



Personal income tax, redistribution and income inequality in Sub-Saharan Africa

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Abstract

We assess the roles of personal income tax and fiscal redistribution in income inequality for 30 Sub-Saharan Africa economies from 1980 to 2020, employing the dynamic common correlated effect and cross-sectional augmented autoregressive distributed lag estimators. Empirical results show that personal income tax positively affects income inequality in the full sample SSA economies. Compared to the full sample, the magnitude of the effect remains positive but smaller for non-least developed countries (countries not classified as least developed countries in our sample). However, personal income tax has a negative effect on income inequality for least developed countries. Additionally, fiscal redistribution increases inequality in Sub-Saharan Africa economies and non-least developed countries, while it lowers inequality for least developed countries. Interestingly, fiscal redistribution reduces the level of the positive impact of personal income tax on inequality over the full sample. The main policy implication of this research is that well-designed redistributive fiscal measures associated with anti-corruption policy and good governance may help policymakers to reduce the positive effect of personal income tax on inequality in Sub-Saharan Africa economies.

Keywords PIT · Income inequality · Fiscal redistribution · DDCE · CS-ARDL

JEL Classification D63 · E62 · H24 · C40

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1 Introduction

Both academics and decision-makers have shown an increased interest in the study of income disparities in recent years (Ravallion and Chen 2021). While Kaldor (1956) claims that a high level of inequality may spur economic growth by giving top capitalists access to rare resources, higher inequality typically leads to less access to healthcare, education, etc., or political and economic instability, which discourage incentive of creating jobs. Many governments have tried to lessen income disparity using redistributive programs funded by the tax system in response to the rising income inequality and its detrimental effects. PIT (personal income tax) is the public policy tool that is commonly taken into account when the major objective is to adjust the post-tax income distribution, according to Poterba (2007). Therefore, the chance of reducing income inequality through taxation is greatly influenced by how progressive a nation's tax system is. Consequently, the redistributive effects of income taxes are a growing source of concern for both industrialized and emerging nations. Recent public discussion has primarily focused on the role of PIT in reducing inequality (Atkinson 2014; Piketty 2015) since the seminal contributions of Piketty (2014), and Atkinson and Piketty (2010) on the long-run evolution of income inequality in developed economies.

Less consideration has been given to PIT's impact in emerging nations. PIT can play a significant role in ensuring the redistribution of income from the rich to the poor because it is widely acknowledged to be one of the most progressive tax policy tools (Datt et al. 2022). According to the progressive taxation hypothesis, since the poor spend more of their income on food than the rich do, redistribution can only occur from the rich to the poor. PIT is therefore viewed as a key component in contemporary tax-benefits regimes. From a redistributive standpoint, PIT countercyclical role has been advised during the 2008 financial crisis Jenkins et al. (2013). Second, PIT may produce unexpected outcomes, particularly if tax rates are more progressive. If tax rates are increased for those with higher incomes, they may retaliate by taking steps to lower their income tax. This can be accomplished either by substituting work for leisure or avoiding tax. Therefore, such policies may widen inequality.

According to the theory of optimal taxation, a rise in income disparity might be interpreted as a widening in the distribution of ability (Mankiw et al. 2009). Mirrlees (1971) has shown that the ideal tax policy is more redistributive as inequality of ability rises (which leads to income inequality). He indicated that societies frequently had higher tax rates and fewer individuals were required to work. Low-ability individuals may profit from leisure pursuits and a certain amount of grant money to help with expenses. The key indicator of the trade-off between efficiency and equality according to Mirrlee's theory is a higher tax rate. This higher tax rate has an efficiency cost since it discourages people from working hard to earn that income. For those with higher incomes, the tax change does not, however, result in any distortion. Both of the aforementioned points of view can undoubtedly be true: Depending on how tax system is constructed, a tax policy (especially PIT) can either raise or decrease inequality.

While some studies assess the relationship between PIT and inequality, other macroeconomic studies debate the importance of fiscal policy, specifically fiscal redistribution in influencing income inequality (IMF 2014). Using the median voter theory, Meltzer and Richard, (1981) show that there is theoretical reason explaining how democracy (which facilitates pro poor redistribution) is expected to reduce income disparity in Africa. This theory contends that if given the option to choose redistribution rationally, voters will favor greater taxes and redistribution for those with higher incomes if the median income is lower than the mean income. When median income approaches mean income, voters' preferences for a high tax rate decline. Evidence from both regression analysis (for example, Alves and Afonso 2017) and microsimulation methods (see, García and Giraldo 2018) reveal that the relationship between redistribution and income inequality is inconclusive.

Contrary to the above researchers that debate the effect of tax system on inequality and the few others that examine the relationship between redistribution and inequality, this study examines the moderating role of fiscal redistribution on the effect of PIT on income inequality in SSA differentiating LDCs from non-LDCs. Therefore, this paper answers two questions: Does PIT affect inequality in SSA differentiating LDCs from Non-LDCs? Does the effect of PIT on inequality depends on fiscal redistribution? The contribution of this study is twofold: The first is analyzing the effect of PIT on income inequality in SSA distinguishing LDCs from non-LDCs. The second contribution is that the effect of PIT on income inequality depends on the extent of fiscal redistribution¹ in the long run.

This paper is the first one that empirically investigates if fiscal redistribution reduces or enhances the effect of PIT on inequality. We use a sample of 30 SSA countries from 1980 to 2020. As an aggregated data may not fully reveal the effect between the variables, we disaggregate our data using LDC and non-LDC within SSA. This helps in elaborating policy recommendation for each group of countries. We also include corruption and governance variables and their interactions terms to find the net effect and the threshold above which PIT reduces inequality. Our results show that there is a long-run relationship among our variables of study in SSA. The empirical analysis, based on the CS-ARDL, shows that PIT increases inequality, with this impact being large in SSA, including LDC than in non-LDC. Furthermore, the main results reveal that a higher amount of fiscal redistribution helps in decreasing the higher income inequality impact of PIT. But above a certain amount of fiscal redistribution, PIT reduces inequality.

The rest of this article has five sections: Sect. 1 presents the introduction. Section 2 covers literature review. Section 3 describes methodology, Sect. 4 interprets and discusses the results. Section 5 provides the conclusion.

¹ Note that while this study expects fiscal redistribution to affect the impact of PIT on income inequality, one should not exclude the prospect that PIT may also influence the level of fiscal redistribution (e.g., Saijo 2020).

2 Literature review

Fiscal policy is “the setting of the level of taxation and government spending by policymakers” (Mankiw 2021). In this section, we take a quick look at how fiscal policy, with a focus on tax policy in particular, affects inequality. According to Bastagli, Coady and Gupta’s (2012) study, fiscal policy is “the key instrument for governments to influence income distribution.” Its three major goals are stated as “to support macroeconomic stability, provide public goods and correct market failures, and redistribute income” (Musgrave 1959). Theoretically, fiscal policy affects how income is distributed through taxes, public spending and transfers. Fiscal policy therefore improves equity plans in two ways. First, according to de Freitas (2012), direct taxes are progressive since they increase income distribution and lower income inequality. Hence, taxes levied on income, distribute resources from the rich to the poor. The rich would be required to pay a larger percentage of their income in taxes. Second, if tax revenues are used to pay for social spending to aid the poor, this has a significant impact on the outcomes of redistribution.

Tax policies have the ability to change the short- and medium-term distribution of income. Regression-based analyses by several researchers shown that increased welfare spending and a larger reliance on income taxes improve inequality (Martnez-Vázquez, Vulovic and Moreno-Dodson 2012). The majority of these studies show that social protection spending reduces inequality and that direct taxes, like income tax are more redistributive than indirect taxes, like sales tax and service tax. A few studies have discussed the impact of tax instruments on inequality and come to ambiguous evidence. Using Error Correction Model (ECM), some scholars (Oboh and Eromonsele 2018) find the effect of tax system on inequality to be positive and statistically significant in Nigeria. Other scholars (Clifton et al. 2020) find a negative effect of PIT on inequality. Malla and Pathranarakul (2022) and Maina (2017) use GMM and OLS, respectively, to examine the relationship between fiscal policy (tax and public spending) and income inequality and find that the impact of income tax on inequality is negative in developing economies.

While the above scholars investigate the relationship between tax and income inequality, few studies examine the association between these two variables through different channels. For instance, Malla and Pathranarakul (2022) assess the role of institutions on the effect of fiscal policy on inequality. This is consistent with Acemoglu et al. (2014), who argue that institutions affect redistributive and economic outcomes. Chan and Ramly (2018) investigate the role of country governance on VAT and income inequality while Mustapha et al. (2017) examine the role of corruption control in moderating VAT and income inequality.

Despite some scholars examine the effect of taxation on inequality and others use different channels to explain this relationship, fiscal redistribution channel when estimating the impact of PIT on inequality in SSA is ignored. To fill this gap, this study theoretically and empirically contributes in the existing literature by investigating the relationship between PIT, fiscal redistribution and inequality in SSA separating LDC from non-LDC using DCCE (dynamic common correlated effect) and DS-ARDL (cross-sectional augmented autoregressive distributed lag). These new

techniques, which controls for slope heterogeneity and cross-sectional dependence, makes it possible to estimate the heterogeneous impacts of PIT and fiscal redistribution on income inequality, in contrast to traditional estimations (GMM, OLS, ECM, etc.). As for econometric side, one can expect either weak or strong forms of cross-sectional dependence by limiting the analysis to SSA economies that share similar economic development and institutional systems (Espoir and Ngepah 2021). If these forms of cross-sectional dependence are not taken into account, the results may be inconsistent. Due to regional economic integration, technological cross-border spillovers, similar financial-economic-pandemic shocks, and regional wars (ECOWAS, SADC, etc.), these two econometrical issues are likely to arise in an area like SSA.

3 Methodology and data

3.1 Empirical specification

This paper empirically investigates effect of PIT and fiscal redistribution on inequality in 30 SSA economies. The design of the sample is guided by two reasons. First, the data availability for SSA over the period of 40 years. Second, SSA countries are considered as not only one of the regions with the highest level of inequality but also as one of the regions with the lowest level revenue mobilization in the world. The time period is from 1980 to 2021. This period is significant for two reasons: First, 1980s were characterized by the introduction of structural adjustment programs by IMF and World Bank in response to African crisis. Second reason, this period includes serious economic and financial crisis between 2007 and 2020. The 2008 recession and COVID-19 have affected most countries, specifically their tax base and the level of tax revenue. In this study, we test how PIT and fiscal redistribution interact in affecting inequality in SSA. We follow a model that builds on existing studies on macroeconomic determinants of inequality (see Alves and Afonso 2017). Following Denvil and Peter (2016), we interact PIT and FISRED in Eq. 1 to test if FISRED affect the relationship between PIT and inequality. A static version of Eq. (1) can be written as:

$$\text{Gini}_{it} = \alpha_{it} + \beta_1 \text{PIT}_{it} + \beta_2 \text{FISRED}_{it} + \beta_3 \text{PIT}_{it} * \text{FISRED}_{it} + \beta_4 \text{GDPpc}_{it} + \beta_5 \text{INFLAT}_{it} + \epsilon_{it} \quad (1)$$

where Gini coefficient refers to net income inequality. Our annual data on aggregate net income inequality is drawn from Gini coefficient series that were recently made available by version 8.2 of the Standardized World Income Inequality dataset (SWIID) published by Solt (2019). In this study, we use disposable Gini as it provides the net picture of inequality in SSA countries. PIT (proxy by PIT revenue) was drawn from the FERDI development indicators. This French institution provides a detailed new PIT dataset for SSA over a long period. It was built for a particular research project in 2007 and updated later for further research at the IMF Fiscal Affairs Department. FISRED represents fiscal redistribution through taxes and transfers. It is computed as the difference between the market income Gini and the net income Gini (see Berg et al. 2018; Gnangnon 2021). Following the SWIID

dataset, redistribution as defined in this study does not capture all the redistributive effects of government on the income distribution. Governments affect income distribution in many ways (for example, education, healthcare, etc.) beyond the fiscal redistribution, which is the aim of our study. The variable PIT*FISRED is incorporated in the vector of variables to describe the interaction between personal income tax and fiscal redistribution. We use GDP per capita and INFLAT (Inflation) as our control variables. These two control variables (GDPpc and INFLAT) were taken from World Development Indicator (WDI). ϵ_{it} stands for an error term. And all our variables are in logarithm form. According to the United Nations, LDCs² are the poorest and most vulnerable economies in the world. Thus, we provided the list of these countries used in this article in Appendix. However, we generate a dummy variable, called “LDC” that takes the value one for LDCs,³ and zero, otherwise. This dummy allows to differentiate the effect of PIT on inequality in LDCs and non-LDCs and recommends some policy measures for each group. Since this study takes into account a dynamic version, Eq. (1) adds an extra parameter, which is the lagged dependent variable to control for the persistence of inequality over time and is described as follows:

$$\begin{aligned} \text{Gini}_{it} = & \alpha_{it} + \beta_0 \text{Gini}_{i,t-1} + \beta_1 \text{PIT}_{it} + \beta_2 \text{FISRED}_{it} + \beta_3 \text{PIT}_{it} * \text{FISRED}_{it} \\ & + \beta_4 \text{GDPpc}_{it} + \beta_5 \text{INFLAT}_{it} + \epsilon_{it} \end{aligned} \quad (2)$$

From the Eq. (2), it is deduced that

$$\frac{d\text{GINI}_{it}}{d\text{PIT}_{it}} = \beta_1 + \beta_3 \text{FISRED}_{it} \quad (3)$$

Equation 2 indicates that fiscal redistribution (FISRED) is the source of nonlinearity between Inequality (Gini) and PIT and that the way PIT impacts Inequality depends on the magnitude of FISRED.

3.2 Empirical strategy

Empirical analysis in this study comprises four steps: (i) Firstly, we employ CD test by Pesaran (2004) to investigate the existence CSD in the series across countries. The null hypothesis is of cross-sectional independence. Secondly, we use CD test by Pesaran (2015) to test if the dependence in the errors are strong or weak under the null hypothesis of weak dependence in the errors. (ii) Due to the presence of CSD, this study utilizes the second-generation cross-sectionally augmented Im-Pesaran-Shin (CIPS) test developed by Pesaran (2007). (iii) To assess for the presence of cointegration among the series, this study applies Westerlund (2007), which deals with CSD and structural-breaks in the data. (iv) After establishing the presence of

² The list and other information regarding the 46 LDCs can be obtained at: <https://www.un.org/ohrrls/content/profiles-ldcs>.

³ In this study, we have considered the LDCs as poorest countries (Gnangnon 2021).

cointegration, we then use DCCE and specifically CS-ARDL to analyze the long-run association among our series.

3.2.1 DCCE

Panel data analysis is used in the study than microsimulation,⁴ time series, etc., because of its many advantages. The horizontal cross-section and time series observations are combined in panel data, which also enables analysis with additional observations. In comparison to time series models, panel data consider more sample variability and degrees of freedom (Meo et al. 2020). As they can examine both short-run and long-run outcomes, dynamic panel data offer an advantage over static models (Sadorsky 2014). In contrast, panel data have some drawbacks if heterogeneity and CSD cannot be taken into account. The previous research heavily relied on estimating techniques that can only take into account homogenous slopes and are unable to account for the cross-sectional effect (Meo et al. 2020). The literature on homogenous slope for time series and panel data frequently makes use of numerous well-known statistical approaches, such as OLS, random and fixed effects models and GMM, which exhibit a higher degree of homogeneity as intercept varies between cross-sectional units. This shows that this assumption is false and leads to inconsistent results (Ditzen 2019). To avoid this, our article used DCCE developed by Chudik and Pesaran (2015) which is a dynamic form of CCE established by Pesaran (2006) to assess the impact of PIT and fiscal redistribution on inequality. For instance, Gbato (2017) used DCCE estimator to test the effect of taxation on economic growth in SSA while Lagravinesea et al (2020) applied DCCE to examine Tax buoyancy in OECD countries. In contrast to Gbato (2017) and Lagravinesea et al (2020), we use DCCE and DS-ARDL to test the role of fiscal redistribution on PIT and income disparity in SSA differentiating LDCs from Non-LDCs. The benefits of applying this technique (DCCE) are as follows: (i) it controls for endogeneity issue due to the presence of the lag dependent variable in the model by adding the $P_T = \sqrt[3]{T}$ lags of the cross-sectional averages; (ii) it tests for slope heterogeneity; (iii) it account for cross-sectional dependence among units and deal with variable non-stationarity internally.

Estimated equation can be written as follows:

$$y_{i,t} = \alpha_i + \lambda_i y_{i,t-1} + \beta_i x_{i,t} + \sum_{i=0}^{PT} \gamma'_{i,1} \bar{z}_{t-1} + \varepsilon_{i,t} \tag{4}$$

$\bar{z}_t = (\bar{y}_t, \bar{x}_t)$ by including \bar{z}_t in Eq. 2, estimated equation becomes:

$$y_{i,t} = \alpha_i + \lambda_i y_{i,t-1} + \beta_i x_{i,t} + \sum_{i=0}^{PT} \gamma'_{i,1,y} \bar{y}_{i,t-1} + \gamma'_{i,1,x} \bar{x}_{i,t-1} + \varepsilon_{i,t} \tag{5}$$

⁴ The key limitations for microsimulation are: first, the lack of detail to model the behavioral responses to tax changes, and second, the restriction of the database to those required to file their tax return.

where P_T represents the number of lags and bar describes the cross-sectional averages. The term \bar{z}_t is cross-sectional averages of all variables in the model. The strong unobserved cross-sectional dependence is estimated by lagging the cross-sectional averages. Individual coefficients are estimated for each unit and then averaged to obtain the MG estimator.

To estimate DCCE through MG and PMG techniques, some requirements need to be met. As we can observe, the four cross-sectional averages (dependent variables, its lag and the regressors) used here are likely to satisfy these criteria because the majority of variation in macroeconomic variables may be explained by a small number of unobserved common factors. In addition, the time series dimension (from 1980 to 2020) is large and the number of lags ($P_T = \sqrt[3]{T}$ lags of the cross-sectional averages) is sufficient to allow us to perform DCCE.

3.2.2 CS-ARDL

A significant econometric technique for dealing with long-run association is cointegration developed by Engle and Granger (1987). However, Pesaran and Smith (1995) expanded this technique for panel data, calling it ARDL approach. Chudik et al. (2015) and Chudik and Pesaran (2015) developed CS-ARDL to control for cross-sectional dependence (CSD) regardless of the order and provide long-run estimates. It also accounts for omitted variable bias. CS-ARDL requires: (i) The dynamic specification of the model, so that the weak exogeneity among the independent variables is considered and the residuals are no longer correlated. (ii) The presence of a long-term association among the variables. The final equation can be described as follows:

$$Y_{it} = C_{yi}^* + \sum_{i=1}^p \phi_i Y_{i,t-1} + \sum_{i=0}^p \beta_i' X_{i,t-1} + \sum_{i=0}^q a_i \bar{Y}_{t-1} + \sum_{i=0}^q b_i' + \bar{X}_{t-1} + \varepsilon_{it} \quad (6)$$

where our dependent variable is Y_{it} and independent variables are represented by X_{it} . \bar{X}_t and \bar{Y}_t are our cross-sectional means.

4 Empirical results

4.1 Cross-sectional dependence results

The findings show that our series are dependent across countries as p-value tests are less than the 5% significance level which reject the null hypothesis. These findings are true for SSA and disaggregated samples (LDC and non-LDC).

The results from cross-sectional dependence⁵ also demonstrate that the test rejects the null hypothesis of weak dependence in the errors at 1% significance

⁵ Cross-sectional dependence results for SSA, LDCs and non-LDCs are available upon request.

level. This indicates that there is a strong CSD in the errors for SSA and LDC and non-LDC.

4.2 Stationarity test results

Another importance of the CD test is that it allows us to know if the first-generation (Levin et al. 2002) and (Im et al. 2003) or CIPS test (Pesaran 2007) are relevant for this paper. Due to the presence of CSD, we use second generation of stationarity tests for the full sample, LDCs and non-LDCs to prevent misleading inferences.⁶ The findings show that the statistic values for the series are less than the critical value at the 1% significance level for the first difference, while that of the level are different. The CIPS test reject the null of non-stationarity for the variables for the first differences. Therefore, the findings in first differences show that all series are I (1).

4.3 Panel cointegration test results

To assess for the presence of cointegration among the series, this study applies Westerlund (2007), which deals with CSD in the data. The rejection of the null hypothesis of no cointegration is made based on the majority of the four statistics (G_t, G_a, P_t, P_a). The results⁷ shows that three test statistics out of four (G_t, P_a and G_a), are statistically significant for the full sample. In addition, four test statistics out of four (G_t, P_a, P_t and G_a) are statistically significant for non-LDC. However, three test statistics out of four fail to reject the null of no cointegration for LDC. Westerlund (2007) findings show that all series are cointegrated after controlling for CSD using a bootstrap procedure with 100 replications.

4.4 DCCE results

We firstly assess the dynamic model-2 in SSA, and findings of this analysis are presented in column-1 of Table 2. We estimate if there is a nonlinear impact of PIT on inequality by analyzing a different specification of model-2 that incorporates PIT square. If we obtain a nonlinear impact whereby the impact of PIT on inequality is positive only after a threshold of “PIT”, then this model specification (PIT square) becomes our baseline model. On the contrary, if we find a nonlinear impact of PIT on income inequality whereby, for instance, the coefficients of both PIT and its square are significantly positive which signifies that extra increase will more increase the positive impact of PIT on income inequality then we will consider the model-2 as our baseline model for the rest of the study. The findings of this are presented in column-1 of Table 1.

⁶ Second generation of stationarity results for SSA, LDCs and non-LDCs are available upon request.

⁷ Panel cointegration results for SSA, LDCs and Non-LDCs are available upon request.

Table 1 Effect of PIT on income inequality

Variables	1 Statistic (Full Sample)		2 Statistic (LDC)		3 Statistic (non-LDC)	
<i>GINI_{i,t-1}</i>	0.212*	(0.095)	2.867***	(0.000)	0.035	(0.669)
<i>PIT</i>	0.307*	(0.164)	0.045	(0.388)	0.572	(0.256)
<i>PITSQ</i>	0.341**	(0.035)				
<i>FISRED</i>	1.351***	(0.000)	0.774**	(0.011)	0.121	(0.814)
<i>PIT*LDC</i>			-0.162**	(0.030)		
<i>FISR*LDC</i>					-0.425*	(0.162)
<i>GDP_{pc}</i>	0.004	(0.986)	0.007***	(0.000)	0.012*	(0.076)

p values are in parentheses. ***, ** and * demonstrate that the null is rejected at 1%, 5% and 10%, respectively

Table 2 Effect of PIT on income inequality for varying level of fiscal redistribution (1), corruption (2) and governance (3)

Variables	Statistic 1		Statistic 2		Statistic 3	
<i>GINI_{i,t-1}</i>	0.151*	(0.161)	0.581**	(0.003)	-0.118*	(0.165)
<i>PIT</i>	2.791*	(0.094)	0.072*	(0.181)	0.521*	(0.287)
<i>FISRED</i>	1.169	(0.372)	0.253	(0.127)	-0.309	(0.774)
<i>PIT*FISRED</i>	-0.877	(0.105)				
<i>CORRUPT</i>			0.011*	(0.064)		
<i>PIT*CORRU</i>			0.016*	(0.107)		
<i>GOV</i>					3.159	(0.475)
<i>PIT*GOV</i>					-1.581*	(0.109)
<i>GDP_{pc}</i>	0.035*	(0.160)	-0.005	(0.778)	-0.029	(0.308)

p values are in parentheses. ***, ** and * demonstrate that the null is rejected at 1%, 5% and 10%, respectively

The rest of empirical study involves a different estimation of model-1. This allows to investigate if there is a differentiated effect of PIT on inequality in LDCs (poor countries) against non-LDCs (non-poor countries).

We use the interaction of LDC dummy with PIT in model-1. And the findings are presented in column-2 of Table 1. We use the similar strategy to estimate if there is a differentiated impact of fiscal redistribution on income inequality in LDC against non-LDC and the findings are described in column-3 of Table 1. We also analyze how PIT and fiscal redistribution interact in affecting income inequality in SSA and the findings are described in column-1 of Table 2. To achieve this, we investigate a different estimation of model-1, which incorporates the interaction term of PIT and FISCREED and the findings are presented in column-1 of Table 2. Following the same procedure in column-2 and column-3 of Table 1, we finally, include corruption and governance variables, and their interaction with PIT to check if these variables

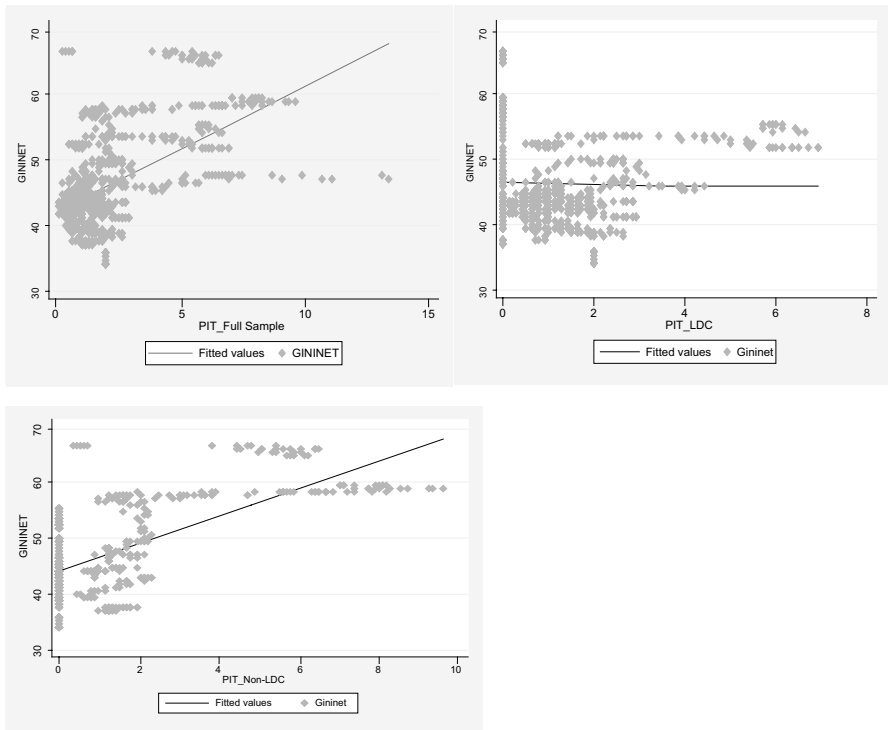


Fig. 1 PIT and INCOME INEQUALITY correlation pattern. Source: Author

influence the relationship between PIT and inequality in SSA and the findings are presented in column-2 and column-3 of Table 2, respectively.

Before interpreting our results, it is helpful to provide in Fig. 1 the scatter plot between PIT and income inequality for SSA, LDCs and non-LDCs. From Fig. 1, it can be seen that for SSA, the correlation pattern between PIT and income inequality is positive, while, it is moderately negative for LDCs and positive for non-LDCs. It is important to note that the negative correlation for LDCs does not imply a negative causal impact of PIT on income inequality, as the latter will be examined by the empirical study based on Eq. (2).

4.5 CS-ARDL results analysis

As it can be seen in all columns of the Tables that most of the lag-coefficient of the regressands are significantly positive, which shows the importance of inspecting the dynamic model-2 in the study, and indicate the existence of a mean reversion in inequality. This means that inequality will tend to converge to its average level over time. Let’s now discuss the results presented in columns 1–3 of Table 1. Findings in column-1 of Table 1 show an insignificant and positive relationship between PIT and income inequality. Our results in column-1 of Table 1 indicate that fiscal

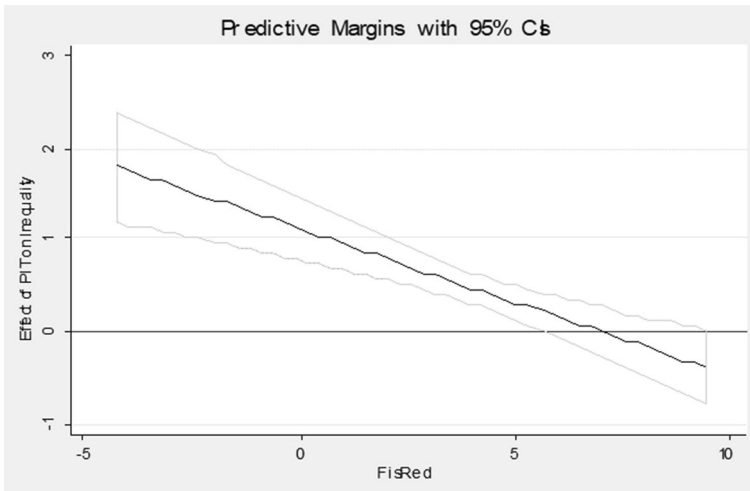


Fig. 2 Marginal effect of PIT on inequality for different amounts of redistribution. Source: Author

redistribution increases inequality, this may reflect the presence of differentiated impacts of fiscal redistribution on inequality across SSA countries in the full sample. Hence, from this finding, one can interpret that redistribution using fiscal instruments in SSA economies might not always help low income earners. Precisely, in the full sample, a 1% increase in fiscal redistribution is associated with 1.4% rise in inequality. Column-2 of Table 1 confirmed the significant positive impact of fiscal redistribution on inequality in SSA. However, column-2 of Table 1 indicates that the coefficients of both PIT and its squared are positive but only significant for PIT square. These findings show that not only does the PIT rises inequality in SSA, but also an additional rise in inequality is amplified by an additional rise in PIT. For instance, a 1 percent increase in the PIT induces a 0.648 ($0.341 + 0.307$) % (net effect)⁸ points increase in the inequality. Findings presented in column-2 reveal that the interaction term coefficient (LDC*PIT) is significantly negative at the 5% level while the coefficient of the PIT variable is significantly positive. Finally, results presented in column-3 reveal that fiscal redistribution negatively impact inequality in LDCs than in non-LDCs. This is demonstrated by significantly negative interaction term “LDC*FISCREd”. For LDCs and non-LDCs, the net impact of fiscal redistribution on inequality is equal to $-0.304 (= 0.121 - 0.425)$ and 0.121, respectively. This means that a 1% rise in fiscal redistribution lowers inequality by -0.304 in LDC but rise it by 0.121 in non-LDC.

It is worth recalling that the main coefficients in our study are the one for PIT and PIT*FISRED. Our results from Table 2 show that the former is significantly positive, while the latter is significantly negative. Following Eq. 2, the threshold is

⁸ To calculate the net effect of PIT on inequality, we only use PIT square coefficient by adding PIT coefficient as both are statistically significant at 5%.

3.182 (=2.791/0.877) and according to descriptive statistics¹⁰ results, this threshold value of FISRED falls between - 4.2 (min) and 9.4 (max). As the effects presented above change across countries in SSA, exhibit different magnitudes, signs and statistical significances across countries, we provide in Fig. 2 a full picture of how PIT influences income inequality for different levels of fiscal redistribution. Figure 2 presents this effect by showing at the 95% confidence intervals, the developments of the marginal effect of PIT on income inequality for different levels of fiscal redistribution. The marginal effects, which are statistically significant at the 95% confidence intervals are those incorporating only the lower and upper bounds of the confidence interval that are either below or above the zero line.

The Fig. 2 reveals the above results, as it indicates that the marginal impact of PIT on income inequality in SSA could be positive and negative, but reduces as the size of fiscal redistribution rises. And it takes negative and positive values but is not always significant. It is not significant for values of redistribution from 5.86 to 8.58. However, for amounts of redistribution from 5.86 to 8.58, PIT has insignificant impact on inequality. Inversely, PIT leads to higher inequality for amounts redistribution smaller than 5.86. This means that in economies which amount redistribution is smaller than 5.86, PIT significantly and positively affect inequality, and the lower the amount of fiscal redistribution, the bigger is the amount of the positive impact of PIT on inequality. However, economies whose amounts redistribution are bigger than 8.58 observe a negative impact of PIT on inequality.

The level of PIT seems to increase inequality in SSA. But why? In Table 1, we introduce PIT, its square and other variables which capture mechanisms whereby PIT has been thought to affect income inequality but the effect of PIT and its square on income inequality is still positive over the full sample. Indeed, when corruption and governance and their interactions with PIT (PIT*Corrupt and PIT*Gov) are included in Table 2 as additional controls, the results show that firstly the coefficient of interaction terms not only falls by more than half compared to that of PIT. Secondly, the relationship is weakly and statistically significant at 10% (not strongly significance). This shows that the impact of PIT on inequality is not only channeled through redistribution but it is also mainly channeled through these additional variables, whose coefficients reflect the indirect effects of PIT on inequality. And the results from Table 2 show that a 1% rise in corruption is linked with 0.011% rise in inequality.

Despite the positive relationship between corruption and inequality, the interaction term variable PIT*corruption also rises inequality. A 1% rise in PIT*corruption leads to a 0.016% rise in inequality while the net impact of corruption on inequality is 0.027% (0.011 + 0.016). Therefore, we conclude that the bigger the amount of corruption, the higher is the amount of the positive effect of PIT on inequality. The findings in column-3 of Table 2 indicate that the relationship between governance and inequality is insignificantly positive, while the relationship between the interaction term "PIT*Gov" and inequality becomes negative and statistically insignificant. By including the lag of governance in the equation, however, the interaction term becomes negative and statistically significant. A 1% rise in PIT*Gov leads to a 1.581% fall in inequality over time. The net effect of governance amounts to 1.581%. The negative and significant effect of the lag PIT*Gov reveal that a rise in

PIT combined with good governance in the previous year leads to inequality reduction in the current year. This means that the lag of interaction term tends to negatively affect inequality over time. While the coefficient of PIT remains positive in column-3 of Table 2, the one for fiscal redistribution becomes negative and insignificant for SSA. The insignificance of the coefficient of fiscal redistribution in column-3 of Table 2 may signify that the fiscal redistribution data are extremely noisy to produce significant findings.

The findings show that as the amount of governance rises, the amount of the positive impact of PIT on inequality reduces, and there is a threshold of governance beyond which the effect of PIT on income inequality turns into negative. Following Eq. 3, the threshold (turning point) amounts to 1.998 ($=3.159/1.581$), which falls between 0 (min) and 4 (max) value of governance as indicated in descriptive statistic results,⁹ our results confirm that the magnitude positive relationship between PIT and inequality reduces as a country increases in good governance.

4.6 Discussion of findings

Our results in column-1 of Table 1 indicate that fiscal redistribution increases inequality, this may reflect the presence of differentiated impacts of fiscal redistribution on inequality across SSA countries in the full sample. Hence, from this finding, one can interpret that redistribution using fiscal instruments in SSA economies might not always help low income earners. We also notice that PIT and additional level PIT significantly contribute to more inequality in SSA. These results violate the progressive taxation theory. And it can be seen that other factors such as corruption and governance could increase inequality in the region as explained below.

However, when we disaggregate our sample, the outcomes reveal that PIT affects negatively and significantly inequality in LDCs than non-LDCs. These signify that PIT reduces inequality in LDCs than non-LDCs. One of the reasons is that most of non-LDC in our sample are most of them from Southern Africa countries such as Namibia, South Africa. These countries are characterized by higher persistent level of inequality, compared to LDC such as Ethiopia and Uganda. This higher persistent level could be one of the factors, which tends to reduce the effectiveness of tax policy in alleviating inequality. This implies that government redistribution through transfers and taxes could not significantly lower a persistent inequality. The reason is that persistence in inequality is of structural rather than cyclical type. Thus, structural measures are required to handle the adverse impacts of increasing and persistent inequality (see Ghoshray et al. 2020).

However, fiscal redistribution decreases inequality in LDC, but rises it in non-LDC. However, it may be hard to elucidate this variation on the impact of fiscal redistribution in non-LDC and LDC in this study. One can elucidate this by the type of fiscal redistribution implemented by the policymakers of each country in LDC or non-LDC, but the findings can as well mask differentiated impacts of fiscal

⁹ Our descriptive statistic results are available upon request.

redistribution on inequality across countries within our sub-sample. For example, a country may suffer from two possible off-setting effects as shown by Berg et al. (2018): Redistribution is probably to lower the labor supply of higher income earners (by paying more tax) and lower income earners (by receiving more cash which lower their motivation of working). For example, one could say that South Africa (non-LDC that redistributes the most but it still remains the most unequal of all African countries) may experience moral hazard in double dimensions that discourage the incentive of working of both rich and poor. This disincentive of working coupled with corruption may absorb the negative relationship between fiscal redistribution and inequality. We also notice that findings regarding control variables¹⁰ are almost the same for Tables 1 and 2.

In column-1 of Table 2, this study examines the role of fiscal redistribution in affecting the relationship between PIT and inequality. The results demonstrate that PIT always increases in inequality in SSA, but the amount of the positive impact of PIT on inequality reduces as the amount of redistribution rises. This means that the bigger the amount of redistribution, the smaller is the amount of the positive impact of PIT on inequality. Despite levels of tax revenue and grants have been gradually rising in Africa, they are still far below than those in West Asian and developed economies. This small level decreases the fiscal flexibility in funding social spending, in Africa. An appropriate redistribution of the total tax burden toward the higher income earners via PIT and reallocations of government spending to support low income earners is a key for inequality reduction in SSA. This is in line with median voter hypothesis developed by Melter and Richard (1981), which states that if given the option to choose redistribution rationally, population will favor greater taxes and redistribution for those with higher incomes as the higher income inequality persists.

To understand the positive relationship between PIT and inequality, we include corruption and governance as an additional control variable. The findings reveal that corruption lead to higher inequality in SSA. This could be that corruption increases inequality by rising tax evasion (the tax burden falls almost on the poor via VAT), thus profiting the rich while also decreasing social spending intended to benefit the poor. This is confirmed by Gupta et al. (2002). Though corruption rises inequality, our results confirm that the magnitude positive relationship between PIT and inequality reduces as a country increases in good governance. We, therefore, conclude that good governance promotes good tax revenue collection, which is crucial for fiscal redistribution process to lower inequality as indicated by Bird and Zolt (2005).

5 Conclusions

We assess the impact of PIT and redistribution on inequality in SSA economies relying on CS-ARDL as it takes into account CSD, omitted variable bias and unobserved common factors with heterogeneous effects across countries. And we further

¹⁰ To avoid any issue of multi-collinearity among our predictors, this study omitted inflation from our results as it seems to have high correlation in the model.

consider the extent to which PIT and fiscal redistribution interact in affecting inequality in SSA economies. The results indicate for SSA that PIT increases inequality, and the amount of this increase is smaller for non-LDC. However, PIT reduces on inequality for LDCs. In addition, fiscal redistribution increases inequality in SSA, but it lowers inequality in LDCs, while rising it in non-LDCs. Attractively, PIT has a positive impact on inequality, while fiscal redistribution lowers the size of this positive impact of PIT on inequality. In addition, we also find that not only corruption affects positively inequality, but also the interaction term variable “PIT*corruption” is significantly positive in affecting inequality in SSA countries. However, while governance influences positively and insignificantly income inequality, the interaction term “PIT*Gov” affects negatively and insignificantly income inequality. When we include the lag of interaction term of PIT*Gov, the results become negative and statistically significant. We then conclude that as the amount of governance increases, the amount of the positive impact of PIT on inequality decreases over time.

Concerning policy recommendations, our results suggest that an appropriate and well-designed redistributive fiscal policy could be an effective tool for policymakers to reduce the positive impact of PIT on inequality in SSA, which are subject to corruption and bad governance etc. However, due to the fact that the type of such fiscal redistribution depends on each country, it could be hard for this study to show the type of fiscal redistribution that could reduce the positive impact of PIT on inequality in SSA countries. In this context, Lustig (2017) has shown that an appropriate recommendation in terms of redistribution measures is needed, including in SSA economies in order to avoid “fiscal impoverishment”. This means that after taxes and transfers incomes of the lower income earners should not be lower than their incomes before fiscal interventions. However, the above policy prescription should be complemented with anti-corruption measures and good governance policy. Anti-corruption measures may reduce inequality in the short run, while good governance policy takes time to lower inequality Kawanaka and Hazama (2016). With regard to study agenda, future scholars are suggested to expand this study at country levels.

Appendix

Full sample: Botswana, Ghana, Lesotho, Burkina Faso, Burundi, Ethiopia, Gambia, Madagascar, Malawi, Mali, Mauritius, Senegal, Swaziland, Cameroon, Central African Republic, Chad, Congo Rep, Côte d’Ivoire, Guinea-Bissau, Guinea, Kenya, Mozambique, Namibia, Niger, Tanzania, Sierra Leone, Uganda, Zambia, Zimbabwe, South Africa.

LDCs: Lesotho, Burkina Faso, Burundi, Ethiopia, Gambia, Madagascar, Malawi, Mali, Sierra Leone, Uganda, Central African Republic, Chad, Zambia, Guinea-Bissau, Guinea, Niger, Senegal.

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Declarations

Conflict of interest The authors declare no competing interests.

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References

- (2001) Les hauts revenus en France au XXe siècle: inégalités et redistributions, 1901–1998, Paris, Bernard Grasset
- Acemoglu D, Gallego FA, Robinson JA (2014) Institutions, human capital, and development. *Annual Rev Econ* 6:875–912. <https://doi.org/10.3386/w19933>
- Afonso A, Alves J (2017) Reconsidering Wagner's law: evidence from the functions of the government. *Appl Econ Lett* 24(5):346–350. <https://doi.org/10.1080/13504851.2016.1192267>
- Atkinson AB and Piketty T (2010) *Top Incomes: a Global Perspective*, Oxford, Oxford University Press.
- (2007), *Top Incomes over the Twentieth Century. A Contrast between Continental European and English-speaking Countries*, Oxford, Oxford University Press
- Atkinson AB (2014) After Piketty?, *The British Journal of Sociology*, vol. 65, No. 4, Wiley
- Bastagli F, Coady D, Gupta S (2012) *Income Inequality and Fiscal Policy*, 2nd Edition. IMF Staff Discussion Notes. SDN/12/08. 28 June 2012. <https://doi.org/10.5089/9781475510850.006>
- Berg A, Ostry JD, Charalambos G, Tsangarides CG, Yakhshilikov Y (2018) Redistribution, inequality, and growth: new evidence. *J Econ Growth* 23:259–305. <https://doi.org/10.1007/s10887-017-9150-2>
- Bird RM, Zolt EM (2005) 'Redistribution via taxation: the limited role of the personal income tax in developing countries. *UCLA Law Rev* 52(6):1627–1695
- Chan SG, Ramly Z (2018) The role of country governance on VAT and income inequality. *Ekonomie*. <https://doi.org/10.15240/tul/001/2018-4-006>
- Chudik A, Pesaran MH (2015) Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *J Econ* 188(2):393–420
- Clifton J, Díaz-Fuentes D, Revuelta J (2020) Falling inequality in Latin America: the role of fiscal policy. *J Latin Am Stud* 52:317–341
- Datt G, Ray R, The C (2022) Progressivity and redistributive effects of income taxes: evidence from India. *Emp Econ* 63:141–178. <https://doi.org/10.1007/s00181-021-02144-x>
- De Freitas J (2012) Inequality, the politics of redistribution and the tax mix. *Public Choice* 151(61):1–630
- Ditzen J (2019) Estimating long run effects in models with cross-sectional dependence using xtdece2. CEERP Working Paper No. 7. <https://ceerp.hw.ac.uk/RePEc/hwc/wpaper/007.pdf>
- Engle RF, Granger CWJ (1987) Co-integration and error correction: representation, estimation, and testing. *Econometrica* 55(2):251. <https://doi.org/10.2307/1913236>
- Espoir DK, Ngepah N (2021) Income distribution and total factor productivity: a cross country panel cointegration analysis. *IIEP* <https://doi.org/10.1007/s10368-021-00494-6>
- García JB, Giraldo MC (2018) Fiscal Policy and Inequality in CGE Model for Colombia
- Gbato A (2017) "Impact of Taxation on Growth in Sub-Saharan Africa:" New Evidence Based on a New Data Set. *International Journal of Economics and Finance*, 2017, 9, 10.5539/ijef.v9n11p173. hal-01673738.
- Ghoshray A, Monfort M, Ordóñez J (2020) Re- examining inequality persistence. *Economics. Open-Access, Open-Assessment E- J* 14:1–9. <https://doi.org/10.5018/economics-ejournal.ja.2020-1>

- Gnangnon SK (2021) Exchange rate pressure, fiscal redistribution and poverty in developing countries. *Econ Chang Restruct* 54:1173–1203. <https://doi.org/10.1007/s10644-020-09300-w>
- Gupta S, Davoodi H, Alonso-Terme R (2002) 'Does corruption affect income inequality and poverty?'. *Econ Gov* 3(1):23–45. <https://doi.org/10.1007/s101010100039>
- Im KS, Pesaran M, Shin Y (2003) Testing for unit roots in heterogeneous panels. *J Econom* 115(1):53–74. [https://doi.org/10.1016/S0304-4076\(03\)00092-7](https://doi.org/10.1016/S0304-4076(03)00092-7)
- IMF (2014) Fiscal policy and income inequality. IMF policy paper. <https://www.imf.org/external/np/pp/eng/2014/012314.pdf>
- Jenkins SP, Brandolini A, Micklewright J, Nolan B (eds) (2013) *The Great Recession and the Distribution of Household Income*. Oxford University Press, Oxford, Oxford
- Kaldor N (1956) Alternative theories of distribution. *Rev Econ Stud* 23(2):83–100
- Kawanaka T, Hazama Y (2016) Political determinants of income inequality in emerging democracies. *Springer Briefs Econ*. https://doi.org/10.1007/978-981-10-0257-1_5
- Lagravinesea R, Paolo Liberatib P, Sacchic A (2020) Tax buoyancy in OECD countries: New empirical evidence. *J Macroecon* 63(2020):103189. <https://doi.org/10.1016/j.jmacro.2020.103189>
- Levin A, Lin C-F, James Chu C-S (2002) Unit root tests in panel data: asymptotic and finite-sample properties. *J Econom* 108(1):1–24. [https://doi.org/10.1016/S0304-4076\(01\)00098-7](https://doi.org/10.1016/S0304-4076(01)00098-7)
- Lustig N (2017) Fiscal policy, income redistribution, and poverty reduction in low and middle-income countries. Center for Global Development working paper, (448)
- Maina WA (2017) The effect of consumption taxes on poverty and inequality in Kenya. *Int J Account Tax* 5(2):56–82
- Malla MH, Pathranarakul P (2022) Fiscal policy and income inequality: the critical role of institutional capacity. *Economies* 10:115
- Mankiw NG (2021) *Principles of economics*, 9th edn. Cengage Learning, Boston
- Mankiw NG, Weinzierl MC, Yagan DF (2009) Optimal taxation in theory and practice. *J Econ Perspect* 23(4):147–174
- Martínez-Vázquez J, Vulovic V, Moreno-Dodson B (2012) The impact of tax and expenditure policies on income distribution: evidence from a large panel of countries. *Hacienda Pública Española, IEF* 200(1):95–130
- Meltzer AH, Richard SF (1981) A rational theory of the size of government. *J Polit Econ* 89(5):914–927
- Meo MS, Nathaniel SP, Khan MM, Nisar QA, Fatima T (2023) Does temperature contribute to environment degradation? Pakistani experience based on nonlinear bounds testing approach. *Glob Bus Rev* 24(3):535–549
- Mirrlees JA (1971) An exploration in the theory of optimal income taxation. *Rev Econ Stud* 38(114):175–208. <https://doi.org/10.2307/2296779>
- Musgrave RA (1959) *The theory of public finance*. McGraw Hill Book Co., New York, pp 532–541
- Oboh T, Emoronsale PE (2018) Taxation and income inequality in Nigeria. *NG J Social Dev* <https://doi.org/10.12816/0046771>
- Pesaran MH (2006) Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica* 74(4):967–1012
- Pesaran MH (2007) A simple panel unit root test in the presence of cross-section dependence. *J Appl Econom* 22(2):265–312. <https://doi.org/10.1002/jae.951>
- Pesaran MH (2015) Testing weak cross-sectional dependence in large panels. *Economet Rev* 34(6–10):1089–1117. <https://doi.org/10.1080/07474938.2014.956623>
- Pesaran M, Smith R (1995) Estimating long-run relationships from dynamic heterogeneous panels. *J Econom* 68(1):79–113. [https://doi.org/10.1016/0304-4076\(94\)01644-F](https://doi.org/10.1016/0304-4076(94)01644-F)
- Pesaran MH, Shin Y, Smith RP (1999) Pooled mean group estimation of dynamic heterogeneous panels. *J Am Stat Assoc* 94(446):621–634. <https://doi.org/10.1080/01621459.1999.10474156>
- Pesaran MH (2004) General diagnostic tests for cross section dependence in panels. Technical Report. CESifo Group Munich
- Piketty T (2014) *Capital in the twenty-first century*. Harvard University Press
- Piketty T (2015) Putting distribution back at the center of economics: reflections on capital in the Twenty-First Century”, *The Journal of Economic Perspectives*, vol. 29, No. 1, Nashville, Tennessee, American Economic Association
- Poterba J (2007) Income inequality and income taxation. *Journal of Policy Modeling* 29:623–633
- Ravallion M, and Chen S (2021) Is That really a kuznets curve? turning points for income inequality in China. (No. W29199; NBER Working Paper Series). <https://doi.org/10.3386/w29199>

- Sadorsky P (2014) The effect of urbanization and industrialization on energy use in emerging economies: implications for sustainable development. *Am J Econ Sociol* 73(2):392–409. <https://doi.org/10.1111/ajes.12072>
- Saijo H (2020) Redistribution and fiscal uncertainty shocks. *Int Econ Rev*. <https://doi.org/10.1111/iere.12449>
- Solt F (2019) Measuring income inequality across countries and over time: the standardized world income inequality database. SWIID Version 8.0, February 2019
- Westerlund J (2007) Testing for error correction in panel data. *Oxford Bull Econ Stat* 69(6):709–748
- Mohd Zulkhairi Mustapha¹, Eric H. Y. Koh², Sok-Gee Chan^{3*}, Zulkufly Ramly⁴. (2017). The Role of Corruption Control in Moderating the Relationship Between Value Added Tax and Income Inequality. *Int J Econ Finan Issues*. 7(4): 459–467

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