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Understanding the drivers of income inequality within and across countries: Some new evidence

Abstract

This paper examines the drivers of income inequality within and across countries using relevant measures of inequality and an estimation technique that jointly accounts for both model and estimation uncertainties. The estimations are applied to a global sample and to three categories of vulnerable developing countries: Africa, least developed countries (LDCs), and landlocked developing countries (LLDCs). We find that multiple factors contribute to income inequality within and across countries but that there are significant differences in the key drivers globally and in Africa, LDCs and LLDCs. We also find strong support for the Kuznets hypothesis in the global and the developing countries samples but not in the Africa, LDC and LLDC samples. These differences underscore the need for policymakers to account for country-heterogeneity in the design of policies to combat inequality within and across countries.

Key words

Income inequality, Gini, Palma ratio, Africa, least developed countries, landlocked developing countries, WALS, model averaging.

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1. Introduction

Up until the late 1970s, questions of inequality and its assessment were prominent in economic research and analysis. However, in the 1980s and the 1990s there was a decline in interest in distributional matters due largely to the spread of the 'Washington Consensus' which discouraged state intervention and advocated an enhanced role of market forces in the allocation of resources in an economy (Kanbur, 2021). Since the beginning of the new Millennium, there has been a renewed interest in issues pertaining to the distribution of income and wealth both in academic and in policy circles. At the academic level, the burst in interest was triggered by recent studies indicating that global inequality is high and that inequality within countries has increased over time (Piketty & Saez, 2003; Stiglitz, 2012; Piketty, 2014; Atkinson & Bourguignon, 2015; Facundo et al., 2018; Chancel et al., 2022). At the policy level, the inclusion of inequality as one of the 17 Sustainable Development Goals adopted by United Nations member States in 2015 brought into global focus the issue of inequality and has also put inequality back at the centre of economic analysis and research. Policymakers care about high inequality because it is unfair, inhibits growth, and fosters social and political instability.

There are three main classes of the recent literature on inequality. The first is made up of studies that measure or assess the extent of inequality (Bourguignon, 2016; Milanovic, 2016; Ravallion, 2018; UNDP, 2019; Chancel et al., 2022) These studies suggest that global inequality remains high but that its evolution has changed since the turn of the new millennium, with between country inequality displaying a downward trend and within-country inequality showing an upward trend.

The second class of literature on inequality consists of studies that examine its impact on growth and socio-economic variables. The growth impact has been extensively studied, with some papers (Alesina & Rodrik, 1994; Persson & Tabellini, 1994; Berg et al., 2018; Gründler & Scheuermeyer, 2018) finding a negative effect of inequality on growth. In contrast with these studies, several papers (Li & Zou, 1998; Forbes, 2000; El-Shagi & Shao, 2019) have also found a positive effect of inequality on growth while others found that the ultimate impact of inequality on growth depends on other factors such as the level of income (Barro, 2000) and the functional form estimated (Banerjee & Duflo, 2003). There is also a more recent study that examines five potential channels through which the effects of inequality are transmitted to growth: human capital, investment, fertility, total factor productivity, and political stability (Blotevogel et al., 2022). The study shows that the role of inequality in these transmission mechanisms is difficult to establish because the empirical results are very sensitive to the choice of an inequality indicator.

The third class of literature on inequality consists of studies that seek to identify the drivers or determinants of inequality. Förster & Tóth (2015) provide a very rich review of the cross-country evidence on the causes of changes in inequality, with a focus on developed countries. They indicated that the empirical studies reviewed report contradictory results for most of the drivers of inequality identified in economic models due mostly to the use of different country samples, data sources, time periods, and estimation techniques. Many studies have also been carried out on the subject using samples comprising developed and developing countries or data for selected developing country regions. Some of these studies tested the Kuznets hypothesis which posits that there is an inverted-U shape relationship between inequality and development. For example, Barro (2000) found support for the hypothesis but showed that it does not explain a large portion of the variation in inequality within and across countries. He also found that the income level of countries plays an important role in the relationship between income and income inequality. Using an innovative estimation technique that accounts for multicollinearity problems in panel data, Shao (2021) found no evidence of the Kuznets relation within and across countries. The findings suggest that investment and employment are the most robust determinants of income inequality within and across countries. Batuo et al. (2022)

have also examined the Kuznets relation, albeit with a focus on Africa. They found that the relationship is unstable when the heterogeneity of income levels in the region is taken into account.

Dabla-Norris et al. (2015) examined the drivers of changes in income inequality within countries using a sample of both developed and developing countries. They found that an increase in labour market flexibility, financial deepening, and technological changes account for most of the increase in inequality in the sample. The study also suggests that financial openness increases income inequality while government spending decreases it. Milanovic (2005) investigated how globalization affects income distribution in rich and poor countries. He found that when income levels are very low, the rich are the beneficiaries of globalization. However, at relatively higher income levels the poor and the middle class benefit more compared to the rich. In addition to the papers discussed above, there is recent literature aimed at identifying robust determinants of income inequality using model averaging techniques. For example, using this technique Furceri & Ostry (2019) found that in the cross-section estimation, the factors that are robust drivers across all cases considered are mortality rates, financial globalization, and unemployment. Interestingly, these determinants seem to have a positive association with inequality. Regarding income inequality within countries, the factors that are robust across specifications are: the share of industry in GDP, access to electricity, age dependency ratio, mortality rate, relative price of investment, trade globalization, financial globalization, and unemployment. Among these factors, the industry share of GDP, access to electricity, relative price of investment, and trade globalization have a negative association with inequality within countries while the other factors have a positive association.

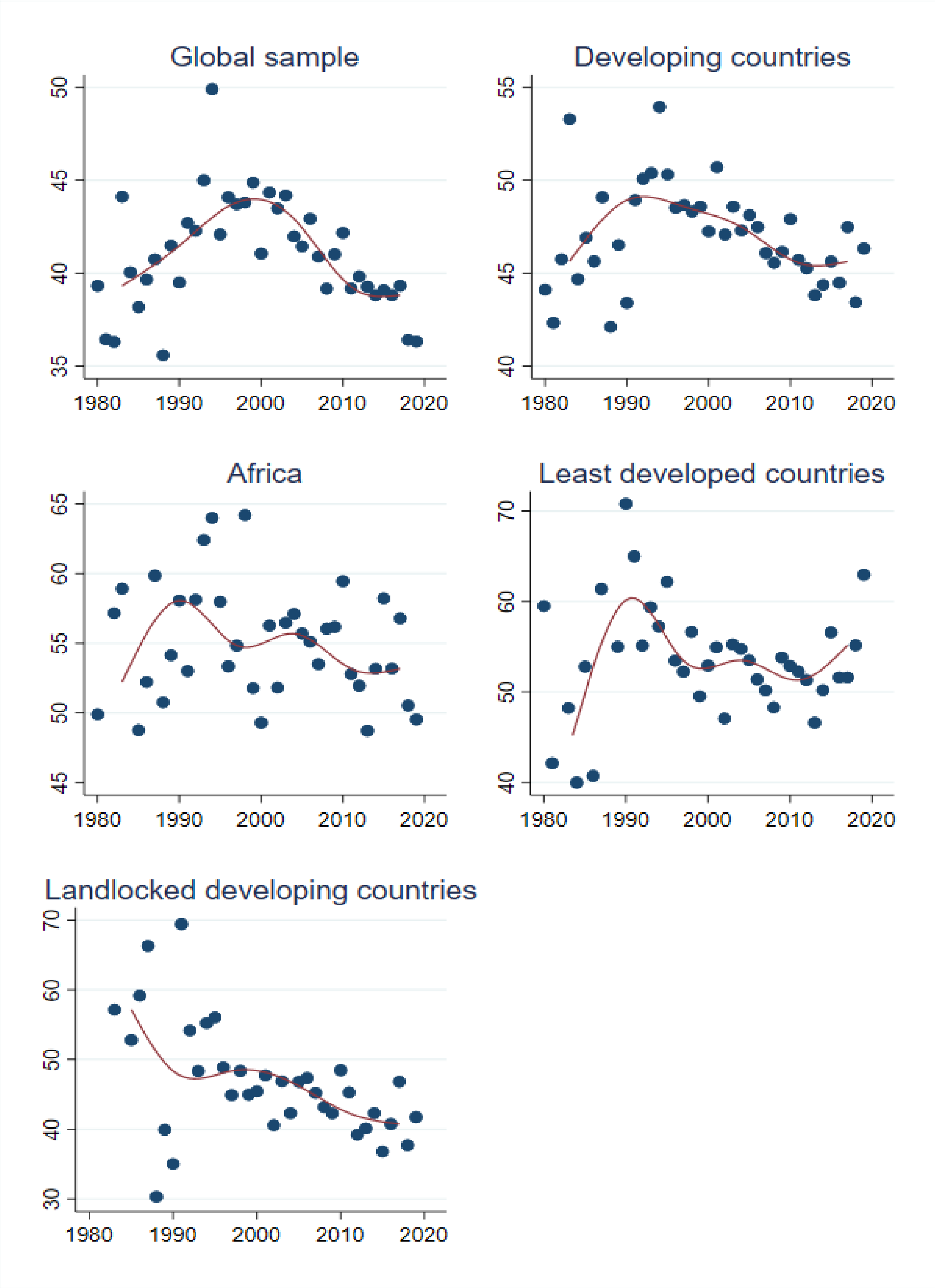
The current paper fits into the third strand of literature, which focuses on the determinants of income inequality. It examines the drivers of income inequality within and across countries using different measures of income distribution and an estimation technique that jointly accounts for both model uncertainty and estimation uncertainty. Within this context, it investigates the Kuznets hypothesis, which states that income inequality follows an inverted-U pattern during economic development. Our paper differs from existing studies in several respects. First, existing studies either do not account for the model uncertainty associated with the choice of the explanatory variables employed in the regressions (Batuo et al., 2022; Dabla-Norris et al., 2015; Milanovic, 2005; Barro, 2000) or assume that explanatory variables have an immediate rather than lagged effect on inequality (Furceri & Ostry, 2019; Shao, 2021).[1] Our paper adopts the weighted average least squares (WALS) technique to address the problem of model and estimation uncertainties. Assessing the determinants of inequality involves choosing among a long list of potential explanatory variables to include in the estimation and theory offers very limited guidance on what should be the appropriate empirical framework. WALS is a recently developed model averaging technique that is increasingly being used to address this problem of model uncertainty arising from many possible regressors and data limitations (Magnus & De Luca, 2016). However, although the standard WALS methodology accounts for endogeneity due to omitted variable bias, it does not address endogeneity issues arising from reverse causality, or simultaneity, and the underlying theory, and routine, for an instrumental variable version of WALS has not been developed (Magnus & De Luca, 2016). Given this constraint and, following Blotevogel et al. (2022) and Fallah & Partridge (2007), we use a time horizon, or lag structure, for the explanatory variables that minimizes the risk of reverse causality.

Second, in contrast to other studies, we investigate the drivers of income inequality in both a global sample and in three categories of vulnerable economies that are increasingly the focus of the work of the United Nations: Africa, the Least Developed Countries (LDCs), and the Landlocked Developing Countries (LLDCs). As shown in Figure 1, the trends and patterns of income inequality differ across country groups, indicating the need to investigate empirically whether the drivers differ across country

[1] Halter et al. (2014) indicate that time horizon or lag structure is important in studying the relationship between inequality and growth.

groups. To the best of our knowledge, there is no study on the drivers of inequality in LLDCs and LDCs. In addition, while some attempts have been made to examine the drivers of inequality in Africa using traditional econometric techniques (Batuo et al., 2022), the issue has not been investigated for Africa using a technique that accounts for model and estimation uncertainties.

Figure 1. Evolution of income inequality by country group, 1980-2020



Note: For each country group, a dot represents a simple average of the Gini index (of pre-tax income) across countries belonging to the group in a given year.

Finally, we use relevant measures of income distribution to investigate the drivers of income inequality within and across countries. We use a measure of income inequality that is sensitive to the middle of the income distribution (the Gini) and a measure of income concentration (the Palma ratio) that is tail sensitive and includes both the lower and upper tails of income distribution. Most studies focus on either the Gini or the Gini and single income shares such as the top 1 percent, top 10 percent or bottom 50 percent. But using these single income shares separately as indicators in regressions is problematic because they only capture one specific tail of the income distribution. Using the Palma ratio rather than single income shares (as a complement inequality indicator to the Gini) is more appropriate in light of the fact that it captures both the lower and upper tails of the distribution and is consistent with evidence that differences in the distribution of income are largely due to the tails rather than the middle of the distribution (Cobham & Sumner, 2013). In this context, the Palma ratio is more relevant for policy discussions on fostering inclusive growth than single income shares often used in empirical studies.

The rest of the paper is structured as follows. The next section (2) discusses the dependent and independent variables used in the analysis and provides the sources of data employed. It also presents the empirical models to be estimated and the associated techniques adopted. Section 3 presents and analyses the estimation results for the drivers of income inequality across countries and then within countries. Section 4 focuses on sensitivity analyses and extensions using labour income share as a measure of inequality and gender as a control variable. The final section (5) contains concluding remarks and policy implications of the results.

2. Methodology

2.1 Variables

In the literature, many variables have been suggested as potential determinants of income inequality, but economic theory does not provide good guidance on the most relevant ones (Förster & Tóth, 2015; Furceri & Ostry, 2019). For ease of exposition, the potential determinants can be classified under seven broad categories: economic development and structure of the economy; education or human capital; demographics; institutions and political regimes; technology and globalization; financial development; and economic policies and macroeconomic conditions. Within each of these categories, we include key indicators and controls, subject to data availability, and let model averaging techniques determine which are the relevant or robust drivers of income inequality.

The first group of determinants is economic development and structural change, which we control for by including both GDP per capita and GDP per capita squared, following the seminal paper by Kuznets (1955) which suggests that inequality follows an inverted-U pattern in the development process. As in Furceri & Ostry (2019), we add the share of agriculture value added in GDP, the share of industry value added in GDP, the share of population in urban areas and the share of population with access to electricity as additional proxies for development and structural change. Education is the second category of determinants and, in general, is expected to reduce income inequality by permitting more people to participate and benefit from activities with higher productivity. But there is also a recognition that an increase in education can increase the share of people with higher education thereby increasing the share of high-wage earners and inequality (Dabla-Norris et al., 2015). We control for education by using the school completion rate from Barro and Lee (2013), with primary and secondary education introduced separately. Regarding the third category of determinants (demographics), we use three variables, namely the age dependency ratio (share of working age population in total population), net immigration, and the mortality rate. An increase in the age dependency ratio is expected to increase inequality because the very young and older people either have no income or have relatively lower incomes than the economically active population. Similarly, an increase in low-skill immigration is expected to increase income inequality by driving a bigger wedge between wages of high and low skilled workers. Higher mortality can also increase inequality by constraining investment in education thereby reducing access to high-skilled jobs.

Regarding the fourth category of determinants, we control for institutions and political regime using the measure of democracy from the Polity V dataset, with higher values reflecting more democratic regimes. The impact of democracy on inequality is in theory ambiguous. Democracy can reduce inequality through enhancing civil rights liberties, discouraging corruption, fostering growth and redistribution of income (Batuo et al., 2022). But democracy can also increase inequality if the democratic process is captured by the rich or create dis-equalizing opportunities (Acemoglu et al. 2015).

For the fifth category of determinants (technology and globalization), we use de facto trade globalization and financial globalization indices from the Swiss Economic Institute (KOF). Higher values of the KOF indices imply a higher degree of trade and financial openness. Technology can exacerbate inequality through increasing the capital intensity of production thereby widening the gap between the factor rewards accruing to owners of capital and labour. We measure technological change by the change in the relative price of investment (Furceri & Ostry, 2019). Financial development, which is the sixth category of determinants, can have either a positive or negative impact on inequality (Dabla-Norris et al., 2015). For example, in an economy with weak institutions, financial development may benefit the rich more than the poor thereby enhancing inequality. By contrast, financial development can reduce inequality by relaxing credit constraints faced by the poor. We controlled for financial development by including domestic credit to private sector as a share of GDP and the ratio of financial system deposits to GDP. Finally, economic policy and macroeconomic conditions are captured by: (i) fiscal policies, proxied by the size of government as measured by the ratio of final government consumption expenditure to GDP, (ii) inflation, and (iii) unemployment. In general, an increase in the size of government is expected to reduce inequality while an increase in unemployment is expected to increase it. Regarding inflation, the effect is ambiguous. On the one hand, it can increase inequality if the poor hold more liquid assets than the rich. On the other hand, inflation resulting from expansionary monetary policy and the associated lower interest rate will likely have a negative impact on savers, who happen to be mostly the rich, thereby reducing inequality.

Two measures of income distribution, namely the Gini coefficient and the Palma ratio are employed as dependent variables. The Palma ratio is defined as the share of income of the top 10 percent of population divided by the share of income of the bottom 40 percent of population (Cobham, Schlögl, & Sumner, 2016). As the sources of data on the Gini coefficient and Palma ratio we use the WIID Companion data prepared by UNU-WIDER experts who made the selection and necessary adjustments to the household survey data that allow comparing levels of inequality between countries or over time (UNU-WIDER, 2021).

In the section dedicated to sensitivity analyses and extensions, we use an alternative measure of income distribution, namely the labour share of income from Penn World Tables (Feenstra, Inklaar & Timmer, 2015). Furthermore, we add a gender dimension to our analysis by including female labour force participation rate (sourced from the ILO and World Bank) among determinants. All variables, their definitions and sources are provided in Table A1 and the list of countries, summary statistics, and correlations are in Tables A2-A4 in the Annex.

The dataset employed in the analyses covers 112 countries, including 74 developing countries, 29 countries in Africa, 21 least developed countries, and 18 landlocked developing countries. The sample used in the estimations covers the period 1990 to 2019[2], aggregated into eight 5-year periods by simple averaging – to account for the unbalanced nature of the dataset and reduce frequent data variations (Shao, 2021).

2.2 Empirical specification

The empirical investigation of the drivers of income inequality across countries is based on the model specified in equation (1).

$$I_{it} = \alpha + \beta' X_{it-1} + \varepsilon_{it} \tag{1}$$

where I_{it} is a measure of income inequality in country i in period t (5-year period), X_{it-1} is a vector of covariates characterising country i in period $t-1$, α is a constant term, and ε_{it} is an error term. Following Furceri & Ostry (2019), we use the weighted-average least squares (WALS) estimation technique, which has been employed in the growth literature and was recently introduced in the income distribution literature, to address the challenge of model uncertainty arising from the choice of covariates (Steel, 2020). Penalized regressions (such as Ridge or LASSO) can also be used to jointly address estimate uncertainty and model selection uncertainty. However, penalized regressions are generally more effective where the number of explanatory variables is very large or greater than the sample size (high-dimensional settings), which is not the case in our paper. Monte Carlo experiments have also shown that the finite sample performance of the WALS estimator is generally better than those of competing estimators (De Luca, Magnus & Peracchi, 2018 and 2022).

In general, if there are k potential explanatory variables to include in a regression, then there are 2k possible model specifications that an investigator must choose from. In the WALS methodology, this model selection uncertainty is addressed jointly with the estimation uncertainty. Explanatory variables in a regression are classified into “focus” regressors and “auxiliary” regressors (Magnus & De Luca 2016; Furceri & Ostry 2019). The focus regressors are those whose parameters are of interest and for which there are strong theoretical reasons to include in the regression. The auxiliary regressors are those for which it is not clear whether they should be in the regression. They are included to determine whether they improve the estimate of the focus parameters. In WALS, the parameters of each model in the model space are estimated and the final WALS estimates are obtained as a weighted average of the conditional estimates from all available models, with the weights representing estimates of the probability of each model based on a mean-squared error criterion (Blotevogel et al., 2022).

In our estimations, the constant is the ‘focus’ regressor while all explanatory variables of vector X_{it-1} are treated as ‘auxiliary’ regressors. In WALS, the t-statistic plays an important role in determining whether a regressor is an important determinant. For example, when the t-statistic of a regressor equals 1, this means that adding or excluding the regressor gives the same mean-squared error of the estimated focus parameter (Poghosyan & Magnus 2012). However, when the t-statistic is greater than 1, adding the regressor increases the adjusted R-squared of the model and lowers its mean-squared error (Blotevogel et al., 2022). Consequently, in WALS an explanatory variable is said to be a robust determinant if its t-statistic is greater than 1 in absolute value.

[2] We have omitted 2020 from the analysis to exclude the impact of the coronavirus pandemic. Also, in the estimations, the sample starts in 1990 due to the paucity of data on access to electricity.

The standard WALS methodology cannot address endogeneity issues due to reverse causality, or simultaneity, and the underlying theory and routine for an instrumental variable version of WALS has not been developed (Magnus & De Luca 2016). Considering this constraint, and the fact that we are using data averaged over five-year periods, following Blotevogel et al. (2022) and Fallah & Partridge (2007) we use a one-period lag structure for the explanatory variables to minimize the risk of reverse causality. We believe this time lag is more plausible than using contemporaneous values of the explanatory variables because the process through which the explanatory variables are expected to affect inequality is not instantaneous and takes time. For example, it is implausible to expect an increase in education, mortality, or trade globalization today to have an instantaneous impact on inequality.

In sum, our estimation of the drivers of inequality across countries differs from Furceri & Ostry (2019) in two ways. First, we lag explanatory variables by one period (representing 5 years) to account for the delayed effect of explanatory variables on inequality and to minimize the risk of reverse causality. Second, we use pooled, rather than cross-section, regression approach. In the estimation, we control for the correlation of the error terms within countries and for any other types of heteroskedasticity by using the bias-corrected WALS estimator recently developed by De Luca, Magnus, & Peracchi (2022)[3].

To investigate the drivers of income inequality within countries we use the specification in equation (2).

$$I_{it} = \beta' X_{it-1} + \mu_i + \gamma_t + \varepsilon_{it} \tag{2}$$

where X_{it-1} is the vector of covariates reflecting characteristics of country i in period $t-1$, μ_i are country effects, γ_t are time effects and ε_{it} is the error term. For each period t, the data for every variable is calculated as a simple average over 5 years. This specification is similar to Furceri & Ostry (2019) but modified to reflect the fact that we are using lagged rather than contemporaneous covariates. As indicated earlier, this timing or lag structure captures the fact that the process through which the explanatory variables affect inequality takes time and is not instantaneous. This timing or lag structure also minimizes the risk of reverse causality (Blotevogel et al., 2022). We estimate equation (2) by WALS with correction for heteroskedasticity as in De Luca, Magnus, & Peracchi (2022).[4]

[3] We thank Giuseppe De Luca for sharing the WALS code used in their paper.

[4] The system generalized method of moments (GMM) is a popular approach used in the literature to address endogeneity issues. However, it suffers from the weak instrument problem and does not address model estimation and model selection uncertainties jointly (Ferreira & Gisselquist, 2022).

3. Empirical findings

3.1 Inequality across countries

The results of the estimation of equation (1) by WALS are presented in Table 1, with income inequality measured by the Gini coefficient in column 1 and by the Palma ratio in column 2. The key statistics for interpreting the results estimated by WALS is the t-ratio, which indicates the contribution of each regressor to the overall fit of the model and the precision of the estimators (Magnus, Powell & Prüfer, 2010). When the t-statistic on a regressor equals 1, this means that adding or excluding the regressor gives the same mean-squared error of the estimated focus parameter (Poghosyan & Magnus, 2012). However, when the t-statistic is greater than 1, adding the regressor increases the adjusted R-squared of the model and lowers its mean-squared error (Blotevogel et al., 2022). Consequently, in WALS an explanatory variable is said to be a robust determinant if its t-statistic is greater than 1 in absolute value.

The first overall observation is a large number of robust determinants of income inequality across countries, confirming the importance of simultaneous multi-factor analysis. The second overall observation is the importance of using different measures of inequality. Although both the Gini coefficient and the Palma ratio tend to identify similar variables as robust determinants, there are several cases where the results differ. For example, secondary education and trade globalization are robust determinants when inequality is measured by the Gini coefficient, but they are not robust based on the Palma ratio. Similarly, financial globalization is a robust determinant according to the Palma ratio but it is not based on the Gini coefficient.

Turning to the other explanatory variables, GDP per capita and GDP per capita squared are robust determinants of inequality, with the coefficients implying an inverted U-shaped relation between income per capita and inequality as postulated in the Kuznets hypothesis. Taking the Palma ratio and the across-country regression as an example, the direction of the relationship changes at the GDP per capita level of 14,500 US dollars, corresponding, for example, to the GDP of Slovakia or Uruguay in 2019. Agriculture value added, industry value added, access to electricity, secondary education, immigration, technology, financial and trade globalization and the size of government have an equalizing effect in the full sample. By contrast, urbanization, age dependency ratio, mortality rate, credit to private sector and unemployment are dis-equalizing in the full sample.

Table 1. Inequality drivers across countries, full sample

Dependent variable:	Gini (1)	Palma (2)
GDP per capita (log)	18.44	2.10
	(3.37)	**(1.92)**
GDP per capita sq. (log)	-1.12	-0.11
	(-3.72)	**(-1.72)**
Agr. value added	-0.24	-0.06
	(-4.19)	**(-3.57)**
Industry value added	-0.05	-0.02
	(-1.25)	**(-2.28)**
Urban population	0.08	0.01
	(3.97)	**(1.28)**
Electricity	-0.17	-0.02
	(-4.51)	**(-2.54)**
Primary education	0.01	0.003
	(0.24)	(0.40)
Secondary education	-0.14	-0.004
	(-4.10)	(-0.53)
Age dependency ratio	0.09	0.03
	(2.06)	**(2.98)**
Mortality rate	0.03	0.01
	(4.79)	**(9.51)**
Immigration	0.11	-0.16
	(0.39)	**(-2.75)**
Democracy	-0.04	0.01
	(-0.49)	(0.51)
Technology: RPI	-5.01	-0.75
	(-2.42)	**(-1.69)**
Fin. globalization	0.02	-0.01
	(0.73)	**(-1.16)**
Trade globalization	-0.04	-0.01
	(-1.70)	(-0.90)
Size of government	-0.34	-0.06
	(-3.99)	**(-3.92)**
Fin. system deposits	0.003	-0.001
	(0.26)	(-0.63)
Credit to pr. sector	0.03	0.01
	(2.84)	**(5.43)**
Inflation	0.001	0.0004
	(0.53)	(0.87)
Unemployment	0.11	0.05
	(1.40)	**(3.08)**
Observations	312	302

Note: t statistics in parentheses, t statistics > 1 are marked in bold; regressors with t > 1 are considered robust.

The next step is to investigate whether there are differences in the robust determinants of inequality across country groups. To identify the effect on country groups we employ the following approach. For example, in the developing country sample, we include among regressors a dummy equal to one if a country belongs to the developing country group (and zero otherwise), as well as the interaction terms of this dummy with each explanatory variable. We estimate the resulting equation using WALS. We repeat the same approach for each country group (Africa, LDC, and LLDCs) and report the results in Table 2, showing the findings for developing countries in columns 1 and 2, for Africa in columns 3 and 4, for LDCs in column 5 and 6, and for LLDCs in columns 7 and 8. For readability and ease of comparison with the results of the full sample, we report the coefficient and t statistics of the linear combination of each variable and its interaction term with the respective group dummy.

The empirical results for developing countries (with column 1 for the Gini and column 2 for the Palma ratio as the dependent variable) provide strong support for the Kuznets hypothesis. In developing countries, agriculture value added, industry value added, access to electricity, primary and secondary education, technology, trade globalization, size of government and financial system deposits decrease inequality. The age dependency ratio, mortality rate, financial globalization and credit to private sector increase inequality. In the sample of African countries (reported in columns 3 and 4), we find some support for the Kuznets hypothesis, but the result is sensitive to the measure of inequality used. The robust determinants of inequality that have an equalizing effect in Africa include agriculture value added, access to electricity, primary education, technology, financial globalization, size of government and inflation. The robust determinants of inequality with dis-equalizing effect in Africa are secondary education, mortality rate, trade globalization and credit to private sector.

In LDCs (columns 5 and 6), we find no support for the Kuznets hypothesis. The coefficients on the GDP per capita and GDP per capita squared are robust but their signs imply a U-shape relation rather than an inverted U-shape. In LDCs, agriculture value added, access to electricity, democracy, financial globalization and inflation are robust determinants of inequality, with an equalizing effect. By contrast, urbanization, secondary education, age dependency ratio, mortality rate, immigration and credit to private sector increase inequality in LDCs.

The determinants of inequality in LLDCs are reported in columns 7 and 8 of Table 2. In LLDCs, the relation between the Gini coefficient and GDP per capita is U-shaped. Among robust determinants of inequality are agriculture value added, access to electricity, share of urban population, technology, financial and trade globalization, financial system deposits and inflation which are found to be inequality reducing in LLDCs. Primary and secondary education, age dependency ratio, mortality rate, immigration, democracy and credit to private sector are factors increasing inequality in LLDCs.

Table 2. inequality drivers across countries, by country group

	Developing countries		Africa		Least developed countries		Landlocked developing countries	
Dependent variable:	**Gini (1)**	**Palma (2)**	**Gini (3)**	**Palma (4)**	**Gini (5)**	**Palma (6)**	**Gini (7)**	**Palma (8)**
GDP per capita (log)	10.81	2.95	9.46	7.62	-68.83	-21.88	-49.05	-0.44
	(1.76)	**(2.23)**	(0.57)	**(2.42)**	**(-1.04)**	**(-1.54)**	**(-1.57)**	(-0.06)
GDP per cap sq. (log)	-0.55	-0.16	-0.49	-0.53	5.62	1.75	3.44	0.07
	(-1.48)	**(-2.01)**	(-0.43)	**(-2.45)**	**(1.08)**	**(1.59)**	**(1.73)**	(0.17)
Agr. value added	-0.29	-0.06	-0.26	-0.05	-0.16	-0.05	-0.32	-0.14
	(-5.43)	**(-4.79)**	**(-2.51)**	**(-2.44)**	**(-1.18)**	**(-1.59)**	(-0.87)	**(-1.79)**
Industry value added	-0.09	-0.03	-0.28	0.04	-0.17	-0.07	0.06	0.07
	(-1.92)	**(-2.60)**	**(-2.13)**	**(1.21)**	(-0.47)	(-0.86)	(0.13)	(0.87)
Urban population	0.01	0.003	-0.004	0.01	0.40	0.05	-0.11	-0.09
	(0.24)	(0.43)	(-0.05)	(0.32)	**(2.03)**	**(1.32)**	(-0.83)	**(-3.62)**
Electricity	-0.13	-0.02	-0.15	-0.02	-0.41	-0.08	-0.04	-0.02
	(-4.01)	**(-2.28)**	**(-2.06)**	**(-1.68)**	**(-2.63)**	**(-2.37)**	(-0.49)	**(-1.06)**
Primary education	-0.06	0.00	-0.02	-0.02	-0.03	0.00	0.33	0.11
	(-1.59)	(-0.12)	(-0.33)	**(-1.66)**	(-0.36)	(0.22)	**(1.66)**	**(2.80)**
Secondary education	-0.11	0.003	0.17	0.06	0.30	0.16	0.09	0.13
	(-3.47)	(0.45)	**(1.57)**	**(3.09)**	**(1.10)**	**(2.82)**	(0.76)	**(4.89)**
Age dependency ratio	0.07	0.03	-0.01	0.00	0.08	0.03	0.27	0.11
	(1.66)	**(2.48)**	(-0.11)	(0.04)	(0.64)	**(1.12)**	**(1.55)**	**(3.30)**
Mortality rate	0.03	0.01	0.03	0.01	0.02	0.01	0.04	0.02
	(4.75)	**(8.52)**	**(2.44)**	**(6.43)**	(0.91)	**(1.96)**	**(1.67)**	**(3.28)**
Immigration	-0.15	-0.08	2.01	-0.21	1.43	0.71	2.50	3.05
	(-0.29)	(-0.60)	(0.57)	(-0.32)	(0.81)	**(1.73)**	(0.53)	**(3.22)**
Democracy	0.06	0.01	0.06	-0.01	-0.51	-0.08	0.18	0.08
	(0.82)	(0.53)	(0.34)	(-0.30)	**(-1.95)**	**(-1.55)**	(0.65)	**(1.51)**
Technology: RPI	-5.73	-1.35	-0.78	-2.20	0.33	-0.80	-7.78	-5.47
	(-2.32)	**(-2.99)**	(-0.11)	**(-1.92)**	(0.02)	(-0.25)	(-0.73)	**(-2.78)**
Fin. globalization	0.07	-0.005	-0.02	-0.02	-0.13	-0.02	-0.09	-0.04
	(2.31)	(-0.69)	(-0.31)	**(-1.59)**	**(-1.44)**	(-0.84)	(-0.96)	**(-2.43)**
Trade globalization	-0.08	-0.01	0.10	0.02	-0.04	-0.003	0.02	-0.03
	(-2.97)	**(-1.83)**	**(1.49)**	**(1.50)**	(-0.36)	(-0.17)	(0.17)	**(-1.01)**
Size of government	0.05	-0.04	-0.23	-0.03	0.21	-0.03	-0.35	-0.06
	(0.54)	**(-1.96)**	**(-1.06)**	(-0.68)	(0.69)	(-0.60)	**(-1.06)**	(-0.96)
Fin. system deposits	-0.07	-0.02	-0.25	-0.07	-0.13	-0.04	0.0005	-0.06
	(-3.96)	**(-3.82)**	**(-3.10)**	**(-4.01)**	(-0.40)	(-0.62)	(0.00)	**(-1.14)**
Credit to pr. sector	0.05	0.03	0.09	0.07	0.57	0.12	0.15	0.17
	(2.83)	**(5.84)**	**(1.59)**	**(6.26)**	**(1.61)**	**(1.79)**	(0.73)	**(3.73)**
Inflation	0.001	0.0001	-0.10	-0.05	-0.17	-0.06	-0.37	-0.19
	(0.45)	(0.38)	(-0.98)	**(-2.56)**	(-0.60)	**(-1.07)**	**(-1.07)**	**(-2.35)**
Unemployment	-0.02	0.05	0.01	-0.05	-0.02	0.03	0.10	-0.04
	(-0.21)	(2.44)	(0.07)	**(-1.24)**	(-0.06)	(0.43)	(0.34)	(-0.73)
Observations	312	302	312	302	312	302	312	302

Note: t statistics in parentheses, t statistics > 1 are marked in bold; regressors with t > 1 are considered robust.

To summarize the discussion on determinants of income inequality across countries, Table 3 highlights the robust determinants for the different cases considered and the direction of their effects. First, we focus on the determinants that have the same effect on inequality in most samples and then delve into differences. Agriculture value added in GDP and access to electricity, proxying the structural features of the economy, as well as technology, size of government and financial system deposits are robust determinants in most samples and have an equalizing effect. Among robust determinants with dis-equalizing effect identified in most samples are demographic factors, namely age dependency ratio and mortality rate, as well as credit to private sector. The effects of education, immigration, globalization and unemployment are robust in some samples, but their direction depends on the country group. More specifically, in the full sample, secondary education has an equalizing effect, while in developing countries both primary and secondary education decrease inequality. The identified relationships change in Africa, LDCs, and LLDCs, where secondary education has a dis-equalizing effect.[5] Immigration is equalizing on average but dis-equalizing in LDCs and LLDCs. Financial globalization has a dis-equalizing effect in developing countries but equalizing in other samples. Trade globalization is equalizing in the full sample, in developing countries and in LLDCs, but dis-equalizing in Africa. Unemployment is a robust determinant with an equalizing effect in the full sample, but not statistically significant in most other sub-samples. GDP per capita is a robust determinant of inequality in all samples, with t statistics above one for both GDP per capita and GDP per capita squared, implying a non-linear relation. The specific shape, however, depends on the sample. In the full sample, developing countries, and in Africa (only in the specification with inequality measured by the Palma ratio) the relation follows an inverted U-shape, confirming the Kuznets hypothesis, while in LDCs and LLDCs the relation between the GDP per capita and inequality follows a U shape.

[5] One of the potential mechanisms of the inequality increasing effect of education can be found in the idea of skill-biased technological change (Berman, Bound, & Machin, 1998).

Table 3. Drivers of income inequality across countries: Summary by country group

	Full sample		Developing countries		Africa		LDCs		LLDCs	
	Gini	Palma	Gini	Palma	Gini	Palma	Gini	Palma	Gini	Palma
GDP per capita (log)	+	+	+	+		+	-	-	-	
GDP per cap. sq. (log)	-	-	-	-		-	+	+	+	
Agr. value added	-	-	-	-	-	-	-	-		-
Industry value added	-	-	-	-	-	+				
Urban population	+	+					+	+		-
Electricity	-	-	-	-	-	-	-	-		-
Primary education			-			-			+	+
Secondary education	-		-		+	+	+	+		+
Age dependency ratio	+	+	+	+				+	+	+
Mortality rate	+	+	+	+	+	+		+	+	+
Immigration		-						+		+
Democracy							-	-		+
Technology: RPI	-	-	-	-		-				-
Fin. globalization		-	+			-	-			-
Trade globalization	-		-	-	+	+				-
Size of government	-	-		-	-				-	
Fin. system deposits			-	-	-	-				-
Credit to pr. sector	+	+	+	+	+	+	+	+		+
Inflation						-		-	-	-
Unemployment	+	+				-				

Note: "+" indicates a robust determinant (t>1) with positive coefficient; "-" is for robust determinants with negative coefficients. LDC stands for least developed country, and LLDC stands for landlocked developing country.

3.2 Inequality within countries

To identify the robust determinants of inequality within countries, we estimate equation (2) using bias-corrected WALS. The results of the estimation of the determinants of within country inequality in the global sample are presented in Table 4. The first observation is the high number of determinants that are robust even in the panel structure with individual and time effects. The positive coefficient on GDP per capita and the negative coefficient on GDP per capita squared lend support to the Kuznets hypothesis postulating an inverted U-shape relation between income inequality and income per capita, with inequality first rising and then declining as a country develops. In the full sample, agriculture and industry value added, access to electricity, primary education, democracy and financial globalization are robust determinants decreasing inequality, while secondary education, age dependency ratio, mortality rate, trade globalization, credit to private sector, inflation and unemployment are robust determinants with a dis-equalizing effect.

Table 4. inequality drivers within countries, full sample

Dependent variable:	Gini (1)	Palma (2)
GDP per capita (log)	18.01	8.84
	(2.53)	**(2.60)**
GDP per capita sq. (log)	-0.91	-0.36
	(-2.33)	**(-1.95)**
Agr. value added	-0.10	-0.01
	(-1.44)	(-0.22)
Industry value added	-0.04	-0.01
	(-1.05)	(-0.73)
Urban population	0.01	0.01
	(0.09)	(0.61)
Electricity	-0.11	-0.03
	(-2.44)	**(-1.92)**
Primary education	-0.04	-0.01
	(-1.04)	(-0.98)
Secondary education	0.05	0.01
	(1.90)	**(1.29)**
Age dependency ratio	0.15	0.03
	(3.30)	**(2.15)**
Mortality rate	0.02	0.01
	(2.55)	**(4.09)**
Immigration	-0.001	0.03
	(-0.00)	(0.39)
Democracy	-0.06	-0.09
	(-1.04)	**(-3.03)**
Technology: RPI	0.07	-0.04
	(0.10)	(-0.15)
Fin. globalization	-0.01	-0.01
	(-0.65)	**(-1.81)**
Trade globalization	-0.003	0.02
	(-0.15)	**(2.11)**
Size of government	-0.05	0.02
	(-0.89)	(0.69)
Fin. system deposits	0.0002	-0.0005
	(0.02)	(-0.12)
Credit to pr. sector	0.02	0.0004
	(2.47)	(0.18)
Inflation	0.001	0.0002
	(1.32)	(0.74)
Unemployment	0.04	0.03
	(0.77)	**(1.56)**
Observations	312	302

Note: t statistics in parentheses, t statistics > 1 are marked in bold; regressors with t > 1 are considered robust.

Regarding the estimation of equation 2 for the within country drivers of inequality for specific country groups, we employ a similar approach as the one used for the across-country estimations, namely constructing a country group dummy and adding interactions between this dummy and each regressor. The estimation was feasible for the sample of developing countries and Africa. But it was not possible to estimate equation (2) for LDCs and LLDCs because several interaction terms are collinear with the country and time effects.

In Table 5 we report the determinants of inequality within developing countries (columns 1 and 2) and Africa (columns 3 and 4). In developing countries, we continue to find support for the Kuznets hypothesis, with inequality first increasing and then decreasing as GDP per capita increases. Agriculture and industry value added, access to electricity, primary education, democracy, technology, financial globalization, financial system deposits and credit to private sector are robust determinants of inequality, with an equalizing effect. Secondary education, age dependency ratio, mortality rate, inflation and unemployment are robust determinants with a dis-equalizing effect. Urban population, trade globalization and the size of government are robust determinants when inequality is measured by the Palma ratio, with the coefficients exhibiting a positive sign.

In Africa (columns 3 and 4), we do not find support for the Kuznets hypothesis, although GDP per capita squared remains a robust determinant of inequality. In both regressions using the Gini and Palma ratio as dependent variables, we find access to electricity, primary education, size of government, financial system deposits and inflation robust determinants with equalizing effect, while age dependency ratio, mortality rate and trade globalization are robust determinants with dis-equalizing effect. Agricultural value added, immigration, democracy and technology are robust determinants with a dis-equalizing effect in regressions where inequality is measured by the Palma ratio.

Table 5. Inequality drivers within countries, by country group

Dependent variable:	Developing countries		Africa	
	Gini	Palma	Gini	Palma
	(1)	(2)	(3)	(4)
GDP per capita (log)	22.33	9.62	-13.98	5.97
	(2.91)	**(2.69)**	(-0.55)	(0.74)
GDP per capita sq. (log)	-1.15	-0.36	1.80	0.66
	(-2.50)	**(-1.82)**	**(1.15)**	**(1.33)**
Agr. value added	-0.08	-0.02	-0.09	0.06
	(-1.10)	(-0.76)	(-0.44)	**(1.02)**
Industry value added	-0.06	-0.01	-0.0002	-0.06
	(-1.29)	(-0.45)	(-0.00)	**(-1.11)**
Urban population	0.04	0.05	0.18	0.08
	(0.47)	**(1.87)**	(0.52)	(0.73)
Electricity	-0.09	-0.02	-0.17	-0.10
	(-1.89)	**(-1.56)**	**(-1.04)**	**(-1.98)**
Primary education	-0.05	-0.02	-0.20	-0.16
	(-1.26)	**(-1.29)**	**(-1.33)**	**(-3.40)**
Secondary education	0.05	0.02	-0.05	-0.05
	(2.03)	**(1.53)**	(-0.76)	**(-2.67)**
Age dependency ratio	0.13	0.02	0.27	0.29
	(2.26)	**(1.29)**	**(1.85)**	**(5.58)**
Mortality rate	0.02	0.01	0.01	0.02
	(2.59)	**(4.37)**	**(1.18)**	**(5.92)**
Immigration	-0.03	0.13	1.85	1.43
	(-0.07)	(0.89)	(0.79)	**(1.88)**
Democracy	-0.06	-0.10	0.15	0.10
	(-0.97)	**(-3.32)**	(0.60)	**(1.20)**
Technology: RPI	-1.63	-1.20	4.19	2.22
	(-1.15)	**(-2.04)**	(0.98)	**(1.54)**
Fin. globalization	-0.01	-0.01	-0.04	-0.06
	(-0.41)	**(-1.39)**	(-0.79)	**(-4.29)**
Trade globalization	0.01	0.02	0.08	0.10
	(0.72)	**(2.68)**	**(1.51)**	**(5.75)**
Size of government	-0.07	0.03	-0.26	-0.20
	(-0.87)	**(1.08)**	**(-1.57)**	**(-4.22)**
Fin. system deposits	-0.04	-0.02	-0.21	-0.04
	(-1.12)	**(-1.19)**	**(-1.96)**	**(-1.45)**
Credit to pr. sector	0.01	-0.01	-0.01	-0.05
	(0.79)	**(-1.46)**	(-0.20)	**(-2.52)**
Inflation	0.001	0.0004	-0.32	-0.30
	(1.64)	**(1.38)**	**(-1.60)**	**(-4.96)**
Unemployment	0.07	0.02	-0.12	-0.03
	(0.98)	(0.77)	**(-1.08)**	(-0.91)
Observations	312	302	312	302

Note: t statistics in parentheses, t statistics > 1 are marked in bold; regressors with t > 1 are considered robust.

In Table 6 we summarize the robust drivers of income inequality within countries, showing the direction of the results for the full sample in columns 1 and 2, for developing countries in column 3 and 4, and for Africa in columns 5 and 6. Every determinant is robust in at least one of three samples. Industry value added, access to electricity, primary education and financial globalization are equalizing in all samples, while age dependency ratio, mortality rate and trade globalization are dis-equalizing. The effects of other variables depend on the sample studied, confirming the need for the analysis by country group. For example, the effect of agricultural value added on inequality within countries is equalizing in all samples but Africa. Urbanization is dis-equalizing only in developing countries but is not among robust determinants in other groups. In the full sample and in the developing countries sample, democracy and technology are equalizing while inflation and unemployment are dis-equalizing, yet these determinants have the opposite sign in the sample of African countries. Comparing the determinants of income inequality within countries (Table 6) to the determinants of income inequality across countries (Table 3) points to several groups of determinants that are robust in all samples. These are structural factors, namely the share of agriculture and industry value added in GDP, demographic factors, including age dependency ratio and mortality rate, as well as access to electricity and education.

Table 6. Drivers of income inequality within countries: Summary by country group

	Full sample		Developing countries		Africa	
	Gini	Palma	Gini	Palma	Gini	Palma
GDP per capita (log)	+	+	+	+		
GDP per capita sq. (log)	-	-	-	-	+	+
Agr. value added	-		-			+
Industry value added	-		-			-
Urban population				+		
Electricity	-	-	-	-	-	-
Primary education	-		-	-	-	-
Secondary education	+	+	+	+		-
Age dependency ratio	+	+	+	+	+	+
Mortality rate	+	+	+	+	+	+
Immigration						+
Democracy	-	-		-		+
Technology: RPI			-	-		+
Fin. globalization		-		-		-
Trade globalization		+		+	+	+
Size of government				+	-	-
Fin. system deposits			-	-	-	-
Credit to pr. sector	+			-		-
Inflation	+		+	+	-	-
Unemployment		+	+		-	

Note: “+” indicates a robust determinant (t>1) with positive coefficient; “-” is for robust determinants with negative coefficients.

4. Sensitivity analyses and extensions

In this section we undertake two extensions. First, we use the labour share of income as an alternative measure of income distribution, and second, we add an indicator related to gender among our regressors.

Table 7 presents the results of regressions with the labour share of income as the dependent variable. Column (1) contains the determinants of labour income share across countries, based on Equation (1), and column (2) shows the determinants of labour income share within countries, based on Equation (2), both estimated using WALS. The GDP per capita is an important determinant of labour income share, both in regressions across countries and within countries. The relationship is non-linear as both GDP per capita and GDP per capita squared are robust. The labour share of income is increasing with higher agriculture value added, size of government and credit to private sector. These relations hold both in the specification estimating the determinants of labour share across countries (column 1) and within countries (column 2). Furthermore, more democratic regimes are associated with an increased labour share of income across countries, and immigration – with an increased labour share within countries. The labour share is negatively related, both in regressions across and within counties, with industry value added, share of urban population, and financial and trade globalization. Furthermore, the labour share has a robust negative relation with age dependency ratio and financial system deposits in regressions across countries and with mortality rate, inflation and unemployment in regressions within countries.

Table 7. Determinants of labour share of income, full sample

Specification:	Across countries	Within countries
Dependent variable:	Labour share (1)	Labour share (2)
GDP per capita (log)	-0.11	0.11
	(-1.85)	**(1.45)**
GDP per capita sq. (log)	0.01	-0.01
	(2.07)	**(-1.20)**
Agr. value added	0.002	0.002
	(1.45)	**(2.00)**
Industry value added	-0.01	-0.002
	(-9.06)	**(-2.49)**
Urban population	-0.001	-0.001
	(-2.91)	**(-1.42)**
Electricity	0.001	-0.0005
	(2.08)	**(-1.21)**
Primary education	0.0003	-0.0002
	(0.85)	(-0.62)
Secondary education	-0.0001	0.0003
	(-0.20)	(0.89)
Age dependency ratio	-0.001	0.0004
	(-1.76)	**(1.02)**
Mortality rate	0.0001	-0.0001
	(1.08)	**(-1.49)**
Immigration	-0.003	0.005
	(-0.75)	**(1.35)**
Democracy	0.001	-0.0002
	(1.21)	(-0.23)
Technology: RPI	0.01	0.01
	(0.38)	(0.70)
Fin. globalization	-0.001	-0.001
	(-1.66)	**(-2.74)**
Trade globalization	-0.0003	-0.001
	(-1.13)	**(-2.86)**
Size of government	0.004	0.003
	(3.95)	**(2.45)**
Fin. system deposits	-0.0002	-0.00005
	(-2.12)	(-0.32)
Credit to pr. sector	0.0005	0.0001
	(3.04)	**(1.03)**
Inflation	0.000005	-0.00002
	(0.22)	**(-1.64)**
Unemployment	-0.0004	-0.001
	(-0.51)	**(-1.42)**
Observations	313	313

Note: t statistics in parentheses, t statistics > 1 are marked in bold; regressors with t > 1 are considered robust.

In Table 8 we report the results of our baseline regression augmented by gender dimension and estimated using WALS. We employ female labour participation rate to proxy for women's empowerment and economic participation. As expected, female labour participation is a robust determinant of inequality with an equalizing effect both within countries (reported in column 1 and 2) and across countries (reported in column 3 and 4). It's important to note that the inclusion of an additional regressor did not impact the stability of the results with all robust determinants retaining their sign and magnitude.

Table 8. Determinants of income inequality, controlling for gender, full sample

Specification:	**Across countries**		**Within countries**	
Dependent variable:	**Gini**	**Palma**	**Gini**	**Palma**
	(1)	**(2)**	**(3)**	**(4)**
GDP per capita (log)	16.96	2.15	16.37	7.64
	(3.10)	**(1.95)**	**(2.35)**	**(2.21)**
GDP per capita sq. (log)	-1.02	-0.11	-0.80	-0.28
	(-3.36)	**(-1.74)**	**(-2.08)**	**(-1.48)**
Agr. value added	-0.23	-0.06	-0.05	0.01
	(-4.05)	**(-3.52)**	(-0.67)	(0.40)
Industry value added	-0.05	-0.02	-0.04	-0.01
	(-1.41)	**(-2.30)**	(-0.97)	(-0.65)
Urban population	0.09	0.01	0.02	0.02
	(4.11)	**(1.26)**	(0.27)	(0.75)
Electricity	-0.181	-0.0196	-0.11	-0.03
	(-4.87)	**(-2.47)**	**(-2.42)**	**(-1.82)**
Primary education	0.03	0.002	-0.02	-0.01
	(0.76)	(0.35)	(-0.54)	(-0.47)
Secondary education	-0.12	-0.004	0.06	0.01
	(-3.61)	(-0.54)	**(2.17)**	**(1.58)**
Age dependency ratio	0.07	0.03	0.15	0.03
	(1.63)	**(2.95)**	**(3.33)**	**(2.08)**
Mortality rate	0.04	0.01	0.02	0.01
	(5.18)	**(9.26)**	**(2.72)**	**(4.25)**
Immigration	0.08	-0.16	-0.05	0.02
	(0.30)	**(-2.72)**	(-0.21)	(0.20)
Democracy	-0.01	0.01	-0.04	-0.08
	(-0.11)	(0.51)	(-0.67)	**(-2.77)**
Technology: RPI	-4.59	-0.74	0.07	-0.05
	(-2.21)	**(-1.67)**	(0.10)	(-0.18)
Fin. globalization	0.03	-0.01	-0.01	-0.02
	(0.99)	**(-1.15)**	(-0.93)	**(-2.08)**
Trade globalization	-0.05	-0.01	-0.003	0.02
	(-1.76)	(-0.90)	(-0.18)	**(2.15)**
Size of government	-0.35	-0.06	-0.07	0.01
	(-4.13)	**(-3.89)**	**(-1.19)**	(0.44)
Fin. system deposits	-0.004	-0.001	0.002	-0.0002
	(-0.35)	(-0.56)	(0.18)	(-0.05)
Credit to pr. sector	0.03	0.01	0.02	0.0008
	(3.14)	**(5.44)**	**(2.60)**	(0.31)
Inflation	0.001	0.0004	0.0004	-0.0001
	(0.52)	(0.86)	(0.39)	(-0.25)
Unemployment	0.07	0.05	0.06	0.04
	(0.86)	**(2.98)**	**(1.18)**	**(1.96)**
Female labour participation	-0.05	-0.0004	-0.11	-0.04
	(-1.94)	(-0.10)	**(-1.94)**	**(-1.95)**
Observations	312	302	312	302

Note: t statistics in parentheses, t statistics > 1 are marked in bold; regressors with t > 1 are considered robust.

5. Conclusions

This paper examines the factors that drive income inequality within and across countries, using different measures of income distribution and an estimation technique that jointly accounts for both model uncertainty and estimation uncertainty. The estimations are applied to both a global sample and to three categories of vulnerable developing countries: Africa, least developed countries (LDCs), and landlocked developing countries (LLDCs). The results suggest that: (i) there are multiple factors that contribute to income inequality within and across countries; (ii) the measure of inequality used in analyses matters for an understanding of the drivers of inequality; and (iii) there are significant differences in the drivers of inequality globally and in Africa, LDCs and LLDCs. Regarding the Kuznets hypothesis of the inverted U-shape relations between inequality and development, we find strong support for the hypothesis in the global and the developing countries samples but not in the Africa, LDC and LLDC samples. These differences underscore the importance of singling out specific groups of countries when analysing the determinants of inequality.

There are several policy implications emanating from the findings in this paper that we would like to highlight. The first is that economic and social policies are drivers of inequality. In this context, inequality is not inevitable and can be addressed through appropriate choice of policies. The second policy implication is that the design of effective policies to combat inequality must account for country heterogeneity because the impact of policy measures on income inequality varies within and across countries. A third policy implication of the analyses is the importance of structural change in combating income inequality. Many developing countries are emphasizing the need to transform the structure of their economies to boost as well as sustain growth and create employment. Often the focus of this transformation agenda is on promoting industrial and not agricultural development. The findings in this paper suggest that an increase in agricultural value added has an equalizing effect in developing countries. Therefore, policies that promote both agricultural and industrial development are likely to be more effective in combating inequality than those that promote industrial expansion at the expense of agricultural development. The final policy implication of the analyses that is worth highlighting is related to the debate on globalisation. In particular, the findings of this paper indicate that trade and financial globalization can have different effects within and across countries. In this regard, the nature of globalization matters for development and there is a need for policies to be put in place to enable those countries and groups that are likely to be negatively affected to better adjust to global trade and financial reforms in the short to medium term.

In future research, it would be interesting to expand the analysis by decomposing government spending by category, such as education and public health, or by controlling for policies that directly impact income distribution, such as employment protection legislation. These extensions were not possible in the current study due to the paucity of data, particularly for Africa, LDCs and LLDCs.

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Appendix A: Data sources, definitions and summary statistics

Table A1. Sources and definitions for the variables used in the analysis

Category	Variable in regression tables	Variable definition and unit of measurement	Source
Measures of income distribution	Gini	Gini coefficient of market (gross) income, standardized	WIID, UNI-WIDER
	Palma	Palma ratio of market (gross) income, i.e., the ratio of top 10% income share to bottom 40% income share	
	Labour share	Share of labour compensation in GDP at current national prices	Penn World Tables
Economic development and structure of the economy	GDP per capita	GDP per capita (constant 2015 US$)	WDI, World Bank
	Agr. value added	Agriculture, forestry, and fishing, value added (% of GDP)	UNCTADStat
	Industry value added	Industry (including construction), value added (% of GDP)	
	Urban population	Urban population (% of total population)	WDI, World Bank
	Electricity	Access to electricity (% of population)	
Education	Primary education	Primary education completed (% of population aged 15 and 64)	Barro & Lee (2013)
	Secondary education	Secondary education completed (% of population aged 15 and 64)	
Demographics	Age dependency ratio	Age dependency ratio (% of working-age population)	WDI, World Bank
	Mortality rate	Mortality rate, adult (per 1,000 adults)	
	Immigration	Net migration, million persons	
Institutions and political regime	Democracy	Polity2 regime measure (higher values mean more democratic regime)	Polity V, Center for Systemic Peace
Technology and globalization	Technology: RPI	Relative price of investment (RPI), measured as price level of capital formation, price level of USA GDPo in 2017=1	Penn World Table, University of Groningen
	Fin. globalization	KOF Financial Globalization Index, *de facto* (higher values mean more openness)	KOF Swiss Economic Institute
	Trade globalization	KOF Trade Globalization Index, *de facto* (higher values mean more openness)	
Fiscal policies and financial development	Size of government	General government final consumption expenditure (% of GDP)	WDI, World Bank
	Fin. system deposits	Financial system deposits to GDP (%)	
	Credit to pr. sector	Domestic credit to private sector (% of GDP)	
Economic policies and macroeconomic conditions	Inflation	Inflation, consumer prices (annual %)	
	Unemployment	Unemployment, total (% of total labor force) (national estimate)	
Gender	Female labour participation	Labour force participation rate, female (% of female population ages 15+)	ILO and the World Bank

Note: All data that support the findings of this study are openly available.

Table A2. List of economies and development groups included in the analysis

	Africa	LDC	LLDC		Africa	LDC	LLDC		Africa	LDC	LLDC
Albania				**Gabon**	x			Norway			
Algeria	x			**Gambia**	x	x		**Pakistan**			
Argentina				Germany				**Panama**			
Armenia			x	**Ghana**	x			**Paraguay**			x
Australia				Greece				**Peru**			
Austria				**Guatemala**				**Philippines**			
Bahrain				**Guyana**				Poland			
Bangladesh		x		**Haiti**		x		Portugal			
Belgium				**Honduras**				Romania			
Benin	x	x		Hungary				Russian Federation			
Bolivia (Plurinational State of)			x	**India**				**Rwanda**	x	x	x
Botswana	x		x	**Indonesia**				**Saudi Arabia**			
Brazil				**Iran (Islamic Republic of)**				**Senegal**	x	x	
Bulgaria				Ireland				**Sierra Leone**	x	x	
Burundi	x	x	x	Israel				**Singapore**			
Cambodia		x		Italy				Slovakia			
Cameroon	x			**Jamaica**				Slovenia			
Canada				Japan				**South Africa**	x		
Chile				**Jordan**				Spain			
China				**Korea, Republic of**				**Sri Lanka**			
Colombia				**Kyrgyzstan**			x	**Sudan**	x	x	
Congo	x			**Lao People's Dem. Rep.**		x	x	Sweden			
Congo, Dem. Rep.	x	x		Latvia				Switzerland			
Costa Rica				**Lesotho**	x	x	x	**Syrian Arab Republic**			
Croatia				Lithuania				**Tanzania, United Rep. of**	x	x	
Cyprus				Luxembourg				**Thailand**			
Czechia				**Malaysia**				**Togo**	x	x	
Côte d'Ivoire	x			**Mali**	x	x	x	**Tunisia**	x		
Denmark				**Mauritius**	x			**Turkey**			
Dominican Republic				**Mexico**				**Uganda**	x	x	x
Ecuador				Moldova, Republic of			x	Ukraine			
Egypt	x			**Mongolia**			x	United States of America			
El Salvador				**Mozambique**	x	x		**Uruguay**			
Estonia				**Nepal**		x	x	**Viet Nam**			
Eswatini	x		x	Netherlands				**Zambia**	x	x	x
Fiji				New Zealand				**Zimbabwe**	x		x
Finland				**Nicaragua**							
France				**Niger**	x	x	x				

Note: Developing countries are marked in bold, based on the Standard Country or Area Codes for Statistical Use of the United Nations Statistics Division.

Table A3. Summary statistics

	N	Mean	SD	Min	Max
Gini	418	42.63	10.95	22.76	74.60
Palma	404	2.71	2.07	0.72	17.70
GDP per capita	418	14'988	19'663	257	107'302
Agr. value added	418	10.16	10.35	0.03	58.91
Industry value added	418	27.31	8.16	5.23	72.05
Urban population	418	61.03	21.09	7.62	100.00
Electricity	418	83.99	26.48	2.99	100.00
Primary education	418	14.40	10.70	0.02	55.24
Secondary education	418	28.55	17.57	0.56	76.71
Age dependency ratio	418	59.18	16.27	16.17	112.39
Mortality rate	418	166.11	99.48	47.51	628.15
Immigration	418	0.06	0.90	-3.25	8.86
Democracy	418	5.67	5.44	-10.00	10.00
Technology: RPI	418	0.56	0.21	0.15	1.85
Fin. globalization	418	61.01	18.88	16.76	98.80
Trade globalization	418	53.87	18.72	17.22	98.97
Size of government	418	15.64	5.17	5.01	39.40
Fin. system deposits	418	52.84	46.14	0.46	428.01
Credit to pr. sector	418	56.60	44.46	0.00	205.20
Inflation	418	16.34	108.11	-1.98	1671.80
Unemployment	418	7.76	4.97	0.39	31.12

Note: Variables used in the analysis (Full sample).

Table A4. Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1) Gini	1.00																				
(2) Palma	0.89	1.00																			
(3) GDP per capita	-0.55	-0.40	1.00																		
(4) Agr. value added	0.42	0.27	-0.53	1.00																	
(5) Industry value added	0.01	0.03	-0.17	-0.23	1.00																
(6) Urban population	-0.41	-0.33	0.57	-0.74	0.06	1.00															
(7) Electricity	-0.64	-0.57	0.41	-0.75	0.18	0.69	1.00														
(8) Primary education	0.34	0.21	-0.25	0.16	0.03	-0.12	-0.17	1.00													
(9) Secondary education	-0.63	-0.44	0.36	-0.54	0.05	0.38	0.61	-0.54	1.00												
(10) Age dependency ratio	0.62	0.52	-0.41	0.68	-0.18	-0.55	-0.83	0.19	-0.62	1.00											
(11) Mortality rate	0.70	0.74	-0.54	0.58	-0.04	-0.60	-0.79	0.14	-0.45	0.66	1.00										
(12) Immigration	-0.14	-0.09	0.34	-0.23	-0.14	0.30	0.15	-0.19	0.16	-0.13	-0.10	1.00									
(13) Democracy	-0.30	-0.21	0.40	-0.47	-0.17	0.44	0.35	-0.16	0.42	-0.36	-0.34	0.19	1.00								
(14) Technology: RPI	-0.41	-0.31	0.63	-0.45	-0.15	0.48	0.33	-0.22	0.33	-0.26	-0.40	0.26	0.35	1.00							
(15) Fin. Globalization	-0.48	-0.33	0.67	-0.56	-0.16	0.50	0.44	-0.27	0.44	-0.43	-0.44	0.28	0.39	0.54	1.00						
(16) Trade globalization	-0.38	-0.29	0.22	-0.19	-0.05	0.07	0.21	-0.27	0.33	-0.29	-0.20	-0.03	0.04	0.14	0.58	1.00					
(17) Size of government	-0.35	-0.14	0.36	-0.45	-0.16	0.36	0.23	-0.18	0.37	-0.23	-0.15	0.20	0.33	0.40	0.44	0.24	1.00				
(18) Fin. system deposits	-0.37	-0.31	0.69	-0.43	-0.17	0.42	0.37	-0.14	0.23	-0.39	-0.44	0.15	0.23	0.33	0.49	0.30	0.21	1.00			
(19) Credit to pr. sector	-0.42	-0.30	0.65	-0.55	-0.07	0.48	0.50	-0.21	0.33	-0.54	-0.52	0.38	0.28	0.47	0.56	0.23	0.33	0.57	1.00		
(20) Inflation	0.08	0.06	-0.06	0.02	0.07	0.03	0.00	0.10	-0.08	0.03	0.05	-0.02	0.01	0.00	-0.15	-0.14	-0.02	-0.05	-0.04	1.00	
(21) Unemployment	0.18	0.31	-0.13	-0.23	0.03	0.13	0.07	-0.02	0.08	-0.03	0.15	0.06	0.04	0.01	0.09	-0.02	0.35	-0.04	-0.01	-0.01	1.00

Note: Variables used in the analysis (Full sample).