Regression and Residual-based Rests for Cointegration in Panel Data [online]. *Journal of Econometrics*, 90(1): 1–44. <https://doi.org/10.1016/S0304-4076(98)00023-2>.

KAO, C., CHIANG, M. (2000). On the Estimation and Inference of a Cointegrated Regression in Panel Data [online]. *Advances in Econometrics*, 15: 179–222. <https://doi.org/10.1016/S0731-9053(00)15007-8>.

KUZNETS, S. (1955). Economic Growth and Income Inequality. *The American Economic Review*, 45(1), 1–28.

LAW, C. H., SOON, S. V. (2020). The Impact of Inflation on Income Inequality: the Role of Institutional Quality [online]. *Applied Economics Letters*, 27(21): 1735–1738. <https://doi.org/10.1080/13504851.2020.1717425>.

LIM, C. Y., SEK, S. K. (2014). Exploring the Two-way Relationship between Income Inequality and Growth [online]. *Journal of Advanced Management Science*, 2(1): 33–7. <https://doi.org/10.12720/joams.2.1.33-37>.

MARX, K. (1867). *Capital: a Critique of Political Economy*. New York, NY: Cosimo.

MENIAGO, C., ASONGU, S. A. (2018). Revisiting the Finance-inequality Nexus in a Panel of African Countries [online]. *Research in International Business and Finance*, 46: 399–419. <https://doi.org/10.1016/j.ribaf.2018.04.012>.

MILL, J. S. (1982). Principles of Political Economy [online]. In: DEAN, G. W., WELLS, M. C. (eds.). *Forerunners of Realizable Values Accounting in Financial Reporting*, Routledge. <https://doi.org/10.4324/9781003051091>.

MINCER, J. (1974). *Schooling, Experience, and Earnings*. Columbia University: Press for the National Bureau of Economic Research.

MONNIN, P. (2014). Inflation and Income Inequality in Developed Economies [online]. *Cep Working Paper Series*. <https://dx.doi.org/10.2139/ssrn.2444710>.

MURYANI, ESQUIVIAS, M. A., SETHI, N., ISWANTI, H. (2021). Dynamics of Income Inequality, Investment, and Unemployment in Indonesia [online]. *Journal of Population and Social Studies*, 29: 660–678. <https://doi.org/10.25133/JPSSv292021.040>.

NANTOB, N. (2015). Income Inequality and Inflation in Developing Countries: an Empirical Investigation. *Economics Bulletin*, 35(4): 2888–2902.
NAYYAR, D. (2014). Why Employment Matters: Reviving Growth and Reducing Inequality [online]. *International Labour Review*, 153(3), 351–364. <https://doi.org/10.1111/j.1564-913X.2014.00208.x>.
NUSSBAUM, M. C. (2000). *Women and Human Development: the Capabilities Approach*. Cambridge University Press.
OECD. (2023). *Income Inequality (indicator)* [online]. Paris: OECD. [cit. 20.7.2024]. <https://doi.org/10.1787/459aa7f1-en>.
PEDRONI, P. (1999). Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors [online]. *Oxford Bulletin of Economics and Statistics*, 61(S1): 653–670. <https://doi.org/10.1111/1468-0084.0610s1653>.
PESARAN, M. H., SHIN, Y., SMITH, R. P. (1999). Pooled Mean Group Estimation of Dynamic Heterogeneous Panels [online]. *Journal of the American statistical Association*, 94(446): 621–634. <https://doi.org/10.1080/01621459.1999.10474156>.
PESARAN, M. H., SMITH, R. (1995). Estimating Long-run Relationships from Dynamic Heterogeneous Panels [online]. *Journal of Econometrics*, 68(1): 79–113. <https://doi.org/10.1016/0304-4076(94)01644-f>.
PHILLIPS, P., HANSEN, B. E. (1990). Statistical Inference in Instrumental Variables Regression with I(1) Processes [online]. *The Review of Economic Studies*, 57(1): 99–125. <https://doi.org/10.2307/2297545>.
PHILLIPS, P., PERRON, P. (1988). Testing for a Unit Root in Time Series Regression [online]. *Biometrika*, 75(2): 335–346. <https://doi.org/10.2307/2336182>.
PIKETTY, T. (2014). *Capital in the twenty-first century*. Harvard University Press.
PSACHAROPOULOS, G., PATRINOS, H. A. (2018). Returns to Investment in Education: a Decennial Review of the Global Literature [online]. *Education Economics*, 26(5): 445–458. <https://doi.org/10.1080/09645292.2018.1484426>.
RICARDO, D. (1817). *On the Principles of Political Economy and Taxation*. Cambridge University Pres.
ROMER, C. D., ROMER, D. H. (1998). Monetary Policy and the Well-being of the Poor. *NBER Working Paper Series Working Paper*, 6793.
SACHS, J. D., LAFORTUNE, G., FULLER, G. (2024). *Sustainable Development Report 2024: the SDGs and the UN Summit of the Future*. Paris: SDSN, Dublin: Dublin University Press.
SEN, A. (1999). *Development as Freedom*. Oxford University Press.
SIAMI-NAMINI, S., HUDSON, D. (2019). Inflation and Income Inequality in Developed and Developing Countries [online]. *Journal of Economic Studies*, 46(3): 611–632. <https://doi.org/10.1108/JES-02-2018-0045>.
SMITH, A. (1776). *An Inquiry into the Nature and Causes of the Wealth of Nations*. Oxford University Press.
SOLT, F. (2020). Measuring Income Inequality across Countries and over Time: the Standardized World Income Inequality Database. *Social Science Quarterly*, SWIID Version 9.7, September 2024.
STOCK, J. H., WATSON, M. W. (1993). A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems [online]. *Econometrica*, 61(4): 783–820. <https://doi.org/10.2307/2951763>.
TARESH, A. A., SARI, D. W., PURWONO, R. (2020). Analysis of the Relationship among Macroeconomics, Monetary and Income Inequality [online]. *Economics Development Analysis Journal*, 9(4): 427–442. <https://doi.org/10.15294/edaj.v9i4.38946>.
THALASSINOS, E., UGURLU, E., MURATOGLU, Y. (2012). Income Inequality and Inflation in the EU. *European Research Studies Journal*, XV(1): 127–140.
TOPALOVA, P. (2007). Trade Liberalization, Poverty and Inequality: Evidence from Indian Districts. In: HARRISON, A. *Globalization and Poverty*, National Bureau of Economic Research, Inc.
UN. (2015). *Transforming our world: the 2030 Agenda for Sustainable Development*. [online] United Nations. [cit. 1.10.2015]. <https://sdgs.un.org/publications/transforming-our-world-2030-agenda-sustainable-development-17981>.
WOLFF, E. N. (2023). *Is there Really an Inflation Tax? Not for the Middle Class and the Ultra-Wealthy* [online]. National Bureau of Economic Research, Working Paper 31775. <https://doi.org/10.3386/w31775>.
YANG, Y., GREANEY, T. M. (2017). Economic growth and income inequality in the Asia-Pacific region: a comparative study of China, Japan, South Korea, and the United States [online]. *Journal of Asian Economics*, 48: 6–22. <https://doi.org/10.1016/j.asieco.2016.10.008>.
YOUNSI, M., BECHTINI, M. (2020). Economic Growth, Financial Development, and Income Inequality in BRICS Countries: Does Kuznets' Inverted U-Shaped Curve Exist? [online]. *Journal of the Knowledge Economy*, 11(2): 721–742. <https://doi.org/10.1007/s13132-018-0569-2>.
YOUNSI, M., BECHTINI, M., LASSOUED, M. (2022). Causal Relationship between Financial Development, Economic Growth, and Income Inequality: Panel Data Evidence from Asian and North African Countries. In: MUGOVA, S., AKANDE, J. O., OLAREWAJU, O. M. (eds.). *Corporate Finance and Financial Development: an Emerging Market*, Springer Nature.
ZANDI, G., REHAN, R., HYE, Q. M. A., MUBEEN, S., ABBAS, S. (2022). Do Corruption, Inflation and Unemployment Influence the Income Inequality of Developing Asian Countries? [online]. *International Journal of Applied Economics, Finance and Accounting*, 14(2): 118–128. <https://doi.org/10.33094/ijaefa.v14i2.688>.
ZHENG, Z., WAN, X., HUANG, C. Y. (2023). Inflation and Income Inequality in a Schumpeterian Economy with Heterogeneous Wealth and Skills [online]. *Economic Modelling*, 121. <https://doi.org/10.1016/j.econmod.2023.106193>.

APPENDIX

Table A1 List of countries

Bangladesh	India	Palestinian Territories
Bolivia	Jordan	Philippines
Cote d'Ivoire	Kenya	Senegal
Egypt	Kyrgyzstan	Sri Lanka
Ghana	Laos	Tanzania
Honduras	Pakistan	Vietnam

Source: Own construction

Table A2 Description of variables and data sources

Variable	Description	Data source
Gini Index	Gini index as a measure of income inequality. Estimate of Gini index of inequality in equivalized (square root scale) household disposable (post-tax, post-transfer) income.	WIID (Solt, 2020)
GDPPC	Gross domestic product (constant 2015 U.S. dollars) divided by midyear population.	WDI
Inflation	Inflation, as measured by the consumer price index, reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. It is a measure of macroeconomic stability.	WDI
Unemployment	The total number of unemployed divided by the labour force (modelled ILO estimate).	WDI
GCF	Gross Capital Formation consists of outlays on additions to the economy's fixed assets (including land improvements) plus net changes in inventories. The variable is presented as a percentage of GDP.	WDI
Trade	Trade is the sum of exports and imports of goods and services measured as a share of gross domestic product.	WDI

Note: WDI – World Development Indicators, WIID – World Income Inequality Database.
Source: Own construction

Table A3 Results of unit root tests

Variable	IPS W-stat		PP Fisher (χ^2)		Result
	Level	1st difference	Level	1st difference	
Ln(GINI)	–1.506	–8.645***	12.161	85.417***	I(1)
Ln(GDPPC)	–0.766	–3.517***	24.766	172.573***	I(1)
(Ln(GDPPC))^2	–0.781	–3.460***	25.078	168.370***	I(1)
INF	–1.353*	–4.737***	11.263	143.111***	I(1)
UNEM	0.497	–3.772***	28.428	347.212***	I(1)
TRADE	1.517	–5.533***	20.359	190.675***	I(1)
GCF	0.952	–7.099***	25.812	233.131	I(1)

Note: *, ** and ***denote rejection of the null hypothesis of unit root at the 10, 5 and 1% significance levels, respectively.
Source: Own construction

Table A4 Results of panel cointegration tests

Pedroni panel cointegration test	Statistic	p-value
Within dimension (panel statistics)		
Panel v-statistic	6.958****	0.002
Panel rho-statistic	–1.242	0.916
Panel PP-statistic	–7.273***	0.000
Panel ADF-statistic	–5.317***	0.002
Between dimension (individual statistics)		
Group rho-statistic	3.147	0.957
Group PP-statistic	–6.268***	0.000
Group ADF-statistic	–5.735***	0.000
Results of Kao residual cointegration test		
Panel ADF statistic	–5.867**	0.000***

Note: *, ** and ***denote rejection of the null hypothesis of no cointegration at the 10, 5 and 1% significance levels, respectively.
Source: Own construction

Table A5 Correlation matrix

	Ln(GINI)	LN(GDPPC)	INF	UNEM	TRADE	GCF
Ln(GINI)	1.00					
Ln(GDPPC)	–0.56	1.00				
INF	0.38	–0.21	1.00			
UNEM	0.43	0.37	–0.10	1.00		
TRADE	0.49	0.34	0.08	0.12	1.00	
GCF	0.08	0.05	–0.10	0.06	0.34	1.00

Source: Own construction