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Financial deepening on income inequality: A quantitative meta-analysis study

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ABSTRACT

There exists a vast empirical literature on Financial Sector Development (FSD) and the income inequality nexus; however, it lacks consensus. To study this, 24 studies with 87 regression estimates on financial institution depth and income inequality were collected. This paper used the most common method of economic meta-analysis, the Partial Correlation Coefficient (PCC), to answer the question: What is the magnitude and impact, if any, of financial institution depth on income inequality? In addition, a multivariate meta-regression model was used to find moderator variables that produced mixed results in the literature. The results show that the global average comovement of financial institution depth (domestic credit) on income inequality is very small but positive; suggesting that growth in domestic credit may widen income inequality. The positive correlation between domestic credit and income inequality highlights how financial institutions use household income and collateral as a signal when deciding on credit applications. Finally, the multivariate regression results suggest that the present heterogeneity within the literature stems from different methodologies and control variables included in the econometric models, and panel studies that mix countries with heterogeneous characteristics. These suggest that different components of FSD may impact income inequality differently.

KEYWORDS

income inequality, financial sector development, domestic credit, meta-analysis

JEL CLASSIFICATION

D63, G20, O11

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1. INTRODUCTION

The financial sector represents institutions, instruments, markets, and legal and regulatory systems providing a channel for credit and savings transactions. A developed financial sector is characterized by reduced cost and increased efficiency, sufficient domestic credit to Gross Domestic Product (GDP; depth), and access to financial services for most adults (Mbona 2022). Financial Sector Development (FSD) shapes income inequality through access to credit for human capital or business financing. This paper aims to conduct a meta-analysis study that only focuses on one of the three broad measures of financial development, namely financial institution depth. The World Bank defines financial institution depth as the size of financial institutions relative to the economy. Financial institution depth is proxied by private credit relative to GDP. Thus, this study quantifies the impact of financial institution depth on income inequality. This is motivated by the available literature on financial sector depth and income inequality, which shows contradicting results in terms of the magnitudes and direction of the impact. Thus, the meta-analysis technique is useful in consolidating these results and providing a conclusion on the magnitude and direction of the impact.

Meta-analysis entails collecting statistical data from empirical studies that answer questions similar or the same as the research questions. The main components of meta-analysis include computing effect size, exploring heterogeneity amongst studies, and investigating publication bias or small-study effects on the results. The multivariate meta-regression produces results on moderator variables, which are found to explain heterogeneity in the empirical results from past studies.

This paper aims to answer the following research questions: What is the impact size (magnitude) of financial institutions' depth on income inequality? Does growth in financial institution depth increase or decrease, or has no impact on income inequality? What are the causes of the mixed results seen in the literature?

Subsequently, the rest of the paper is structured as follows: Section 2 provides a brief theoretical and empirical literature review on FSD and income inequality. Section 3 describes how the data was selected and collected for analysis. Section 4 focuses on the applied methodology, models for computing effect size and presents the meta-analysis summary results. Section 5 presents the multivariate regression method, its results, and the results of the publication bias test. Section 6 concludes the study.

2. THEORETICAL AND EMPIRICAL LITERATURE

The basic theories on the relationship between financial sector development and income inequality were laid down by Banerjee and Newman (1993), Galor and Zeira (1993), Greenwood and Jovanovic (1996), Zingales and Rajan (2003), Tan and Law (2012). The presence of asymmetric information and imperfect loan contracts between financial institutions and borrowers impacts credit availability. Banerjee and Newman (1993) and Galor and Zeira (1993) argue that credit expansions and relaxed credit constraints as the financial sector develops will narrow income inequality. While the finance widening inequality theory introduced by Zingales and Rajan (2003) suggests individuals who are credit constrained generally have limited access to collateral and wealth, making them excluded from formal financial services. A recent study by Mbona and Major (2023) shows that individuals with low income, education, and no mobile phone are excluded from the formal financial sector in selected developing nations.

The Greenwood and Jovanovic (1996) suggest going beyond the linear relationship by testing a nonlinear relationship (squared term of FSD). The nonlinear channel between financial sector depth and income inequality from Greenwood and Jovanovic (1996) was inverted U-shaped, but a new shape emerged as a simple U-shaped curve (Tan – Law 2012).

There is a large and growing empirical literature testing the four theories above on the impacts of financial development on income inequality (Banerjee – Newman 1993; Galor – Zeira 1993; Greenwood – Jovanovic 1996; Zingales – Rajan 2003; Tan – Law 2012). The mixed empirical literature on FSD and income inequality is classified into two broader theories, namely the linear and nonlinear finance-inequality nexus.

Figure 1 summarises the four theories on financial sector development and income inequality. Subsequently, the next subsections discuss the empirical literature testing these theories. The finance narrowing inequality nexus suggests an increase in financial access reduces inequality (Burgees – Pande 2005; Demirguc et al. 2008; Liang 2008; Batuo et al. 2010; Dabla-Norris et al. 2015; Kapingura 2017). Increased access to financial services and a better loan market has found to reduce income inequality in 22 African countries (Batuo et al. 2010). In India, more bank branches in rural areas versus urban areas reduce income inequality (Burgess – Pande 2005). While other studies suggest that an efficient financial sector reduces inequality by allocating financial resources across households and businesses without imposing unnecessary rent on them (Banerjee – Newman 1993; Galor – Zeira, 1993). The evidence for the financial narrowing nexus is also found in stable economies and financial environments, mainly developed countries (Fig. 2).

The finance widening inequality nexus suggests that an imperfect credit market excludes poor households from financial opportunities, and thus financial development increases income inequality (Zingales – Rajan 2003; Wahid et al. 2012; Jaumotte et al. 2013; Seven – Coskun 2016; Chiu-Lee 2019). This strand of literature postulates that growth in financial sector depth (domestic credit) tends to benefit mostly the rich household with collateral and good credit score, while the poor and unbanked households get no or limited credit (Zingales – Rajan 2003). Others found that income inequality increases with financial globalization and foreign direct investment as the latter tend to invest in the highly skilled labour force (Jaumotte et al. 2013). Others further found evidence of the finance widening hypothesis in unstable economies (Chiu – Lee 2019). Better quality institutions are necessary to correct the widening finance-inequality hypothesis.

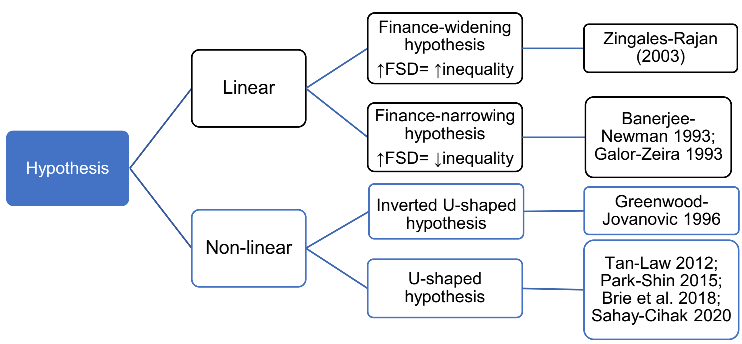

Fig. 1. Summary of the empirical literature on finance-inequality theories
***Source:* author.**

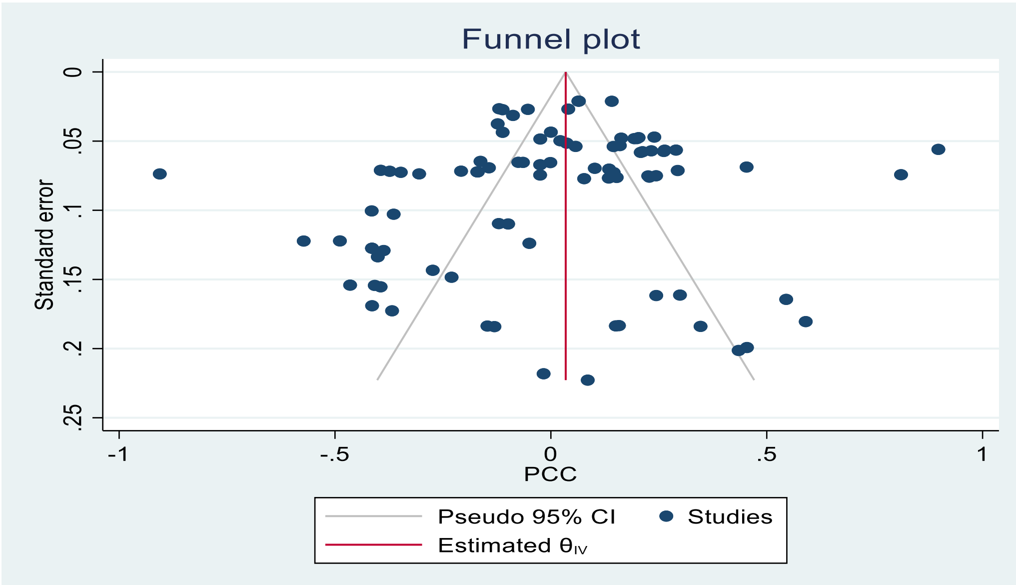

Fig. 2. Funnel plot for publication bias
Source: author.

The nonlinear inverted U-shaped nexus is the finance-inequality Kuznets relationship suggested by Greenwood and Jovanic (1996). The inverted U-shaped hypothesis claims that income inequality first increases in the early stages of financial development and later inequality decrease as FSD gets to mature stages (Batuo et al. 2010; Shahbaz et al. 2015; Nguyen et al. 2019; Younsi – Bechtini 2020; Mbona 2022). This is because an unorganized market characterizes the early stages of financial development, while at mature stages, the financial sector is more efficient and has higher levels of financial access. The inverted U-shaped nexus has been confirmed in Brazil, Russia, India, China, and South Africa (BRICS) based on data from 1995 to 2015 (Younsi – Bechtini 2020), in 21 emerging market economies (Nguyeni et al. 2019), and in Iran (Shahbaz et al. 2015).

The nonlinear U-shaped nexus is a new strand of the literature and has been confirmed on the impacts of financial sector depth (domestic credit) on income inequality (Park – Shin 2015; Sahay et al. 2015; Mbona 2022). The empirical literature on this strand suggests that when financial institutions possess relatively lower levels of domestic credit as a share of GDP, there are reducing factors on income inequality. However, once a certain threshold on domestic credit levels is reached, growth in domestic credit produces widening effects on income inequality (Park – Shin 2015). The threshold of the nonlinear model is usually around the sample mean of financial development (Park – Shin 2015). The U-shaped nexus is confirmed worldwide; for example, it was confirmed in 162 countries by Park and Shin (2015).

Evidence of the U-shaped finance-inequality nexus supports the too much finance hypothesis. This is because higher levels of domestic credit do not translate into higher levels of domestic credit per capita, as access to credit correlates with income levels. For instance, financial institutions use the income levels of businesses and households when deciding on loan applications. There is also evidence that businesses granted loans tend to grow faster than those rejected for loans (Delis et al. 2014).

The above sections provided a brief literature review on financial sector development and income inequality. For extensive theoretical and empirical literature on this topic, please review Mbona (2022). The four strands of the dense literature suggest that there is no agreement in the regarding the impact of FSD on income inequality. Subsequently, a meta-analysis study will be conducted to close the gap in the literature by finding a rule of thumb for the impact of financial development on inequality.

3. DATA AND METHODS

3.1. Data

This paper contributes to the literature by trying to answer this research question: What is the global average impact of financial institution depth on income inequality? I attempt to answer this question by utilizing a meta-analysis method. There are seven steps followed when conducting a meta-analysis. The first step; define the research question. Second, determine study eligibility criteria: which studies should be included in the search? The third step is to conduct the search using keywords; the fourth step is to collect the data. In the fifth step, we calculate the effect size and estimate the multivariate regression in the sixth. Lastly, a test on publication bias in the topic is conducted, which addresses steps 1 to 4 of the abovementioned meta-analysis.

Step 2 is one of the essential steps in conducting a meta-analysis. In this step, the researcher determines study eligibility criteria, i.e. makes a decision on which studies to include from the broad literature on financial development and income inequality. Proxy variables measuring financial institution depth include domestic credit to GDP, M2 to GDP, pension, and mutual fund assets as a share of GDP. This study focuses only on one measure of financial institution depth, domestic credit as a share of GDP. Domestic credit as a share of GDP is the most preferred measure for financial deepening, and it refers to the size of financial institutions to GDP. This study also focuses on one income inequality measure: the Gini index. The Gini index shows the share of the population against the income share received. It ranges from 0 to 1, where 0 represents perfect equality, and 1 is perfect inequality. In collecting data for meta-analysis, only studies employing the Gini index (both after-tax and before-tax) will be considered.

Data was collected from the available literature on financial sector development and income inequality. This literature can be grouped into two broader categories: the linear and nonlinear models. This study focused only on the linear models (Equation 1). Within the linear model approach, the literature branches into two hypotheses: the finance-inequality narrowing hypothesis and the widening hypothesis. Subsequently, Equation (1) is presented in the panel data structure, but removing "*i*" can transform the equation into a time-series, while removing "*t*" leads to and cross-sectional format.

$$\text{Inequality}_{\text{it}} = \beta_0 + \beta_1 \text{FSD}_{\text{it}} + \beta_2 X_{\text{it}} + \varepsilon_{\text{it}} \tag{1}$$

Where "*i*" and "*t*" represent country and time, respectively, income inequality is measured by the Gini index. FSD is financial institution depth measured as domestic credit to the private sector ratio to GDP. X is a set of control variables, which tend to account for other driving factors of income inequality and level of FSD, including GDP per capita, education proxies, trade openness, urban/growth in population, and macroeconomic stability such as monetary and fiscal policy. The former is captured by the consumer price index (CPI) or inflation, and the latter by government spending as a share of GDP. Finally, ε is an error term.

This study used an online bibliographic database (ideas.repec.org or IDEAS) and Google Scholar to search for literature using the following keywords: 'financial sector development/ financial sector' and 'income inequality'. IDEAS is one of the largest databases for economic literature, which was supplemented with peer-reviewed articles on Google Scholar. Both journal publications and working papers were considered as they were deemed to represent the quality of the study. Working papers, economic policy institution working papers, and top-rank journals of economics, finance, and development were included to avoid sample publication bias. The number of citations of each study included in the data set for meta-analysis indicated the quality of the studies.

The literature search yielded 35 papers using the keywords mentioned above. From these papers, 24 were selected as they had empirical results on the impacts of financial depth (domestic credit) and income inequality. The meta-analysis data is based on these covers 2004 to 2021. Data on the 24 studies, including authors and title, the journal name, the number of citations suggested by Google Scholar, and the publication date can be found in Appendix A.

3.2. Methods

3.2.1. Calculating the effect of size. A meta-analysis study quantifies how a parameter of interest, such as the impact of financial depth, varies across the estimates from different studies (Wardman 2022). Thus meta-analysis is well suited for explaining how the impact of financial depth on income inequality varies. From the six step presented above, this section focuses on step 5, which discusses the method used to calculate the effect size. Approaches to calculating the effect size include using means, binary data (2x2 matrix), and correlations (Borestein et al. 2021). The magnitude of the impact size of financial sector depth on income inequality is calculated using partial correlation coefficients (PCC). The standardized PCC method is the most used in economic meta-analysis. The PCC method is used rather than the average (mean) of the estimated coefficients from the selected studies because different studies use different units of measurement (e.g., log of domestic credit or domestic credit), making the estimates presented not directly comparable (Heimberger 2020). This study used Equation (2) to calculate a PCC, which measures the impact of domestic credit on income inequality while holding other factors fixed. Since I consider studies based on time series, cross-sectional and panel studies, the PCC is an attractive method for meta-analysis. Meta-analysis based on the mean is limiting as not all studies publish full descriptive statistics. PCC is a standardized method for comparing and summarising effect size across various studies (Heimberger 2020; Havranek et al. 2013). The PCC method relies on the *t*-statistics of the regression estimates and their respective degrees of freedom (df).

$$\mathrm{PCC}_{ij} = t_{ij} \,/\sqrt{t_{ij}^2 + \mathrm{df}_{ij}} \tag{2}$$

Where "*i*" represents the regression estimate and "*j*" represents the study id. In this study, "*i*" sum up to 87 econometric models, and "*j*" sum up to 24 studies. To ensure these econometric models are comparable, only models estimating the impact of financial depth on income inequality were considered. The dependent variable, income inequality, was measured only as the Gini index (net and market), and the explanatory variable, financial sector depth, was measured only as domestic credit as a share of GDP. Standardized PCC is a better method for summarising these coefficients into one because though the data is strictly collected based on these two variables of interest, some econometric models used the log of these variables while others did not; thus, PCC was the ideal method in this case. The 87 econometric results (β_1) on the impact of domestic credit on the Gini index from the 24 studies are presented in Appendix B and D, showing how many models were taken from each study. For example, a single paper can have 4 econometric models based on explanatory variables or methods. t is the t-statistics from the regression "i" and study "j" and "df" is the corresponding degrees of freedom. The PCC sign remains identical to that of β_1 in Equation (1). In other words, the t-value used in the PCC reflects the sign of the coefficient (β_1). PCC is easy to compare as they range from -1 to 1. Subsequently, the study needed to compute corresponding standard errors (SE) using Equation (3) to conduct the meta-analysis technique.

$$\mathrm{SEpcc}_{ij} = \mathrm{PCC}_{ij} / t_{ij} \tag{3}$$

Where SEpcc_{ij} is the standard error of the PCC_{ij}, again, "t" is the t-statistics as in Equation (2). This study utilized Equations (1–3) in estimating the PCC for effect size, where the inverse of variance was used as a weight on each estimation, as done by Heimberger (2020) and Havranek et al. (2013).

3.2.2. Modelling the effect size in stata. There are three models to be considered under PCC modelling in Stata: Random, Common, and Fixed effect models. These three PCC models, mainly the weights assigned, differ in their underlying assumptions. The Common Effect (CE) model assumes that different empirical studies employ the same underlying parameters and have the same effect sizes, implying that variability in studies stems from sampling errors. The Fixed Effects (FE) model assumes mixed and different effect sizes from the collected studies. FE only bases the inference on collected studies, thus assuming these studies define the whole population of interest. The effect sizes are weighted with the inverse variance in the CE and FE model. Finally, the Random Effect (RE) model assumes different effect sizes, with studies collected from a large population randomly. It thus shows inference for a population of studies from the randomly collected ones. The RE model goes beyond sampling variability by estimating heterogeneity parameters (between-study variance) among the collected studies. This paper uses the restricted maximum likelihood (REML) method to estimate the heterogeneous parameter. REML is an iterative method and assumes that the distribution of random effects is normal. RE model weights are calculated as the inverse of the total variance (which includes the heterogeneity parameter).

4. RESULTS

4.1. Meta-Analysis summary results

The results (Table 1) answer the following questions: (1) How much is the magnitude of the impact of financial depth on income inequality? In other words, how much does domestic credit

Table 1. Meta-analysis results

Observations				
Number of studies				24
Number of estimates				87
Median PCC				4.4E−11
	Averages	**95% Confidence Interval**		***P*-value**
Unweighted simple PCC	−0.00196			
Fixed-effects PCC	0.034359	0.023	0.046	0
Common-effect PCC	0.034359	0.023	0.046	0
Random-effects PCC	0.000219	−0.063	0.063	0.995

Source: author.

affect income inequality? (2) What is the impact of domestic credit on income inequality – does it increase or decrease or has no impact on income inequality?

Table 1 presents summary statistics for overall effect sizes (average PCC) based on RE, FE, and CE models. Under the null hypothesis test that Theta = 0, the p-value is 0 in the FE & CE model, implying that the overall impact size of financial institution depth is statistically significantly different from zero. The FE and CE model yields a PCC of 0.034 and is significant at 1%, suggesting a weak and positive relationship between financial institution depth and income inequality. The FE and CE PCC differs from the RE PCC, as the RE model assumes that heterogeneity among the effect sizes is random and unobservable. The RE model presents the meta-analysis summary results, which also show heterogeneity statistics.[1]

Regarding the collected studies' homogeneity, the Q test is 1272.92 with a p-value of 0.00. The I^2 result is 96.25, which suggests that about 96% of the variability in the reported effect size stems from the difference between studies and their respective regressions. We can conclude from the Q test and I^2 that these results show strong heterogeneity amongst the studies and their respective regressions.

From Table 1, it can be inferred that the magnitude of the impact of financial institution depth (effect size) on income inequality is small, ranging between 0.022% and 3.4% (PCC averages from FE, CE, and RE models). According to Stanley et al. (2013), a correlation of this magnitude is weak. Finally, the results in Table 1 confirm a small and positive effect size, suggesting that financial institution depth increases income inequality. These results are in line with the findings of Delis et al. (2014). The positive relationship between financial depth (domestic credit) and income inequality highlights the significance of income levels on credit applications, as income is used as a signal on credit applications (Mbona 2022). In addition, countries with a higher level of inequality face widening inequality as domestic credit increases, since credit tends to be distributed unevenly towards the top income group with collateral and

[1] A full detailed model results, as well as data and the Stata do file can be found on Github: https://github.com/nokumbona/Financial-deepening-on-income-inequality-A-quantitative-meta-analysis-study.

high credit scores. It is worth noting that domestic credit is one of many components of FSD, and other components, such as access and efficiency of the financial sector, are praised for reducing income inequality. Also, according to the literature, domestic credit increases income inequality without increased access to financial services. Increased access to financial services allows poor households to be incorporated into the formal economy, allows the unbanked to be banked, and thus start building credit scores. Additionally, FSD also has positive economic growth impacts across the globe.

4.2. Multivariate meta-regression

There is strong evidence of heterogeneity among the studies and their respective results. As such, this study proceeds by performing a multivariate meta-regression. The literature on FSD and income inequality lacks consensus, which motivated this line of research. The heterogeneity in the literature is mainly because of the following characteristics:

- use of different measurements of FSD (mainly broader proxies);
- applied methodology;
- the geographical region of studies includes heterogeneity in levels of development and income levels;
- data structures: sample periods applied in the study;
- control variables;
- the gap between the interest rate and GDP growth;

Benczur and Kvedara (2021) investigated the relationship between financial deepening and income inequality in developed economies. Their study suggests that the gap between the interest rate and GDP growth explains the mixed results in the empirical literature on financial deepening and income inequality. This is because the impact of financial deepening on income inequality is conditional and dependent on the size of financial penetration. Thus, inequality increases when growth in domestic credit (deepening) is accompanied by growth in interest that is larger than GDP growth (Benczur – Kvedara 2021). Subsequently, they found that if the gap between the interest rate and GDP growth is negative, growth in domestic credit reduces income inequality (Benczur – Kvedara 2021).

To estimate the multivariate regression results, the study assumed that the PCC of the "*i*th" estimate from study "*j*" is also influenced by a vector (Z_{ki}), which includes control variables and the above characteristics that explain differences in the underlying relationship between income inequality and financial sector depth. This assumption allows us to accommodate the above characteristics.

$$\mathrm{PCC}_{ij} = \beta 0 + \Sigma \beta \mathrm{k} \mathrm{Zk} ij + \mathrm{e} ij \tag{4}$$

Equation (4) is adopted from Heimberger (2020), a study on a meta-analysis of economic globalization and income inequality. Meta-regression is useful in explaining study heterogeneity, as it shows the impact of moderator variables (study characteristics) on effect size. To estimate Equation (4), the study used the same data to calculate the effect size as in section 4.1. The effect size is calculated using the coefficient of domestic credit on Gini (beta 1 in Equation 1). However, when estimating the multivariate regression, the study looked at other factors included in the 87 estimates. Appendix B and D provides the full data set used from the 24 collected studies. In the full data set, there are 5 moderator variables: the methodology used in the econometric models, data type, geographic location of the study, transformation on Gini or not, and number of control variables in the econometric models. For example, two studies may find contradicting results on finance deepening and inequality due to the geographic region of the studies or the methodologies used in the two studies. These 5 moderator variables (Z_{ki}) are expected to be the core causes of the mixed results in the literature; thus, they are encoded into numbers using Stata, allowing us to be able to estimate (Z_{ki}) in the multivariate regression model. This study does not consider the different measures of FSD as the collected 24 studies and their 87 regression only used domestic credit to measure FSD.

Table 2 below presents the results of multivariate meta-regression, where all models have the PCC as the effect size and the RE model is applied. These results aim to investigate the contribution of moderator variables in the different estimation results reported in the selected studies. The reported I^2 statistic (last row of Table 2) ranges between 95.46% and 95.92%, suggesting high levels of heterogeneity. Thus around 96% of the variability is explained by with-in-study variation. The adjusted R-squared variable in Table 2 shows the share of

Table 2. Multivariate meta-regression results

	Model 1	Model 2	Model 3	Model 4
Constant	−0.764***	−0.390*	−0.349**	−0.824***
	(0.22)	(0.21)	(0.168)	(0.258)
Number of control variables	0.0289**		0.016	0.0317**
	(0.0134)		(0.013)	(0.013)
Dummies for dependent variables				
Gini index	0.690***			0.652***
	(0.214)			(0.225)
Growth of Gini	0.710***			0.58**
	(0.218)			(0.238)
Log Gini	0.471**			0.477**
	(0.218)			(0.225)
Dummies variables for type of methodology	No	Yes	No	No
Dummies variables for data structure	No	No	Yes	No
Dummies variables for geographic location	No	No	No	Yes
Observations	87	87	87	87
R-squared (%)	7.42	3.11	7.74	11.47
I^2 (%)	95.9	95.51	95.86	95.46

Standard errors in parentheses, ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.
Source: author.

between-study variance as defined by the covariance of the included moderator variables in the respective models.

The results in Table 2 confirm that at a 10% significant level, heterogeneity seen in the finance-inequality literature stems from chosen methodology, the number of control variables in the regression model, the data structure (panel), and the geographical region of the study. Models 1 and 4 of Table 2 show that transforming the dependent variable (Gini index) has a positive and significant impact (at 5%) on the estimates of between-study heterogeneity. In models 1 and 4, the coefficient for the log of the Gini index is around 0.47, while the growth and raw Gini index have a coefficient ranging between 0.58 and 0.71. So, choosing the log of the Gini index as a dependent variable yields a lower effect from FSD than using the raw Gini index or growth in the Gini index. This suggests the transformation of the dependent variable may be relevant. In terms of methodology dummies, at 5% and 10% significant levels, only the FE, RE, SURE GMM, and IV models significantly moderate the impact of domestic credit on income inequality (model 2 in Table 2). In other words, choosing econometric models is important in this nexus, as FSD and income inequality also have a bidirectional relationship. Thus, the results are mixed as some models account for heterogeneity while others do not.

Adding to this, the results on the structures of data (model 3) show that at the 10% significance level, only panel data structure produces heterogeneity in the finance-inequality literature. This is because studies on time series tend to focus on a single country, unlike panel studies which can be based on many countries with different characteristics. Lastly, model 4 shows that studies or econometric regression conducted on countries with mixed characteristics and those conducted on emerging market countries produce mixed findings in the literature. This is because when econometric estimation is based on countries with different characteristics, some countries may dominate the model and, thus, the results. The results from models 2, 3, and 4 suggest that studies on the finance-inequality nexus should also include econometric analysis based on regions with similar income levels, as grouping countries with heterogeneous characteristics produces mixed results. While panel studies focusing on developed countries agree on the finance narrowing hypothesis, this study has not tested for these effects. Time-series studies have mixed results, suggesting the impact of FSD on inequality also depends on individual country characteristics, which tend to influence both inequality and FSD.

4.3. Publication bias

This subsection explores whether the literature on financial institution depth and income inequality is contaminated by publication selection bias. This meta-analysis step determines whether published studies are chosen based on the preferred sign of the parameter (the sign of the β1 from equation 1) and based on statistical significance (Stanley et al. 2013). The motive for publication bias can be because of the global positive sentiments regarding FSD. Publication bias may produce a blurry picture of the underlying relationship between financial institution depth and income inequality. This study employs the funnel plot to visualize evidence of publication bias in the selected 24 studies and their 87 respective estimates. The funnel plot is the most frequently applied graphical visualization of publication bias. The funnel plot is a scatterplot visualizing effect sizes (PCC) against measures of study precisions.

The funnel plot suggests there may be evidence of publication bias, as most of the studies (and their estimated regression) are randomly scattered outside the confidence interval region

Table 3. Regression-based Egger test for small-study effects

Random-effects model	
Method: REML	
H0: beta 1 = 0; No small-study effects	
Beta 1	−0.73
SE of beta 1	0.645
Z	−1.13
P-value	0.2589

Source: author.

and do not resemble a funnel shape. Importantly, the results of the funnel plot may imply the presence of publication bias or other reasons (heterogeneity), as the RE model results suggested higher levels of heterogeneity in the regression. The presence of funnel plot asymmetry/publication bias could be attributed to the large variability between studies. Thus, the last step is to test for publication bias/funnel plot asymmetry using a regression-based test. The Egger (1997) test investigates the connection between study effect size and study precision. From Table 3, the regression slope is represented by Beta 1, which describes the asymmetry of the funnel plot and shows the magnitude of the small study effects.

Table 3 shows that Beta 1 equals −0.73, with a Z-test of −1.13 and a *p*-value of 0.258. Thus, the study cannot reject the null hypothesis of panel plot symmetry (H0: Beta 1 = 0; no small-study effects), and thus it is concluded that there is no evidence of publication bias in the literature on financial depth-inequality nexus. However, there is strong evidence of heterogeneity amongst the studies and their respective coefficients.

5. CONCLUSION

The basic theories on financial sector development and income inequality lie in how capital market imperfection affects access to human capital financing and capital investment. The dense empirical literature on FSD and income inequality lacks agreement. This study performed a comprehensive meta-analysis of 87 regression models from 24 selected studies covering 18 years. The study aimed to find the magnitude and impact of financial institution depth on income inequality. The studies from the literature were selected based on the measurement variables of inequality (Gini index) and financial institution depth (domestic credit as a share of GDP). The study relied on Stata and employed the RE and FE models to calculate the PCC.

The meta-summary analysis results show that financial institution depth positively impacts income inequality, but the magnitude of the impact is very small. Thus, the results suggest that growth in financial institution depth increases income inequality by a small amount. This is because a positive correlation exists between domestic credit and income, as a household's income is used as a signal for credit application decisions. However, these conclusions do not imply that FSD is bad, as FSD is praised for its positive contribution to economic growth.

Additionally, FSD can reduce income inequality when there is growth in excess to financial services and when the financial sector is efficient. This suggests that different components of FSD may impact income inequality differently. The study found no evidence of publication bias on this topic.

Finally, the multivariate meta-regression aimed to find/quantify moderator variables that produced mixed results in the literature. The results show strong evidence of high heterogeneity in past studies on financial institution deepening and income inequality. The results suggest that the different signs and magnitude of financial sector depth coefficients reported in the literature come from different methodologies applied in past papers. Subsequently, studies focussing on developed countries tend to agree and confirm the narrowing relationship between domestic credit and income inequality.

For FSD to reduce inequality, policies on financial reforms should emphasize increasing access to financial services. This is because access to financial services promotes the participation of poor households in economic activity and helps reduce the economic vulnerability of these households. This study leaves the global impact size of financial access to inequality for future research, as panel data on this nexus started in 2004, and thus empirical results are still limited.

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Appendices

Appendix A. Meta analysis data, 24 studies

Study ID	Author	Year	Title	Journal	Number of Citations[2]
1	Kapingura	2017	Financial sector development and income inequality in South Africa	African Journal of Economic and Management Studies	20
2	Beck et al.	2004	Finance, Inequality, and Poverty: Cross-Country Evidence	NBER Working Papers	923
3	Clarke et al.	2006	Finance and Income Inequality: What Do the Data Tell Us?	Southern Economic Journal	770
4	Liang	2006	Financial Development and Income Inequality in Rural China 1991–2000	UNU-WIDER paper	8
5	Prete	2013	Economic literacy, inequality, and financial development	Economics Letters	37
6	Ali et al.	2021	Revisiting Financial Inclusion and Income Inequality Nexus: Evidences from Selected Economies in Asia	The Journal of Asian Finance, Economics and Business	5
7	Wahid et al.	2012	Does Financial Sector Development Increase Income Inequality? Some Econometric Evidence from Bangladesh	Indian Economic Review	29
8	Jaumotte et al.	2008	Rising income inequality: technology, or trade and financial globalization?	IMF Economic review	865
9	Seven and Coskun	2016	Does financial development reduce income inequality and poverty? Evidence from emerging countries.	Emerging Market Review	272
10	Shahbaz and Islam	2011	Financial development and income inequality in Pakistan: An application of ARDL approach.	Journal of Economic Development	219

(continued)

[2]Citations based on Google Scholar.

Continued

Study ID	Author	Year	Title	Journal	Number of Citations[2]
11	Shahbaz et al.	2014	Financial development and income inequality: is there any financial Kuznets curve in Iran?	Social Indicators Research	149
12	de Haan and Sturm	2017	Finance and income inequality: A review and new evidence	European Journal of Political Economy	465
13	Kim and Lin	2011	Nonlinearity in the financial development–income inequality nexus	Journal of Comparative Economics	263
14	Tan and Law	2011	Nonlinear dynamics of the finance-inequality nexus in developing countries	The Journal of Economic Inequality	154
15	Weychert	2020	Financial development and income inequality.	Central European economic Journal	16
16	Le and Nguyen	2019	Financial development and income inequality in emerging markets: a new approach	Journal of Risk and Financial Management	32
17	Olohunlana and Dauda	2019	Financial development and economic growth in Africa: Lessons and prospects.	Business and Economic Research,	38
18	Nasreddine and Mensi	2016	Financial development and income inequality: The linear versus the nonlinear hypothesis.	Economics Bulletin	16
19	Majeed,Tariq	2013	Inequality, Financial Development and Government: Evidence from Low-Income Developing Countries.	Munich Personal RePEc Archive	4
20	Rosemy and Masih	2017	What is the link between financial development and income inequality? evidence from Malaysia.	Munich Personal RePEc Archive	22
21	Serafim	2021	Financial deepening, stock market, inequality and poverty: some african evidence	REM Working Paper	
22	Sugiyanto and Zefania	2020	The effect of financial deepening on economic growth, inequality, and poverty: Evidence from 73 Countries.	South East European Journal of Economics and Business	8

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Study ID	Author	Year	Title	Journal	Number of Citations[2]
23	Zhang and Naceur	2019	Financial development, inequality, and poverty: Some international evidence	International Review of Economics and Finance	318
24	Hsieh et al.	2019	Financial structure, bank competition and income inequality.	The North American Journal of Economics and Finance	32

Source: author.

Appendix B. Meta-data

How to read Appendix B.

Study ID corresponds to the Study ID in Appendix A. So for example, Study ID number 1 refers to Kapingura (2017). The next two columns show the sample period which the respective study uses in the analysis. The following column shows how many regression estimates were taken from each study, while the next column gives an exact reference to these. The column following this provides details on methodology. The methodologies used in the collected studies are: ARDL: Autoregressive Distributed Lag, GMM: Generalized Method of Moments, OLS: Ordinary Least Squares, IV: Instrumental Variable; RE: Random Effects, FE: Fixed Effects, 2SLS: Two-Stage Least-Squares Regression; SUR: Seemingly Unrelated Regressions, ECM: Error Correction Model; GLS: Generalized Least Squares; PMG: Pooled Mean Group. For time series studies we have a clear geographic point of the county of analysis in the study. While some studies took homogenous countries in terms of development levels or income levels others used a mix of heterogeneous countries. The Gini index is the dependent variable in all of the chosen 87 econometric models, but some studies used the Gini index as it is and others transformed Gini index to logs or growth rates; this is shown in the last but one column. The final column shows how many control variables the models use. These ranged from 2 to 7. Readers wishing to read more, or replicate or expand the this study are encouraged to download the full data set and Stata codes used in the analysis from the author's GitHub.

Study ID	Sample period start -end date of data sample		Number of regression estimate	Reference for the econometric estimates for each study	The methodology used in the econometric models	Data type	Geographic location of the study	Transformation of Gini	Number of control variables in the econometric models
1	1990	2012	3	Table 6; Model 1, 2 & Table 7	ARDL	Time series	South Africa	Gini	Yes
2	1960	1999	5	Table 4, model 1,2,3,4,5	OLS & IV	Panel	Developed & developing countries	Growth Gini	Yes
3	1960	1995	6	Table 2, 3, & 4: model 1 & 5	OLS, 2SLS, RE, &IV	Cross-Sectional Panel	Developed & developing countries	Log Gini	Yes
4	1991	2000	4	Table 3, Model 1–4	GMM	Panel	Chine's province	Log Gini	Yes
5	1980	2005	6	Table 2, Model 1, -6	OLS	Panel	Mixed	Growth Gini	Yes
6	1997	2017	1	Table 3, model F	GMM	Panel	Asian countries	Gini	Yes
7	1985	2006	2	Table 4 &Table 5 model 1	ARDL	Time series	Bangladeshi	Gini	Yes
8	1981	2003	6	Table 1, model 1–6	SUR & IV	Panel	20 Developed and 31 developing	Log Gini	Yes
9	1987	2011	7	Table 2, model 1–7	OLS & GMM	Panel	Emerging countries	Growth Gini	Yes
10	1971	2005	2	Table 4 & 5, model 1	ARDL & ECM	Time series	Pakistan	Log Gini	Yes
11	1965	2011	2	Table 5 & 6, model 1	ECM ARDL	Time series	Iran	Log Gini, Change in log of Gini	Yes
12	1975	2005	7	Table 1, model 2, 4–9	GMM, FE	Panel	Mixed	Gini	Yes

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Study ID	Sample period start -end date of data sample		Number of regression estimate	Reference for the econometric estimates for each study	The methodology used in the econometric models	Data type	Geographic location of the study	Transformation of Gini	Number of control variables in the econometric models
13	1960	2005	6	Table 1 & 2, model 1–2	IV Threshold	Panel	Mixed	Growth Gini	Yes
14	1980	2000	2	Table 1, model 1 and Table 3 model 1	GMM	Panel	Mixed/EM	Gini	Yes
15	2003	2014	3	Table 1, model 1 & 6	FE	Panel	Mixed	GINI	Yes
16	2002	2016	2	Table 2, model 1	GMM	Panel	Vietnam provinces	Gini	Yes
17	1996	2017	2	Table 6 & 7	ARDL	Time series	Nigeria	Gini	Yes
18	1980	2012	5	Table 3, 4,5,6 & 7 model 1	GLS & RE	Panel	138 countries grouped by income level	Gini	Yes
19	1970	2008	4	Table 5.1 model 2,3,4 & 6	OLS	Panel	Low-income developing countries	Log Gini	Yes
20	1970	2007	2	Table 4.2 & 4.3, model 1	ARDL	Time series	Malaysia	Gini	Yes
21	1992	2018	4	Table 5, model 1, 2, 3 & 4	PMG-ARDL	Panel	9 African countries	Gini	Yes
22	1991	2015	1	Table 4.2, model 1	FE	Panel	32 Advanced & 41 EME countries	Gini	Yes

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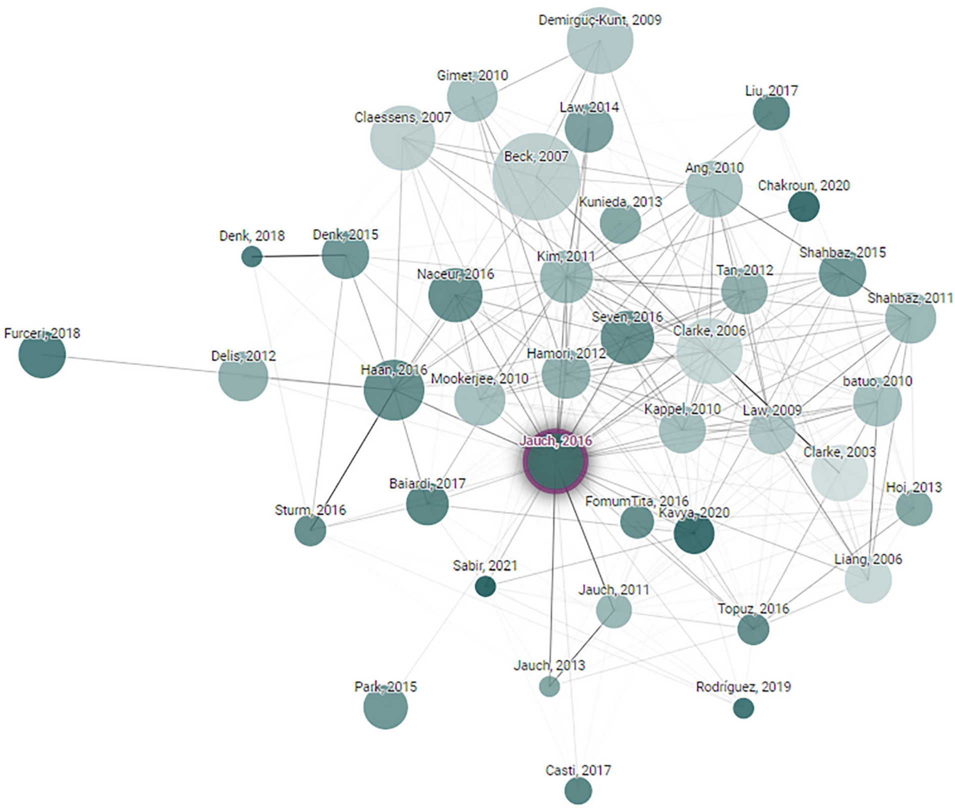
Study ID	Sample period start -end date of data sample		Number of regression estimate	Reference for the econometric estimates for each study	The methodology used in the econometric models	Data type	Geographic location of the study	Transformation of Gini	Number of control variables in the econometric models
23	1961	2011	3	Table 4, model 1 & 2, Table 8, model 3	OLS & IV	Panel	143 Developing and developed countries	Gini	Yes
24	1989	2014	2	Table 2, model 1 & 2	CUP-FM	Panel	86 Developed and developing countries	Gini	Yes

Source: author.

Appendix C. Studies on financial sector development and income inequality

The figure presents further connected papers, derived by searching the topic financial sector development and income inequality. This study only focused on one measure of financial sector development namely depth (domestic credit). As a results, not all the studies in the diagram below were selected for the analysis, mainly because they used different measurements of financial sector depth and income inequality. However, almost half of the studies in this diagram are included in this meta-analysis study.



Source: author.

Appendix D. Coefficients on the impact of financial institution depth on income inequality

Author	Year	Study_id	i_regression_estimate	Coefficient	Sample_size	No_countries	Data_type	Geographic	Methodology	Dependent_Var
Kapingura	2017	1	1	−0.0012	22	1	Time series	South Africa	ARDL	Gini
		1	2	−0.11	44	2	Time series	South Africa	ARDL	Gini
		1	3	−0.007	66	3	Time series	South Africa	ECM	Change Gini
Beck et al.	2004	2	1	−0.004	52	52	Panel	Developed & developing countries	OLS	Growth Gini
		2	2	−0.015	52	52	Panel	Developed & developing countries	IV	Growth Gini
		2	3	−0.013	52	52	Panel	Developed & developing countries	IV	Growth Gini
		2	4	−0.013	52	52	Panel	Developed & developing countries	IV	Growth Gini
		2	5	−0.015	48	**48**	Panel	Developed & developing countries	IV	Growth Gini
Clarke et al.	2006	3	1	−0.053	83	83	Cross-Sectional	Developed & developing countries	OLS	Log Gini
		3	2	−0.3133	83	83	Cross-Sectional	Developed & developing countries	2SLS	Log Gini
		3	3	−0.0456	83	83	Cross-Sectional	Developed & developing countries	OLS	Log Gini
		3	4	−0.266	83	83	Cross-Sectional	Developed & developing countries	2SLS	Log Gini
		3	5	0.0291	205	83	Panel	Developed & developing countries	RE	Log Gini
		3	6	−0.114	205	83	Panel	Developed & developing countries	IV RE	Log Gini
Liang	2006	4	1	−0.0383	168	21	Panel	Chines province	GMM	Log Gini
		4	2	−0.0358	168	21	Panel	Chines province	GMM	Log Gini

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Author	Year	Study_id	i_regression_estimate	Coefficient	Sample_size	No_countries	Data_type	Geographic	Methodology	Dependent_Var
		4	3	−0.0309	168	21	Panel	Chines province	GMM	Log Gini
		4	4	−0.0315	168	21	Panel	Chines province	GMM	Log Gini
Prete	2013	5	1	−0.006	30	30	Panel	Mixed	OLS	Growth Gini
		5	2	−0.005	30	30	Panel	Mixed	OLS	Growth Gini
		5	3	−0.003	30	30	Panel	Mixed	OLS	Growth Gini
		5	4	−0.002	30	30	Panel	Mixed	OLS	Growth Gini
		5	5	0.011	30	30	Panel	Mixed	OLS	Growth Gini
		5	6	0.011	30	30	Panel	Mixed	OLS	Growth Gini
Ali et al.	2021	6	1	0.12	378	18	Panel	Asian countries	GMM	Gini
Wahid et al.	2012	7	1	0.171	21	1	Time series	Bangladeshi	ARDL	Gini
		7	2	0.2073	21	1	Time series	Bangladeshi	ARDL	Change Gini
Jaumotte et al.	2008	8	1	0.063	292	51	Panel	20 Developed and 31 developing	SURE	Log Gini
		8	2	0.052	288	51	Panel	20 Developed and 31 developing	SURE	Log Gini
		8	3	0.054	292	51	Panel	20 Developed and 31 developing	SURE	Log Gini
		8	4	0.053	288	51	Panel	20 Developed and 31 developing	SURE	Log Gini
		8	5	0.05	283	51	Panel	20 Developed and 31 developing	SURE	Log Gini
		8	6	0.068	284	51	Panel	20 Developed and 31 developing	IV	Log Gini
Seven and Coskun	2016	9	1	−0.001	181	45	Panel	Emerging countries	OLS	Growth Gini
		9	2	0.006	169	45	Panel	Emerging countries	OLS	Growth Gini
		9	3	0.007	168	45	Panel	Emerging countries	OLS	Growth Gini
		9	4	0.003	168	45	Panel	Emerging countries	OLS	Growth Gini

(continued)

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Author	Year	Study_id	i_regression_estimate	Coefficient	Sample_size	No_countries	Data_type	Geographic	Methodology	Dependent_Var
		9	5	0.231	181	45	Panel	Emerging countries	GMM	Growth Gini
		9	6	0.389	169	45	Panel	Emerging countries	GMM	Growth Gini
		9	7	0.0617	168	45	Panel	Emerging countries	GMM	Growth Gini
Shahbaz and Islam	2011	10	1	−0.1221	34	1	Time series	Pakistan	ARDL	Log Gini
		10	2	−0.0167	34	1	Time series	Pakistan	ECM ARDL	Change log Gini
Shahbaz et al.	2014	11	1	−0.2529	46	1	Time series	Iran	ARDL	Log Gini
		11	2	−0.0975	46	1	Time series	Iran	ECM ARDL	Change log Gini
de Haan and Sturm	2017	12	1	0.0652	426	121	Panel	Mixed	GMM	Gini
		12	2	0.0518	426	121	Panel	Mixed	FE	Gini
		12	3	−0.0168	426	121	Panel	Mixed	FE	Gini
		12	4	0.0349	426	121	Panel	Mixed	FE	Gini
		12	5	0.0297	345	121	Panel	Mixed	FE	Gini
		12	6	0.0464	345	121	Panel	Mixed	FE	Gini
		12	7	0.0247	338	121	Panel	Mixed	FE	Gini
Kim and Lin	2011	13	1	0.2901	27	60	Panel	Mixed	IV Threshold	Growth Gini
		13	2	−0.695	36	60	Panel	Mixed	IV Threshold	Growth Gini
		13	3	0.4139	63	63	Panel	Mixed	IV Threshold	Growth Gini
		13	4	1.0979	27	27	Panel	Mixed	IV Threshold	Growth Gini
		13	5	−0.6382	36	36	Panel	Mixed	IV Threshold	Growth Gini
		13	6	0.4297	63	63	Panel	Mixed	IV Threshold	Growth Gini
Tan and Law	2011	14	1	−0.0055	700	35	Panel	Mixed/EM	GMM	Gini
		14	2	−0.0051	520	33	Panel	Mixed/EM	GMM	Gini
Weychert	2020	15	1	0.02	186	53	Panel	Mixed	FE	GINI

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Author	Year	Study_id	i_regression_estimate	Coefficient	Sample_size	No_countries	Data_type	Geographic	Methodology	Dependent_Var
		15	2	0.03	165	53	Panel	Mixed	FE	GINI
		15	3	0.03	169	53	Panel	Mixed	FE	GINI
Le and Nguyen	2019	16	1	0.0023	415	60	Panel	Vietnam provinces	GMM	Gini
		16	2	0.0022	415	60	Panel	Vietnam provinces	GMM	Gini
Olohunlana and Dauda	2019	17	1	−0.059534	21	1	Time series	Nigeria	ARDL	Gini
		17	2	0.016704	21	1	Time series	Nigeria	ARDL	Gini
Nasreddine and Mensi	2016	18	1	−0.25	2184	138	Panel	138 Countries with Heterogenous GDP levels/Classified groups into 4 income levels	GLS	Gini
		18	2	0.04	200	138	Panel	Low Income countries	RE	Gini
		18	3	0.004	405	138	Panel	Average Income countries	RE	Gini
		18	4	0.00002	529	138	Panel	Upper-Middle income	FE	Gini
		18	5	−0.01	1005	138	Panel	High income countries	GLS	Gini
Tariq	2013	19	1	−0.01	223	50	Panel	Low-income developing countries	OLS	Log Gini
		19	2	−0.06	187	50	Panel	Low-income developing countries	OLS	Log Gini
		19	3	−0.05	187	50	Panel	Low-income developing countries	OLS	Log Gini
		19	4	−0.05	187	50	Panel	Low-income developing countries	OLS	Log Gini
Rosemy and Masih	2017	20	1	0.08	37	1	Time series	Malaysia	ARDL	Gini
		20	2	0.018	36	1	Time series	Malaysia	ARDL	Gini
Serafim	2021	21	1	−0.168	234	9	Panel	9 African countries	PMG-ARDL	Gini
		21	2	−0.202	234	9	Panel	9 African countries	PMG-ARDL	Gini

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Author	Year	Study_id	i_regression_estimate	Coefficient	Sample_size	No_countries	Data_type	Geographic	Methodology	Dependent_Var
		21	3	−0.285	234	9	Panel	9 African countries	PMG-ARDL	Gini
		21	4	−0.0004	234	9	Panel	9 African countries	PMG-ARDL	Gini
Sugiyanto and Zefania	2020	22	1	0.006	1386	73	Panel	32 Advanced economies and 41 EMDE	FE	Gini
Zhang and Naceur	2019	23	1	−0.045	1393	143	Panel	143 Developing and developed countries	OLS	Gini
		23	2	−0.041	1328	143	Panel	143 Developing and developed countries	IV	Gini
		23	3	−0.059	1364	143	Panel	143 Developing and developed countries	IV	Gini
Hsieh et al.	2019	24	1	0.027	2236	83	Panel	86 Developed and developing countries	CUP-FM	Gini
		24	2	0.027	2236	83	Panel	86 Developed and developing countries	CUP-FM	Gini

Source: author.