Effects of Financial Sector Development on Income Inequality

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LIST OF ABBREVIATIONS

AM	Advanced Markets
BRICS	Brazil Russia India China South Africa
BC	Business Correspondent
CE	Common Effect
CPI	Consumer Price Index
EME	Emerging market economies
FD	Financial Development index
FIA	Financial Institution Access Index
FID	Financial Institution Depth Index
FI	Financial Institutions Index
FMA	Financial Market Access Index
FMD	Financial Market Depth Index
FM	Financial Markets Index
FSD	Financial Sector Development
FDI	Foreign Direct Investment
GMM	Generalised Method of Moments
GDP	Gross Domestic Product
IPS	Im-Pesaran-Shin
IMF	International Monetary Fund
LIML	Limited Maximum Likelihood
LIC	Low-income countries
OLS	Ordinary Least Square
MFI	Micro-Finance Institutions
PCC	Partial Correlation Coefficients
PPP	Purchasing Power Parity
RE	Random Effect
REML	Restricted Maximum Likelihood
SWIID	Standardized World Income Inequality Database
SDGs	Sustainable Development Goals

WG	Within Groups
WDI	World Development Indicator
WGI	Worldwide Governance Indicator

1 INTRODUCTION

This chapter first introduces and links the three central articles forming this dissertation on Financial Sector Development (FSD) and income inequality. Its goal is to describe the research problem, define the research questions, and highlight the significance of the study. This thesis links three articles with a common theme on FSD and income inequality. In essence, each of the three articles consisting of this article-based thesis addresses its own research questions, which are, in the end, interlinked to the paradigm of FSD and income distribution. As such the three articles are related to the central theme because they explore FSD and income distribution and are different in the sense that they individually explore different data and different empirical methodologies. Of these three articles, two were single-authored (Articles 1 & 2), and one was co-authored with Major Klara (Article 3). The three articles answer different research questions, have 3 different titles, and are not numbered based on the date of publication but rather in the order of the research questions of this thesis. Article 1 is titled "Impacts of Overall Financial Development, Access and Depth on Income Inequality", and Article 2 is titled " Financial Deepening on Income Inequality: A Quantitative Meta-Analysis Study". Article 3 is titled " Determinants of using formal vs informal financial sector in BRICS group".

Increasing income inequality is generally referred to as rising income differences, where the rich get richer at a faster pace than the poor. Economic inequality, which refers to monetary inequality, can be analysed from the perspective of wealth and or income inequality. At the same time, inequality of outcome can also be measured by income, wealth, and expenditure. Inequality of opportunities refers to the unfair distribution of opportunities and, thus, outcome, as household circumstances are beyond individuals' control. Examples of inequality of opportunity include gender, ethnicity, place of birth and family background. All the types of inequality are related and provide different information on the phenomenal. In this thesis, the focus is sorely on income inequality and how it is affected by financial sector development. This is because income has direct effects on households' consumption and is often a concern of policymakers.

There are various measures of income inequality, e.g., Gini coefficient, Theil index, and distribution tables showing the share of different deciles and centiles in total income. The Gini coefficient is the most widely used measure of monetary income inequality (Batuo, Guidi and Mlambo 2010; Brie, Ferri and Gambacorta 2018; Demirgüç-Kunt, Beck and Honohan 2008; Dabla-Norris et al.,2015). The Gini coefficient tracks changes in the income share of individuals, with a range from 0 to 1. A Gini value above zero is an indication of an unequal income distribution. The highest Gini coefficient (one) denotes an unequal income distribution (one person takes all income), while zero means a perfectly equal income distribution (same income for all).

Using Standardized World Income Inequality Database (SWIID) data from 145 countries, Darvas (2019) demonstrates that between 1988 to 2015, global income inequality declined by 9.2 Gini points. Darvas (2019) developed a novel numerical method to decompose changes in global and regional Gini coefficients into three branches, the within-country inequality, the between-country inequality and relative population size. The calculations of Darvas (2019) show that between the 1988 to 2015 period, within-country inequality first increased and gradually fell after the year 2007, demonstrating an average decline in within-country net inequality since 2007. Darvas (2019) also shows that population size increased global Gini by 1,3 Gini points between 1988 and 2015. In essence, the global Gini coefficient decline seen between 1988 to 2015 was driven by convergence in the per capita income, however, we do not see large declines in global Gini mainly due to increases in within-country inequalities coupled with population growth of poor and high unequal nations (Darvas, 2019).

The SWIID data of the 120 countries investigated in Chapter 2 of the thesis, shows between the years 2004 to 2019, the after-tax Gini coefficients of advanced economies remained below 0.4. In Europe, countries like Denmark, Spain, Croatia, and Romania recorded an increase in after-tax Gini between 2019 and 2004, however, the after-tax inequality of these countries remained below 0.4. Over the same period, the after-tax Gini coefficients for emerging market economies and low-income countries fluctuated mostly below 0.5, with countries like Brazil, Colombia, Panama and Peru moving away from above 0.5 Gini points to below 0.5. For example, between the years 2004 to 2015, the after-tax Gini coefficient of India had an average of 0.486, with the inequality of India increasing by 0.049 Gini points. Between 2004 and 2019, China also recorded an increase of 0.035 points in after-tax Gini coefficients, with a mean of 0.4228 over the same period. However, on average, income inequality remains stubbly high in Sub-Sahara Africa, with Namibia and South Africa having the highest Gini coefficient hovering around 0.67 and 0.63, respectively. The level of inequality in Namibia and South Africa are persistently high over the 2004 to 2019 period. Inequalities of Rwanda, Zambia and Côte d'Ivoire also remained above 0.5 but below 0.6 over the same period. Africa's population accounts for a larger share of the world population, and the increase in these countries' inequality pushes up the global Gini, however, since most other countries in the world are experiencing declines or constant low levels of Gini (below 0.4) there has not been a global increase in after-tax Gini between 2004 and 2019.

A general synthesis of the literature on income inequality postulates that wage income, which is associated with a skills premium (Bhorat, Van der Westhuizen, and Jacobs 2009; Francese and Granados 2015), has been the main driver of income inequality worldwide. Rising income inequality from the skills premium is explained mainly by human capital development. The main argument is that an increase in education increases the skilled labour supply, pushing down the relative wage of the skilled, leading to declining income inequality (Friedman, Heckman, and Krueger 2003; Batuo, Guidi and Mlambo 2010). However, skills premium can increase income inequality when the supply of skilled labour is smaller than the supply of unskilled labour in the country. Progressive personal income tax, corporate income tax policies, and social transfers are praised for their contribution to reducing income inequality (Guvenen, Kuruscu and Ozkan, 2009; Park and Shin, 2009; Dabla-Norris et al.,2015). Tax policies and cash transfers differ by country in terms of size; thus, so will the impact across the globe. Income inequality is also explained by several other social economic factors such as inequality of opportunities (e.g., social and income mobility) and duration of unemployment. For instance, higher levels of income inequality, coupled with lower human capital investment for low-income households, are unfavourable for mobility. Adding to the above drivers of inequality, the International Monetary Fund (IMF), noted by Dabla−Norris, Kochhar, Suphaphiphat, Ricka, and Tsounta (2015), asserts the following drivers of higher income inequality across the globe just as these factors also contributed to positive economic growth. These drivers include but are not limited to:

(i) Technological changes: New technology drives up demand for capital and skilled labour, simultaneously eliminating unskilled labour by replacing them with automation. This change thus increases skill premium, which results in increased labour income inequality. In other words, technological change would increase income inequality when the demand for skilled labour exceeds the supply of skilled labour.

(ii) Labour market institutions: These are an essential factor because labour market regulations such as unionisation, social security, and minimum wage improve income inequality. Thus, the absence or lessening of these regulations can increase income inequality and is more pronounced in advanced economies (Dabla-Norris et al., 2015).

(iii) Increased trade openness/globalization: Empirical evidence asserts that the average increase in trade has a long-term positive impact on economic growth. However, the benefits have not been spread globally, as low integration into global markets left many Latin American and Caribbean countries behind (Beaton, Cebotari and Komaromi, 2017). As such, without vigorous growth, income inequality grew. Dabla-Norris et al. (2015) also argued that the impact of trade openness on inequality greatly depends on the countries' relative factor abundance and production capacity.

(iv) Foreign Direct Investment (FDI): An increase in FDI and portfolio flow increases income inequality in emerging and advanced economies (Freeman 2010; Dabla-Norris et al.2015). This is explained by the concentration of these funds on high skills and technology−intensive sectors, which again lift the skills premium (Dong, 2014).

(v) Financial sector development: Financial deepening and an inclusive financial sector are essential, as the absence of this could increase income inequality. Individuals with higher income and/or assets can largely access finance, which will increase skills premium and rent on capital (Banerjee and Newman, 1993; Galor and Zeira, 1993; Dabla−Norris et al.,2015).

While there is large literature on income inequality and other factors discussed above, the literature on financial sector development (FSD) and income inequality lacks consensus. Generally, financial sector development is concerned with associated costs in the sector. Subsequently, increases in financial institution mergers and acquisitions indirectly increase competition and innovation and thus improve efficiency, i.e. cost of banking. Empirical literature postulates that financial sector development significantly contributes to economic development and poverty reduction. Goldsmith (1969) and Levine (2004) argues that financial sector development endorses economic growth as it results in an increased pool of saving and mobilised savings, with eased access to investment information. Financial development also promotes the inflows of foreign capital. At the same time, advanced economies are leading in terms of financial sector development while developing countries are catching up.

1.1 Problem statement

Increasing income inequality has been at the forefront of public debate. For instance, alleviating income inequality is goal number ten of the Sustainable Development Goals (SDGs) for the 2030 Agenda of the United Nations. Subsequently, policymakers worldwide are concerned about the economic and social consequences of rising income inequality. At the same time, financial sector development has been on the rise, growing in terms of credit, volumes of trade and geographical presence. In addition, the UN Secretary-General's high-level panel on the post-2015 Millennium Development Goals (MDGs) recommended bank accounts for females and increased access to financial services as an enabling target for economic growth, poverty, and inequality alleviation. As such, FSD and financial inclusion are key tools for addressing the UN SGD goals: poverty (SDG-1), gender equality (SDG-5), and reducing inequality (SGD-10).

Borderless banks in the present era continue to prosper; it is natural to study their effects on income distribution as FSD also affects income inequality through the composition of labour demand, access to finance human capital, and rent from capita. In addition, literature also suggests that top-income groups tend to hold more financial assets/investments, while middle-income groups invest in property with little investment in financial assets. The literature on the effects of FSD on income inequality lacks consensus, some say FSD is beneficiary, while others say it's harmful to income inequality, and others argue that there is a threshold beyond which growth in FSD may increase or decrease income inequality. However, as Demirguc-Kunt and Levine (2009) highlighted, the literature lacks a consensus, and to close the gap, they state that further empirical evidence is needed. The grounds for further research lie in finding precise measures or rules of thumb for the impact of FSD on inequality and growth. This is because the theory mirrors a skeleton of inequality trends due to imperfect credit markets. The major limitation of the previous studies is that they use financial institution depth measures as a proxy of aggregated FSD indicators. Financial depth alone does not consider the complex dimensions of FSD, making it hard to conclude on FSD's effects on income inequality. As such, the grounds for further research lie in finding precise measures or rules of thumb for the impact of aggregated and alternative FSD indicators on inequality. The findings are important for policy reforms on financial sector development and income inequality.

1.2 Research questions

This thesis answered 7 research questions, which were divided into three articles making this thesis. As such, Article 1 (chapter 2 of the thesis) answers two questions:

1. What are the effects of overall (aggregated) financial sector development on income inequality?
2. How does increased access to financial services and increase in financial depth affect income inequality?

Empirical results from these questions can be informative for financial sector reform and fair shared prosperity. Thereafter, Article 2 (chapter 3 of the thesis) uses meta-analysis to quantify the mixed and large literature on FSD and inequality by answering three questions:

3. What is the magnitude of the effect of financial institutions' depth on income inequality?
4. Does growth in financial institutions increase or decrease or have no correlation with income inequality?
5. What are the causes of the mixed results seen in the literature? Question 5 is addressed using the multivariate meta-regression method.

Lastly, the study connects the use of formal and informal financial sectors (financial inclusion) in Article 3 (chapter 4 of the thesis) by answering the following questions:

6. What are the factors determining financial inclusion in BRICS countries?
7. What are the factors determining the choice of either formal or informal financial services in the BRICS countries for savings and borrowing?

1.3 Significance of the study

The literature on financial sector development (FSD) and income inequality lacks consensus. Different methodologies, different levels of development/income, and different proxy measures of the FSD and income inequality bring about mixed empirical results. Some say FSD reduces income inequality through increased access to the sector. Others suggest that FSD increases inequality due to institutions and imperfect credit markets. Subsequently, the debate on testing the nonlinear relationship between FSD and income inequality endures. Park and Shin (2015) also argue that the since FSD has the nonlinear relationship with economic growth, it makes sense to also include the nonlinear term to see the benefits and harmful effects of FSD on income inequality.

Some argue that FSD is beneficial but up until a threshold and beyond, which FSD has an increasing effect on income distribution (Tan and Law, 2012; Park and Shin,2015). Another strand of the literature says beyond the threshold, inequality declines (Greenwood and Jovanovic, 1990). By testing both the linear and nonlinear models, the thesis captured complex patterns in the data and captured threshold effects in the non-linear models.

This thesis contributes to the literature by using recent data from 2004-2019 and provides a comprehensive comparison of the estimated effects of different FSD indicators on both before and after-tax income inequality. Secondly, this thesis contributes towards finding a size or impact factor between FSD and income inequality by using quantitative meta-analysis. The meta-analysis is based on, twenty-four studies where eighty-seven regression estimates on financial institution depth and income inequality were collected. Thirdly, this thesis also takes account of the inclusion in both the formal and informal financial sector especially for emerging market economies. Specifically, the study looked at the determinants of using the formal vs the informal financial sector in the BRICS nations. As such, the novelty of Article 3, chapter 4 of the thesis is the use of the most recent 2021 comprehensive database, which also covers the period of COVID-19. In chapter 4, the thesis contributes to the literature by using individual level data which shares light on both the formal and informal financial sector, as literature on the informal sector is limited.

1.4 Overview of chapters in Thesis

Chapter 1: Lays the introduction of the thesis. This chapter first introduces and links the three central articles forming this dissertation on Financial Sector Development (FSD) and income inequality. Its goal is to describe the research problem, define the research questions, and highlight the significance of the study.

Chapter 2: Focuses on Article 1, the effects of overall FSD on income inequality. Furthermore, the main theoretical and empirical literature summary on the theme of financial sector development and income inequality is presented. The goal of section 2.2 is to familiarise the reader briefly with the central theories and literature of this thesis (mainly Chapters 2 and 3).

Chapter 3: Presents Article 2, where the focus is drawn on one measure of FSD. The goal of this chapter is to find the global effect size of financial institution depth on inequality. Chapter 4 of the thesis is based on Article 3, which dives into the financial inclusion component of FSD.

Chapter 5 presents the thesis conclusions. Chapter 6 lists of publications of the discussed articles forming this thesis.

2 IMPACTS OF OVERALL FINANCIAL DEVELOPMENT, ACCESS, AND DEPTH ON INCOME INEQUALITY: ARTICLE 1

2.1 Introduction

Chapter two of this thesis focuses on Article 1, titled the impacts of overall financial development, access, and depth on income inequality. As such, chapter two begins with the theoretical and empirical literature on the effects of financial sector development on income inequality. Thereafter, the methods used to test FSD effects on income inequality are presented, and subsequently the data used for the analysis is also presented. The chapter proceeds with empirical results, paired with the discussion of the results. Finally, chapter two concludes the empirical findings of the chapter and provide relevant policy implications of the chapter.

2.2 Theoretical framework and empirical literature

This section summarizes the theoretical framework for FSD's effects on income inequality. Then, the empirical literature review on FSD's effects on economic activity is presented. Thereafter, empirical literature on the effects of FSD on income inequality is presented.

2.2.1 Theoretical framework on FSD and income inequality

The link between financial sector development, economic growth, and income inequality is complex as these variables exhibit a bidirectional relationship. For the theoretical framework, we begin our analysis by building on the outstanding work of Demirguc-Kunt and Levine (2009), specifically focusing on their contribution to finance in theories of persistent inequality. Where persistent inequality refers to the degree to which the gap between the rich and poor persists across different generations (Demirguc-Kant and Levine 2009). By decomposing total income into income from labour and physical capital, we can analyse how FSD can affect inequality (Demirguc-Kant and Levine 2009). The argument goes as follows: Wage income accounts for around 70 per cent of income inequality and is highly correlated with human capital development (Bhorat, Van der Westhuizen and Jacobs 2009; Demirguc-Kunt and Levine 2009; Francese and Granados 2015). At the same time, income from physical capital magnifies inequality through rent-seeking (Demirguc-Kant and Levine 2009; Piketty 2014; Mihalyi and Szelenyi 2019). The argument is that inequalities from physical capital are larger than from labour income. For example, Piketty (2014) focused on the rent earned by the top 1% income group and postulated inheritance wealth; the capitalist environment and growth of profits exacerbate inequality.

Mihalyi and Szelenyi (2019) emphasised that rent is accruing to the top 20% income group by distinguishing different types of rent in the capital system. Contrary to Piketty's (2014) findings, Mihalyi and Szelenyi (2019) placed a distinction between profits and rent. From this distinction, Mihalyi and Szelenyi (2019) find higher profits and wage income positively affect economic growth, while rent growth lowers it. Subsequently, the theories of persistent inequality in financial sector development are discussed concerning wage and physical capital income inequalities. Demirguc-Kunt and Levine (2009) argue that financial institution's imperfection (e.g., information and contract costs that hinder investment screening and monitoring of financial contracts) outlines the dynamics of inequality, such as wealth and education accumulation.

The difference between the income of skilled versus unskilled labour is the primary direct source for rising income inequality, as wage income typically reflects an individual’s education level. In the perfect credit market, parents' education and wealth are not crucial, as households can borrow to finance education (Demirguc-Kant and Levine 2009). While in the presence of imperfect credit markets on education investment, inequality of opportunity explains the distribution of skills. Parents’ education and wealth constrain the next generation's access to human capital. Thus, in the absence of public education, borrowing constraints negatively impact human capital accumulation. This creates a gap in human capital accumulation, thereby increasing wage inequality (Demirguc-Kant and Levine, 2009). Increased access to financial services for education investment to poor households who were previously excluded reduces income inequality through human capital accumulation (Galor and Zeira 1993; Demirguc-Kant and Levine 2009).

On the other hand, the developed financial sector curbs shocks to the income of poor households, allowing them to continue investing in human capital instead of opting for low-skill employment when hit by income shocks. This suggests developed financial sector helps households to smooth income shocks (Demirguc-Kant and Levine 2009). FSD lacking increased access to financial services can increase inequality as the sector only caters to selected individuals with financial investments (Greenwood and Jovanovic 1990). FSD increases in financial institution size, and innovation can boost economic growth, thereby pushing up labour market demand, signifying that the effects of FSD on labour market demand and income inequality are a double-edged sword. In the sense that FSD increases demand solely for skilled labour, this magnifies income inequality. FSD also increases wage inequality between sectors. For example, the compensation of portfolio managers from financial institutions increases with the complexity of the financial instrument, and in addition, their bonus compensation is usually based on profits.

Capital income contains real estate and financial capital; thus, owners of capital benefit extensively from FSD. Generally, physical capital such as bond certificates/share ownership and property embody more wealth inequality; however, inequality of wealth has direct transmission on income inequality. For example, wealthy households tend to live in more advanced and developed districts, impacting the quality of schools around and other forms of economic opportunities. Education may be centralised or free, but education institutions always allow private funding, which will be coming from the wealthy residents of the district- through such funding, these schools get better and more advance technology than public schools. In the long run, income inequality will also grow due to the gap in skills and human capital development. Another argument from the book by Piketty (2014) is that capital is not equally distributed. Middle-income households tend to invest more in property, while wealthy households have paid up properties and gain more rent from financial assets, stocks, and bonds in the financial markets. Eurofound (2021) suggests homeownership increases the bottom quintile wealth levels, and there is a relatively lower number of renters holding financial assets beyond deposits within the EU member state. At the same time, the top wealthiest groups in the EU member state tend to earn income from a self-employed business, holding financial assets and real estate. This distribution of capital suggests that different income group benefits differently from financial rent.

To summarise, the theories on persistent income inequality stress the importance of access to financial services, specifically for human capital investment, to reduce income inequality. While wealth inequality is different from income inequality, inequalities in wealth amplify income inequality in an environment of imperfect financial markets. Financial sector development can increase or decrease wage inequalities depending on their respective labour market demands surge. Lastly, policies improving financial literacy should be incorporated into financial reforms to ensure that a large portion of society understands financial market opportunities and provides fair distributions from financial market gains.

2.2.2 Literature Review on FSD and Economic Activity

There is a large and growing evidence that suggests that financial sector development plays a substantial role in economic development (Goldsmith 1969; Levine 2004; Gründler and Weitzel 2013; Coskun and Seven 2016; Paun, Topan and Musetescu 2019; Ongena and Mendez-Heras 2020). The financial sector is important for the saving ratio of a country, as it determines the distribution of savings and the stock of intangible assets appropriate for different groups of savers (Goldsmith 1969). Adding to this, access and confidence in the country's financial sector determine the savings ratio and distribution of savings. As such, according to Goldsmith (1969), the financial sector influences economic growth through savings, which are lent out to borrowers.

There are positive gains in economic growth when there is growth in:

a. numbers of financial sector branches, b. stock traded and net foreign assets, c. financial systems and inclusion (represented by financial access and market sophistication), d. the quality of financial systems such as markets, institutions, and financial instruments (Bittencourt 2012; Worku 2014; Paun et al.,2015; Gural and Lomachynska 2017; Setiawan 2015; and Kapingura 2017). Other studies suggest a bidirectional relationship between financial sector development and growth (Oluitan 2012 and Sunde 2012;). Using the Generalised Method of Moments (GMM) estimation technique, data from 31 African countries for the period 1970 to 2005, Oluitan (2012) found that economic growth and FSD positively affect each other. Ductor and Grechyna (2015) showed the impact of financial sector development on economic growth depends on the growth of the private credit ratio on real GDP growth. Thus, in developing and developed countries, when there is negative growth, FSD has negative growth effects. Their findings suggest an optimal level of financial development determined by the characteristics of the economy.

2.2.3 Literature Review on FSD and Income Inequality

The previous chapter summarised the impact of FSD on economic growth as theories of growth overlap those of inequality. Next, I show that there is no consensus in the empirical literature on FSD and income inequality. As such, subsection 2.2 briefly discusses the literature review for Article 1 and Article 2. There is a large literature on FSD and income inequality. However, as Demirguc-Kunt and Levine (2009) highlighted, the literature lacks a consensus, and to close the gap, they state that further empirical evidence is

needed. The grounds for further research lie in finding precise measures or rules of thumb for the impact of FSD on inequality and growth. This is because the theory mirrors a skeleton of inequality trends due to imperfect credit markets.
Additionally, before 2004, there were no global cross-country data on financial access measures. This implies that before the year 2004, there were limited global studies on how financial access affects inequality. Simultaneously, the literature on the impacts of financial depth on economic growth and inequality grew (this is also discussed further in Article 2). The literature on FSD and income inequality is divided into four strands: (1) the financial narrowing hypothesis, (2) the financial widening hypothesis, (3) the inverted U-shaped hypothesis (GJ) of Greenwood and Jovanovic (1990), and (4) the U-shaped hypothesis.
The financial narrowing hypothesis suggests that income inequality declines in the presence of an efficient financial market (Banerjee and Newman 1993; Galor and Zeira 1993). These theories emphasise the exacerbating effects of imperfect credit markets on initial wealth distribution and, subsequently long-run impacts on income inequality (Beck, Demirguc-Kunt and Levine 2004; Burgess and Pande 2005[1]; Clarke, Xu, and Zou 2006; Liang 2008; Rehman, Khan and Ahmed 2008 Odhiambo 2009; Ang, 2010; Batuo et al.,2010; Kappel 2010; Mookerjee and Kalipioni 2010; Tan and Azman-Saini 2010; Shahbaz and Islam, 2011[2]; Bittencourt 2012; Prete 2013; Law, Delis, Hasan and Kazakis 2014; Li and Yu 2014; Shahbaz et al., 2015[3]; Kapingura 2017; Haffejee and Masih 2018 and Mbona 2022).

Beck et al. (2004) conducted their study in 52 developing and developed countries, using data from 1960 to 1999. Their study utilised credit to the private sector by financial intermediaries to measure FSD, the income of the poorest quintiles, and the Gini Index (GNI) to measure income inequality. The results of the instrumental variable methodology, using legal origins, natural resource endowment, and ethnic fractionalisation as instruments, found that FSD reduces inequality at a faster speed than average GDP per capita (Beck et al., 2004).

Clarke et al. (2006) employed data from 83 developed and developing countries between 1960 and 1995 and found that the long-run increase in financial depth (FSD) reduces inequality, whereas Clarke et al. (2006) utilised the panel ordinary least square (OLS), Two-Stage least squares (2SLS), random effect model and instrumental variable technique and failed to confirm the nonlinear Greenwood and Jovanic hypothesis between FSD and inequality. Batuo et al. (2010) presented evidence on the relationship between financial development and income distribution for 22 African countries from 1990 to 2004. In their study, Batuo et al. (2010) used the commonly used measure of FSD, namely, financial development index, Domestic credit to bank sector as % of GDP, M2 as % of GDP, and Liquidity liabilities as % of GDP. Their results from the GMM system suggest that financial development reduces income inequality in African countries. This finding means that African countries can reduce income inequality by widening access to financial markets, especially for people with low incomes in rural areas. Batuo et al. (2010) and Kapingura (2017) also found that higher inflation levels increase income inequality in Africa. Kapingura (2017) examined the relationship between FSD and inequality in South Africa, using both the standard measures of financial deepening and more recent measures of financial access (ATM data).

Kapingura's (2017) results suggest that inequality in South Africa can be reduced through economic growth, increase in access to financial sector, external trade, and government activities. Burgess and Pande (2005) and Liang (2008) use micro-domestic data to show that access to financial services is key to reducing inequality, especially in the rural areas of India and China.

The study of Liang (2008), which is part of a book series, was based on examining credit/loans to rural provinces of China. As such, Liang (2008) developed an indicator of rural FSD based on the ratio of total loans to rural GDP and employed GMM. Burgess and Pande (2005) employed data from India from 1977 to 1990, where FSD is measured by the number of bank branches per 100,000 people and the number of banks opened in rural versus urban areas. Contradicting results to those of Burgess and Pande (2005) were reported in India by Kockar (2005). Kochar (2005) used bank branch data and instrumental variables, the fixed effect method, and found an increase in the district bank branch increases consumption inequality. Others argue that FSD reduces income inequality through the political institution and economic institution quality (Delis et al.,2014; Law et al.,2014).

Law et al. (2014) employed Threshold regression using data from 81 countries from 1985 to 2010 and found evidence of the narrowing hypothesis that is only associated with a threshold level of institutional quality. Law et al. (2014) assert that there is no relationship between FSD and inequality in countries below this institutional quality threshold. Lastly, the financial narrowing hypothesis maintains an increase in access to financial services to reduce inequality.

The financial widening hypothesis was enriched by the book of (Rajan and Zingales 2003) as the title of Chapter 1 of the book was 'Does Finance Benefit Only the Rich?'Rajan and Zingales (2003) posit that FSD increases income inequality as its benefits spread to rich households who had initial access to the credit market. Those who lack collateral view requirements for borrowing as follows: 'You can borrow provided you do not need', and connections to credit imply 'you can borrow provided I know and trust you/your business' (Rajan and Zingales, 2003). They argue for good institutions characterised by better legal enforcement, higher levels of general trust, esteem property rights, and the developed market to ensure that there is access to finance for all. Empirical evidence of the finance widening hypothesis was confirmed in low−income countries (Dollar and Kraay, 2002; Wahid, Shahbaz, Shah and Salahuddin, 2012; Jaumotte, Lall and Papageorgiou, 2013; Kunieda, Okada, and Shibata, 2014; Sehrawat and Giri, 2016; Seven and Coskun, 2016; de Haan and Sturm, 2017; Chiu and Lee, 2019).

Benczur and Kvedara (2021) investigated the relationship between financial deepening and income inequality in developed economies. Their study suggests that the gap between 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 and Kvedara, 2021). Subsequently, they found that if the gap between interest rate and GDP growth is negative, growth in domestic credit reduces income inequality (Benczur and Kvedara, 2021).

The inverted U−shaped hypothesis (GJ) argues that the relationship between income inequality and financial development is not linear but somewhat resembles the inverted U−shaped curve like the Kuznets curve (Greenwood and Jovanovic, 1990). Greenwood and Jovanovic (1990) examined the financial development− growth and distribution of income nexus. The study found an inverted U−shaped curve between financial development and income inequality. Greenwood and Jovanovic's (1990) model implies that in the early development stage of the financial sector, which is characterised by unorganised exchange and slow growth, income inequality increases with financial development. The increase in income level then foresters the intermediate development stage in the financial structure, thus accelerating economic growth and, subsequently, income inequality. As the financial sector development moves to the intermediate and later to the developed stage (maturity), income inequality declines with an increase in financial development, thus forming an inverted U−shape curve (Greenwood and Jovanovic, 1990). At maturity, the economy's financial sector is fully developed, and therefore, more households have access to the financial markets (Greenwood and Jovanovic, 1990). Fully developed financial sectors also result in a higher growth rate. The inverted U−curve relationship between financial development and income inequality was confirmed in Turkey, BRICS nations, and emerging market countries (Shahbaz et al.,2015; Azam and Raza, 2018; Younsi and Bechtini,2018; Bittencourt et al.,2019; Emrah and Nisfet, 2019; Nguyen et al.,2019).

The simple U-shaped relationship is a new paradigm in the FSD-inequality nexus. Like the GJ hypothesis, the U-shaped proposes a nonlinear relationship of finance-inequality nexus depending on the level of FSD. It suggests that financial sector development reduces income inequality up until it reaches a point. Beyond that point, income inequality starts to rise. This strand of literature is common in studies testing the nonlinear relationship between financial depth on income inequality (Tan and Law, 2012; Park and Shin,2015; Brie et al.,2018; Sahay and Cihak, 2020; Mbona, 2022).

2.3 Methodology

The literature on FSD and income inequality lacks consensus, as shown above. A possible reason for this could be those different measurements of FSD (mainly proxies used), methodology, differences in country coverage, and stages of development within the selected countries investigated in the literature.

This study contributes to the literature by investigating the effects of the overall FSD on income inequality and the effects of FSD dimensions (access and depth) on income inequality using the generalized methods of moments (GMM) estimation technique. Where the analysis first focuses on a larger number of countries (120), using unbalanced data from 2004 to 2019. Thereafter, using IMF classifications, the analysis splits the data into three subsamples (advanced markets (AM), Emerging market economies (EME), and Low-income economies (LIC). As such, these analyses will yield results on the relationship between FSD and income inequality. This study is interested in testing both the linear and nonlinear relationship, as different stages of financial development can have different effects on income inequality. Secondly, the nonlinear relationship is tested as empirical studies on the nonlinear relationship hypothesis suggest that measures of FSD be expressed in both linear and nonlinear forms (Greenwood and Jovanovic, 1990).

2.3.1 Applied Generalised Method of Moments (GMM) Methods

Both the system and 1st difference (GMM) are used to investigate the effects of FSD on income inequality. The GMM of Blundell and Bond (1998) and Roodman (2009) is designed for estimates of larger panels and smaller T and can also be applied to a single time series (i, and t=1). GMM is a dynamic estimator used for panel data that uses instrumental variables and tries to correct for endogeneity. The first difference is that GMM attempts to remove endogeneity by transforming the data to remove fixed effects and instrumenting with variables that are uncorrelated with the fixed effects (Roodman, 2009).

As such, the full sample is analysed using both the system and the first difference GMM. This is because the unit root test of the dependent and independent variables is only stationary at 1st difference, not in levels. The first difference, GMM, is a dynamic estimator that begins with 1st differencing data. The first difference generalised method of moments (GMM) of Arellano and Bond (1991) tests is also used to test the finance-inequality nexus, focusing on the subsamples.

The GMM estimation techniques provide the following diagnostic tests: the serial correlation AR (2), the Sargan test and the Hansen test, where the null hypothesis for the Sargan and Hansen test is that instruments are valid for the model. The Sargan and Hansen test investigates the validity of the chosen instruments of the model. The Sargan test of overidentifying restrictions is a special case of the Hansen test, as it assumes homoskedasticity and no serial correlation in the error terms, while the Hansen test does not rely on these strong assumptions (Roodman, 2007). The Hansen test of overidentifying restrictions depends on the estimate of an optimal or robust weighting matrix, while the Sargan test does not (Roodman, 2007). Thus, the Hansen and Sargan test results have different p-values.

In estimating the GMM, the log of the after-tax Gini index on its first lag was regressed. Corruption variables entered as an exogenous instrumental variable. This variable serves as a proxy for institutional quality. Initial GDP per capita and first-lagged after-tax Gini are used as endogenous instruments. Subsequently, the models considering the before-tax Gini as a dependent variable are set up the same as the after-tax Gini models. The choice of instruments is guided by the literature (Park and Shin, 2015; Cihak and Sahay, 2020). The collapse instrument option applied in the GMM helps to reduce the number of instruments. Subsequently, all the estimated GMM results have a lesser number of instruments than the number of observations (N). Finally, the linear model and nonlinear model are estimated using Equations (2.1) and (2.2), respectively.

$$\text{Log}\_Gini_{it} = \alpha_i + \beta_0 Log\_Gini_{it-1} + \beta_1 FSD_{it} + \beta_2 X_{it} + \varepsilon_{it} \dots\dots\dots\dots\dots\dots\dots 2.1$$

$$Log\_Gini_{it} = \alpha_i + \beta_0 Log\_Gini_{it-1} + \beta_1 FSD_{it} + \beta_2 FSD^2{}_{it} + \beta_3 X_{it} + \varepsilon_{it} \dots\dots\dots 2.2$$

where i and t represent countries and time, respectively, while FSD represents the FSD dimensions investigated, X is a set of control variables discussed in the data section, and ε is the error term.

2.3.1.1 GMM Asymptotic properties

In terms of the asymptotic properties of the GMM, focusing on the estimator behaviour regarding the sample size and the number of countries (panel) in the sample. As the number of countries approaches infinity, the GMM estimator exhibits properties such as efficiency, consistency, and robustness. According to Roodman (2009), the system and 1st difference GMM are designed for scenarios of small T and larger panels (i).

Alvarez and Arellano (2003) established the asymptotic properties of the GMM and other panel estimators for a first-order autoregressive model with individual effects where both i and T approach infinity. In the case where T/ i is approaching c, for 0<c≤2, and the GMM, Within Groups (WG), and Limited Maximum Likelihood (LIML) estimators are consistent as a bigger number of instruments is associated with larger values of T, which also pushes the endogeneity bias towards zero as T tends to infinity. Alvarez and Arellano (2003) also show that in cases where T is less than i, the asymptotic biases of GMM are always smaller than those of WG estimators. Bias from the LIML estimator is smaller than those of GMM and WGI in this case. Alvarez and Arellano (2003) also show that when T/i approaches zero, thus T is fixed the results for GMM and LIML remain valid. Alvarez and Arellano (2003) also suggest that GMM that does not incorporate first difference structures of the errors are inconsistent as T approaches infinity while arguing that GMM excluding the first difference is sufficient for cases when T is fixed, and i tends to infinity.

As an initial step before the panel model estimation, the Im-Pesaran-Shin (IPS) unit-root test was carried out on the variables to understand the nature and behaviour of the data series. The IPS unit-root test is suitable for unbalanced panel data, as it relaxes the assumption that all panels share a common autoregressive parameter, and it assumes that the number of times (T) is fixed while countries (i) approaches infinity by allowing for a heterogeneous variance across panels (Im, Pesaran and Shin, 2003). The IPS unit-root test results are Appendix A, **Table 2.0**, where the null hypothesis states that all panels contain a unit root. All the variables become stationary after the first difference, with few exceptions of the FSD indices which were stationary at level.

Subsequently, the dynamic GMM estimator is ideal for studying the inequality-FSD nexus relationship. This is because empirical studies on the topic emphasize issues of endogeneity and reverse-causality problems (Brie et al.,2018; Demirguc-Kunt and Levine, 2009). In addition, a dynamic model is also ideal in this empirical analysis, as factors affecting FSD may be correlated with the Gini index as well.

2.4 Data on the Measurements of Financial Sector Development

The concept of financial sector development (FSD) is compounded mainly in terms of structure and regulatory framework. However, we can decompose FSD first into two broad components: financial institutions (FI) and financial markets (FM). Financial institutions and markets are developed if they are characterised by increased depth, access, efficiency, and stability. There is a limited number of studies considering the multidimensions of FSD and aggregated FSD effects on income inequality. Figure 2.1 summarizes the multidimensions of FSD and only a selected few from the proxy variables for each category.

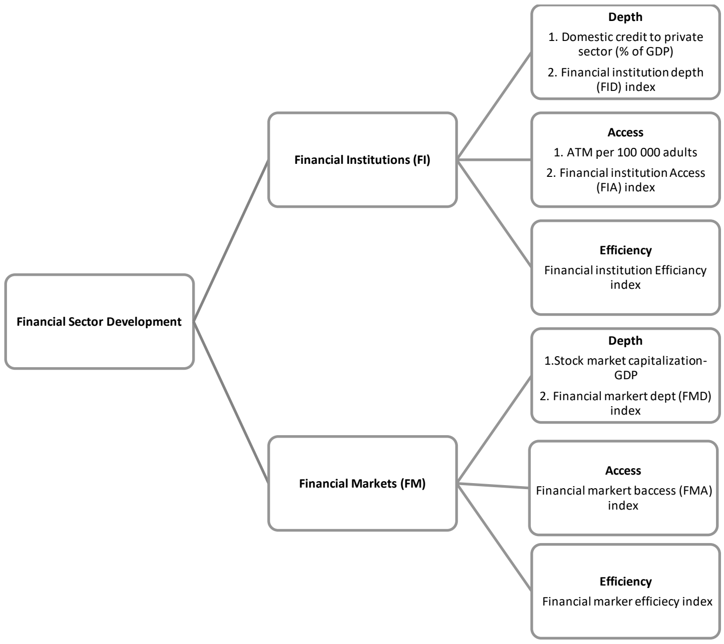


Figure 2.1. Measuring FSD (Source: Own processing based on Figure 3.1, on page 12 of Sahay et al. (2015), and Table 3.3.1 of Svirydzenka (2016)).

Table 2.1. Descriptive statistics for the full sample.

Variable	Obs	Mean	Std. Dev.	Min	Max	Source
gini disp	1666	.382	.085	.23	.674	SWIID
gini mkt	1666	.463	.066	.219	.725	SWIID
FD	1903	.367	.244	.029	1	IMF
FI	1903	.445	.226	.047	1	IMF
FM	1903	.279	.281	0	.989	IMF
FIA	1903	.376	.283	.005	1	IMF
FMA	1903	.275	.294	0	1	IMF
FID	1903	.314	.283	.008	1	IMF
FMD	1903	.279	.3	0	1	IMF
ATMadult	1738	.499	.48	0	2.886	IMF
Dom credit	1736	.605	.473	0	3.046	IMF
GDP	1903	2.03	2.133	.06	16.652	PWT
CPI	1900	1.613	1.075	.99	25.777	WDI
yr sch	1903	8.322	3.333	.759	15.802	PWT
Trade op	1903	.648	.555	.059	5.079	PWT
Gov	1852	.157	.053	.035	.435	WDI
Corruption	1903	.083	1.041	-1.673	2.47	WGI

The panel data used in the study are sourced from different databases. This study employs yearly panel data of 120 countries (ccode) from the years 2004 to 2019 and the before- and after-tax Gini index from the Standardized World Income Inequality Database

(SWIID). SWIID is one of the leading databases for global coverage inequality. To test the effects of FSD on income inequality, seven financial development indices of the IMF are used, together with the domestic credit as a ratio of GDP from the World Bank is used. The financial development indexes were sourced from the International Monetary Fund (IMF) under the financial development index database.

The financial intuition index (FI), financial market index (FM), and financial development index (FD) present aggregated values, thus the overall level of development of both financial institutions and markets. The FD index shows the ranking of countries in terms of access, depth, and efficiency to financial institutions and markets. The FD index over the sample period shows a noticeable progression in the financial development of both advanced and emerging market economies. FI index and FM index are calculated using aggregates of the institution/ markets access, depth and efficiency index.

Financial institution access index (FIA) and financial market access index (FMA), all measure access to the financial sector. FIA represent data on bank branches and ATMs per 100 000. The latter measure is one of the two financial access indicators for the UN 2030 SDGs target 8.10. The variable ATM per 100 000 adults is calculated by saying one hundred thousand multiplied by the number of ATMs, divided by the number of adult populations in the respective country and is sourced from the IMF database. While FMA data constitute percentages of the market capitalization of the top 10 largest companies and the total number of issuers' debt per 100,000 adults.

Depth is measured with the financial institution depth index (FID), financial market depth (FMD), and domestic credit to the private sector as a share of GDP (Dom credit). The FID index is calculated using 4 components, namely the bank credit to the private sector as a share of GDP, pension fund and mutual fund assets to GDP, and insurance premiums to GDP. FMD index is calculated using stock market capitalization to GDP, stock traded and international debt securities of government to GDP, and total debt securities to GDP. All the FSD indices data scale ranges from zero to one(where one suggests the country's financial sector is fully developed). Domestic credit to the private sector represents financial resources (e.g. loans, purchases of nonequity, trade credits and other receivables) given by financial corporations with a claim for repayment.

The study also includes a set of control variables such as, average school years in the population aged 25 and older enters the model as a proxy for the education variable. The level of economic development has a direct impact on the level of FSD, while trade openness can bring about financial integration. As such, GDP per capita and trade openness (Trade_op) also entered the model as control variables and were sourced from Pen World Tables (PWT). Trade openness is measured as the difference between the share of merchandise exports and imports at current purchasing power parity (PPP).

The World Development Indicator (WDI) of the World Bank provides the domestic credit measures, inflation rate and general government final consumption expenditure as a percentage of GDP(Gov). The consumer price index (CPI) is calculated using inflation data, where the year 2004 is the base year. The control for corruption variable reflects the 'perception of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests' (Kaufmann et al., 2010). The corruption variable is sourced from the Worldwide Governance Indicator (WGI) of the World Bank. A detailed summary statistic of the data by subsamples is given on the **Appendix A**, **Table 2.1**. FSD indicators are chosen based on the available limited sample coverage in the panel set-up whilst trying to incorporate other proxy variables that are under test in the empirical literature.

2.5 Empirical results for after-tax Gini

This section presents the linear and nonlinear empirical model results on the impacts of financial sector development (FSD) on after-tax income inequality. Thus, the results on the effects of overall FSD on income inequality are presented, where overall FSD represents the development of both institutions and the market in terms of efficiency, depth, and access and is measured using the FD index. This section also investigates the effects of FSD components on income inequality. The dependent variable of the results presented in subsection 2.5 of the thesis is the log of the after-tax Gini index. This is because the after-tax Gini index is an important measure of income inequality, as progressive tax policies are praised for reducing income inequality. While FSD is expected to have a more direct relationship with before-tax inequality. The results using the before-tax Gini index as the dependent variable are presented in subsection 2.6 of the thesis.

2.5.1 Overall Effects of FSD on After-tax Income Inequality

This subsection presents and discusses the results of the effects of overall FSD indices on after-tax income inequality using a full sample of 120 countries and subsamples. The overall impact of financial institutions (i.e. banks) and market (i.e. stock market) development is also considered on after-tax income inequality in Table 2.2. The analysis in Table 2.2 starts with the base model results (models 1-3), where the control variables are not included in the system GMM estimation, and thereafter, Table 2.2 reports the results of the full sample for the linear model, including the control variables. Contrary to the findings of Brie et al. (2018), who confirmed a significant U-shaped relationship between the FD index on a panel of advanced and emerging market economies, table 2.2 does not include the nonlinear models as they were all insignificant.

Table 2.2. Effects of overall financial sector development on after-tax income inequality.

	(1) Financial development Index (FD)	(2) Financial Institution Index (FI)	(3) Financial Market Index (FM)	(4) Financial development Index (FD)	(5) Financial Institution Index (FI)	(6) Financial Market Index (FM)
L1. Log After-tax Gini	0.819***	0.578*	1.100***	0.710***	0.735***	0.726***
	(0.0594)	(0.333)	(0.0479)	(0.125)	(0.105)	(0.121)
FinDev	-0.0987**	-0.258	0.0650**	-0.0643**	-0.0618*	-0.0434**
	(0.0398)	(0.207)	(0.0278)	(0.0261)	(0.0353)	(0.0187)
GDP				0.00417	0.00295	0.00488
				(0.00376)	(0.00347)	(0.00380)
Log-CPI				0.0106	0.0134	0.00930
				(0.00871)	(0.00820)	(0.00826)
Trade_op				-0.00239	-0.00104	-0.00445
				(0.00704)	(0.00730)	(0.00699)
LogGov				0.00765	0.0113	0.00260
				(0.0186)	(0.0203)	(0.0179)
L1.Log-education				-0.0913	-0.0803	-0.0977*
				(0.0582)	(0.0524)	(0.0579)
Constant	-0.141***	-0.298	0.0775*	-0.0728	-0.0590	-0.0647
	(0.0450)	(0.236)	(0.0394)	(0.0807)	(0.0772)	(0.0791)
Observations	1,546	1,546	1,546	1,508	1,508	1,508
Number of ccode	120	120	120	120	120	120
AR 2 test (p-value)	0.014	0.775	0.023	0.555	0.395	0.527
Sargan test (p-value)	0.341	0.840	0.058	0.263	0.303	0.833
Hansen test (p-value)	0.043	0.127	0.002	0.226	0.594	0.196

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.2 presents the system GMM results of the full sample. The system GMM estimator uses data in levels and only differentiates the instruments, thus not accounting for non-stationary series in levels. As such, the 1st difference in GMM results is presented in the Appendix A**, Table 2.2 (A).** In line with the growing plethora of literature, models 1, 2, 4, 5, and 6 confirm the overall narrowing effects of FSD on after-tax income inequality. The narrowing hypothesis is confirmed only at 10% in the overall development of financial institutions (model 5), while in the base model, the coefficient was negative and insignificant (model 2). The results for overall financial market development (FM) were inconsistent between the base model and the model with control variables, suggesting that the direct relationship between FM and after-tax inequality is positive and significant (model 3). While model 6 accounted for additional variables that may influence this relationship, the results show FM has a reducing effect on inequality. Notably, so, the results of model 3 in Table 2.2 also suffered from issues of serial correlation, as indicated by the AR 2 test. Table 2.2(A) in the appendix shows the 1st difference results, where model 3 shows overall FM index significantly narrows after-tax income inequality.

Table 2.2 results suggest that the overall FD index reduces inequality with a range of 0.064 to 0.099 Gini points. The coefficients of the FD index (models 1 and 4) were negative and significant at 5%. Brie et al. (2018) found an insignificant and negative 0.038 effect of the FD index on after-tax Gini. Also, Table 2.2 above demonstrates that the FI index which is an overall financial institution index accounting for access, depth, and efficiency of financial institutions narrows inequality by 0.062 Gini points. The negative relationship between overall FD, FI, and FM on after-tax inequality aligns with the negative correlation coefficients presented in **Table 2.2 of** Appendix A. The weak to moderate negative correlation found between the overall FSD index and after-tax income inequality also aligns with the negative yet small GMM coefficients. The results of the system GMM presented above and the results of 1st difference GMM in **Appendix A Table 2.2 (A)** were almost the same. This suggests that for a larger sample in terms of the countries compared to the time, the GMM estimator provides consistent results. In terms of the other explanatory variables, previous years' higher levels of average school years in the population aged 25 and older appear to reduce after-tax income inequality and were significant at the 10% level in model 6 of Table 2.2.

Table 2.3. Impacts of overall financial sector development on after-tax income inequality (Subsample results).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Financial development Index (FD)						Financial Institution Index (FI)						Financial Market Index (FM)					
	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC
L1. Log After-tax Gini	0.817***	0.865***	0.892***	0.789***	0.872***	0.659***	0.899***	0.791***	0.890***	0.870***	0.968***	0.855***	0.773***	0.958***	0.927***	1.007***	0.997***	0.809***
	(0.148)	(0.0464)	(0.0542)	(0.215)	(0.0502)	(0.164)	(0.141)	(0.0785)	(0.0546)	(0.121)	(0.170)	(0.0793)	(0.178)	(0.0325)	(0.0414)	(0.208)	(0.0485)	(0.175)
FinDev	-0.00281	-0.0918***	-0.0420	-0.0896	-0.270	-0.680	0.0544	-0.0594**	-0.0253	-0.203	-0.472*	-0.111	-0.0286	-0.0254	-0.0608	0.525*	0.214	-1.147*
	(0.0304)	(0.0320)	(0.0338)	(0.534)	(0.233)	(0.462)	(0.0350)	(0.0274)	(0.0201)	(0.240)	(0.257)	(0.167)	(0.0227)	(0.0255)	(0.0841)	(0.273)	(0.276)	(0.631)
$FinDev^2$				0.0643	0.295	2.033				0.177	0.574	0.164				-0.429**	-0.355	5.904*
				(0.393)	(0.349)	(1.607)				(0.162)	(0.365)	(0.329)				(0.202)	(0.401)	(3.429)
Observations	446	757	459	446	757	459	446	757	459	446	757	459	446	757	459	446	757	459
Number of ccode	34	62	48	34	62	48	34	62	48	34	62	48	34	62	48	34	62	48
AR 2 test (p-value)	0.245	0.10	0.678	0.348	0.067	0.956	0.220	0.185	0.659	0.280	0.152	0.520	0.279	0.103	0.688	0.230	0.116	0.593
Sargan test (p-value)	0.315	0.619	0.784	0.253	0.470	0.968	0.503	0.433	0.847	0.365	0.930	0.751	0.231	0.633	0.447	0.414	0.646	0.748
Hansen test (p-value)	0.251	0.247	0.945	0.300	0.104	0.628	0.427	0.048	0.987	0.302	0.714	0.794	0.233	0.937	0.082	0.549	0.937	0.597

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.3 above presents the 1st difference GMM baseline results of the three groups (subsamples) on the effects of overall FSD on after-tax income inequality. The models with control variables of the sub-sample results are presented in Appendix A, **Table 2.2.1**(A). Like the full sample results, the squared term of overall financial sector development (FD) was not significant in all three groups (models 4, 5, & 6) and was not reported. Across all three groups, the linear model results in columns 1, 2, and 3 show a narrowing effect of the FD index on after-tax income inequality. Intuitively, for emerging market economies, the effect size was relatively larger than others and was significant at a one per cent level (model 2). The coefficient for FD in the full sample results in Table 2.2 was -0.0987, while the coefficient for FD in the emerging market groups was -0.0918, suggesting that the relationship between FD and after-tax income inequality is robust and consistent across both the full sample of 120 countries and the subgroup of emerging markets. The significant contribution of FD on inequality is visible in the EM groups, which had a mean value of 0.41 and 0.34 for inequality and the FD index, respectively. The maximum value of FD and Gini index for emerging markets economies was 0.67 and 0.74, respectively (Appendix A **in Table 2.1**). Nguyen et al. (2019) also used the IMF FD index and found an inverted U-shaped relationship between both before and after-tax Gini of 21 emerging market economies. The FD index results of this thesis also differ from the findings of Nguyen et al. (2019) in terms of magnitudes, as Nguyen et al. (2019) find FD increases inequality on average by 10 Gini points and squared term of FD reduces inequality by 18 Gini points.

Models 7 to 12 of Table 2.2.1 present the results of overall FI index on after-tax income inequality. The results confirm a significant narrowing hypothesis for emerging market subgroups (models 8 and 11). The narrowing effect of FI on income inequality for emerging market economies ranged between -0.472 and -0.0594 in the base model. The coefficients of FD for emerging market economies remain negative in both the base model and the model, with control variables[1] showing a consistent relationship. The base model results for low-income countries were insignificant and had a negative coefficient (model 8); the model with control variables was also insignificant and had a positive coefficient. Model 10 in Table 2.2.1 suggested an insignificant U-shaped relationship between FD and income inequality of advanced economies. Since the mean value of the FI index is

[1] Table 2.2.1 (A) in the appendix page.

0.72 for advanced markets, this suggests that inequality is decreasing as the FI index grows from 0.38 (the minimum value of FI in the group) up until the FI index reaches 0.72 points, beyond which growth in FI index starts to increase inequality.

Models 13 to 18 of Table 2.2.1 present the results of overall financial market development (FM) on after-tax income inequality. Across all three subgroups, the results show an insignificant and yet narrowing effect of the FM index on income inequality (models 13-15). In the nonlinear model, the results differ by subgroup. Model 16 of Table 2.2.1 shows there is a significant inverted U-shaped relationship between FM and income inequality for advanced economies. Contrarily, for low-income countries, the relationship between FM and income inequality resembled a simple U-shaped hypothesis.

There is a huge striking difference between these two subgroups (AM and LIC). For example, from the summary statistics table in **Table 2.1** of **Appendix A**, it is seen that the minimum and maximum values of the FM index for LIC were 0 and 0.21, and for AM are 0.04 and 0.99, respectively. While the mean for the FM index for LIC was 0.02 and for AM was 0.563. Thus, for the AM group, as the FM index increases from 0.04, income inequality increases up until FM reaches 0.563 and beyond this point, increases in FM are associated with decreases in inequality as the FM index increases towards 1. Unfortunately for the LIC group, the current levels of FM are low, thus suggesting lower levels of FSD development in terms of FM (efficiency, access, and depth). As such, as the FM index increases from zero to 0.02, inequality is decreasing, and beyond 0.02, inequality is increasing till FM reaches 0.21. At lower levels of development, which are indicated by the maximum value of the FM index for the LIC group, the market is disorganised, with lower levels of access and efficiency in the stock market. Of the other explanatory variables, education proxied as average school years in the population aged 25 and older was negative and significant in the advanced market as suggested by models 1, 7, and 13 of Table 2.21 (A) of Appendix A.

2.5.2 Effects of Access to Financial Institutions and Market on After-tax Income Inequality

This subsection presents the results on the effects of access to financial institutions and the market on income after-tax inequality. Table 2.4 below presents the system GMM results of the full sample, while the 1st difference GMM results are presented in the Appendix A, **Table 2.3 (A),** which also confirms the system GMM results.

The FIA index represents access to both bank branches and ATMs per 1000 adults. Models 1 and 7 represent the linear FIA index models, where the narrowing effects of FIA on inequality were significant, with coefficients ranging between -0.05 to -0.07. Thus, in the base model showing the direct relationship between FIA and inequality, the coefficient is larger than in the model with other macroeconomic factors that may influence the relationship between dependent and independent variables. In the nonlinear models, the base model results (model 4) show a significant U-shaped relationship between the FIA index and after-tax income inequality, while the model including control variables was insignificant but showed narrowing effects of FIA on inequality (model 10). However, model 4 failed the test of instrument validity. Brie et al. (2018) created an overall access index using averages of access in both financial institutions and markets and found no relationship between the financial access index and after-tax Gini.

When looking at access to financial services as measured by the number of ATMs per 1000 adults only (one component of FIA), results in Table 2.4 confirm a narrowing hypothesis in both the linear and nonlinear models (2,5,8, 11). As such increase in the number of ATMs has a reducing effect on income inequality, as suggested by the ATM coefficients ranging between -0.027 to -0.095 in Table 2.4. These results concur with Sahay and Cihak (2020) who show in a full sample of 105 countries, access measured as ATM numbers reduces after-tax income inequality by ranging of –0.02 to –0.06. Sahay and Cihak (2020) also find the effect size of ATM had a stronger narrowing effect on after-tax Gini compared to the number of bank branches which reduced inequality by a range of –0.004 to –0.016.

The results in Table 2.4, suggest that the number of ATMs is a more important measure of access than the combination of ATM and number of bank branches (FIA); this is because the increase in bank branches typically reflects more bank branches being open, but mostly in urban areas. While ATM expansions also go beyond the urban areas, making it more accessible for all. As such, increases in bank branches in urban areas increase access to financial services for certain groups of people, thus increasing inequality. Table 2.4, models 1, 2, and 3 suffer from serial correlations and thus inclusion of control variables results in to reverse of the coefficient signs. Model 1-3 in Table 2.6. A of appendix A does not suffer from serial correlation issues, suggesting the inclusion of control variables in the model helps reduce issues of serial correlation.

The FMA index results for the full sample suggest that there is a significant narrowing linear effect on income inequality (model 3); however, the inclusion of control variables makes the effects of FMA insignificant on income inequality. The insignificant nonlinear model 12 results suggest an inverted U-shaped relationship between FMA and income inequality. These nonlinear model 12 results of Table 2.4 using system GMM are also consistent with the FM index model 6 results of Table 2.3. (A) in appendix A which is based on 1st difference GMM.

Table 2.4 also shows that the coefficient for CPI is positive and significant across models 7 to 12, suggesting inflation widens after-tax income inequality. In models 8, 9, 11, and 12, the proxy variable for education is negative and significant, suggesting education in the presence of increased financial access can reduce after-tax inequality. Table 2.6. (A) appendix A, shows trade openness and education narrow after-tax income inequality.

Table 2.4. Impact of access to financial institutions and markets on after-tax income inequality.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Financial Institution Access Index (FIA)	ATM per Adults	Financial Institution Access Index (FMA)	Financial Institution Access Index (FIA)	ATM per Adults	Financial Institution Access Index (FMA)	Financial Institution Access Index (FIA)	ATM per Adults	Financial Institution Access Index (FMA)	Financial Institution Access Index (FIA)	ATM per Adults	Financial Institution Access Index (FMA)
L1. Log After-tax Gini	0.880***	0.940***	0.867***	1.013***	0.996***	0.746***	0.754***	0.801***	0.812***	0.744***	0.794***	0.853***
	(0.0377)	(0.0170)	(0.0452)	(0.0328)	(0.0431)	(0.173)	(0.118)	(0.0852)	(0.0832)	(0.125)	(0.0835)	(0.0784)
Financial Access	-0.0734***	-0.0203***	-0.0717***	-0.190***	-0.0967*	-0.415	-0.0541**	-0.0278*	0.00812	-0.0282	-0.0650**	0.156
	(0.0209)	(0.00611)	(0.0270)	(0.0451)	(0.0539)	(0.315)	(0.0233)	(0.0145)	(0.00986)	(0.107)	(0.0316)	(0.0994)
Financial Access^2				0.238***	0.0735	0.351				-0.0266	0.0217	-0.121
				(0.0502)	(0.0468)	(0.274)				(0.100)	(0.0161)	(0.0844)
GDP							0.00143	0.00473	0.00363	0.00205	0.00158	0.00211
							(0.00355)	(0.00340)	(0.00290)	(0.00370)	(0.00277)	(0.00276)
lCPI							0.0183*	0.0205**	0.0131*	0.0182*	0.0221**	0.0172**
							(0.0103)	(0.00874)	(0.00688)	(0.0110)	(0.00848)	(0.00807)
Trade_op							0.00797	0.000953	-0.00461	0.00778	0.00387	-0.00755
							(0.00713)	(0.00657)	(0.00598)	(0.00748)	(0.00687)	(0.00668)
lGov							0.0252	0.0218	0.00197	0.0264	0.0186	-0.00715
							(0.0225)	(0.0199)	(0.0164)	(0.0219)	(0.0198)	(0.0158)
L1.Log-education							-0.0882	-0.0891*	-0.0892**	-0.0982	-0.0651*	-0.0892**
							(0.0541)	(0.0483)	(0.0433)	(0.0605)	(0.0367)	(0.0429)
Constant	-0.0905***	-0.0503***	-0.112***	0.0303	0.00760	-0.192	-0.00894	0.0233	-0.0129	-0.00133	-0.0270	-0.00832
	(0.0302)	(0.0144)	(0.0383)	(0.0268)	(0.0418)	(0.129)	(0.0876)	(0.0849)	(0.0718)	(0.0868)	(0.0846)	(0.0719)
Observations	1,546	1,449	1,546	1,546	1,449	1,546						
Number of ccode	120	119	120	120	119	120	1,508	1,416	1,508	1,508	1,416	1,508
AR 2 test (p-value)	0.091	0.013	0.002	0.263	0.197	0.450	0.498	0.211	0.338	0.636	0.226	0.361
Sargan test (p-value)	0.229	0.045	0.081	0.047	0.085	0.441	0.653	0.604	0.249	0.608	0.584	0.358
Hansen test (p-value)	0.035	0.002	0.050	0.002	0.001	0.266	0.997	0.791	0.572	0.972	0.703	0.633

Robust standard errors in paratheses. *** p<0.01, **p<0.05, *p<0.1

Table 2.5. Effects of Access to Financial Institutions and Markets on Income Inequality (Subsample results).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
	Financial Institution Access (FIA)						Financial Market Access (FMA)						ATM per Adults					
	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC
L1. Log After-tax Gini	0.940***	0.765***	0.820***	0.933***	0.744***	0.827***	0.800***	0.920***	0.948***	0.696**	0.932***	0.948***	0.721**	0.798***	0.801***	0.618	0.816***	1.000***
	(0.145)	(0.121)	(0.107)	(0.136)	(0.240)	(0.120)	(0.182)	(0.0339)	(0.0275)	(0.260)	(0.0361)	(0.0296)	(0.265)	(0.121)	(0.156)	(0.374)	(0.119)	(0.241)
Financial access	0.0243	-0.0383	-0.0452*	-0.0913	-0.0128	-0.0105	-0.0304	0.0478	-0.0256	0.161	-0.0799	-0.0145	0.0270	-0.0112	-0.0389	-0.00163	-0.0222	-0.0980***
	(0.0174)	(0.0255)	(0.0261)	(0.119)	(0.276)	(0.0293)	(0.0202)	(0.0294)	(0.0457)	(0.163)	(0.133)	(0.250)	(0.0207)	(0.0111)	(0.0302)	(0.128)	(0.0149)	(0.0286)
Financial access2				0.0947	-0.0374	-0.129				-0.161	0.122	-0.0246				0.0143	0.0105	0.325***
				(0.101)	(0.398)	(0.124)				(0.133)	(0.134)	(0.573)				(0.0605)	(0.00800)	(0.0806)
Observations	446	659	321	446	659	321	446	659	321	446	659	321	442	624	264	442	624	264
Number of ccode	34	53	33	34	53	33	34	53	33	34	53	33	34	53	32	34	53	32
AR 2 test (p-value)	0.130	0.353	0.818	0.114	0.721	0.889	0.095	0.119	0.792	0.497	0.098	0.778	0.552	0.197	0.862	0.859	0.123	0.861
Sargan test (p-value)	0.445	0.725	0.764	0.377	0.728	0.779	0.341	0.565	0.516	0.609	0.427	0.441	0.391	0.631	0.183	0.345	0.736	0.249
Hansen test (p-value)	0.348	0.205	0.562	0.006	0.136	0.432	0.492	0.676	0.179	0.352	0.412	0.114	0.446	0.272	0.054	0.569	0.112	0.463

Robust standard errors in paratheses. *** p<0.01, **p<0.05, *p<0.

Table 2.5 presents the 1st difference GMM baseline results of the three groups (subsamples) on the effects of increases in access to financial institutions (FIA), financial markets (FMA) and ATM per adult. The models with control variables of the sub-sample results are presented in Appendix A, **Table 2.3.1**. The linear model results show a narrowing effect of FIA on income inequality in emerging markets and low-income countries. More so, at a ten per cent significant level, the FIA index has a negative 0.05 effect on the income inequality of LIC (model 3). Access to financial institutions is important for reducing inequality in low-income countries because these countries tend to have limited access to financial services, including formal banking, insurance, and credit; as such, the FIA index is essential for managing risk by investing the funds from informal business or income, and for investing in education. Kapingura (2017) also confirmed the narrowing effect of financial institution access measured by ATM on the inequality of South Africa, but the study did not test for the squared term of ATM.

The EME and LIC results are in line with the full sample linear results. For advanced economies, the results suggest a widening hypothesis, but the coefficient was insignificant. Also, amongst the three groups, the LIC had the lowest highest levels of the FIA index at 0.70, while the maximum value of the FIA index for EM and AM was 1. The nonlinear results were insignificant for all the groups, but the coefficients also suggest a simple U-shaped relationship between the FIA index and inequality.

Access to financial institutions is also measured using the number of ATMs per 100,000 adults, and the results are presented in models 13 to 18 Appendix A, **Table 2.3.1.** For emerging market economies, the linear model confirms a narrowing hypothesis on income inequality. For low-income countries, linear model 15 confirms an insignificant narrowing hypothesis, while nonlinear model 18 confirms a simple U-shaped relationship with inequality. Thus, the LIC results suggest that FIA reduces inequality while the ATM component of FIA first reduces and then increases inequality. These results may seem odd, but intuitively, in most LIC, there are lower levels of maintenance of ATMs, especially near rural and less economically developed cities; thus, the number of ATMs per adult may be increasing, but the number of actual functioning ATMs may be less. This is one of the limitations of this thesis, as macro data does not provide such details.

In terms of the FMA index, growth in FMA is associated with increases in income inequality in emerging market economies. More particular, model 8 shows there is an insignificant widening effect of FMA on the income inequality of EMEs. For emerging markets and advanced markets, FMA had a negative effect on inequality. The results for the nonlinear model suggest there is an insignificant inverted U-shaped relationship between FMA and income inequality of AM, an insignificant simple U-shaped relationship between FMA and income inequality of EM, and an insignificant narrowing hypothesis for LIC. Finally, Table 2.3.1 in appendix A demonstrate the widening effect of inflation on after-tax income inequality of advanced markets (model 1, 4, 13, and 16). Within the advanced market countries, increase in education level of the nations had reducing effect on after-tax income inequality.

2.5.3 Effects of Financial Institution and Market depth on after-tax Income Inequality

This subsection presents the results on the effects of financial institutions and market depth on income after-tax inequality. Table 2.6 presents the system GMM results of the full sample, while the 1st difference GMM results are presented in the appendix page, Table 2.4 A, which also confirms these system GMM results. Table 2.6 presents the results of the linear model (models 1- 3 & 7- 9) and nonlinear model (models 4–6 and 9-12) on the impact of the financial institution and market depth on income inequality. At, first, financial institution depth is measured using the FID index and 2nd one of the FID components, the domestic credit as a share of GDP is also estimated. Model 1 shows growth in domestic credit relative to GDP and confirms a significant narrowing hypothesis on income inequality, while the non-linear model suggests a significant U-shaped relationship (model 4). Model 2 of Table 6 which does not include control variables shows FID index narrows after-tax income by 0.199 Gini point, but the coefficient was insignificant. Sahay and Cihak (2020) also found an insignificant narrowing effect (-0.368) of FID and FMD indices on after-tax income inequality in the base model results.

In Table 2.6 shows, the study finds that the Too Much Finance hypothesis holds. In other words, in the nonlinear models, the financial institution depth index (models 5 & 11) also confirms a U-shaped relationship with income inequality. Lastly, the nonlinear models of FMD depth also confirm a U-shaped relationship (model 6). The U-shaped finance depth and income inequality relationship suggests that increasing depth first narrows income inequality and, after reaching a threshold, growth in depth produces widening effects on income inequality. Thus, excessive credit could widen income inequality.

The U-shaped relationship between finance depth and income inequality was also confirmed in the literature (Brei et al.,2018; Cihak and Sahay, 2020; and de la Cuesta-González et al.,2020). For instance, Cihak and Sahay (2020) confirm the U-shaped finance depth and inequality nexus using financial institution and market depth. In the base model of Sahay and Cihak (2020) the GMM coefficients of FID index and FID index squared were –2.103 and 3.728 respectively on after-tax Gini of 128 countries using data firm 1980 to 2015. Compared to the results presented in model 5 of Table 2.6 were insignificant, but the coefficient for FID index and FID index squared is –0.388 and 0.268 respectively. However, model 11 confirms the U-shaped relationship between FID index and after-tax income inequality. FMD index results reported in table 2.6 models 6 and 12 are in line with the results of Sahay and Cihak (2020) and differ by magnitudes. Sahay and Cihak (2020) GMM results show FMD index decreases log after-tax income inequality by 1.782 Gini points, while the squared term of FMD increased log after-tax Gini by 2.587 Gini points. The reported effects sizes of FMD on income inequality in table 2.6 are smaller than those of Sahay and Cihak (2020). Model 6 of Table 2.6 shows FMD decreases inequality by 0.225 and FMD squared increases inequality by 0.259 Gini points. Brei et al. (2018) also confirms a U-shaped relationship between Depth index (measured as combination of market and institution depth) and income inequality of a panel of advanced and emerging market economies. In terms of magnitudes of the effect size, Brei et al. (2018) used system GMM and shows Depth index reduced log after-tax Gini by 2.206 and the squared term of Depth index increase inequality by 3.736 Gini points.

De la Cuesta-González et al. (2020) confirm the U-shaped hypothesis using both domestic credits as a share of GDP and stock market capitalization on the income inequality of nine OECD countries, using a two-step GMM. The widening effect of higher credit on inequality is explained by how credit is highly dependent on collateral, firm structure, and sector of activity. Bank credit decisions can have a negative or positive influence on an individual's future income. According to Delis et al. (2021), in 5 years, individuals who are accepted for loan applications can grow their future income by 11% versus those who were rejected. For example, an individual accepted for a mortgage loan will have a higher net worth than those rejected. A firm receiving a loan for investment tends to be more profitable than those rejected for loans. These firms are expected to develop and implement certain rules as per the loan agreement. The growth of these firms with accepted loans produces increases in their wages, thus widening income inequality as the wages and productivity of the firms who were declined credit do not increase. Thus, income distribution is much tighter among accepted loan applications versus the wider distribution seen on a rejected loan application.

In addition, when the credit market triggers speculative investment, domestic credit increases income inequality in Vietnam (Le and Nguyen, 2020). Financial policies focusing on alleviating income inequality should also incorporate credit policy provisions whilst reviewing the banking business model to safeguard credit distribution in the direction of inclusive growth and sustainable development (de la Cuesta-González et al.,2020). The widening impact of domestic credit on inequality can also be reduced through policy interventions to increase access to credit efficiently. For example, the European Bank for Reconstruction and Development (EBRD) provides credit to individuals, firms and SMEs that are credit-constrained but have good investment plans or good business financials.

Finally, Table 2.6 shows the proxy variable for education has a narrowing effect on after-tax income inequality (model 7 to 12).

Table 2.6. Effects of financial institution and market depth on after-tax income inequality.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Domestic Credit % of GDP	Financial Institution Depth (FID)	Financial Market Depth (FMD)	Domestic Credit % of GDP	Financial Institution Depth (FID)	Financial Market Depth (FMD)	Domestic Credit % of GDP	Financial Institution Depth (FID)	Financial Market Depth (FMD)	Domestic Credit % of GDP	Financial Institution Depth (FID)	Financial Market Depth (FMD)
L1. Log After-tax Gini	0.850***	0.567	1.077***	0.862***	0.673***	0.986***	0.770***	0.821***	0.782***	0.771***	0.761***	0.775***
	(0.0576)	(0.371)	(0.0352)	(0.0648)	(0.200)	(0.0374)	(0.116)	(0.0661)	(0.0890)	(0.115)	(0.0814)	(0.0883)
Financial Depth	-0.0484**	-0.199	0.0464***	-0.201***	-0.388	-0.225***	-0.0199*	0.0196	-0.01000	-0.0215	-0.232**	-0.0326
	(0.0207)	(0.178)	(0.0175)	(0.0622)	(0.280)	(0.0767)	(0.0115)	(0.0350)	(0.0114)	(0.0384)	(0.103)	(0.0299)
Financial Depth^2				0.0943***	0.268	0.259***				0.000783	0.185**	0.0212
				(0.0358)	(0.216)	(0.0857)				(0.0184)	(0.0843)	(0.0260)
GDP							0.00519	0.00341	0.00395	0.00517	0.000849	0.00383
							(0.00425)	(0.00273)	(0.00306)	(0.00450)	(0.00285)	(0.00313)
lCPI							0.0171	0.0137	0.0116	0.0171	0.00803	0.0113
							(0.0114)	(0.00837)	(0.00733)	(0.0113)	(0.00772)	(0.00746)
Trade_op							0.000720	-0.00463	-0.00629	0.000752	0.000734	-0.00608
							(0.00757)	(0.00559)	(0.00654)	(0.00778)	(0.00617)	(0.00663)
lGov							0.0255	-0.00236	0.00164	0.0256	0.00843	0.00138
							(0.0246)	(0.0180)	(0.0168)	(0.0243)	(0.0195)	(0.0168)
L1.Log-education							-0.110*	-0.0929*	-0.0882*	-0.109	-0.0411	-0.0874*
							(0.0628)	(0.0486)	(0.0461)	(0.0671)	(0.0479)	(0.0467)
Constant	-0.120***	-0.362	0.0604**	-0.0707	-0.246	0.00479	0.0393	-0.00834	-0.0387	0.0390	-0.101	-0.0451
	(0.0451)	(0.309)	(0.0297)	(0.0537)	(0.149)	(0.0319)	(0.108)	(0.0755)	(0.0736)	(0.110)	(0.0750)	(0.0724)
Observations	1,412	1,546	1,546	1,412	1,546	1,546	1,383	1,508	1,508	1,383	1,508	1,508
Number of ccode	120	120	120	120	120	120	119	120	120	119	120	120
AR 2 test (p-value)	0.559	0.643	0.015	0.511	0.446	0.018	0.727	0.280	0.353	0.929	0.184	0.383
Sargan test (p-value)	0.267	0.110	0.027	0.097	0.706	0.024	0.942	0.560	0.765	0.929	0.900	0.953
Hansen test (p-value)	0.100	0.640	0.003	0.048	0.428	0.057	0.920	0.291	0.276	0.923	0.578	0.590

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7. Effects of financial institutions and market depth on income inequality (Subsample results).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
	Domestic Credit % of GDP						Financial Institution Depth (**FID**)						Financial Market Depth (**FMD**)					
	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC
L1. Log After-tax Gini	0.794***	0.785***	0.731***	0.797***	0.798***	0.743***	0.856***	0.806***	0.837***	0.864***	0.907***	0.853***	0.825***	0.938***	0.907***	1.145***	0.954***	0.801***
	(0.128)	(0.0966)	(0.118)	(0.132)	(0.111)	(0.113)	(0.161)	(0.0931)	(0.0994)	(0.182)	(0.0973)	(0.105)	(0.150)	(0.0317)	(0.0612)	(0.233)	(0.0461)	(0.105)
Financial depth	0.0138	-0.0575**	-0.0416	-0.00573	-0.0774	-0.0601	-0.0120	-0.100	-0.129*	-0.407	-0.232	-0.319	-0.00283	-0.0108	-0.0504	0.463	-0.120	-0.603
	(0.00958)	(0.0281)	(0.0281)	(0.0432)	(0.0566)	(0.0596)	(0.0299)	(0.0715)	(0.0653)	(0.309)	(0.142)	(0.282)	(0.0152)	(0.0128)	(0.0422)	(0.406)	(0.151)	(0.444)
Financial depth^2				0.00752	0.0174	0.0467				0.280	0.327	1.194				-0.376	0.170	2.531
				(0.0147)	(0.0479)	(0.114)				(0.224)	(0.207)	(1.770)				(0.308)	(0.228)	(2.048)
Observations	413	594	285	413	594	285	446	659	321	446	659	321	446	659	321	446	659	321
Number of ccode	34	53	33	34	53	33	34	53	33	34	53	33	34	53	33	34	53	33
AR 2 test (p-value)	0.156	0.265	0.618	0.122	0.279	0.664	0.214	0.066	0.835	0.139	0.109	0.945	0.248	0.077	0.831	0.055	0.145	0.581
Sargan test (p-value)	0.308	0.751	0.741	0.295	0.720	0.713	0.344	0.200	0.799	0.415	0.568	0.823	0.314	0.521	0.356	0.695	0.613	0.348
Hansen test (p-value)	0.304	0.901	0.705	0.439	0.601	0.652	0.165	0.239	0.682	0.481	0.304	0.859	0.238	0.672	0.044	0.348	0.634	0.051

Table 2.7 above presents the 1st difference GMM baseline results of the three groups (subsamples) on the effects of increases in depth to financial institutions (FID), financial markets (FMD) and domestic credit as a share of GDP on after-tax inequality. The models with control variables of the sub-sample results are presented in Appendix A, **Table 2.4.1. A**.

Domestic credit as a share of GDP is one of the components of financial institution depth (FID) and was found to have significant and reducing effects on net income inequality of emerging market economies. All the subgroup nonlinear model results were insignificant, but in line with full sample results, the domestic credit coefficients suggest a U-shaped relationship between domestic credit and income inequality of all the groups. These results are different to the findings of Nguyen et al. (2019) a significant inverted U-shaped relationship with both after and before-tax inequality. The U-shaped relationship between private credit as a share of GDP and after-tax inequality was confirmed by Park and Shin (2015) using 162 countries and data from 1960 to 2011.

The linear model results on the effects of the FID index on inequality were negative across all three subgroups, and only the coefficient for LIC was significant in model 9. This suggests that the other 3 components of FID (pension fund and mutual fund assets to GDP and insurance premiums to GDP) are significant for LIC countries, while the domestic credit share to GDP component of FID seems to have a significant effect on EME inequality. As such, these three components of FID are important for LIC as avenues for saving for investment or retirement, and insurance can reduce inequality by mitigating unforeseen risks. Like the full sample results, the three subgroup results suggest a U-shaped relationship between FID and income inequality (models 10-12).

The FMD index shows an insignificant narrowing effect on income inequality of the three groups (model 13-15). While the coefficient for EM and LIC groups were insignificant in the nonlinear model, the results suggest there exists a U-shaped relationship, while results for advanced economies suggest an insignificant inverted U-shaped relationship. Table 2.4.1 (A) in Appendix A shows in advanced economies, inflation increases after-tax income inequality, while education reduces after-tax inequality in advanced economies.

2.6 Empirical results for before-tax Gini

This section of Chapter 2 presents the results on the effects of FSD on before-tax income inequality. Similar to section 2.5, the full sample results using the 120 countries are presented first, and after that, the results for the three subgroups are presented. Subsequently, section 2.6 proceeds as follows: first, the overall FSD results on before-tax income inequality are presented (section 2.6.1), section 2.6.2 looks at the effects of access to financial institutions and markets on inequality and finally, section 2.6.3 present the effects of financial institutions and market depth on before-tax income inequality. As such, the dependent variable of the results presented in this subsection of the thesis is the log of the before-tax Gini index.

2.6.1 Overall Effects of FSD on Before-tax Income Inequality

This subsection presents and discusses the results of the effects of overall FSD indices on before-tax income inequality using full samples and subsamples. Table 2.8 presents the full sample results of overall FSD (FD, FI, & FM) effects on before-tax income inequality using the system GMM. For robustness of the results, the 1st difference GMM results is presented in the Appendix A, Table 2.5 (A). The analysis in Table 2.8starts with the base model results (models 1-3), where the control variables are not included in the estimation, and thereafter, Table 2.8 reports the results of the full sample for the linear model, including control variables.

The results from Table 2.8 below show a significant widening hypothesis of FSD effects on before-tax income inequality (model 3-6). First, the coefficients suggest that FD, FI, and FM increase before-tax income inequality by a range of 0.0184 to 0.165 (model 3-6). Intuitively developed financial institutions and markets can lead to higher demand for skilled labour, resulting in higher income for skilled individuals, thus increasing before-tax inequalities. Secondly, FSD is also associated with financial integration, which boosts the demand for domestic financial assets and can bring about increases in asset prices- the growth in asset prices results in higher income for those with assets, thus widening the before-tax income inequality. Altunbas and Thornton (2019) also confirmed a widening effect between the FI index and the before-tax Gini of 121 countries. In terms of magnitude, the coefficient for the FI index in model 5 of Table 2.8 is 0.125 which is in line with the empirical findings of Altunbas and Thornton (2019) which showed the FI index increases before-tax income inequality by ranged a of 0.05 to 0.10 Gini points.

The fact that FD, FI, and FM have widening effects on before-tax income inequality (Table 2.5) and narrowing effects on after-tax income inequality (Table 2.2) suggests that the implementation of income tax policies results in the redistribution of income and thus reduces inequalities. These results differ from the findings of Nguyen et al., (2019) who confirmed an inverted U-shaped relation between the FD index and both before and after-tax income inequality of 21 emerging markets. The widening effect of FD on before-tax was confirmed by Altunbas and Thornton (2019) in 121 economies. In terms of other explanatory variables in the model, more GDP per capita, government spending and increase in price levels appear to have an increasing effect on before-tax income inequality. The proxy variable for education levels of the country demonstrates a narrowing effect on before-tax income inequality.

Table 2.8. Effects of overall financial sector development on before-tax income inequality.

	(1) Financial Development Index (FD	(2) Financial Institution Index (FI)	(3) Financial Market Index (FM)	(4) Financial Development Index (FD	(5) Financial Institution Index (FI)	(6) Financial Market Index (FM)
L1. Log After-tax Gini	1.042***	1.087***	0.946***	0.671***	1.010***	1.030***
	(0.0253)	(0.0337)	(0.0236)	(0.0473)	(0.0935)	(0.0828)
Findev	0.00146	-0.00767	0.0184***	0.165**	0.125***	0.0762***
	(0.00480)	(0.00605)	(0.00624)	(0.0761)	(0.0435)	(0.0206)
GDP				0.0141**	0.00338	-0.000526
				(0.00704)	(0.00254)	(0.00248)
lCPI				0.0125	0.00617	0.0150**
				(0.0161)	(0.00601)	(0.00643)
Trade_op				-0.00265	-0.00953	-0.00108
				(0.0102)	(0.00704)	(0.00430)
lGov				0.0522*	-0.00991	0.00524
				(0.0268)	(0.0157)	(0.0139)
L1.Log-education				-0.175**	-0.0782**	-0.0448**
				(0.0817)	(0.0302)	(0.0202)
Constant	0.0312	0.0705**	-0.0487**	0.103	0.0871	0.0971
	(0.0213)	(0.0278)	(0.0201)	(0.167)	(0.0816)	(0.0740)
Observations	1,546	1,546	1,546	1,393	1,508	1,508
Number of ccode	120	120	120	120	120	120
AR	0.037	0.051	0.030	0.380	0.174	0.040
Sargan	0.036	0.001	0.000	0.007	0.001	0.000
Hansen	0.001	0.085	0.002	0.771	0.136	0.003

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.11 presents the 1st difference GMM baseline results of the three groups (subsamples) on the effects of overall FSD on before-tax income inequality. The models with control variables of the sub-sample results are presented in **Appendix A**, Table 2.5.1. The results presented in Table 2.11 show overall financial institutions and market development (FD) suggest that at a 10% significant level (models 1 & 3), FD widens before-tax income inequality of advanced economies (AM), while FD narrows the before-tax inequality for low-income countries (LIC). Altunbas and Thornton (2019) also had similar findings, where they found the FD index to increase before-tax income inequality in high-income countries. Model 1 of table 2.9 shows the FD index increases before-tax inequality of AM by 0.043 Gini point which is less than the FD coefficients ranging between 0.09 to 0.113 of Altunbas and Thornton (2019) on high-income subsample results. The FD widening hypothesis confirmed for the AM group is in line with the full sample result and the results for the EM group (model 2 of Table 2.5.1). The levels of FD for AM and LIC differ by group, as suggested by the summary table of the three groups; as such, for LIC, there seems to be benefits from increasing FD in both the net and gross Gini.

In terms of the development of only financial institutions, models 7 and 10 of **Appendix A**, Table 2.5.1 confirms the same patterns seen in the FD model. Model 7 of **Appendix A**, Table 2.5.1 confirms widening and significance at 5% level FI effects on inequality of the AM group. Model 9 of **Appendix A**, Table 2.5.1 confirms a narrowing and significant FI effect on the before-tax inequality of the LIC group. EM group also shows an insignificant narrowing hypothesis. The FI widening hypothesis confirmed for the AM group is in line with the full sample result. Interestingly, the effects of FI have narrowing effects on both the before and after-tax Gini of the EM and LIC groups.

The effects of overall FM development confirm a significant and widening hypothesis on the before-tax income inequality of AM groups (model 16). While the coefficients were insignificant, models 14 and 17 show FM has a widening effect on the before-tax of the EM group and models 15 and 18 show FM has a narrowing effect on the inequality of the LIC group. FM index has a reducing effect on both the before and after-tax inequality of the LIC group. A look at Table 2.1 of **Appendix A** shows that the maximum value for FM in the LIC group is 0.209, while for AM and EM is 0.989 and 0.735, respectively. Lastly, other explanatory variables suggest that in advanced markets, inflation increases before-tax income inequality, while the increase in education reduces before-tax income inequality.

Table 2.9. Impacts of overall financial sector development on before-tax income inequality (Subsample results).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Financial Development Index (FD)						Financial Institution Index (FI)						Financial Market Index (FM)					
	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC
L1. Log Before-tax Gini	0.855***	0.953***	0.777***	0.859***	0.948***	0.673***	0.882***	0.935***	0.796***	0.856***	1.081***	0.788***	0.831***	0.945***	0.821***	0.939***	0.963***	0.702**
	(0.0720)	(0.0368)	(0.118)	(0.0775)	(0.0417)	(0.131)	(0.0709)	(0.0821)	(0.0963)	(0.0871)	(0.213)	(0.0961)	(0.0781)	(0.0252)	(0.168)	(0.110)	(0.0331)	(0.264)
Findev	0.0427*	0.000606	-0.146**	0.231	0.0922	-0.950	0.0759**	-0.00642	-0.0853**	0.232	-0.185	-0.247	0.0151	0.00871	-0.275	0.446*	0.164	-0.771
	(0.0250)	(0.0233)	(0.0615)	(0.225)	(0.208)	(0.634)	(0.0361)	(0.0264)	(0.0316)	(0.215)	(0.160)	(0.233)	(0.0173)	(0.0171)	(0.213)	(0.251)	(0.153)	(0.567)
Findev				-0.147	-0.143	3.046				-0.117	0.274	0.385				-0.332*	-0.217	2.542
				(0.168)	(0.319)	(2.320)				(0.151)	(0.264)	(0.518)				(0.185)	(0.203)	(2.768)
Observations	446	659	321	446	659	321	446	659	321	446	659	321	446	659	321	446	659	321
Number of ccode	34	53	33	34	53	33	34	53	33	34	53	33	34	53	33	34	53	33
AR 2 test (p-value)	0.304	0.080	0.871	0.155	0.131	0.902	0.417	0.085	0.632	0.387	0.117	0.641	0.327	0.084	0.823	0.112	0.156	0.887
Sargan test (p-value)	0.302	0.065	0.232	0.149	0.080	0.427	0.297	0.065	0.308	0.390	0.219	0.313	0.270	0.062	0.107	0.213	0.144	0.128
Hansen test (p-value)	0.410	0.735	0.700	0.439	0.714	0.833	0.438	0.362	0.739	0.430	0.570	0.771	0.555	0.948	0.180	0.720	0.638	0.294

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.

2.6.2 Effects of Access to Financial Institutions and Market on After-tax Income Inequality

This subsection presents the results on the effects of access to financial institutions and the market on income before-tax inequality. Table 2.10 below presents the system GMM results of the full sample, while the 1st difference GMM results are presented in the **Appendix A**, Table 2.6. A, which also confirms the system GMM results.

Model 3 of Table 2.6 demonstrates that in the linear model, FIA significantly increases before-tax inequality by 0.11 Gini points. Models 2 and 4 represent the nonlinear FIA index model results, where the coefficients suggest a U-shaped relationship between FIA and before-tax income inequality. This suggests the FIA index reduces inequality up until the threshold, beyond which, an increase in the FIA index increases before-tax inequality. The U-shaped FIA-inequality nexus was also confirmed in the base model using after-tax inequality.

The results on the effects of the FMA index on before-tax inequality are presented from models 5-8 where nonlinear model 6 shows a significant U-shaped relationship. While model 6 reflects the direct effect size as it does not account for other drivers of the dependent variable, model 8 with control variables shows an inverted U-shaped relationship between the FMA index and inequality. In addition, the results for model 8 with control variables are preferred over model 6 results, model 6 also suffers from issues of serial correlation as indicated by AR 2 test results. The FMA index nonlinear results suggest an inverted U-shaped for both the before and after-tax Gini. The ATM per adults' model 11 shows growth in the number of ATMs increases before tax-income inequality.

Table 2.10. Effects of Access to Financial Institutions and Markets on Before-tax Inequality.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Financial Institution Access (FIA)				Financial Market Access (FMA)				ATM per Adults			
L1. Log Before-tax Gini	1.055***	0.898***	1.081***	0.806***	1.063***	1.126***	1.016***	0.673***	1.065***	0.934***	0.828***	0.364
	(0.0211)	(0.0530)	(0.119)	(0.125)	(0.0326)	(0.0818)	(0.105)	(0.203)	(0.0264)	(0.0971)	(0.137)	(0.631)
Financial Access	-0.00121	-0.161***	0.107***	-0.261**	-0.00251	-0.219**	0.0650**	0.468*	-0.00184	-0.0843	0.0687*	-0.0667
	(0.00380)	(0.0540)	(0.0363)	(0.107)	(0.00616)	(0.104)	(0.0296)	(0.261)	(0.00246)	(0.061)	(0.0348)	(0.1095)
Financial Access2		0.217***		0.291***		0.264**		-0.379*		0.072		0.0849
		(0.0673)		(0.108)		(0.121)		(0.205)		(0.052)		(0.0973)
GDP			0.00528	0.00131			0.00154	0.00571			0.00687	0.00804
			(0.00340)	(0.00323)			(0.00264)	(0.00507)			(0.00430)	(0.0101)
lCPI			-0.00173	0.00107			0.0161	0.0113			-0.0164	-0.0292
			(0.00619)	(0.00843)			(0.0101)	(0.0173)			(0.0117)	(0.0340)
Trade_op			-0.0236*	-0.00134			0.0121	-0.00647			-0.00603	0.00565
			(0.0126)	(0.00715)			(0.00735)	(0.00967)			(0.00810)	(0.00884)
lGov			-0.0318	0.0148			0.0322	0.0211			0.0149	0.0583
			(0.0226)	(0.0145)			(0.0199)	(0.0298)			(0.0199)	(0.0558)
L1.Log-education			-0.0541**	0.0179			-0.0776**	-0.109			-0.0960*	-0.0750
			(0.0235)	(0.0305)			(0.0363)	(0.0836)			(0.0508)	(0.115)
Constant	0.0424**	-0.0681*	0.0742	-0.129	0.0490*	0.115	0.194	-0.0787	0.0503**	-0.0455	0.0515	-0.249
	(0.0171)	(0.0384)	(0.0855)	(0.123)	(0.0268)	(0.0718)	(0.118)	(0.144)	(0.0210)	(0.0700)	(0.128)	(0.423)
Observations	1,546	1,546	1,508	1,508	1,546	1,546	1,508	1,508	1,449	1,449	1,416	1,416
Number of ccode	120	120	120	120	120	120	120	120	119	119	119	119
AR 2 test (p-value)	0.041	0.448	0.237	0.962	0.043	0.048	0.009	0.947	0.045	0.048	0.825	0.613
Sargan test (p-value)	0.020	0.104	0.179	0.533	0.009	0.705	0.433	0.763	0.016	0.705	0.266	0.559
Hansen test (p-value)	0.018	0.168	0.017	0.255	0.203	0.433	0.069	0.185	0.090	0.433	0.243	0.500

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.11. Effects of Access to Financial Institutions and Markets: Sub sample 1st GMM results for before tax.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Financial Institution Access (FIA)						Financial Market Access (FMA)						ATM per Adults					
	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC
L1. Log Before-tax Gini	0.896***	0.869***	0.680***	0.955***	0.690	0.676***	0.834***	0.940***	0.918***	0.768***	0.940***	0.915***	0.751***	0.939***	0.658**	0.828***	0.976***	0.769**
	(0.0686)	(0.0910)	(0.202)	(0.0779)	(0.448)	(0.231)	(0.0964)	(0.0250)	(0.0584)	(0.138)	(0.0250)	(0.0614)	(0.135)	(0.0822)	(0.271)	(0.112)	(0.0919)	(0.283)
Financial Access	0.0382**	-0.0176	-0.0735*	-0.167	0.116	-0.0294	-0.0350**	0.0325	-0.189	0.203*	0.0321	-0.130	0.0382**	0.000751	-0.0540	0.108	-0.0124	-0.122**
	(0.0148)	(0.0183)	(0.0424)	(0.163)	(0.294)	(0.0724)	(0.0140)	(0.0225)	(0.189)	(0.105)	(0.0859)	(0.188)	(0.0156)	(0.00722)	(0.0500)	(0.0727)	(0.0127)	(0.0548)
Financial Access^2				0.173	-0.218	-0.182				-0.193**	0.000408	-0.134				-0.0285	0.0141	0.301**
				(0.139)	(0.483)	(0.253)				(0.0910)	(0.0812)	(0.603)				(0.0312)	(0.0108)	(0.124)
Observations	446	659	321	446	659	321	446	659	321	446	659	321	442	624	264	442	624	264
Number of ccode	34	53	33	34	53	33	34	53	33	34	53	33	34	53	32	34	53	32
AR 2 test (p-value)	0.141	0.101	0.341	0.095	0.868	0.403	0.230	0.058	0.752	0.872	0.063	0.715	0.325	0.082	0.437	0.096	0.161	0.500
Sargan test (p-value)	0.225	0.106	0.411	0.241	0.329	0.528	0.204	0.194	0.124	0.411	0.153	0.097	0.335	0.068	0.332	0.290	0.176	0.258
Hansen test (p-value)	0.360	0.120	0.342	0.389	0.932	0.855	0.960	0.376	0.357	0.781	0.440	0.249	0.939	0.194	0.343	0.595	0.030	0.259

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A, Table 2.6.1 presents the 1st difference in GMM baseline results of the three groups on the effects of access to financial institutions (FIA), financial markets (FMA) and ATM per adult. The models with control variables of the sub-sample results are presented in **Appendix A**, Table 2.6.1.A. Table 2.6.1 shows that there is a significant and narrowing effect of the FIA index on the before-tax income inequality of the LIC group. For the AM group, model 1 of **Appendix A**, Table 2.6.1 shows a positive and significant coefficient, suggesting a widening hypothesis. Again, the summary statistics in Table 2.1 on **Appendix A** shows a clear gap that can be seen in the levels of FIA for LIC versus AM groups.

In terms of the FMA index, advanced markets show a narrowing effect in the linear model 7 and an inverted U-shaped relationship in the nonlinear model 10. The coefficients of FMA effects on inequality of the EM group were positive (models 8 & 11) but insignificant. While the coeffects in models 9 and 12 show, FMA reduces before-tax inequality of the LIC group. However, the coefficients in models 9 & 12 were insignificant. The inverted U-shaped relationship of the FMA index and before-tax inequality confirmed in the full sample results above is also confirmed for the AM group.

The number of ATMs per adult had an insignificant narrowing effect on the inequality of the LIC group in the linear model 15, while the nonlinear model reveals a significant U-shaped relationship. Similar to the full sample results, the number of ATMs per adult significantly widens before-tax inequality of AM groups.

2.6.3 Effects of Financial Institution and Market depth on before-tax Income Inequality

This subsection presents the results on the effects of financial institutions and market depth on income before-tax inequality. Table 2.12 presents the system GMM results of the full sample, while the 1st difference GMM results are presented in **Appendix A**, Table 2.7. A, which also confirms the GMM results. Model 1-4 of Table 2.7ble 2.12 presents the effects of financial institution depth measured as domestic credit as a share of GDP, where the linear models confirm narrowing effects on before-tax income inequality (models 1 & 3). Model 2 shows there is a direct U-shaped relationship between domestic credit and before-tax inequality. The GMM results reported in Table 2.12 model 2 show domestic credit as a share of GDP reduces inequality by 0.134 Gini points and the squared term increases before-tax Gini by 0.091 Gini points. Park and Shin (2015) also confirmed a U-shaped relationship between domestic credit as a share of GDP and before-tax income inequality. Using the fixed effect panel model, Park and Shin (2015) show domestic credit first reduces before-tax Gini by 0.131, while its squared term increases Gini by 0.019 Gini points. However, Nguyen et al. (2019) found an inverted U-shaped relationship between domestic credit and before-tax income inequality in 21 emerging market economies.

When looking at overall financial institution depth (FID), there is a U-shaped relationship, as suggested by model 6 of Table 2.7. However, when accounting for other factors models 7 and 8 suggested FID increases inequality. The linear results of FID suggest a widening effect, while the after-tax results suggest a narrowing effect. However, the U-shaped hypothesis between FID, FMD, Domestic credit and inequality is confirmed in both the models of before and after-tax Gini. The findings of Park and Shin (2015) confirmed a U-shaped relationship between liquid liabilities as a share of GDP and both before and after-tax income inequality. Iacoviello (2008) argues economic cycles have an influence on credit demand which leads to an increase in the indebtedness of households and further widens inequality. The findings of Iacoviello (2008) highlight the reversal-causality in the FSD and income inequality relationship. Iacoviello (2008) argues that macroeconomic development has effects on both the trend and the cyclical behaviour of debt. The argument is that as the economies develop, so will the credit access market and households' balance sheets be procyclical over the business cycles, which makes credit highly correlated with GDP.

Finally, FMD also tends to increase inequality, as suggested by models 9 and 11 of Table 2.72.12. The proxy variable of education was negative and significant in models 11 and 12 of Table 2.12.

Table 2.12. Effects of financial institution and market depth on before-tax income inequality.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Domestic Credit % of GDP				Financial Institution Depth (**FID**)				Financial Market Depth (**FMD**)			
L1. Log Before-tax Gini	0.948***	0.873***	0.762***	0.759***	0.993***	0.872***	0.841***	0.963***	0.997***	0.993***	0.915***	0.997***
	(0.0184)	(0.0839)	(0.151)	(0.172)	(0.0218)	(0.0668)	(0.107)	(0.0880)	(0.0211)	(0.0218)	(0.0816)	(0.0944)
Financial Depth	0.0107***	-0.134***	0.0533**	0.0418	-0.016	-0.301**	0.129*	0.311*	0.00844**	-0.0381	0.0599***	0.179**
	(0.00252)	(0.0490)	(0.0219)	(0.0383)	(0.0095)	(0.126)	(0.0778)	(0.178)	(0.00381)	(0.0245)	(0.0228)	(0.0692)
Financial Depth^2		0.0912***		0.00553		0.364**		-0.159		0.0542*		-0.128**
		(0.0326)		(0.0170)		(0.150)		(0.104)		(0.0274)		(0.0561)
GDP			0.00766	0.00766			0.00406	0.00350			0.00381	0.00202
			(0.00521)	(0.00517)			(0.00402)	(0.00425)			(0.00329)	(0.00286)
lCPI			-0.00551	-0.00537			0.0120	0.0195			0.00958	0.0127
			(0.0107)	(0.0119)			(0.0130)	(0.0158)			(0.00766)	(0.00794)
Trade_op			-0.0122	-0.0119			0.00567	-0.00204			0.00865	0.00329
			(0.00833)	(0.00851)			(0.00572)	(0.00575)			(0.00558)	(0.00500)
lGov			-0.00688	-0.00561			0.00801	-0.0118			0.0233	0.00917
			(0.0180)	(0.0167)			(0.0148)	(0.0156)			(0.0168)	(0.0171)
L1.Log-education			-0.0621	-0.0600			-0.120	-0.142			-0.0768**	-0.0656**
			(0.0466)	(0.0475)			(0.0793)	(0.0946)			(0.0380)	(0.0310)
Constant	-0.0487***	-0.0736	-0.113	-0.114	0.1235	-0.0710	0.0764	0.151	-0.00571	-0.00495	0.0986	0.106
	(0.0151)	(0.0624)	(0.147)	(0.162)	(0.0533)	(0.0437)	(0.129)	(0.152)	(0.0176)	(0.0182)	(0.0930)	(0.0885)
Observations	1,412	1,412	1,383	1,383	1,546	1,546	1,508	1,508	1,546	1,546	1,508	1,508
Number of ccode	120	120	119	119	120	120	120	120	120	120	120	120
AR 2 test (p-value)	0.027	0.657	0.572	0.588	0.089	0.099	0.479	0.417	0.035	0.066	0.061	0.009
Sargan test (p-value)	0.001	0.259	0.484	0.363	0.098	0.253	0.333	0.422	0.000	0.002	0.006	0.120
Hansen test (p-value)	0.008	0.309	0.394	0.364	0.634	0.519	0.284	0.167	0.001	0.001	0.150	0.055

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.13. Effects of the financial institution and market depth on before-tax income inequality.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Domestic Credit % of GDP						Financial Institution Depth (**FID**)						Financial Market Depth (**FMD**)					
	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC
L.lgini_mkt	0.867***	0.901***	0.701***	0.817***	0.928***	0.737***	0.847***	0.956***	0.762***	0.825***	0.965***	0.784***	0.817***	0.957***	0.795***	0.921***	0.953***	0.647**
	(0.0706)	(0.0694)	(0.157)	(0.0844)	(0.0827)	(0.111)	(0.0886)	(0.0754)	(0.138)	(0.0840)	(0.0688)	(0.144)	(0.0791)	(0.0260)	(0.206)	(0.118)	(0.0271)	(0.238)
Financial Depth	0.0227***	-0.0225	-0.0569**	0.0646	-0.0589	-0.143**	-0.0239	0.00260	-0.173**	0.0871	-0.00620	-0.361	0.00599	0.0152	-0.142	0.268	0.0494	-0.700
	(0.00816)	(0.0193)	(0.0252)	(0.0399)	(0.0352)	(0.0628)	(0.0319)	(0.0493)	(0.0748)	(0.140)	(0.0776)	(0.374)	(0.0116)	(0.00931)	(0.101)	(0.188)	(0.0896)	(0.462)
Financial Depth^2				-0.0167	0.0319	0.204*				-0.0740	0.0235	1.190				-0.206	-0.0527	2.521
				(0.0139)	(0.0282)	(0.102)				(0.101)	(0.110)	(2.326)				(0.148)	(0.137)	(2.196)
Observations	413	594	285	413	594	285	446	659	321	446	659	321	446	659	321	446	659	321
Number of Ccode	34	53	33	34	53	33	34	53	33	34	53	33	34	53	33	34	53	33
AR 2 test (p-value)	0.114	0.119	0.079	0.686	0.121	0.172	0.245	0.096	0.465	0.309	0.102	0.660	0.414	0.085	0.639	0.034	0.095	0.968
Sargan test (p-value)	0.363	0.069	0.258	0.354	0.083	0.238	0.361	0.066	0.351	0.303	0.046	0.301	0.303	0.129	0.075	0.261	0.172	0.145
Hansen test (p-value)	0.906	0.799	0.751	0.234	0.577	0.837	0.835	0.703	0.841	0.797	0.698	0.950	0.896	0.414	0.164	0.371	0.405	0.349

Appendix A, Table 2.7.1 presents the 1st difference GMM baseline results of the three groups (subsamples) on the effects of increases in depth to financial institutions (FID), financial markets (FMD) and domestic credit as a share of GDP on before-tax inequality. The models with control variables of the sub-sample results are presented on **Appendix A**, Table 2.7.1 (A). For the AM group, domestic credit has a widening effect on the before-tax inequality. On the other hand, the results LIC group suggest domestic credit reduces inequality in the linear model, while the nonlinear model 6 of **Appendix A**, Table 2.7.1 suggests a U-shaped relationship. Again, FID had a negative and significant effect on the before-tax inequality of the LIC group. On the contrary, the results for FMD on before-tax inequality suggest that FMD may not have a significant effect on the income inequality of the selected groups.

2.7 Diagnostics test

All the GMM results in **Appendix A**, Tables 2.1–2.7.1 present the GMM diagnostic test results in the last three rows, where the models showed no evidence of serial correlation[2], as indicated by the Arellano–Bond test for serial correlation (AR2).

The Sargan and Hansen test investigates the validity of the chosen instruments of the model. The Sargan test of overidentifying restrictions is a special case of the Hansen test, as it assumes homoskedasticity and no serial correlation in the error terms, while the Hansen test does not rely on these strong assumptions (Roodman, 2007). The Hansen test of overidentifying restrictions depends on the estimate of an optimal or robust weighting matrix, while the Sargan test does not (Roodman, 2007). Thus, the Hansen and Sargan test results have different p-values. The p-values for both Sargan and Hansen tests in all the above results[3] are above 5%, suggesting that, under both assumptions on error terms, the model instruments are valid. For robust standard errors, this study emphasizes the Hansen test on instrument validity. The debate in the literature regarding the p-values of the Hansen test and the number of instruments in GMM continues; hence, this study also uses the collapse option to ensure that the number of instruments does not produce bias in the test of instrument validity (Roodman 2007).

[2] With exception for only model 1 and 3 of table 2.2, Model 5 of table 2.2.1, model 3 of table 2.3 , model 3 and 6 of table 2.4. The before-tax results which failed the test were; model 1 & 6 of table 2.5, model 1 , 5, & 7 of table 2.6, model 1 & 9 of table 2.7; model 16 of table 2.7.1.

[3] With exception of model 1 and 3 of table 2.2, model 1, 2, 4 , 5 of table 2.3, model 4, of table 2.3.1. The before-tax results which failed the test were; model 3 & 6 of table 2.5; model 1 of table 2.6; model 9 & 10 of table 2.7.

2.8 Conclusion

The literature on income inequality and financial sector development (FSD) is complex, with extensive studies using financial institution depth as a proxy measure of FSD. The more recent approach of the IMF on FSD dimensions provides a comprehensive view of both financial institutions and markets and their respective dimensions of development. This study adds to the literature by looking first at the overall effects of FSD on income inequality using the FSD index, as done by Nguyen et al. (2019), whilst also investigating individually the effects of financial market and institution development on income inequality. This chapter also investigates the multidimensional perspective of FSD on income inequality. More specifically, this chapter investigates the effects of financial sector depth (domestic credit) and access to the financial sector on income inequality. Panel data of 120 countries from 2004 to 2019 is applied to the system GMM and 1st difference GMM estimator.

The study also enriches the investigation by studying the effects of FSD components on advanced, emerging, and low-income countries' income inequality. The findings of the study showed that the empirical results from the full sample of 120 countries demonstrate a negative and significant overall effect of FSD (FD, FI, & FM index) on after-tax income inequality. The narrowing effects of overall financial development (FD) and financial institution (FI) indices on after-tax income inequality were also confirmed for the EME. The results reveal a significant and more pronounced reducing effect of FD and FI on after-tax inequality of emerging markets.

On the other hand, the results from the full sample using before-tax income inequality as the dependent variable suggest that increases in FD, FI and FM widen inequality. In terms of the subgroups, growth in FD increased the before-tax inequality of advanced markets while it reduced the before-tax inequality of low-income countries. Intuitively, the levels of the FD index in LIC are far smaller than those of the AM group. The smaller levels of the FD index suggest the countries have the least in terms of financial system development. The observed contradiction between the before-tax and after-tax results was expected. After-tax Gini represents the net basis of inequality, with the taxed income often used for social benefits and other redistribution policies of income. Secondly, an increase in FSD tends to demand highly skilled individuals, which pushes up their respective wages and increases before-tax inequality.

This chapter also investigated the two components of FSD, namely access and depth of financial institutions and markets on both after and before-tax inequality. The study used two measures of access to financial institutions: the FIA index and the number of ATMs per adult. The full sample results show an increase in FIA narrows after-tax income inequality. In addition, the full sample results also show that increases in the number of ATMs per adult also narrow income inequality. More specifically, the effects of increased access to financial institutions (FIA) reduce after-tax inequality of LIC and EM groups. The linear model results also suggest an increase in the number of ATMs reduces the inequality of EM and LIC groups.

On the contrary, in the nonlinear model, ATM has a U-shaped relationship with the after-tax inequality of the LIC group. These results may reflect the levels of maintenance of ATMs, especially near rural and less economically developed cities; thus, the number of ATMs per adult may be increasing, but the number of actual functioning ATMs may be less. This is one of the limitations of this thesis, as macro data does not provide such details. The narrowing hypothesis of financial access on inequality is evident in the literature, especially in the case of India, where the national bank used a policy mandate to broaden access to finance in rural areas. This includes poor households in the formal economy, allowing them to save and invest; it allows informal workers such as street vendors in Africa to bank their income and thus start building credit for future loans. As such, access to financial institution services is the most important component of FSD when it comes to income inequality.

Contrary to other indicators of FSD, the FMA index results from this chapter demonstrate a U-shaped effect with both before and after-tax Gini. Suggesting the effects of FMA are not muchly affected by tax policies. This may reflect the use of financial products (stock) as collateral for borrowing while the individuals are not paying taxes on unsold stocks.

The finding of the effects of FIA on before-tax income inequality also suggests a narrowing hypothesis. This means an increase in access to financial institutions reduces both the before and after-tax inequality. The number of ATMs had an increasing effect on before-tax inequality as suggested by full sample results. The chapter also finds a FIA significantly narrows the before-tax income inequality of the LIC group while widening an inverted U-shaped relationship between the before-tax inequality of AM.

Finally, the results of the chapter conclude that for financial institutions and markets, depth in the full sample suggests a narrowing effect in the linear model, while the nonlinear model suggests a simple U-shaped relationship with after-tax income inequality. While depth measured as domestic credit has a significant reducing effect on after-tax income inequality of emerging market economies. For low-income groups, FID had a negative and significant reducing effect on after-tax inequality.

This study does not disregard the other factors driving income inequality, such as wages (skills/education); however, the study points out other measures that can be taken to tackle inequalities. Exclusion from the financial sector reflects exclusion from the formal economy.

3 FINANCIAL DEEPENING ON INCOME INEQUALITY: A QUANTITATIVE META-ANALYSIS STUDY. ARTICLE 2

3.1 Introduction

Chapter 3 of this thesis is based on Article 2, titled: " Financial Deepening on Income Inequality: A Quantitative Meta-Analysis Study'. This chapter builds on the work done in the previous chapter by conducting a quantitative meta-analysis study, focusing only 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 Gross Domestic Product (GDP). Financial institution depth has been intensively studied, and yet the results show no consensus. By focusing on one component of FSD, the analysis can find the exact effect size of financial institution depth. Thus, this study quantifies the effects of financial institution depth on income inequality.

The topic of the effects of financial sector development on income inequality has been intensively investigated, as presented in section 2.2.3 of chapter 2. Mainly, the four strands of the effects of FSD on income inequality allude to conflicting theoretical predictions. For example, one strand of the literature suggests FSD reduces income inequality, another strand of the literature suggests FSD increases inequality, while the other two standards suggest FSD effects on inequality are nonlinear and follow an inverted U-shaped curve or a simple U-shaped curve. These studies are mostly empirical by nature, thus depending on past studies which were mostly empirical and on econometric methods for more evidence. Subsequently, the current literature should be summarized to find the true effect of FSD on income inequality. Thus, the meta-analysis technique is useful in consolidating these results and providing a conclusion on the effect size.

As such, this chapter first discusses the steps of conducting a quantitative meta-analysis in the materials subsection; the discussion of the data collection methods and sources follows this. Thereafter, the chapter proceeds with a discussion of methods used to calculate and model the effect size of FSD on income inequality. Finally, section 3.3 presents the results, and section 3.4 concludes the chapter.

3.2 Materials and Methods

3.2.1 Materials

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? The paper attempts to answer this research question by utilizing a meta-analysis method. There are seven steps followed when conducting a meta-analysis, and they are: The first step; define the research question. Second step; 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, calculate the effect size and 6^{th} step is to estimate the multivariate regression. The seventh and last step is, to test for publication bias in the topic.

Step 2 is one of the essential steps in conducting a meta-analysis. In this step, the researcher determines study eligibility criteria. Thus, 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 coefficient tracks changes in the income share of individuals, with a range from 0 to 1. In collecting data for meta-analysis, only studies employing the Gini index (both after-tax and before-tax) will be considered.

3.2.2 Data collection

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

$$Inequality_{it} = \beta_0 + \beta_1 FSD_{it} + \beta_2 X_{it} + \varepsilon_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 3.1$$

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; herein written as 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, of which this study was supplemented with peer-reviewed articles on Google Scholar. Both journal publications and working papers were considered. The number of citations of each study included in the data set for meta-analysis indicates the quality of the studies.

The literature search yielded 35 papers using the keywords mentioned above. From these papers, the analysis of these 24 studies was selected as they had empirical results on the impacts of financial depth (domestic credit) and income inequality. The meta-analysis data is based on the literature of 24 studies from the year 2004 to the year 2021. Thus, the study looked at studies over 17 years on the impact of domestic credit (FSD) on income inequality (Gini). 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 B

3.2.3 Method of 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 the impact of financial depth on income inequality. In Section 3.2.1, the six steps were presented that are followed when conducting a meta-analysis study. This section focuses on step 5, which discusses the method used to calculate the effect size. Several 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 3.2 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. While meta-analysis based on the mean is as 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).

$$PCC_{ij} = \frac{t_{ij}}{\sqrt{t_{ij} + df_{ij}}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.2$$

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, PPC was the ideal method in this case. The 87 econometric results (Beta 1) on the impact of domestic credit on the Gini index from the 24 studies are presented in Appendix C and Appendix D, where the study showed 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 β1 in Equation 3.1. In other words, the t-value used in the PCC reflects the sign of the coefficient (β1). PCC is easy to compare as they range from -1 to 1. Subsequently, the study needed to compute corresponding standard errors (SE) using Equation 4.3 to conduct the meta-analysis technique.

$$SEpcc_{ij} = \sqrt{\frac{1 - PCC_{ij}}{df_{ij}}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.3$$

Where $SEpcc_{ij}$ is the standard error of the PCC_{ij}, again, "t" is the t-statistics. This study utilized Equations 3.1- 3.3 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).

3.2.4 Method of Modelling the Effect Size on 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 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.

The Random Effect (RE) model assumes different effect sizes and studies collected from a large population randomly show inference for a population of studies from the randomly collected studies. RE model goes beyond the sampling variability by estimating heterogeneity parameters (between-study variance) among the collected studies. This study used 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).

3.3 Results

3.3.1 Meta-Analysis Summary Results

This subsection begins with the summary statistics of the coeffects, calculated PCC and respective standard error. Then, the chart showing the distribution of the PCC estimates and the respective standard errors from the 24 studies is presented. Section 3.3.1 ends with the meta-analysis results.

Table 3.1. Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
PCC	87	-.002	.313	-.918	.903
SEpcc	87	.102	.066	.02	.262
Coefficient from the 24 studies	87	.001	.199	-.695	1.098

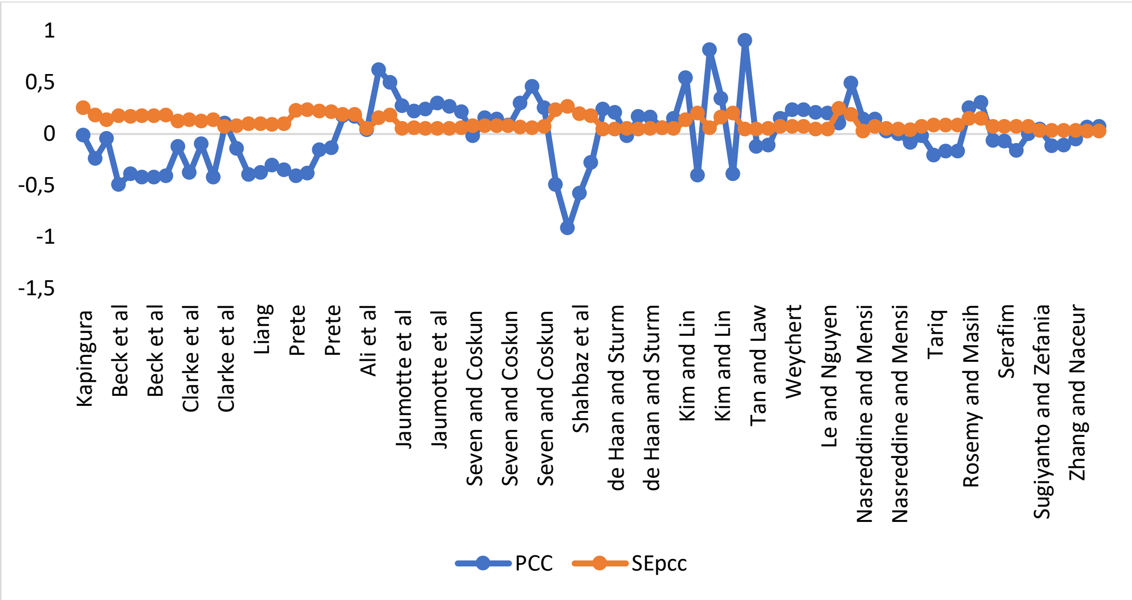


Figure 3.1. Distribution of PCC and SE of the 24 studies.

Table 3.1 shows that the 87 coefficients from the 24 studies range from negative 0.695 to 1.098, with a standard deviation of 0.199, suggesting low levels of variation in the data. In terms of the mean, the summary statistics show a positive yet very weak effect size of FSD on income inequality. While from the calculated PCC, the lowest value is negative 0.903, and the highest was 0.903, as shown in Figure 3.1 and the summary statistic table above.

The results in Table 3.2 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 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 3.2. 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	-0.018			
Fixed-effects PCC	0.078506	0.067	0.089	0

Common-effect PCC	0.078506	0.067	0.089	0
Random-Effects PCC	0.019663	-0.041	0.081	0.528

.

Table 3.2 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 and CE model, implying that the overall effect size of financial institution depth is statistically significantly different from zero. The FE and CE model yields a PCC of 0.079 and is significant at 1%, suggesting a weak and positive relationship between financial institution depth and income inequality. The identical effect size produced by the fixed and common effect model confirms that the two approaches are computed the same (same weighted average). However, the CE relies on assumptions of study homogeneity, which is not the case in this thesis. Subsequently, the FE and RE models are preferred for this analysis, where FE assumes different true effect sizes by study is preferred for this analysis.

The FE and CE PCC differ from the RE PCC, as the RE model assumes that heterogeneity among the effect sizes is random and unobservable. RE model presents the meta-analysis summary results, which also show heterogeneity statistics[4]. Regarding the collected studies' homogeneity, the Q test is 1316.51 with a p-value of 0.00. The I^2 result is 95.94 and 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 3.2, it can be inferred that the magnitude of the financial institution depth (effect size) on income inequality is small, ranging between 0.019 to 0.078 (PCC averages from FE, CE, and RE models). According to Stanley et al. (2013), the correlation of this magnitude is small. Finally, the results in Table 3.2 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 the financial depth (domestic credit) and income inequality highlights the significance of income levels on a credit application- as income is used as a signal on credit application

[4] A full detailed RE model results can be found on the Author's Github (https://github.com/nokumbona/Financial-deepening-on-income-inequality-A-quantitative-meta-analysis-study).

(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 high credit scores. It is worth noting that domestic credit is one of many components of FSD, and other components of FSD, 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 starts building credit scores. Additionally, FSD also has positive economic growth impacts across the globe.

3.3.2 Multivariate Meta-analysis Results

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 (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 interest rate and GDP growth

To estimate the multivariate regression results, the study assumed that the PCC of the “ith” 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.

$$PCC_{ij} = \beta_0 + \sum \beta k Z k_{ij} + \varepsilon_{ij} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.4$$

Equation 3.4 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 moderate variables (study characteristics) on effect size. To estimate Equation 3.4, the study used the same data to calculate the effect size. The effect size was calculated using the coefficient of domestic credit on Gini (Beta 1 in Equation 3.1). However, when estimating the multivariate regression, the study looked at other factors included in the 87 estimates. Appendix B and Appendix D provide the full data set used from the 24 collected studies. In the full data set, there are 5 moderate 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 methodology used in the two studies. These 5 moderate 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 regressions only used domestic credit to measure FSD.

Table 3.3 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 moderate variables in the different estimation results reported in the selected studies. The reported I^2 res statistic (last row of Table 3.3) ranges between 95.11 to 95.95, suggesting high levels of heterogeneity. Thus, around 96% of the variability is explained by between-study variation. The adjusted R-squared variable in Table 3.3 shows the share of between-study variance as defined by the covariance of the included moderator variables in the respective models.

The results in Table 3.2 confirm that at a 10% significant level, heterogeneity seen in the finance-inequality literature stems from the 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 3.3.3 show that transforming the dependent variable (Gini index) has a positive and 5% significant impact on the between-study/ estimates heterogeneity. In models 1 and 3, 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 0.56 to 0.67. 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, the ADRL, FE, RE, SURE GMM, and IV models significantly moderate the impact of domestic credit on income inequality (model 4 of Table 3.3). 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 don't.

Adding to this, the results on the structures of data (model 2) show that at 10% significance, 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 that 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, other countries may dominate the model and, thus, the results. The results from models suggest that studies on the finance-inequality nexus should also provide econometric analysis based on regions and income levels, as grouping countries with heterogeneous characteristics produced mixed results in the literature. While panel studies focusing on developed countries agree on the finance narrowing hypothesis- this study has not tested for these effects. While time-series studies have mixed results, suggesting the impact of financial development on inequality also depends on individual country characteristics, which tend to influence both inequality and financial development.

Table 3.3. Multivariate meta-regression results[2].

Model	Model 1	Model 2	Model 3	Model 4
NoControl	0.0272**	0.0145	0.0310**	
	(0.0124)	(0.0119)	(0.0132)	
Dummies for Dependent Variables				
Gini	0.617***		0.593**	
	(0.237)		(0.251)	
Growth in Gini	0.665***		0.559**	
	(0.241)		(0.262)	
Log Gini	0.407*		0.424*	
	(0.241)		(0.253)	
Data structures				
Panel Data		0.305**		
		(0.152)		
Time series		0.284		
		(0.174)		

Methodology				
ADRL				0.385*
				(0.225)
CUP-FM				0.464
				(0.283)
ECM				0.348
				(0.364)
FE				0.522**
				(0.226)
GLS				0.427
				(0.283)
GMM				0.407*
				(0.224)
IV				0.450**
				(0.225)
OLS				0.311
				(0.222)
RE				0.487*
				(0.263)
SURE				0.655***
				(0.243)
Geographic sample				
Asian countries			0.0606	
			(0.131)	
Average Income countries			-0.0303	
			(0.277)	
Developed & developing countries			0.0254	
			(0.125)	
Emerging countries			0.255	
			(0.159)	
High-income countries			-0.140	
			(0.274)	
Low-Income countries			0.0453	
			(0.169)	
Mixed countries			0.193*	
			(0.113)	
Upper-Middle income countries			-0.0524	
			(0.276)	
Constant	-0.678***	-0.340**	-0.757***	-0.400*
	(0.241)	(0.164)	(0.278)	(0.211)
Observations	87	87	87	87
R-squared	14.18	2.88	11.84	2.89
I^2	95.19	95.80	95.95	96.11

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.3.3 Publication Bias

This subsection explored whether literature on financial institution depth and income inequality was contaminated by publication selection bias. This meta-analysis step determines whether published studies were chosen based on the preferred sign of the parameter (the sign of the β1 from Equation 3.1) 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 employed the funnel plot to visualize evidence of publication bias in the selected 24 studies and their 87 respective estimates. The funnel plot was the most applied graphical visualization of publication bias. The funnel plot was a scatterplot visualizing effect sizes (PCC) against measures of study precisions.

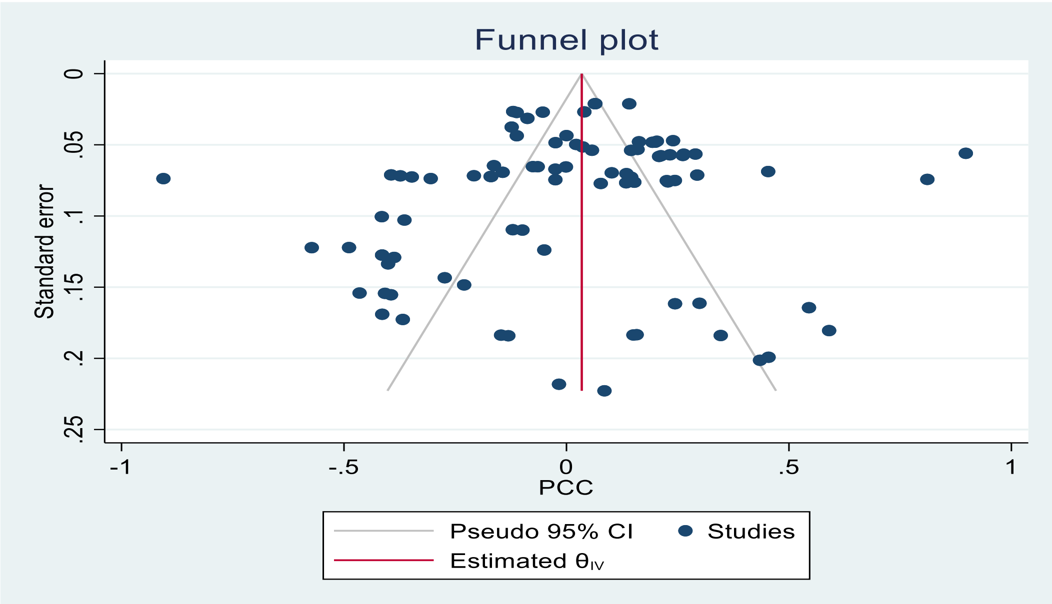


Figure 3.2. Funnel plot for publication bias.

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 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 regression. Presents of funnel plot asymmetry/publication bias could be attributed to evidence of large variability between studies. Thus, the last step is to test for publication bias/funnel plot asymmetric using the regression-based test. The Egger (1997) test investigates the connection between study effect size and study precision. From Table 3.4, 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 3.4. 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

Table 3.4 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: beta1 = 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. As such, this study performs a multivariate meta-regression to find the source or sources of heterogeneity within the results.

3.4 Conclusion

The basic transmission mechanisms of the effects of financial sector development on 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 using the Partial correlation coefficient from 87 regression models of the 24 selected studies worldwide covering 18 years. This 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 PCC is calculated using Equation 3.2 above, where the RE and FE models are employed to estimate the common component of the PCCs derived from individual estimates.

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. This study found no evidence of publication bias on this topic.

Lastly, the multivariate meta-regression aims to find/ quantify moderator variables that produce mixed results in the literature. Multivariate meta-regression results show strong evidence of high heterogeneity in past studies on financial institution deepening and income inequality. The results of the multivariate regression 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. This study leaves the global impact size of financial access to inequality for future research, as panel data on this nexus started in the year 2004- thus, there are limited empirical results.

4 DETERMINANTS OF USING FORMAL VS INFORMAL FINANCIAL SECTOR IN BRICS GROUP.

4.1 Introduction

Chapter 4 of this thesis is based on Article 3, titled " Determinants of using formal vs informal financial sector in BRICS group". As such, this chapter of the thesis dives into financial inclusion by looking at the use of financial services to save and borrow in both informal and formal financial channels. Subsequently, the chapter begins with a brief review of the literature; then, section 4.3 presents the stylized macroeconomic and financial inclusion facts of the selected BRICS countries. This is followed by the discussion of applied methodologies and databases used in section 4.4. Thereafter, the chapter presents the empirical results (section 4.5) and concludes the chapter.

The empirical literature on the determinants of using formal and informal financial services relies mostly on probit, logit, multinomial, and instrumented variable models (Allen et al., 2016; Bathula and Gupta, 2021). Literature on BRICS nations using individual-level data is limited. Adding to this, the literature on the informal financial sector has been limited, with larger literature focusing on the formal financial sector due to data availability. Subsequently, this article uses the most comprehensive individual-level data from the global financial index database of the World Bank. The study's objective was to identify and quantify the factors driving the use of the formal or informal financial sectors in Brazil (BRA), Russia (RUS), India (IND), China (CHN), and South Africa (ZAF). The following research questions are addressed: (1) What are the factors determining financial inclusion in BRICS countries? To answer this question, descriptive statistics, and decision tree visualisation are used. (2) What are the factors determining the choice of either formal or informal financial services in the BRICS countries for savings and borrowing?

4.2 Literature Review on the use of formal vs informal financial sector

Financial inclusion is defined as access and use of affordable financial products and services (Allen et al., 2016). However, financial institutions can be classified into informal and formal. The former is based on interpersonal relationships, and the latter depends on anonymous interaction between a client and a formal institution (Aliber, 2015). Informal finance is not regulated but formal is regulated by central banks. Thus, formal financial institutions include banks, micro-finance institutions (MFI), credit unions, cooperatives, insurance companies, mobile money service providers (MMP), and other formally registered financial companies (Aliber, 2015).

Formal financial institutions provide account owners with safety and affordability when it comes to storing and transecting money while allowing them to plan for emergencies and make fruitful investments for health, business, and education. People using the informal financial sector (no bank accounts, mostly using cash) are posed with risks, less reliable, and more expensive methods (such as loan shucks). Thus, the informal financial sector tends to cater to small farmers in rural areas and low-income and less-educated households. While the formal sector Favors large farmers and middle-high-income clientele.

The literature on the determinants of using the formal financial sector has grown over the years, but most of the studies offering country comparisons relied on country-level proxy data, such as the number of banks per capita. Allen et al. (2016) posit that these proxies come with limitations, including not accounting for one individual with more than one bank account. Secondly, the use of these proxies makes it impossible to assess the determinants of using the formal financial sector without having household-level information such as income, gender, and age. Thirdly, these proxies provide information on the formal financial sector while neglecting the determinants of using the informal sector. This debate has resulted in a growing literature focusing mainly on household and individual-level data when it comes to financial inclusion.

Allen et al. (2016) used the Global Findex database, a sample of 123 countries and 124,000 individuals, to examine how individual characteristics affect the use of formal financial services. The study found lower account costs, distance to financial intermediaries, and politically stable conditions to increase the likelihood of using financial services (increases financial inclusion). Bathula and Gupta (2021) also used individual-level data from the Global Findex database but only focused on India. Where the use of financial services to save and borrow are the proxies for formal financial inclusion, while digital financial services are measured using debit and credit cards to pay bills using the internet. Using the binary probit model, the study finds a positive and significant association between higher income, education, workforce participation and the choice of using formal savings.

Bathula and Gupta (2021) also found formal credit increases with workforce participation and decreases the probability of using formal credit when an individual is a woman.

Lastly, the study finds individuals with higher education and income also tend to use more digital financial services.

Very few studies examine the determinants of using both the formal and informal financial sectors. In Nigeria, Babajide (2011) used designed questionnaires for data collection, which resulted in 200 respondents in executive levels, to examine the link between the use of formal and informal financial services. The study finds a significant association between saving in banks and saving informally. In terms of credit, the study found no significant association of borrowing formally and informally.

Weill and Zins (2016) investigated the determinants of financial inclusion in 37 African countries using the 2014 Global Findex database and a probit model. The study found a negative probability of having a formal savings account for women individuals. Like Bathula and Gupta (2021) in India, Weill and Zins (2016) also find a positive association between higher education and financial inclusion in selected African countries. The study finds different characteristics seem to be important for the informal financial sector of African countries- for instance, female individuals had a higher probability of saving informally than in a formal institution, and education had no significant effect on informal savings (Weill and Zins,2016).

Lastly, the findings of Weill and Zins (2016) also suggest individuals with low income tend to use informal credit channels than individuals in the higher income quintiles. Kede and Zogning (2022) used the 2018 Global Findex database and focused on Cameroon. Using a probit model, the study finds women have a higher probability of using informal services, and the main reason for obtaining credit is to start a business for individuals working in the informal sector of Cameroon (Kede and Zogning, 2022). Fungacova and Weill (2015) used the 2011 Global Findex Database to analyse the level of financial inclusion in China in comparison with BRICS countries. Using summary statistic tables, the study shows higher levels of saving in formal financial institutions for China compared to other BRICS countries. However, when it comes to the reason for financial inclusion, all the BRICS countries cite lack of money, distance, required documents, and trust in banks as the main causes of not having a formal financial account (Fungacova and Weill,2015).

From the probit model, the study finds no significant association between education, higher income and saving in formal financial institutions in China (Fungacova and

Weill,2015). Finally, the study also finds poor individuals borrow more from informal sources, suggesting income plays a role in the choice of formal or informal credit, while gender was insignificant in the case of formal and informal credit.

In Brazil, Santos et al. (2018) used 2023 observations of households, data from the 'National Survey on Financial Inclusion and the Use of Banking Correspondents in Brazil' from the year 2012. The multinomial logistic regression analysis shows family structure has a higher predicting power for the sector chosen for a loan. Santos et al. (2018) found that larger families with children under the age of 16 have a high likelihood of borrowing in the informal sector. In Brazil, the use of the formal financial sector is more pronounced in the South, with a larger number of credit unions available, while individuals residing in the north of Brazil tend to use informal credit. The study also finds individuals who pay their bills late have a high likelihood of using informal credit (Santos et al.,2018).

4.3 Stylized Facts

According to the 2021 World Bank data, Russia had the highest GDP per capita, followed by China, then Brazil- with South Africa and India ranking lower on the list, respectively. According to the World Bank data, under the United Nations Population Division, the majority of the BRICS population lives in urban areas. For instance, data shows in 2021, Brazil (87%) had the highest share of the total population living in an urban area, followed by Russia (75%), South Africa (68%), China (63%) and India (57%). BRICS nations are one of the major emerging market economies, so it is normal to ask if the determinants of formal vs informal financial inclusion are the same across the BRICS nations or if they differ in comparison.

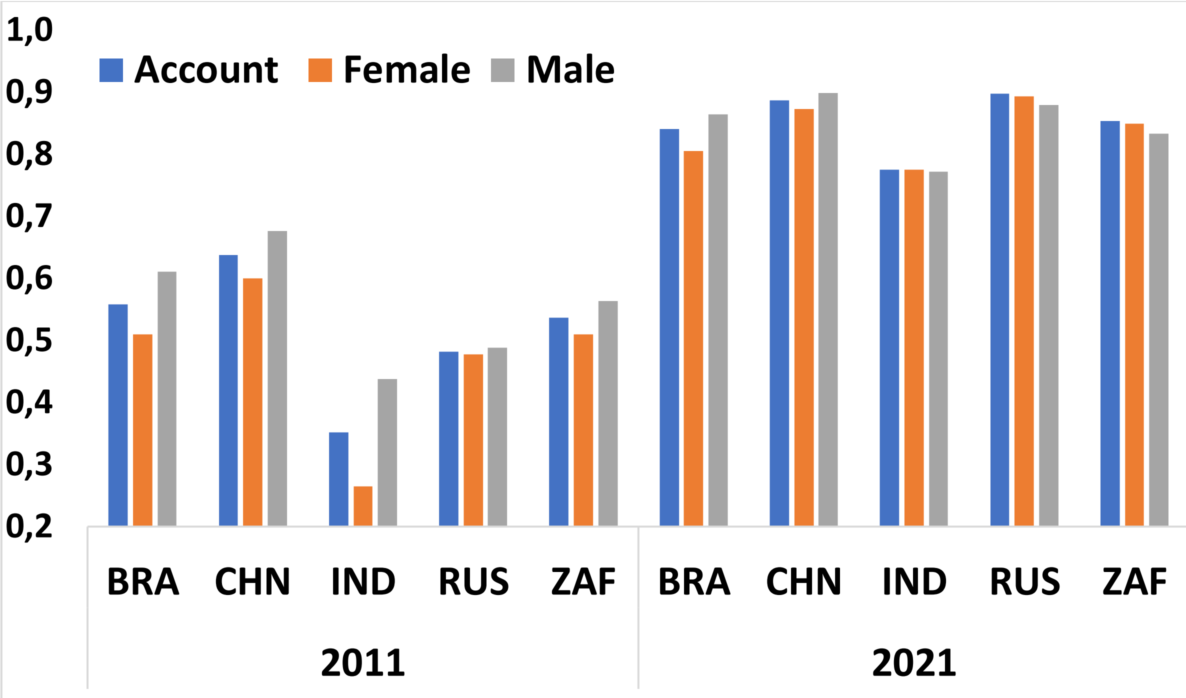


Figure 4.1. Account ownership in BRICS (Source: Global Findex database 2021).

The 2021 Global Findex data shows across the globe, 76% of adults have an account in a formal financial institution. Account ownership was at 71% for developing economies; however, BRICS nations had higher levels of account ownership, with Russia at 90%, China at 89%, South Africa at 85%, Brazil at 84%, and India at 78%. The gender gap in account ownership in developing economies has declined to 6%. While within the BRICS countries, India, Brazil and China had the highest gap in male account ownership in 2011, and in 2021, India reported a zero-gender gap in account ownership.

Table 4.1. Percentage of respondents.

Region	**Saved in Banks**		**Save Informally**		**Borrows from Banks**		**Borrows Informally**		**Financial Literacy**
	2011	2021	2011	2021	2011	2021	2011	2021	2021
BRA	0.103	0.228	0.021	0.062	0.063	0.407	0.156	0.247	0.588
CHN	0.321	0.447	0.024	0.047	0.073	0.392	0.250	0.264	0.442
IND	0.116	0.128	0.032	0.083	0.077	0.118	0.197	0.310	0.255
RUS	0.109	0.179	0.005	0.015	0.077	0.297	0.235	0.284	0.624
ZAF	0.221	0.372	0.135	0.264	0.089	0.182	0.343	0.445	0.512

Sources: Global Findex database 2021.

Table 4.1 shows the percentage of respondents who report saving or setting aside any money at a financial institution or using informal channels in the past year. For example, in Brazil, 23% of savings are with Banks, and 6% is saved informally (savers club). In contrast, South Africans save 37% with Banks and 26% informally. Intuitively, it also sees South Africans and Indians borrowing significantly more from friends and family than from Banks. In terms of financial literacy measured as ‘adult can use an account at the bank or financial institution without assistance/help’, Table 4.1 shows India has the lowest levels, followed by China and then South Africa.

4.4 Data and Methodology

The analysis uses 2021 individual-level data of BRICS nations from the Global Findex database of the World Bank surveys. Of the individuals in the sample, 55% and 48% had borrowed or saved in the year before the survey, respectively. However, most of them used the formal sector, and the use of the informal sector is less widespread. In the analysis of the decision tree, financial inclusion is measured using the financial transaction variable, which is based on the decision to save/borrow in either one or both sectors. In the probit model analysis, the main variables of interest are dummies describing if an individual saves or borrows either formally or informally. Table 4.2 describes the main variables used in this chapter of the thesis. While Table 4.2.1 the shows the descriptive table of the data used in this chapter.

Table 4.2. Definition and categorization of data variables.

Variable	Description	Definition
	Dependent variables (Y)	
Financial transactions	Adults who have borrowed or saved in the past 12 months.	1 = If either borrow or save, yes. 0 otherwise.
Formal	Adults who have borrowed or saved in the past 12 months using the formal financial sector.	1 = If either borrow_formal or save_formal yes. 0 otherwise.
Informal	Adults who have borrowed or saved in the past 12 months using the informal financial sector.	1 = If either borrow_informal or save_informal yes. 0 otherwise.
Borrow	Adults who have borrowed money in the past 12 months.	1 = If either borrow_formal or borrow_informal yes. 0 otherwise.
borrow_formal	Adults who borrowed using the formal financial sector.	1 = If borrowed from the bank or using registered mobile money services 0 otherwise.
borrow_informal	Adults who borrowed using the informal financial sector.	1 = If borrowed from friends & family or through savers club. 0 otherwise.
Save	Adults who have saved money in the past 12 months, irrespective of the channel.	1 = If either save_formal or save_informal yes, 0 otherwise.

save_formal	Adults who have saved money in the past 12 months using the formal financial sector.	1 = If saved with a bank or using registered mobile money services 0 otherwise
save_informal	Saved through Savers club	1 = If saved through the savers club 0 otherwise.
	Explanatory variables (individual characteristics)	
Gender	Female (F) and Males(M)	M =1; F=0
Age	Age of respondents in years	Range: 15-99
Primary (education)	Individuals highest level of education is completed primary or less	Yes = 1; No = 0
Tertiary(education)	Individuals highest level of education is completed tertiary or more	Yes = 1; No = 0
receive_wage	Does the individual receive wage payments?	Yes = 1; No = 0
mobile_owner	Does the individual own a mobile phone?	Yes = 1; No = 0
richest, richest2nd, middle, poorest2nd	Income quintiles. "Poorest" is the lowest 20% of household income (not included due to multicollinearity).	1= Poorest 20% (lowest household income quintile). 2= 2^{nd} lowest household income 3= Middle 20% 4= 2^{nd} richest: highest household income 5= Richest: highest income

The analysis uses several methods to identify the factors behind the abovementioned variables. First, the Conditional Inference Tree – the 'Ctree' – algorithm is applied, which estimates a regression relationship by binary recursive partitioning response variable in a conditional inference framework (Hothorn et al., 2006; Kuhn and Johnson, 2018). In this procedure, the dataset is randomly partitioned into two subsamples, a test and a training sample, with 7486 and 2981 observations, respectively. The regression tree method is particularly important as it reveals that a different behaviour often accompanies certain characteristics. Ctree models can handle different types of data, and unlike linear models, with trees, you do not need to set the form of the predictor relationship with the response (Hothorn et al., 2006; Kuhn and Johnson, 2018). From the initial results of the regression tree, a probit model is specified to quantify the importance and significance of each explanatory variable.

4.5 Empirical results

This section presents the main empirical findings of the chapter. Where first the results of a decision tree on how individual characteristics determined the use of either formal or informal financial sector. Thereafter, this section presents the probit model results; in both cases, first, the full sample results of BRICS countries are presented, and then the individual country results are presented.

4.5.1 Regression tree

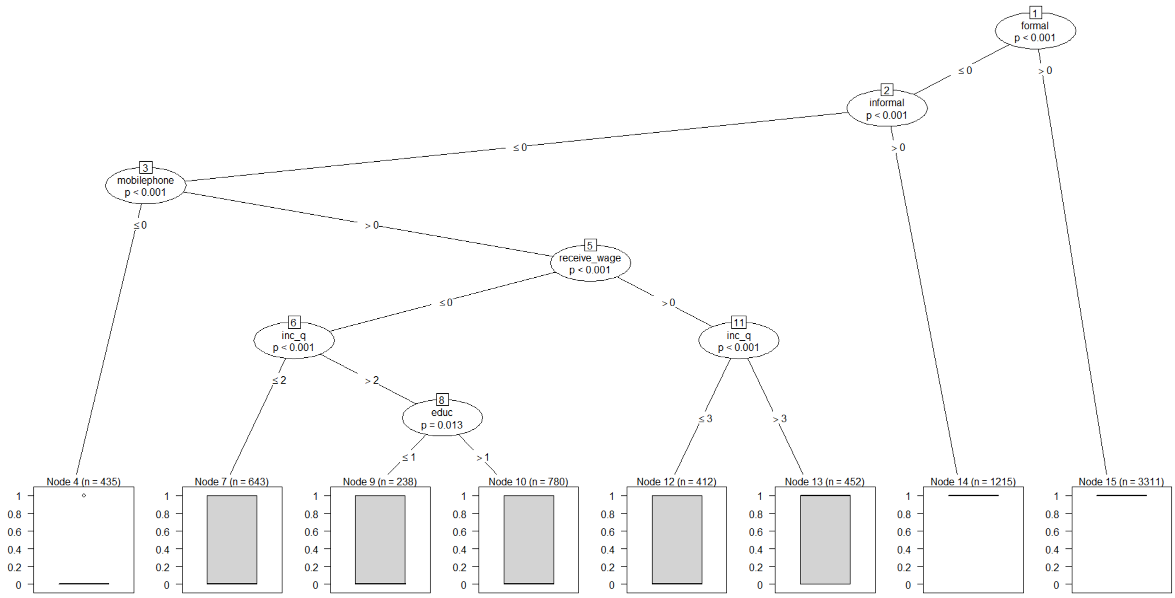


Figure 4.2. Regression tree – Factors determining the decision to participate in financial transactions (Source: R-output).

Figure 4.2 shows a boxplot as a decision tree presented downward with 15 nodes obtained from the test sample. Terminal nodes are presented by the shaded box plot (inter-quartile range) of our response variable (Financial Transaction) and can take a value of 1 or 0. Thus, the main target variable measures financial inclusion in both formal and informal sectors combined. The R-part algorithm first splits the data based on the target variable, which is why in nodes 1 and 2 the individuals are split between those using the formal sector and those using the informal sector. The goal of the initial split is to create a clear homogenous group in the data. Thereafter the algorithm further splits focus on trying to split the data based on other factors such as owning a mobile phone and further split the data with the goals of maximizing the homogeneity of subgroups concerning the target variables. As such the gives a clear visualization of how individuals' characteristics interact when it comes to financial inclusion.

Node1 represents the most important variable in our tree. Nodes 1 and 2 suggest that the formal and informal financial sectors are substitutes in the BRICS. This is because the majority of the sample prefers the formal financial sector, and the informal sector is less widespread in the BRICS nations. In addition, terminal node 13, 14, and 15 show that the majority of those who saved or borrowed used the formal sector (node 15), node 14 shows fewer people used the informal sector and node 13 shows even fewer used both the formal and informal sector. These results are different from those of Mpofu and Sibindi (2022) in Nigeria, where the formal financial sector complements the informal. In node 1, individuals are split into 2; those who use the formal sector for financial transactions go to node 15, about 3311 observations from the test sample (45%). In terminal node 14, we see 1215 individuals (16% of the test sample) that opt only for informal financial transactions.

In node 3, the data is further split using a mobile phone variable, this groups the data into a homogenous sample where those who own a phone go to terminal node 4 and represent individuals who are financially excluded. From node3, individuals who own a phone are further split based on whether they received a wage or not in the past 12 months. Terminal node 13 represents individuals who do financial transactions in either formal or informal or both sectors and these individuals own a mobile phone (node 3); these individuals also receive a wage in the past 12 months (node 5) that is above the middle-income quintile (node 11). As such node 13 shows individuals who were in the initial split can be further divided using other variables like owning a mobile phone.

These results support the argument that higher income and owning a mobile phone increase the probability of having access to digital finance (Bathula and Gupta, 2021; Pandey et al., 2023). Terminal node 7 shows a group of individuals with a mobile phone, who have not received wage income in the past 12 months and declare their income to be within low-income quantile are excluded from the financial transaction. This suggests that individuals who did not receive wages in the past 12 months, (assumed to be unemployed) are financially excluded in both sectors. Overall, the results of node 7 are in line with previous studies, where a positive marginal effect was found between workforce participation and formal financial inclusion in India (Bathula and Gupta, 2021). Nodes 9 and 10 show the level of education is not important for financial inclusion if one is unemployed (has not received a wage in the past 23 months), as these individuals did not do any financial transactions. The effects of individual attributes on financial transactions are larger, and owning a mobile phone alone does not translate to a financial transaction unless one receives a wage within the high-income quintile.

4.5.2 Regression results

Regression analysis is used to detect how different individual factors influence the usage of the financial sector. First, financial inclusion is analysed where no distinction is made regarding whether individuals borrow or save in the formal or informal sector. This analysis is complemented by understanding the differences between borrowing and saving decisions. Secondly, the analysis focuses on how individual factors determine the use of formal vs informal financial institutions to save and borrow.

4.5.3 Probit models on financial inclusion

Individuals' relationship with the financial sector is heterogeneous; more than every fourth person in the sample reports neither saving nor borrowing using either of the two sectors. Table 4.3 below presents the full sample probit model results for saving and borrowing as marginal effects. Model 1 to 3 of Table 4.3 displays the results for the main indicator of financial inclusion from a savings perspective. While in models 4-6 of Table 4.3 financial inclusion is measured from the credit perspective.

Table 4.3. Probit regression on using formal vs informal financial sectors -BRICS nations.

	(1)	(2)	(3)	(4)	(5)	(6)
	Saved	Formal Saving	Informal Saving	Borrowed	Formal_Borrowing	Informal Borrowing
gender_Male=1; female =0	0.0289	0.0880***	-0.179***	0.0663***	0.222***	0.0748***
	(0.0255)	(0.0264)	(0.0365)	(0.0251)	(0.0293)	(0.0263)
age	0.0321***	0.0368***	0.0370***	0.0743***	0.0707***	0.0327***
	(0.00452)	(0.00486)	(0.00738)	(0.00465)	(0.00617)	(0.00502)
age2	-0.000396***	-0.000466***	-0.000486***	-0.000915***	-0.000859***	-0.000469***
	(5.22e-05)	(5.69e-05)	(8.93e-05)	(5.44e-05)	(7.41e-05)	(5.97e-05)
primary	-0.485***	-0.455***	-0.142***	-0.147***	-0.218***	0.0783**
	(0.0326)	(0.0355)	(0.0470)	(0.0316)	(0.0388)	(0.0327)
tertiary	0.128***	0.209***	-0.272***	0.0794***	0.105***	-0.207***
	(0.0307)	(0.0308)	(0.0450)	(0.0306)	(0.0343)	(0.0327)
Richest	0.531***	0.494***	0.323***	0.0899**	0.0704	-0.126***
	(0.0405)	(0.0417)	(0.0585)	(0.0401)	(0.0464)	(0.0422)
richest2nd	0.320***	0.295***	0.149**	0.0397	0.0524	-0.0813*
	(0.0402)	(0.0420)	(0.0597)	(0.0399)	(0.0467)	(0.0418)
middle	0.151***	0.119***	0.0974	0.0515	0.0111	0.00213
	(0.0413)	(0.0438)	(0.0618)	(0.0410)	(0.0486)	(0.0426)
poorest	-0.213***	-0.271***	-0.0522	-0.0101	-0.0571	0.136***
	(0.0448)	(0.0494)	(0.0679)	(0.0432)	(0.0524)	(0.0444)
Constant	-0.743***	-1.240***	-1.961***	-1.241***	-2.324***	-0.999***
	(0.0957)	(0.102)	(0.150)	(0.0967)	(0.126)	(0.103)
Observations	10,404	10,404	10,404	10,404	10,404	10,404
Pseudo R2	0.0708	0.0760	0.0233	0.0275	0.0311	0.0190

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

From Table 4.3, it is observed that a significant relation between individual characteristics and the measures of financial inclusion in the BRICS group. Across all 6 models in Table 4.3, age has a nonlinear relation with financial inclusion indicators. The marginal effect for age is positive and significant, while the squared term of age was negative and significant. This suggests financial inclusion increases with age, up until individuals reach a certain age, beyond which an increase in age is associated with lesser financial inclusion. The inverted U-shaped nonlinear relation between age and financial inclusion is also confirmed by Allen et al. (2016) using world data, also by Fungacova and Weill (2015) in China and Weill and Zins (2016) in 36 African countries.

Table 4.3 also shows being male gender significantly reduces the probability of saving in the informal sector (model 3) and increases the probability of saving in the formal sector (model 2) and borrowing in both the formal and informal sectors.

Education is also a significant determining factor in financial inclusion in BRICS. The results show individuals with primary education have a negative and significant probability of being financially included in both sectors except the informal credit sector. Model 6 shows that individuals with primary education have positive and significant probabilities of borrowing in the informal sector. From Table 4.3we can also observe that individuals with tertiary education have a positive and significant association with using the formal financial sector (models 2 and 5) and a significant and negative association with informal financial transactions (models 3 & 6).

In terms of income, Table 4.3 shows the top two income quantiles in the BRICS group save in both the formal and informal sectors; however, these individuals have a negative association with borrowing in the informal sector. Lastly, the poorest group in BRICS nations have a significant and negative probability of saving and saving in the formal sector but have a positive association of borrowing in the informal sector.

Table 4.4. Probit regression on using formal vs informal financial sectors in Brazil.

	(1) Saved	(2) Formal Saving	(3) Informal Saving	(4) Borrowed	(5) Formal_Borrowing	(6) Informal Borrowing
gender_Male=1; female =0	0.302***	0.247***	0.213	0.0678	0.163*	-0.150
	(0.0870)	(0.0895)	(0.133)	(0.0864)	(0.0928)	(0.0936)
age	-0.0650***	-0.0288**	-0.00193	0.0384***	0.0400**	0.0121
	(0.0140)	(0.0140)	(0.0234)	(0.0138)	(0.0167)	(0.0179)
age2	0.000483***	0.000140	-0.000125	-0.000520***	-0.000486***	-0.000364*
	(0.000151)	(0.000154)	(0.000268)	(0.000151)	(0.000187)	(0.000212)
primary	-0.0769	-0.239	0.456**	-0.245*	-0.0315	-0.139
	(0.135)	(0.154)	(0.205)	(0.127)	(0.149)	(0.145)
tertiary	0.380***	0.535***	0.293*	0.264**	0.149	-0.221*
	(0.108)	(0.107)	(0.158)	(0.110)	(0.113)	(0.121)
Richest	0.782***	0.709***	0.488**	0.329**	0.272*	-0.311**
	(0.145)	(0.149)	(0.245)	(0.141)	(0.163)	(0.157)
richest2nd	0.353**	0.195	0.380	0.311**	0.398**	0.0203
	(0.141)	(0.149)	(0.246)	(0.138)	(0.158)	(0.149)
middle	0.0457	-0.135	0.308	0.182	0.137	0.131
	(0.157)	(0.173)	(0.269)	(0.152)	(0.180)	(0.163)
poorest	-0.221	-0.196	-0.104	-0.0631	0.160	0.105
	(0.172)	(0.190)	(0.328)	(0.161)	(0.191)	(0.173)
Constant	1.202***	-0.00234	-1.828***	-0.427	-1.870***	-0.367
	(0.318)	(0.318)	(0.516)	(0.311)	(0.372)	(0.371)
Observations	980	980	980	980	980	980
Pseudo R2	0.1473	0.1473	0.0530	0.0526	0.0258	0.0703

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4.5 above displays the probit model results for Brazil. The age has a nonlinear relation with financial inclusion in Brazil. Model 1 and 2 shows a U-shaped relation between age and savings and savings in the formal sector of Brazil. In models 4 and 5, the nonlinear relation of age and borrowing or borrowing in the formal sector suggests an inverted U-shaped. The results in models 1 and 2 suggest individuals in Brazil do not save money up until they get to age 41(mean of age in Brazil data), and only at this age do they start to save money. While model 4 and 5 suggest that the people of Brazil have a positive probability of borrowing money till the age of 41, beyond which they have a negative probabilities of borrowing money. In terms of education factors, we can see individuals with primary education have a significant and positive association with saving in the informal sector (model 3) and a negative probability of borrowing in general (model 4). On the other hand, individuals with tertiary education in Brazil have positive and significant chances of saving in both the formal and informal sectors (models 1-3) and a negative association with borrowing in the informal sector (model 6). Gender does not seem to have a significant effect on financial inclusion in Brazil; however, male individuals tend to use the formal financial sector for savings (model 2).

The income of individuals explains large disparities when it comes to financial inclusion. In Brazil, the rich and 2nd richest income groups have a significant and positive probability of using both the formal and informal financial sector to save and borrow. While individuals falling in the income of the poorest and middle quintile had no significant effect on the financial inclusion of Brazil.

Table 4.5. Probit regression on using formal vs informal financial sectors in Russia.

	(1) Saved	(2) Formal Saving	(3) Informal Saving	(4) Borrowed	(5) Formal_Borrowing	(6) Informal Borrowing
gender_Male=1; female =0	0.143**	0.188***	0.120	-0.0170	0.102	0.0363
	(0.0602)	(0.0673)	(0.141)	(0.0584)	(0.0639)	(0.0613)
Age	-0.0390***	-0.0163	-0.00243	0.0557***	0.0772***	0.00240
	(0.0108)	(0.0120)	(0.0278)	(0.0114)	(0.0142)	(0.0119)
age2	0.000324***	0.000104	-6.50e-05	-0.000761***	-0.000967***	-0.000173
	(0.000114)	(0.000127)	(0.000309)	(0.000124)	(0.000158)	(0.000130)
Primary	-0.135	-0.0942	-0.199	-0.000404	-0.184	0.00533
	(0.159)	(0.196)	(0.398)	(0.146)	(0.173)	(0.149)
Tertiary	0.168***	0.259***	0.0206	-0.0596	0.0241	0.00549
	(0.0623)	(0.0699)	(0.149)	(0.0608)	(0.0668)	(0.0641)
Richest	0.800***	0.765***	-0.0786	0.0720	0.113	-0.212**
	(0.0921)	(0.104)	(0.207)	(0.0896)	(0.0963)	(0.0937)
richest2nd	0.512***	0.601***	-0.0734	-0.0393	0.104	-0.260***
	(0.0937)	(0.107)	(0.215)	(0.0915)	(0.0994)	(0.0972)
Middle	0.199**	0.191*	-0.266	0.0227	0.00959	-0.0632
	(0.0960)	(0.114)	(0.242)	(0.0926)	(0.102)	(0.0961)
Poorest	-0.208**	-0.317**	-0.0484	-0.0316	-0.304***	0.112
	(0.105)	(0.136)	(0.221)	(0.0954)	(0.109)	(0.0974)
Constant	0.286	-0.883***	-1.878***	-0.702***	-2.119***	-0.237
	(0.249)	(0.278)	(0.601)	(0.256)	(0.309)	(0.266)
Observations	1,999	1,999	1,999	1,999	1,999	1,999
Pseudo R2	0.0839	0.0936	0.0154	0.0352	0.0397	0.0274

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.5 presents the probit model results for Russia. Like the results of Brazil and Russia, model 1 of Table 4.5shows a U-shaped relation between saving decisions and age. However, an inverted U-shaped relation is confirmed between age and borrowing in the formal financial sector of Russia (model 5). The turning point of the U-shaped and inverted U-shaped relation is the sample mean of Russia, which was 42.8, slightly higher than that of Brazil. Again, like Brazil, gender does not seem to have a significant association with financial inclusion in Russia except for saving in the formal sector. Table 4.5 also shows in Russia, primary education is associated with lower levels of financial inclusion while tertiary education is associated with the formal financial sector (model 2). In Russia, the richest, 2nd richest, and middle-income groups have a positive and significant probability of using the formal financial sector to save, and model 6 shows a negative and significant probability of borrowing in the informal sector. While individuals with income falling in the lowers quintile have negative and significant probabilities of saving and borrowing in the formal sector.

Table 4.6. Probit regression on using formal vs informal financial sectors in India.

	(1) Saved	(2) Formal Saving	(3) Informal Saving	(4) Borrowed	(5) Formal_Borrowing	(6) Informal Borrowing
gender_Male=1; female =0	-0.0798	-0.0301	-0.367***	-0.0613	0.0599	-0.0476
	(0.0537)	(0.0609)	(0.0705)	(0.0481)	(0.0641)	(0.0497)
Age	0.0331***	0.0164	0.0687***	0.0593***	0.0483***	0.0498***
	(0.00913)	(0.0102)	(0.0143)	(0.00845)	(0.0118)	(0.00900)
age2	-0.000316***	-0.000112	-0.000780***	-0.000719***	-0.000554***	-0.000634***
	(0.000109)	(0.000122)	(0.000178)	(0.000102)	(0.000144)	(0.000110)
Primary	-0.333***	-0.374***	-0.317***	-0.0578	-0.215***	0.0177
	(0.0609)	(0.0695)	(0.0790)	(0.0548)	(0.0718)	(0.0565)
Tertiary	0.254***	0.421***	-0.0498	-0.0729	-0.0858	-0.0966
	(0.0851)	(0.0884)	(0.110)	(0.0827)	(0.107)	(0.0867)
Richest	0.567***	0.489***	0.566***	0.0418	-0.0426	0.00307
	(0.0841)	(0.0934)	(0.113)	(0.0768)	(0.100)	(0.0798)
richest2nd	0.307***	0.265***	0.289**	0.00116	-0.0431	0.0123
	(0.0835)	(0.0941)	(0.115)	(0.0747)	(0.0979)	(0.0776)
Middle	0.108	0.0356	0.0460	0.0809	-0.0243	0.0424
	(0.0862)	(0.0993)	(0.122)	(0.0751)	(0.0986)	(0.0779)
Poorest	-0.158*	-0.339***	0.0946	0.117	-0.172	0.194**
	(0.0922)	(0.113)	(0.122)	(0.0760)	(0.105)	(0.0781)
Constant	-1.421***	-1.452***	-2.569***	-1.145***	-1.998***	-1.314***
	(0.181)	(0.202)	(0.272)	(0.164)	(0.227)	(0.173)
Observations	2,989	2,989	2,989	2,989	2,989	2,989
Pseudo R2	0.0638	0.0871	0.0618	0.0143	0.0152	0.0131

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6 above presents the probit model results for India. Different from the results of Brazil and Russia, in India, gender has a significant association with the use of the informal sector. In India, males have a negative and significant association with savin in the informal sector. Again, different to the results of Brazil and Russia, in India, the nonlinear relation with age and financial inclusion variables confirms an inverted U-shaped relation. The average age in the sample of India was 36, suggesting the turning point is around the age of 36, which is far less than those of Brazil and Russia.

Primary education had a negative and significant association with financial inclusion in India. The results show having tertiary education significantly increases the use of both formal and informal financial sectors to save. This supports the findings of Bathula and Gupta (2021), who find higher education to be positively linked with having a formal financial institution account in India.

Table 4.6 also shows that greater income is associated with saving in the formal financial sector. Model 2 shows the richest and 2nd richest income groups have a positive and significant marginal effect on the decision to save in the formal sector. While individuals with the lowest income reported significant and negative marginal effects on the use of the formal financial sector to save (model 2), and model 6 shows these individuals have a positive probability of borrowing in the informal sector. Finally, gender does not have a significant effect on formal financial inclusion in India; however, the results show being a male significantly reduces the probability of saving in the informal sector. Bathula and Gupta (2021) also show no significant effect of gender when it comes to formal financial accounts but found women gender only face barriers to digital financial services. Bathula and Gupta (2021) argue that the insignificance of gender in formal financial accounts in India is associated with the national mission aimed at financial inclusion, which includes the allowance of unbanked individuals to open Basic Saving Bank Deposit (BSBD) or Business Correspondent (BC) outlet.

Table 4.7. Probit regression on using formal vs informal financial sectors in China.

	(1) Saved	(2) Formal Saving	(3) Informal Saving	(4) Borrowed	(5) Formal_Borrowing	(6) Informal Borrowing
gender_Male=1; female =0	0.0154	0.0945**	0.0372	0.360***	0.520***	0.413***
	(0.0461)	(0.0443)	(0.0693)	(0.0450)	(0.0513)	(0.0496)
Age	0.0542***	0.0558***	0.0566***	0.131***	0.129***	0.0367***
	(0.00963)	(0.00977)	(0.0209)	(0.0103)	(0.0151)	(0.0109)
age2	-0.000587***	-0.000620***	-0.000859***	-0.00164***	-0.00181***	-0.000515***
	(0.000117)	(0.000121)	(0.000285)	(0.000128)	(0.000200)	(0.000135)
Primary	-0.440***	-0.444***	-0.290**	-0.0556	0.00791	0.238***
	(0.0630)	(0.0627)	(0.113)	(0.0633)	(0.0717)	(0.0660)
Tertiary	0.0396	0.132***	-0.0867	0.168***	-0.00732	-0.170***
	(0.0535)	(0.0505)	(0.0766)	(0.0516)	(0.0572)	(0.0576)
Richest	0.349***	0.341***	0.0482	0.0978	0.118	-0.247***
	(0.0740)	(0.0707)	(0.107)	(0.0717)	(0.0811)	(0.0795)
richest2nd	0.213***	0.144**	-0.0443	0.0751	0.0453	-0.125*
	(0.0711)	(0.0683)	(0.107)	(0.0698)	(0.0797)	(0.0758)
Middle	0.121*	0.125*	-0.0174	0.0348	0.0288	-0.0548
	(0.0723)	(0.0702)	(0.110)	(0.0717)	(0.0822)	(0.0768)
Poorest	-0.262***	-0.208***	-0.316**	0.0437	0.183**	0.229***
	(0.0801)	(0.0806)	(0.148)	(0.0814)	(0.0918)	(0.0840)
Constant	-0.668***	-1.140***	-2.288***	-2.390***	-3.270***	-1.491***
	(0.197)	(0.198)	(0.380)	(0.205)	(0.284)	(0.221)
Observations	3,432	3,432	3,432	3,432	3,432	3,432
Pseudo R2	0.0478	0.0447	0.0241	0.0533	0.0600	0.0487

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.7 presents the probit model results for China. Like India, the association between age and financial inclusion in China has an inverted U-shaped nonlinear relation. Fungacova and Weill (2015) also found a similar nonlinear relation between age and financial inclusion in China. The average age in the sample of China was 35, suggesting the turning point is around the age of 35, which is far less than those of Brazil and Russia and slightly lower than India's average age. The slight difference between the mean age of India compared to China is also reflected in the marginal effect size of age and age squared in Table 4.6 and Table 4.7, respectively. In China having primary education is negatively associated with saving in both formal and informal financial sectors, whilst having primary education is also positively associated with informal credit. These results are like the findings of Fungacova and Weill (2015) based on 2011 Global Findex data in China.

In contrast, having tertiary education is positively associated with saving in the formal financial sector and negatively associated with borrowing through the informal channel. Model 2 of Table 4.7 shows individuals within the richest, 2nd richest and middle-income quintiles have a positive and significant probability of using the formal financial sector to save. For these individuals, the probability of them using the informal sector to borrow money was negative and ranged between negative 0.05 and -0.247 (model 6).

Income in China does not seem to be the determining factor of financial inclusion. Models 1, 2, and 3 show there is a significant and negative marginal effect for the poorest individuals to save in both sectors in China. In fact, across all the individual BRICS results discussed so far, the marginal effect of the poorest individuals is negative when it comes to saving in both sectors.

What is different in China is that the poorest individuals have a positive and significant probability of using both the formal and informal sectors for credit. While in all the individual BRICS country results presented in this chapter, China is the only country where individuals falling in the poorest income quintile reported positive and significant marginal effects on formal credit. Using 2015 and 2018 household data, Wu, Cui, and Jiang (2022) analysed the effects of microcredit programs on public health in rural China and found the formal credit amount from microcredit programs related to the demand for health levels and insurance. As such, the positive likelihood of the poorest income household using formal credit in China may be associated with the increased access to formal credit in China, and the poorer may be using it for health reasons. Finally, in China, the is a higher likelihood of male borrowing in both formal and informal sectors; however, the marginal effect for formal credit was higher than that of informal credit.

Table 4.8. Probit regression on using formal vs informal financial sectors in South Africa.

	(1) Saved	(2) Formal Saving	(3) Informal Saving	(4) Borrowed	(5) Formal Borrowing	(6) Informal Borrowing
gender_Male=1; female =0	-0.101	0.0685	-0.388***	-0.180**	-0.119	-0.142*
	(0.0858)	(0.0846)	(0.0903)	(0.0831)	(0.0999)	(0.0818)
Age	0.0425***	0.0525***	0.0502***	0.0498***	0.0700***	0.0352**
	(0.0158)	(0.0164)	(0.0169)	(0.0153)	(0.0210)	(0.0153)
age2	-0.000362*	-0.000570***	-0.000464**	- 0.000617***	-0.000733***	-0.000487***
	(0.000192)	(0.000199)	(0.000201)	(0.000185)	(0.000253)	(0.000186)
Primary	-0.218	-0.256	0.0510	0.122	-0.238	0.0979
	(0.149)	(0.156)	(0.156)	(0.149)	(0.198)	(0.147)
Tertiary	0.0307	0.196	-0.135	0.220*	0.102	0.0176
	(0.133)	(0.126)	(0.135)	(0.126)	(0.137)	(0.121)
Richest	0.807***	0.795***	-0.00481	0.00821	0.439***	-0.185
	(0.138)	(0.136)	(0.145)	(0.135)	(0.169)	(0.131)
richest2nd	0.526***	0.594***	0.203	-0.0164	0.428**	0.137
	(0.142)	(0.142)	(0.150)	(0.142)	(0.177)	(0.138)
Middle	0.303**	0.183	0.279*	0.0339	0.270	0.124
	(0.141)	(0.144)	(0.149)	(0.144)	(0.182)	(0.140)
Poorest	-0.196	-0.308**	-0.163	-0.492***	-0.121	-0.450***
	(0.138)	(0.149)	(0.154)	(0.140)	(0.196)	(0.140)
Constant	-0.899***	-1.548***	-1.666***	-0.470	-2.665***	-0.466
	(0.320)	(0.333)	(0.350)	(0.312)	(0.432)	(0.311)
Observations	1,004	1,004	1,004	1,004	1,004	1,004
Pseudo R2	0.0815	0.1030	0.0440	0.0334	0.0483	0.0279

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.8 above presents the probit model results for South Africa (SA). Like India and China, the association between age and financial inclusion in SA has an inverted U-shaped nonlinear relation. The average age in the sample of SA is around that of China and India at 35.5. The marginal effect for education dummies was mostly insignificant in SA; however, for individuals with primary education, the sign of the effect sizes is negative for formal financial inclusion and positive for informal inclusion. Having tertiary education in SA had a significant association with the decision to borrow (model 4). However, like the findings of Weill and Zins (2016) in 37 African countries, having a tertiary education in South Africa is not significantly related to the decision to save either in either sector. This suggests South Africa is the only country within the BRICS where tertiary education is not associated with saving and saving in the formal sector.

Higher income in SA is associated with higher levels of formal financial inclusion. Model 3 of Table 4.8 shows a positive and significant marginal effect of 0.795 for the richest income quantile and 0.594 for the 2nd income quantile dummy on the decision to save in the formal financial sector. Model 5 also shows that the top 2 income quantile groups of SA have a positive and significant probability of using formal credit. The middle-income group of SA who save have a higher and significant probability of saving through the informal sector. In SA, individuals in the poorest income quantile face serious borrowing constraints in both the formal and informal financial channels (models 4-6). These findings suggest that not everyone has equal access to informal credit in South Africa. A look at the 2021 Global Findex data shows that from the used sample, 72% of South Africans reported having faced financial difficulties in the last 12 months, while only 25% of the Chinese sample declared financial difficulties.

In James (2015) the informal financial sector of South Africa was found to cater for the demand for financial transactions from poorer relatives or neighbours, low educated and those belonging to savers clubs. The results of Table 4.8 above are slightly different from those of James (2015), as recent 2021 data results of Table 4.8 demonstrate the level of education is not significant but rather that income level matters when it comes to financial inclusion in South Africa.

4.6 Conclusion

This chapter of the thesis focused on the determinants of financial inclusion in the BRICS group. This is the only chapter in the thesis that used micro-level data, which was sourced from the World Bank's Global Fidex Survey. This chapter used the decision tree methods and probit model for the full sample (BRICS). Thereafter, the individual countries' results are also presented. The decision tree method provides graphic information on how individual factors influence financial transactions (financial inclusion). The tree shows the effects of individual attributes on financial transactions are larger and relatively higher income is associated with financial inclusion.

The results of the full sample of the 5 BRICS nations confirm the life cycle hypothesis on age and financial inclusion. The inverted U-shaped nonlinear relationship between age and financial inclusion is also confirmed in the individual country results of India, China, and South Africa. In contrast, for Brazil and Russia, there exists a U-shaped relation between age and the decision to save in either sector. The results for Brazil and Russia only confirm the life cycle hypothesis when it comes to credit in both formal and informal sectors.

Across all the BRICS nations, education is a determining factor in financial inclusion. Individuals with primary education are more associated with informal credit. While people with tertiary education and higher income save more and tend to use the formal financial sector to save and borrow. Within the BRICS nation, the marginal effect of the poorest individuals is negative when it comes to saving in both sectors. However, in China, individuals in the poorest income group have a positive and significant probability of using both the formal and informal sectors for credit. This highlights the increased access to credit in China through microcredit programs. In SA, individuals in the poorest income quantile are mostly excluded from access to credit in both the formal and informal channels. This is because around 70% of the SA sample reported having financial difficulties in the past year, suggesting higher credit demands in SA.

Finally, in the full sample results of BRICS, the male gender had a negative probability of saving in the informal sector but a positive probability of using the formal sector to save and borrow in both sectors. In Brazil, males also prefer to save and borrow in the formal sector; in India and South Africa, the probability of male individuals saving through informal channels was negative.

5 OVERALL CONCLUSION FROM THE THESIS

In this chapter, the overall conclusion of the thesis on the effects of financial sector development (FSD) on income inequality is discussed. This thesis is comprised of three published articles. The research questions and the significance of this study are discussed in chapter one of the thesis. All three articles presented above are linked to the central theme of financial sector development (FSD) and income distribution.

This chapter of the thesis first highlights how the three articles speak to each other and the novelty of this thesis. Thereafter, the three articles are concluded concerning the central theories and literature gap, data, methods, and empirical findings. The primary goal of the three articles was to map FSD and its effects on income inequality. In doing so, these articles cover all the components of FSD, including financial inclusion, which is covered in Chapter 4 (Article 3). Chapter 2 of the thesis (article 1) focused on the effects of FSD on before and after-tax income inequality. This chapter dives into the different structures of overall financial institutions and market development (FSD), and the dimensions of FSD (access and depth).

With literature in agreement that access to the financial sector reduces income inequality, and with no consensus in the literature on the effects of financial depth on inequality, Chapter 3 (Article 2) of the thesis conducts a quantitative meta-analysis study on financial institution depth and income inequality. In the literature on FSD and inequality, macro-level proxies' data have been intensively used as it is easily available, and since the data is measured by the formal regulated financial sectors. As such, by using micro-level data with information on the decision to participate in both formal and informal financial channels, the thesis adds to the literature on financial inclusion.

In Chapters 2, 3, and 4, the various methods and data used in the three central articles for this thesis were presented. The novelty of this thesis lies in the use of robust methodologies and new and broader data on the dimensions of financial sector development. The three articles forming this thesis have brought consensus on the impacts of financial sector development on income inequality. There are limited studies empirically testing the impacts of the overall financial institution and market indexes on income inequality. Rather, what is common in the literature is studies using mostly financial depth to proxy overall FSD. Figure 2.1 makes clear distinctions and definitions of the components of financial sector development. This figure is fundamental in clarifying which proxies measure on FSD dimension and helps to group the literature by FSD dimensions instead of mixing it all whilst the variable used does not reflect overall FSD. This is because the common measure of financial sector depth used in the literature does not fully take into account of the multidimensions of FSD. Secondly, different stages of FSD components have heterogeneous impacts on income inequality and differ by country's characteristics or development levels.

In Chapter 3, SWIID is the main source of inequality data, and robust GMM methodology is estimated 1st on a large data sample of 120 countries and three subsamples, i.e. advanced economies (AM), emerging market economies (EME), low-income countries (LIC). The empirical findings from both the linear and non-linear relationship model on the effects of FDS and its components on both before and after-tax income inequality were as follows:

Firstly, the overall FSD index (FD) reflecting the development of both institutions and markets in terms of access, depth, and efficiency narrows after-tax income inequality in the full sample results. The narrowing hypothesis of the FD index and financial institution development index (FI) on after-tax income inequality was statistically significant in EME. However, FD had an insignificant reducing effect on the after-tax inequality of AM and LIC groups. The overall effect of the financial market development index (FM) showed a significant inverted U-shaped effect for AM after-tax inequality while confirming a significant U-shaped effect on after-tax-income inequality of LIC. The results from before-tax income inequality show a widening effect of FD, FI, and FM indices. The fact that FSD has widening effects on before-tax income inequality and narrowing effects on after-tax income inequality suggests that the implementation of income tax policies results in social welfare programs and thus reduces the inequalities. However, the question of tax seems not to matter for LIC; for example, results show FI index narrows both the before and after-tax inequality of LIC while the FI index widens before-tax of advanced markets.

Secondly, when looking at the effects of access to financial institutions and the market on income after-tax inequality, the findings were as follows: the full sample results confirmed a narrowing hypothesis in both the linear and linear model when access to financial institutions is measured as the number of ATMs per adults. These findings are in line with the UN’s emphasis on the impacts of financial inclusion on inequality reduction and are in line with the findings of Sahay and Cihak (2020). The LIC and EME groups also found a narrowing hypothesis between ATM and after-tax income inequality. LIC also confirmed the U-shaped relationship on the before-tax income inequality. Thus, the LIC results suggest that FIA reduces inequality while the ATM component of FIA first reduces and then increases inequality. These results may seem odd, but intuitively, in most LIC, there are lower levels of maintenance of ATMs, especially near rural and less economically developed cities; thus, the number of ATMs per adult may be increasing, but the number of actual functioning ATMs may be less. This is one of the limitations of this thesis, as macro data does not provide such details.

Thirdly, the empirical findings on the effects of financial depth on income inequality were as follows: in the non-linear model, the relationship is U-shaped between financial depth and both before and after-tax income inequality. The results by subsample were also in line with the full sample results except for advanced economies, which confirmed the inverted U-shaped relation between financial market depth and after-tax income inequality. However, financial institution depth had a negative and significant effect on the before-tax income inequality of LIC.

These results suggest that growth in domestic credit as a share of GDP, growth in financial institutions and market depth reduce income inequality up until a certain threshold, beyond which growth in financial sector depth increases income inequality. This explains how small firms that were granted loans 5 years ago vs those who were rejected can grow and become more profitable from the loan vs those who were rejected. The signalling of collateral ensures that only high-income individuals benefit more from a flexible domestic credit market. This is because individuals' incomes are used in loan applications; thus, if you have regular income, you have access to credit, which you can use to buy property and rent it out to a low-income earner at the same price as the bond fee. This further widens income inequality. In addition, when the credit market triggers speculative investment, domestic credit increases income inequality in Vietnam (Le and Nguyen, 2020). Financial policies focusing on alleviating income inequality should also incorporate credit policy provisions whilst reviewing the banking business model to safeguard credit distribution in the direction of inclusive growth and sustainable development (de la Cuesta-González et al.,2020). Iacoviello (2008) argues economic cycles have an influence on credit demand which leads to an increase in the indebtedness of households and further widens inequality. The findings of Iacoviello (2008) highlight the reversal-causality in the FSD and income inequality relationship.

Chapter 3 of this thesis presented the quantitative meta-analysis on the impacts of FSD (depth component) on income inequality. This chapter aimed to close the gap in the literature by focusing on the impact of one of the most studied components of FSD on income inequality. Meta-analysis studies are important in topics that have large literature, as they give a clear summary of the topic. The findings of the meta-analysis based on the partial correlation and multivariate analysis were as follows: The FE and CE model yields a PCC of 0.07 and is significant at 1%, suggesting a weak and positive relationship between financial institution depth and income inequality. The multivariate meta-regression results showed that the heterogeneity seen in the finance-inequality literature stems from the chosen methodology, the number of control variables in the regression model, the data structure (panel), and the geographical region of the study.

Chapter 4 of this thesis focuses on the dynamics of formal and informal financial services. The World Bank's Global Findex 2021 data is used to study the determinants of using formal vs informal financial sectors in the BRICS nations, where the probit model and regression trees are used as methodology. The findings were as follows: The results of the full sample of the 5 BRICS nations confirm the life cycle hypothesis on age and financial inclusion. The inverted U-shaped nonlinear relationship between age and financial inclusion was confirmed in India, China, and South Africa. Brazil and Russia had a U-shaped relation between age and the decision to save in either sector. Brazil and Russia only confirm the life cycle hypothesis when it comes to credit in both formal and informal sectors. The probit model results also show individuals with lower education have a higher probability of borrowing in the informal channel, while those with tertiary education tend to borrow and save in the formal financial sector.

Within the BRICS nation, the marginal effect of the poorest individuals is negative when it comes to saving in both sectors. What is different is in China, the poorest individuals have a positive and significant probability of using both the formal and informal sectors for credit. Finally, in the full sample results of BRICS, the male gender had a negative probability of saving in the informal sector but a positive probability of using the formal sector to save and borrow.

As such all aspects of financial sector development on income distribution have been analysed in this thesis. This results in the conclusion that the financial sector can reduce income inequality through increased access to financial services. The evolution of the financial sector shows that other financial institutions have started providing credit based on potential cashflows of businesses. The likes of Klarna Bank offer innovative credit facilities such as buy now, pay later at the online store checkout. A certain level of access to credit that is flexible allows the low-income group the chance to build up their assets; for instance, credits based on the tenure of the employment contract instead of past credit should be considered for buying property. However, as the findings of the thesis demonstrate that credit is not necessarily a good tool for income inequality, caution needs to be taken when reviewing and creating more accommodative credit.

Furthermore, to reduce income inequality, the developed financial sector should be responsible for the financial literacy levels of countries. Increased levels of financial literacy will afford those relying on the informal sector (for example, “stokvels” in South Africa) who borrow at ridiculous interest rates more access to the regulated formal financial sector. While the data used in this thesis was new, the data is, to some degree, a limitation of this thesis. For example, measuring the number of ATMs per population is a good proxy for financial access, but if half of the ATMs are barely functioning or face low maintenance and thus do not operate, this means the data shows a greater number of ATMs than what is accessible.

6 LIST OF PUBLICATIONS RELATED TO THE TOPIC

This thesis consists of three main published articles. All these three articles were published in high-impact peer-reviewed journals classified under Q2, Q3 and Q1 by the Scimago Journal ranking and were published through open access. The first article, covered in Chapter 2, is titled "The impacts of overall financial development, access, depth on income inequality" and was published in the Economies journal, which is an open access. This paper is accessible through here: https://www.mdpi.com/2227-7099/10/5/118. The second article, covered in Chapter 3, was published in the Economy and Society Journal and can be found here: https://doi.org/10.1556/204.2023.00026. Finally, the third article discussed in Chapter 4 above, titled "Determinants of using formal vs informal financial sector in BRICS group", was published with the Finance Research Letters, and the article can be accessed here: https://doi.org/10.1016/j.frl.2023.103956.

7 REFERENCES

Allen, F., Demirguc-Kunt, A., Klapper, L. and Peria, M.S.M., 2016. The foundations of financial inclusion: Understanding ownership and use of formal accounts. *Journal of Financial Intermediation*, *27*, pp.1-30.

Altunbas, Y. and Thornton, J., 2019. The impact of financial development on income inequality: A quantitative regression approach. Economics Letters, 175, pp.51-56.

Arellano, M. and Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of Economic Studies*, *58*(2), pp.277-297.

Babajide, A., 2011. The relationship between the informal and formal financial sector in Nigeria: A case study of selected groups in Lagos metropolis. *International Journal of Research in Computer Application and Management, Volume No. I, Issue No*, *10*.

Banerjee, A.V. and Newman, A.F., 1993. Occupational choice and the process of development. *Journal of Political economy*, *101*(2), pp.274-298.

Bathula, S. and Gupta, A., 2021. The determinants of Financial Inclusion and Digital Financial Inclusion in India: A Comparative Study. *The Review of Finance and Banking*, *13*(2).

Batuo, M.E., Guidi, F. and Mlambo, K., 2010. Financial development and income inequality: Evidence from African Countries. *African Development Bank*, *44*, pp.1-27.

Beck, T., Demirguc-Kunt, A. and Levine, R., 2004. Finance, inequality, and poverty: Cross-country evidence. NBER Working Papers (10979).

Benczúr, P. and Kvedaras, V., 2021. Nonlinear impact of financial deepening on income inequality. *Empirical Economics*, *60*(4), pp.1939-1967.

Bittencourt, M., 2012. Financial development and economic growth in Latin America: Is Schumpeter right? *Journal of Policy Modeling*, *34*(3), pp.341-355.

Bittencourt, M., Chang, S., Gupta, R. and Miller, S.M., 2019. Does financial development affect income inequality in the US States? *Journal of Policy Modeling*, *41*(6), pp.1043-1056.

Blundell, R. and Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), pp.115-143.

Borenstein, M., Hedges, L.V., Higgins, J.P. and Rothstein, H.R., 2021.*Introduction to meta-analysis*. John Wiley & Sons.

Brei, M., Ferri, G. and Gambacorta, L., 2018. *Financial structure and income inequality* (No. 13330). CEPR Discussion Papers.

Burgess, R. and Pande, R., 2005. Do rural banks matter? Evidence from the Indian social banking experiment. *American Economic Review*, *95*(3), pp.780-795.

Chiu, Y.B. and Lee, C.C., 2019. Financial development, income inequality, and country risk. *Journal of International Money and Finance*, *93*, pp.1-18.

Cihak, M.M. and Sahay, M.R., 2020. *Finance and inequality*. International Monetary Fund *Staff Discussion Note*. SDN/20/01.

Dabla-Norris, M.E., Kochhar, M.K., Suphaphiphat, M.N., Ricka, M.F. and Tsounta, M.E., 2015. *Causes and consequences of income inequality: A global perspective*. International Monetary Fund.

Daud, S.N.M. and Ahmad, A. H., 2023. Financial inclusion, economic growth and the role of digital technology. *Finance Research Letters*, *53*, p.103602.

Darvas, Z,.2019. Global interpersonal income inequality decline: The role of China and India. *World Development*, 121, pp.16-32.

de Haan, J. and Sturm, J.E., 2017. Finance and income inequality: A review and new evidence. *European Journal of Political Economy*, *50*, pp.171-195.

de la Cuesta-González, M., Ruza, C. and Rodríguez-Fernández, J.M., 2020. Rethinking the income inequality and financial development nexus. A study of nine OECD countries. *Sustainability*, *12*(13), p.5449.

Delis, M.D., Fringuellotti, F. and Ongena, S.R., 2021. Credit, Income, and Inequality. FRB of New York Staff Report No. 929. In *Proceedings of Paris December 2020 Finance Meeting EUROFIDAI—ESSEC. Available online: https://ssrn.com/abstract* (Vol. 3631252).

Delis, M.D., Hasan, I. and Kazakis, P., 2014. Bank regulations and income inequality: Empirical evidence. *Review of Finance*, *18*(5), pp.1811-1846.

Demirgüç-Kunt, A. and Levine, R., 2009. Finance and inequality: Theory and evidence. *Annu. Rev. Financ. Econ.*, *1*(1), pp.287-318.

Demirgüç-Kunt, A., Klapper, L.F. and Panos, G.A., 2016. Saving for old age. *World Bank Policy Research Working Paper*, (7693).

Demirgüç-Kunt, Beck, T. and Honohan, P., 2008. *Finance for all?: Policies and pitfalls in expanding access*. World Bank.

Denk, O., 2015. *Financial sector pay and labour income inequality: Evidence from Europe* (No. 1225). OECD Publishing.

Dollar, D. and Kraay, A., 2002. Growth is Good for the Poor. *Journal of Economic Growth*, *7*, pp.195-225.

Ductor, L. and Grechyna, D., 2015. Financial development, real sector, and economic growth. *International Review of Economics & Finance*, *37*, pp.393-405.

Egger, M., Smith, G.D., Schneider, M. and Minder, C., 1997. Bias in meta-analysis detected by a simple, graphical test. *Bmj*, *315*(7109), pp.629-634.

Eurofound (2021), *Wealth distribution and social mobility*, Publications Office of the European Union, Luxembourg.

Francese, M. and Mulas-Granados, C., 2015. Functional Income Distribution and Its Role in Explaining Inequality. *IMF Working Papers*, *2015*(244).

Galor, O. and Zeira, J., 1993. Income distribution and macroeconomics. *The review of Economic Studies*, *60*(1), pp.35-52.

Gnangoin, Y.T.B., Du, L., Assamoi, G., Edjoukou, A.J. and Kassi, D.F., 2019. Public spending, income inequality and economic growth in Asian countries: A panel GMM approach. *Economies*, *7*(4), p.115.

Goldsmith, R.W., 1969. Financial structure and development. New Haven: Yale University Press.

Goodstein, R.M. and Rhine, S.L., 2017. The effects of bank and nonbank provider locations on household use of financial transaction services. *Journal of Banking & Finance*, *78*, pp.91-107.

Greenwood, J. and Jovanovic, B., 1990. Financial development, growth, and the distribution of income. *Journal of Political Economy*, *98*(5, Part 1), pp.1076-1107.

Gründler, K. and Weitzel, J., 2013. *The financial sector and economic growth in a panel of countries* (No. 123). Wirtschaftswissenschaftliche Beiträge.

Gural, A. and Lomachynska, I., 2017. FDI and financial development as determinants of economic growth for V4 countries. *Baltic Journal of Economic Studies*, *3*(4), pp.59-64.

Gutierrez, E. and Singh, S., 2013. What regulatory frameworks are more conducive to mobile banking? Empirical evidence from Findex data. *Empirical Evidence from Findex Data (October 1, 2013). World Bank Policy Research Working Paper*, (6652).

Hasan, I., Horvath, R. and Mares, J., 2020. Finance and wealth inequality. *Journal of International Money and Finance*, *108*, p.102161.

Havránek, T., Horváth, R. and Valícková, P., 2013. Financial development and economic growth: a meta analysis. *Czech National Bank "(CNB Working Paper Series, 5/2013)*.

Heimberger, P., 2020. Does economic globalisation affect income inequality? A meta-analysis. *The World Economy*, *43*(11), pp.2960-2982.

Hendel, I., Shapiro, J. and Willen, P., 2005. Educational opportunity and income inequality. *Journal of Public Economics*, *89*(5-6), pp.841-870.

Hothorn, T., Hornik, K. and Zeileis, A., 2006. Unbiased recursive partitioning: A conditional inference framework. *Journal of Computational and Graphical Statistics*, *15*(3), pp.651-674.

https://github.com/nokumbona/Financial-deepening-on-income-inequality-A-quantitative-meta-analysis-study

Iacoviello, M., 2008. Household Debt and Income Inequality, 1963-2003. *Journal of Money, Credit and Banking, 40(5).*

James, D., 2015. 'Women Use their Strength in the House': Savings Clubs in a Mpumalanga Village. *Journal of Southern African Studies*, *41*(5), pp.1035-1052.

Jaumotte, F., Lall, S. and Papageorgiou, C., 2013. Rising income inequality: technology, or trade and financial globalization? *IMF Economic Review*, *61*(2), pp.271-309.

Jaumotte, F., Lall, S. and Papageorgiou, C., 2013. Rising income inequality: technology, or trade and financial globalization? *IMF Economic Review*, *61*(2), pp.271-309.

Kapingura, F.M., 2017. Financial sector development and income inequality in South Africa. *African Journal of Economic and Management Studies*, *8*(4), pp.420-432.

Kaufmann, D., Kraay, A. and Mastruzzi, M., 2010. *The worldwide governance indicators: A summary of methodology, data and analytical issues. World Bank Policy Research* (Vol. 5430). working paper.

Kede Ndouna, F. and Zogning, F., 2022. Financial inclusion and gender income inequalities in informal entrepreneurship: The case of Cameroon. *The Journal of Entrepreneurial Finance*, *24*(3), pp.33-47.

Kim, D.H. and Lin, S.C., 2011. Nonlinearity in the financial development–income inequality nexus. *Journal of Comparative Economics*, *39*(3), pp.310-325.

Klapper, L. and Singer, D., 2015. The role of informal financial services in Africa. *Journal of African Economies*, *24* (suppl_1), pp.i12-i31.

Koçak, E. and Uzay, N., 2019. The effect of financial development on income inequality in Turkey: An estimate of the Greenwood-Jovanovic hypothesis. *Review of Economic Perspectives*, *19*(4), pp.319-344.

Kuhn, M. and Johnson, K., 2018. Applied Predictive Modeling, 2nd 2018 Edition.

Kuznets, S., 1955. American Economic Association. *The American Economic Review*, *45*(1), pp.1-28.

Le, Q.H. and Nguyen, B.N., 2020. The impact of credit on income inequality in Vietnam. *The Journal of Asian Finance, Economics and Business*, *7*(5), pp.111-118.

Levine, R., 2004. Finance and growth: theory and evidence [Working Paper 10766]. *Recuperado de http://www.nber.org/papers/w10766. pdf*.

Liang, Z., 2008. Financial development and income inequality in rural China 1991–2000. In *Understanding Inequality and Poverty in China: Methods and Applications* (pp. 72-88). London: Palgrave Macmillan UK.

Majoka, Z. and Palacios, R.J., 2017. *What can we learn about pensions from the FINDEX data? World Bank Policy Research Working Paper*, (113484).

Mbona, N. and Major, K., 2023. Determinants of Using Formal vs Informal Financial Sector in BRICS Group. *Available at SSRN 4361330*.

Mbona, N., 2022. Impacts of overall financial development, access and depth on income inequality. *Economies*, *10*(5), p.118.

Méndez-Heras, L. and Ongena, S., 2020. "Finance and growth" re-visited. *Journal of Financial Management, Markets and Institutions*, *8*(01), p.2050001.

Mihályi, P. and Szelényi, I., 2019. *Rent-seekers, profits, wages and inequality*: *The Top 20%*. Springer International Publishing.

Mpofu, O. and Sibindi, A.B., 2022. Informal finance: A boon or bane for African SMEs? *Journal of Risk and Financial Management*, *15*(6), p.270.

Nguyen, T., Ngoc Vu, T., Hong Vo, D. and Thi-Thieu Ha, D., 2019. Financial development and income inequality in emerging markets: a new approach. *Journal of Risk and Financial Management*, *12*(4), p.173.

Nguyen, T. C., 2022. The effects of financial crisis on income inequality. *Development Policy Review*, 40, e12600. https://doi.org/10.1111/dpr.12600

Oluitan, R.O., 2012. Financial development and economic growth in Africa: Lessons and prospects. *Business and Economic Research*, *2*(2).

Pandey, A., Kiran, R. and Sharma, R.K., 2023. Investigating the determinants of financial inclusion in BRICS economies: panel data analysis using fixed-effect and cross-section random effect. *Sustainability*, *15*(2), p.1603.

Park, D. and Shin, K., 2015. Economic Growth, Financial Development, and Income Inequality. *Asian Development Bank Economics Working Paper Series*, (441).

Paun, C.V., Musetescu, R.C., Topan, V.M. and Danuletiu, D.C., 2019. The impact of financial sector development and sophistication on sustainable economic growth. *Sustainability*, *11*(6), p.1713.

Piketty, T., 2014. Capital in the Twenty-First Century. Cambridge: Belknap Press.

Prete, A.L., 2013. Economic literacy, inequality, and financial development. *Economics Letters*, *118*(1), pp.74-76.

Rajan, R.G. and Zingales, L., 2003. The road to prosperity: saving capitalism from capitalists. *Transition*, *14*(7-9), pp.1-3.

Roodman, D., 2007. A short note on the theme of too many instruments. *Center for Global Development Working Paper*, *125*(10.2139).

Roodman, D., 2009. How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal*, *9*(1), pp.86-136.

Sahay, R., Cihak, M., N'Diaye, P., Barajas, A., Ayala Pena, D., Bi, R., Gao, Y., Kyobe, A., Nguyen, L., Saborowski, C. and Svirydzenka, K., 2015. *Rethinking financial deepening: Stability and growth in emerging markets* (No. 2015/008). International Monetary Fund.

Santos, D.B., Mendes-Da-Silva, W. and Gonzalez, L., 2018. Lower financial literacy induces use of informal loans. *Revista de Administração de Empresas*, *58*, pp.44-59.

Setiawan, S., 2015. Financial depth and financial access in Indonesia. *Journal of Indonesian Economy & Business*, *30*(2).

Seven, U. and Coskun, Y., 2016. Does financial development reduce income inequality and poverty? Evidence from emerging countries. *Emerging Markets Review*, *26*, pp.34-63.

Shahbaz, M. and Islam, F., 2011. Financial development and income inequality in Pakistan: An application of ARDL approach. *Journal of Economic Development*, *36*(1).

Shahbaz, M., Loganathan, N., Tiwari, A.K. and Sherafatian-Jahromi, R., 2015. Financial development and income inequality: is there any financial Kuznets curve in Iran? *Social Indicators Research*, *124*, pp.357-382.

Stanley, T.D., Doucouliagos, H., Giles, M., Heckemeyer, J.H., Johnston, R.J., Laroche, P., Nelson, J.P., Paldam, M., Poot, J., Pugh, G. and Rosenberger, R.S., 2013. Meta-analysis of economics research reporting guidelines. *Journal of Economic Surveys*, *27*(2), pp.390-394.

Sunde, T., 2012. Financial sector development and economic growth nexus in South Africa. *International Journal of Monetary Economics and Finance*, *5*(1), pp.64-75.

Svirydzenka, K., 2016. Introducing a New Broad-based Index of Financial Development1. *IMF Working Papers*, *2016*(005).

Tan, H.B. and Law, S.H., 2012. Nonlinear dynamics of the finance-inequality nexus in developing countries. *The Journal of Economic Inequality*, *10*, pp.551-563.

Wahid, A.N., Shahbaz, M., Shah, M. and Salahuddin, M., 2012. Does financial sector development increase income inequality? Some econometric evidence from Bangladesh. *Indian Economic Review*, pp.89-107.

Wardman, M., 2022. Meta-analysis of price elasticities of travel demand in Great Britain: Update and extension. *Transportation Research Part A: Policy and Practice*, *158*, pp.1-18.

Younsi, M. and Bechtini, M., 2020. Economic growth, financial development, and income inequality in BRICS countries: does Kuznets' inverted U-shaped curve exist? *Journal of the Knowledge Economy*, *11*, pp.721-742.

Zins, A., and Weill, L.,2016. The Determinants of Financial Inclusion in Africa. *Review of Development Finance*, 6, 46-57. https://doi.org/10.1016/j.rdf.2016.05.001

Zuzana Fungáčová, Laurent Weill, 2015. Understanding financial inclusion in China. *China Economic Review*,34,196-206.

Appendices

APPENDIX A

Table 2 : List of the 120 countries in the analysis

Country list							
Albania	Korea	Canada	Myanmar	Burkina Faso	Moldova	Estonia	Poland
Algeria	Kyrgyzstan	Chile	Namibia	Burundi	Mongolia	Ethiopia	Portugal
Angola	Laos	China	Nepal	Cambodia	Morocco	Fiji	Qatar
Armenia	Latvia	Colombia	Netherlands	Cameroon	Mozambique	Finland	Romania
Australia	Lesotho	Congo-Brazzaville	New Zealand	Iceland	Sri Lanka	France	Russia
Austria	Lithuania	Croatia	Nicaragua	India	Sudan	Gabon	Rwanda
Bangladesh	Luxembourg	Cyprus	Niger	Indonesia	Sweden	Gambia	Saudi Arabia
Barbados	Madagascar	Czech Republic	Nigeria	Iran	Switzerland	Germany	Senegal
Belgium	Malaysia	CÃ´te d'Ivoire	Norway	Ireland	Tajikistan	Ghana	Serbia
Benin	Maldives	Denmark	Pakistan	Israel	Tanzania	Greece	Singapore
Bolivia	Malta	Dominican Republic	Panama	Italy	Thailand	Guatemala	Slovakia
Botswana	Mauritania	Ecuador	Paraguay	Jamaica	Togo	Honduras	Slovenia
Brazil	Mauritius	Egypt	Peru	Japan	Tunisia	Hong Kong	South Africa
Bulgaria	Mexico	El Salvador	Philippines	Jordan	Turkey	Hungary	Spain
Kenya	Ukraine	Zambia	United Kingdom	Kazakhstan	Uganda	Vietnam	Uruguay

Table 2.0. Stationary test

Variable	Level	1st Difference	Conclusion
Log_Gini(after-tax)	-0.1801	-7.37***	I(1)
Log_Gini(before-tax)	0.27	-5.69***	I(1)
	Main explanatory variable		
Dom_credit	2.03652	-17.0054***	I(1)
FD	-4.61***	-19.37***	I(0)
FIA	-1.51*	-8.34***	I(1)
FMA	-8.32219***	-30.7306***	I(0)
FID	1.60941	-26.9918***	I(1)
FMD	-23.4072***	-41.0861***	I(0)
	Control variables		
Trade openness	-5.16***	-18.99***	I(0)
Average years at school	6.08	-3.67***	I(1)
Log_Gov_consuption (	-1.37366*	-24.9893***	I(1)
Corruption index	-1.29*	-18.07***	I(1)
GDP	4.68	-12.86***	I(1)
ATM	3.87787	-12.6723***	I(1)

Im-Pesaran-Shin test[5] of Unit root, where number of lags equals to one and the panel mean of each variable is included sequentially in the test.

[5] The IPS unit-root test the HO: All panels contain a unit-root. The IPS test fits each panel separately and averages the resulting t-statistic.

Table 2.1: Summary statistics by subgroups (Advanced Markets (AM), Emerging Markets (EM), and Low-income countries (LIC)

AM group	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
After-Tax Gini	514	.303	.041	.23	.411
Before-Tax Gini	514	.47	.042	.333	.563
FD	540	.65	.189	.21	1
FI	**540**	**.717**	**.143**	**.375**	**1**
FM	**540**	**.564**	**.261**	**.02**	**.989**
FIA	540	.676	.206	.202	1
FMA	540	.538	.288	.018	1
FID	540	.635	.24	.121	1
FMD	540	.59	.302	.024	1
ATMadult	**529**	**.933**	**.51**	**.296**	**2.886**
Dom credit	500	1.093	.456	.002	3.046
GDP	540	4.38	1.601	1.443	11.294
CPI	540	1.186	.157	.99	2
Education	540	11.626	1.486	6.636	15.802
Trade op	540	1.183	.714	.332	5.079
Gov	540	.192	.04	.084	.279
Corruption index	540	1.386	.716	-.189	2.47
EM group	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
After-Tax Gini	765	.414	.081	.258	.674
Before-Tax Gini	765	.462	.079	.219	.725
FD	847	.336	.146	.081	.739
FI	**847**	**.41**	**.137**	**.152**	**.74**
FM	**847**	**.253**	**.205**	**.001**	**.735**
FIA	847	.354	.202	.024	1
FMA	**847**	**.269**	**.231**	**0**	**1**
FID	847	.251	.196	.016	.885
FMD	847	.224	.208	.001	.863
ATM_adult	**788**	**.431**	**.322**	**.007**	**2.593**
Dom credit	767	.524	.319	.081	1.654
GDP	847	1.575	1.742	.21	16.652
CPI	847	1.686	.886	1	9.04
Education	847	8.363	2.197	2.205	13.091
Trade op	847	.496	.265	.098	1.752
Gov	842	.145	.044	.044	.316
Corruption index	847	-.243	.624	-1.444	1.725
LIC group	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
After-Tax Gini	387	.425	.06	.319	.561
Before-Tax Gini	387	.457	.062	.351	.595
FD	516	.122	.039	.029	.257
FI	**516**	**.217**	**.067**	**.047**	**.502**
FM	**516**	**.024**	**.035**	**0**	**.209**
FIA	516	.1	.115	.005	.701
FMA	516	.012	.045	0	.333
FID	516	.08	.051	.008	.265

FMD	516	.046	.064	0	.256
ATMadult	**421**	**.08**	**.089**	**0**	**.509**
Dom credit	469	.215	.153	0	1.142
GDP	516	.319	.258	.06	1.914
CPI	513	1.942	1.63	1	25.777
Education	516	4.797	2.622	.759	12.934
Trade op	516	.338	.228	.059	1.861
Gov	470	.139	.061	.035	.435
Corruption index	516	-.745	.427	-1.673	.762

Table 2.2. Correlation table using raw data (Pairwise correlations).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) After-tax Gini	1.000																
(2) Before-tax Gini	0.494*	1.000															
	(0.000)																
(3) FD	-0.449*	0.161*	1.000														
	(0.000)	(0.000)															
(4) FI	-0.480*	0.171*	0.932*	1.000													
	(0.000)	(0.000)	(0.000)														
(5) FM	-0.378*	0.136*	0.957*	0.787*	1.000												
	(0.000)	(0.000)	(0.000)	(0.000)													
(6) FIA	-0.531*	0.082*	0.773*	0.887*	0.607*	1.000											
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)												
(7) FMA	-0.366*	0.082*	0.808*	0.697*	0.818*	0.581*	1.000										
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)											
(8) FID	-0.337*	0.243*	0.897*	0.907*	0.802*	0.635*	0.672*	1.000									
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)										
(9) FMD	-0.364*	0.136*	0.928*	0.795*	0.943*	0.584*	0.725*	0.844*	1.000								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)									
(10) ATMadult	-0.421*	0.011	0.751*	0.797*	0.638*	0.827*	0.550*	0.627*	0.610*	1.000							
	(0.000)	(0.654)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)								
(11) Dom_credit	-0.413*	0.061*	0.812*	0.818*	0.730*	0.643*	0.645*	0.826*	0.747*	0.577*	1.000						
	(0.000)	(0.017)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
(12) GDP	-0.499*	0.053*	0.741*	0.694*	0.707*	0.619*	0.719*	0.641*	0.710*	0.545*	0.560*	1.000					
	(0.000)	(0.030)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
(13) CPI	0.094*	-0.197*	-0.243*	-0.222*	-0.235*	-0.166*	-0.205*	-0.247*	-0.230*	-0.151*	-0.223*	-0.204*	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
(14) yr_sch	-0.582*	0.006	0.679*	0.727*	0.574*	0.716*	0.561*	0.613*	0.544*	0.632*	0.558*	0.628*	-0.188*	1.000			
	(0.000)	(0.803)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(15) Trade_op	-0.360*	0.058*	0.481*	0.518*	0.404*	0.387*	0.389*	0.551*	0.442*	0.268*	0.439*	0.571*	-0.214*	0.480*	1.000		
	(0.000)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(16) Gov	-0.303*	0.287*	0.383*	0.441*	0.299*	0.397*	0.178*	0.421*	0.314*	0.330*	0.303*	0.310*	-0.094*	0.343*	0.266*	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(17) corruption	-0.470*	0.210*	0.794*	0.811*	0.704*	0.622*	0.656*	0.837*	0.730*	0.551*	0.698*	0.769*	-0.285*	0.636*	0.600*	0.462*	1.000

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

*** p<0.01, ** p<0.05, * p<0.1

Overall FSD, Financial Institutions and Market results

Table 2. 2(A). Impacts of overall financial sector development on income inequality (After tax – 1st difference GMM full sample).

	(1) FSD	(2) FI	(3) FM
L1. Log After-tax Gini	0.710***	0.735***	0.726***
	(0.125)	(0.106)	(0.121)
FinDev	-0.0643**	-0.0618*	-0.0434**
	(0.0261)	(0.0353)	(0.0187)
GDP	0.00417	0.00294	0.00488
	(0.00376)	(0.00347)	(0.00380)
Log-CPI	0.0106	0.0133	0.00929
	(0.00871)	(0.00820)	(0.00827)
Trade_op	-0.00238	-0.00102	-0.00444
	(0.00704)	(0.00729)	(0.00698)
LogGov	0.00764	0.0113	0.00259
	(0.0186)	(0.0203)	(0.0179)
L1.Log-education	-0.0911	-0.0801	-0.0976*
	(0.0582)	(0.0524)	(0.0580)
Constant	-0.0730	-0.0594	-0.0648
	(0.0809)	(0.0774)	(0.0793)
Observations	1,508	1,508	1,508
Number of ccode	120	120	120
AR 2 test (p-value)	0.555	0.394	0.527
Sargan test (p-value)	0.263	0.969	0.835
Hansen test(p-value)	0.228	0.599	0.197

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2. 2.1 (A). Impacts of overall financial sector development on income inequality (After tax – 1st difference GMM full sample).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	FD						FI						FM					
	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC
L1. Log After-tax Gini	0.740**	0.862**	0.323	0.251	1.046*	0.338	0.898**	0.789**	0.366	0.453**	1.089**	0.153	0.656**	0.846**	0.287	0.821**	1.012***	0.107
	(0.325)	(0.380)	(0.527)	(0.257)	(0.545)	(0.571)	(0.399)	(0.381)	(0.564)	(0.171)	(0.436)	(0.642)	(0.288)	(0.386)	(0.490)	(0.374)	(0.358)	(0.396)
Findev	-0.0768	-0.0569	0.0827	-0.988	-0.539	-0.100	-0.0881	-0.0462	0.0525	-0.623	-0.459*	0.451	-0.0549	-0.0389	0.0446	0.249	-0.239	-0.405
	(0.0714)	(0.0426)	(0.167)	(1.185)	(0.486)	(0.705)	(0.0921)	(0.0492)	(0.0795)	(0.727)	(0.267)	(0.447)	(0.0528)	(0.0309)	(0.174)	(0.266)	(0.192)	(0.614)
Findev^2				0.699	0.682	0.566				0.420	0.557	-0.674				-0.228	0.263	2.478
				(0.831)	(0.666)	(2.059)				(0.491)	(0.343)	(0.641)				(0.209)	(0.270)	(3.375)
GDP	0.00122	-0.00576	-0.00447	-0.00682	-0.00727	-0.00343	-0.000152	-0.00458	0.00320	-0.00754	-0.00175	-0.00943	0.00167	-0.00784	-0.0140	-0.000788	-0.00549	-0.0269
	(0.0121)	(0.00915)	(0.0684)	(0.0160)	(0.0116)	(0.0704)	(0.00843)	(0.0104)	(0.0734)	(0.0106)	(0.0128)	(0.0886)	(0.0139)	(0.00942)	(0.0537)	(0.0102)	(0.0120)	(0.0514)
Log-CPI	0.145**	-0.00295	-0.0195	0.167**	0.00340	-0.0187	0.125	0.00634	-0.0171	0.186***	0.00805	-0.0219	0.151**	-0.00967	-0.0246	0.142*	-0.0138	-0.0288
	(0.0674)	(0.0133)	(0.0179)	(0.0679)	(0.0303)	(0.0190)	(0.0840)	(0.0190)	(0.0198)	(0.0594)	(0.0273)	(0.0244)	(0.0611)	(0.0140)	(0.0238)	(0.0784)	(0.0203)	(0.0299)
Trade_op	-0.0182	0.00473	-0.00553	-0.0121	0.0104	-0.00361	-0.0148	-0.00305	-0.00905	-0.0164	0.00100	-0.0135	-0.0192	0.00857	0.00307	-0.0183	-0.00299	0.0106
	(0.0117)	(0.0233)	(0.0243)	(0.0142)	(0.0326)	(0.0240)	(0.0122)	(0.0257)	(0.0266)	(0.0121)	(0.0313)	(0.0379)	(0.0117)	(0.0239)	(0.0123)	(0.0123)	(0.0332)	(0.0139)
LogGov	-0.0321	-0.00574	0.00336	-0.0296	-0.00911	0.00347	-0.0222	-0.0144	0.00158	-0.0511	-0.0109	-0.000382	-0.0359	-0.00527	0.00675	-0.0499	-0.0188	0.00796
	(0.0388)	(0.0187)	(0.0110)	(0.0604)	(0.0337)	(0.0107)	(0.0432)	(0.0196)	(0.0124)	(0.0402)	(0.0295)	(0.0210)	(0.0369)	(0.0208)	(0.0170)	(0.0346)	(0.0350)	(0.0228)
L1.Log-education	-0.381*	0.0317	-0.0190	-0.318	0.0649	-0.0156	-0.346*	-0.00925	-0.0247	-0.337	0.00426	-0.0467	-0.378*	0.0439	0.00313	-0.331	0.100	0.00784
	(0.211)	(0.111)	(0.0462)	(0.306)	(0.132)	(0.0491)	(0.185)	(0.102)	(0.0550)	(0.249)	(0.117)	(0.0778)	(0.223)	(0.112)	(0.0556)	(0.197)	(0.113)	(0.0698)
Observations	446	655	287	446	655	287	446	655	287	446	655	287	446	655	287	446	655	287
Number of ccode	34	53	32	34	53	32	34	53	32	34	53	32	34	53	32	34	53	32
AR 2 test (p-value)	0.822	0.399	0.248	0.231	0.089	0.295	0.689	0.537	0.30	0.325	0.229	0.276	0.689	0.537	0.300	0.325	0.229	0.276
Sargan test (p-value)	0.259	0.400	0.771	0.414	0.746	0.789	0.329	0.238	0.792	0.607	0.778	0.914	0.329	0.238	0.792	0.607	0.778	0.914
Hansen test(p-value)	0.126	0.024	0.757	0.228	0.096	0.725	0.120	0.01	0.934	0.333	0.097	0.849	0.120	0.011	0.934	0.333	0.097	0.849

Access to Financial Institutions and Market results

Table 2.3.(A). Impact of access to financial institutions and markets on income inequality. (After tax – 1st difference GMM full sample).

	(1) FIA	(2) ATM	(3) FMA	(4) FIA	(5) ATM	(6) FMA
L1. Log After-tax Gini	0.754***	0.801***	0.812***	0.744***	0.794***	0.853***
	(0.118)	(0.0853)	(0.0832)	(0.125)	(0.0834)	(0.0785)
Financial Access	-0.0541**	-0.0278*	0.00812	-0.0282	-0.0648**	0.156
	(0.0233)	(0.0145)	(0.00986)	(0.107)	(0.0316)	(0.0995)
Financial Access^2				-0.0267	0.0217	-0.121
				(0.100)	(0.0161)	(0.0844)
GDP	0.00143	0.00472	0.00363	0.00205	0.00158	0.00212
	(0.00355)	(0.00340)	(0.00290)	(0.00370)	(0.00277)	(0.00276)
lCPI	0.0183*	0.0204**	0.0131*	0.0182*	0.0221**	0.0172**
	(0.0102)	(0.00874)	(0.00688)	(0.0109)	(0.00846)	(0.00808)
Trade_op	0.00797	0.000970	-0.00461	0.00778	0.00388	-0.00756
	(0.00713)	(0.00656)	(0.00597)	(0.00747)	(0.00686)	(0.00668)
LogGov	0.0252	0.0218	0.00196	0.0264	0.0186	-0.00715
	(0.0225)	(0.0199)	(0.0164)	(0.0219)	(0.0198)	(0.0158)
L1.Log-education	-0.0881	-0.0889*	-0.0892**	-0.0982	-0.0649*	-0.0893**
	(0.0541)	(0.0483)	(0.0433)	(0.0605)	(0.0366)	(0.0429)
Constant	-0.00909	0.0230	-0.0130	-0.00142	-0.0273	-0.00825
	(0.0878)	(0.0850)	(0.0720)	(0.0870)	(0.0847)	(0.0721)
Observations	1,508	1,416	1,508	1,508	1,416	1,508
Number of ccode	120	119	120	120	119	120
AR 2 test (p-value)	0.497	0.210	0.337	0.635	0.225	0.361
Sargan test(p-value)	0.933	0.559	0.898	0.926	0.868	0.758
Hansen test(p-value)	0.995	0.795	0.573	0.974	0.700	0.632

Table 2. 3.1: Impact of access to financial institutions on income inequality. (After tax – 1st difference GMM Sub- sample full model).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	FIA						FMA						ATM					
	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC
L1. Log After-tax Gini	0.635*	0.626	0.323	0.770**	0.418	0.325	0.813**	0.500	-0.0721	0.742**	0.477	-0.0536	1.055*	0.697**	0.588*	0.337	0.660*	0.769**
	(0.324)	(0.437)	(0.552)	(0.359)	(0.533)	(0.551)	(0.338)	(0.445)	(0.365)	(0.357)	(0.452)	(0.350)	(0.564)	(0.334)	(0.301)	(0.375)	(0.343)	(0.333)
Findev	-0.0799	-0.0851**	-0.00940	0.328	0.0514	0.00836	0.00119	0.0584*	0.186	0.121	0.126	0.141	-0.0628	-0.0357	0.0717	-0.266	-0.0507	0.0346
	(0.0873)	(0.0345)	(0.142)	(0.478)	(0.213)	(0.223)	(0.0160)	(0.0322)	(0.286)	(0.0974)	(0.119)	(0.360)	(0.0499)	(0.0271)	(0.0744)	(0.319)	(0.0305)	(0.117)
Findev2				-0.349	-0.189	-0.0241				-0.107	-0.0639	0.110				0.111	0.0197	0.0975
				(0.345)	(0.299)	(0.140)				(0.0820)	(0.103)	(0.782)				(0.130)	(0.0395)	(0.224)
GDP	-0.00268	0.00647	-0.00684	0.00843	0.00850	-0.00856	-0.000612	-7.67e-05	-0.0620	0.00102	0.00320	-0.0614	0.00423	-0.00153	0.0222	-0.00270	0.00288	0.0214
	(0.0139)	(0.0117)	(0.0523)	(0.0124)	(0.0140)	(0.0513)	(0.00769)	(0.0115)	(0.0551)	(0.00883)	(0.0130)	(0.0525)	(0.0125)	(0.00969)	(0.0290)	(0.0219)	(0.0107)	(0.0283)
Log-CPI	0.194**	0.0128	-0.0237	0.184**	0.00751	-0.0229	0.110	0.00833	-0.0387	0.0911	0.00204	-0.0372	0.168*	0.0280	-0.0134	0.189**	0.0193	-0.00820
	(0.0751)	(0.0315)	(0.0201)	(0.0870)	(0.0495)	(0.0180)	(0.0718)	(0.0387)	(0.0431)	(0.0751)	(0.0421)	(0.0420)	(0.0865)	(0.0253)	(0.0236)	(0.0859)	(0.0277)	(0.0276)
Trade_op	-0.0144	0.00970	0.00257	-0.0157	0.0112	0.00231	-0.0130	-0.0207	0.0173	-0.0134	-0.0266	0.0167	-0.0118	-0.000967	-0.00671	-0.0195	0.000697	-0.00935
	(0.0110)	(0.0289)	(0.0245)	(0.0123)	(0.0342)	(0.0250)	(0.0106)	(0.0407)	(0.0204)	(0.0115)	(0.0443)	(0.0189)	(0.0135)	(0.0203)	(0.0105)	(0.0156)	(0.0190)	(0.0105)
LogGov	-0.0251	0.0305	0.00722	0.00956	0.0349	0.00580	-0.0212	-0.0233	0.00620	-0.0188	-0.0230	0.00628	0.00244	0.000953	-0.00393	-0.0359	0.0129	-0.00418
	(0.0489)	(0.0273)	(0.0209)	(0.0502)	(0.0317)	(0.0247)	(0.0345)	(0.0417)	(0.0194)	(0.0340)	(0.0444)	(0.0195)	(0.0579)	(0.0315)	(0.0215)	(0.0514)	(0.0229)	(0.0186)
L1.Log-education	-0.498	-0.0755	0.00518	-0.623*	-0.0965	0.000757	-0.267*	-0.132	0.0279	-0.236	-0.125	0.0245	-0.456*	-0.0792	-0.0651	-0.460	-0.0931	-0.0519
	(0.370)	(0.124)	(0.0461)	(0.344)	(0.148)	(0.0493)	(0.145)	(0.129)	(0.0922)	(0.149)	(0.136)	(0.0934)	(0.236)	(0.103)	(0.0934)	(0.464)	(0.109)	(0.0585)
Observations	446	655	287	446	655	287	446	655	287	446	655	287	442	620	235	442	620	235
Number of ccode	34	53	32	34	53	32	34	53	32	34	53	32	34	53	31	34	53	31
AR 2 test (p-value)	0.335	0.973	0.261	0.407	0.503	0.267	0.728	0.590	0.045	0.853	0.626	0.042	0.884	0.790	0.182	0.295	0.856	0.303
Sargan test(p-value)	0.732	0.715	0.553	0.868	0.792	0.704	0.193	0.654	0.811	0.365	0.544	0.722	0.585	0.720	0.909	0.407	0.630	0.842
Hansen test(p-value)	0.375	0.097	0.387	0.237	0.195	0.308	0.066	0.255	0.728	0.111	0.222	0.654	0.261	0.306	0.492	0.215	0.266	0.399

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Depth of Financial Institutions and Market on income inequality

Table 2.4.(A). Impacts of financial institution and market depth on income inequality (After tax – 1st difference GMM full sample difference).

	(1) Dom_Credit % of GDP	(2) FID	(3) FMD	(4) Dom_Credit % of GDP	(5) FID	(6) FMD
L1. Log After-tax Gini	0.770***	0.821***	0.782***	0.771***	0.761***	0.774***
	(0.116)	(0.0661)	(0.0890)	(0.115)	(0.0815)	(0.0884)
Financial Depth	-0.0199*	0.0196	-0.0100	-0.0214	-0.232**	-0.0327
	(0.0115)	(0.0350)	(0.0114)	(0.0384)	(0.103)	(0.0299)
Financial Depth^2				0.000750	0.185**	0.0213
				(0.0184)	(0.0844)	(0.0260)
GDP	0.00519	0.00341	0.00395	0.00516	0.000844	0.00383
	(0.00425)	(0.00274)	(0.00306)	(0.00450)	(0.00285)	(0.00313)
lCPI	0.0170	0.0137	0.0116	0.0170	0.00800	0.0113
	(0.0114)	(0.00837)	(0.00733)	(0.0113)	(0.00772)	(0.00746)
Trade_op	0.000731	-0.00464	-0.00629	0.000762	0.000744	-0.00608
	(0.00757)	(0.00559)	(0.00653)	(0.00778)	(0.00617)	(0.00663)
LogGov	0.0255	-0.00237	0.00162	0.0256	0.00844	0.00136
	(0.0246)	(0.0180)	(0.0168)	(0.0244)	(0.0194)	(0.0168)
L1.Log-education	-0.110*	-0.0929*	-0.0882*	-0.109	-0.0410	-0.0873*
	(0.0629)	(0.0486)	(0.0461)	(0.0671)	(0.0479)	(0.0467)
Constant	0.0391	-0.00841	-0.0388	0.0389	-0.101	-0.0453
	(0.108)	(0.0757)	(0.0738)	(0.110)	(0.0751)	(0.0725)
Observations	1,383	1,508	1,508	1,383	1,508	1,508
Number of ccode	119	120	120	119	120	120
AR 2 test (p-value)	0.726	0.281	0.353	0.711	0.184	0.383
Sargan test(p-value)	0.942	0.560	0.766	0.972	0.902	0.954
Hansen test(p-value)	0.920	0.291	0.277	0.580	0.580	0.591

Robust standard errors in parentheses

Table 2. 4.1.(A): Impact of depth to financial institutions and markets on income inequality. (After tax – 1st difference GMM Sub- sample).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	FID						**FMD**						**Dom_Credit as % of GDP**					
	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC
L1. Log After-tax Gini	0.715**	0.728*	0.156	0.427**	0.951**	-0.175	0.842**	0.785**	0.325	0.845**	0.762**	0.320	0.809	0.781	0.828**	0.300	0.672	1.034**
	(0.319)	(0.367)	(0.413)	(0.195)	(0.417)	(0.347)	(0.335)	(0.362)	(0.530)	(0.339)	(0.351)	(0.668)	(0.712)	(0.480)	(0.369)	(0.321)	(0.467)	(0.415)
Findev	0.0328	-0.0173	0.261	-0.533	-0.227	0.755	-0.0148	-0.00898	-0.00654	0.281	0.0254	0.00218	-0.0312	-0.0756	-0.00895	-0.0536	-0.0784	-0.119
	(0.0320)	(0.0524)	(0.569)	(0.643)	(0.168)	(1.361)	(0.0234)	(0.0120)	(0.0814)	(0.394)	(0.0939)	(0.446)	(0.0716)	(0.0674)	(0.0627)	(0.0886)	(0.0618)	(0.176)
Findev2				0.393	0.331	-2.553				-0.233	-0.0527	-0.0428				0.0256	0.0457	0.236
				(0.457)	(0.309)	(4.947)				(0.306)	(0.150)	(2.410)				(0.0260)	(0.0666)	(0.268)
GDP	-0.000749	-0.00700	-0.0100	-0.00802	-0.00110	-0.0127	-0.000445	-0.00547	-0.00774	-0.000580	-0.00490	-0.00751	0.00612	-0.00319	0.0514	-0.00684	0.00129	0.0472
	(0.00925)	(0.0102)	(0.0770)	(0.0110)	(0.0122)	(0.0997)	(0.00784)	(0.0104)	(0.0615)	(0.00780)	(0.0108)	(0.0568)	(0.0250)	(0.0133)	(0.0647)	(0.0185)	(0.0102)	(0.0770)
Log-CPI	0.115*	-0.00129	-0.0181	0.190**	0.00494	-0.0289	0.122*	-0.00558	-0.0236	0.117	-0.00785	-0.0238	0.165	0.00685	0.0108	0.142	-0.0239	0.0184
	(0.0670)	(0.0174)	(0.0182)	(0.0757)	(0.0199)	(0.0257)	(0.0698)	(0.0138)	(0.0207)	(0.0789)	(0.0160)	(0.0162)	(0.104)	(0.0503)	(0.0200)	(0.130)	(0.0380)	(0.0282)
Trade_op	-0.0113	-0.00244	-0.00971	-0.0242	-0.00506	-0.00758	-0.0164	-0.00505	0.00148	-0.0165	-0.00413	0.00156	-0.0133	0.0132	-0.0113	-0.0117	0.0191	-0.0171
	(0.00990)	(0.0265)	(0.0361)	(0.0208)	(0.0281)	(0.0481)	(0.0120)	(0.0271)	(0.0127)	(0.0129)	(0.0279)	(0.0143)	(0.0131)	(0.0441)	(0.0206)	(0.0165)	(0.0360)	(0.0238)
LogGov	-0.0226	-0.0176	-0.00514	-0.0597	-0.0148	-0.00479	-0.0285	-0.0167	0.00578	-0.0262	-0.0148	0.00576	0.0263	0.0171	0.00142	-0.0344	0.0122	-0.00229
	(0.0345)	(0.0237)	(0.0180)	(0.0545)	(0.0224)	(0.0215)	(0.0359)	(0.0216)	(0.0133)	(0.0377)	(0.0231)	(0.0140)	(0.104)	(0.0347)	(0.0183)	(0.0695)	(0.0316)	(0.0208)
L1.Log-education	-0.278*	-0.00523	-0.0570	-0.329	-0.00293	-0.0686	-0.300*	0.0137	0.00378	-0.254	0.0159	0.00368	-0.460	-0.00685	-0.0641	-0.182	0.0243	-0.0636
	(0.151)	(0.103)	(0.103)	(0.233)	(0.112)	(0.141)	(0.165)	(0.0993)	(0.0534)	(0.186)	(0.0991)	(0.0567)	(0.568)	(0.173)	(0.0668)	(0.528)	(0.162)	(0.0830)
Observations	446	655	287	446	655	287	446	655	287	446	655	287	413	590	261	413	590	261
Number of ccode	34	53	32	34	53	32	34	53	32	34	53	32	34	53	31	34	53	31
AR 2 test (p-value)	0.967	0.696	0.133	0.424	0.337	0.109	0.704	0.561	0.256	0.388	0.597	0.386	0.686	0.641	0.399	0.819	0.925	0.572
Sargan test(p-value)	0.222	0.181	0.724	0.578	0.418	0.727	0.216	0.185	0.644	0.495	0.118	0.538	0.495	0.554	0.450	0.501	0.362	0.591
Hansen test(p-value)	0.140	0.010	0.926	0.441	0.037	0.690	0.106	0.009	0.315	0.047	0.005	0.309	0.199	0.745	0.785	0.179	0.309	0.646

*** p<0.01, ** p<0.05, * p<0.1

Before tax Tables

Table 2. 5.(A): Impacts of overall financial sector development on before-tax income inequality full sample first difference results.

	(1) FSD	(2) FI	(3) FM
L1. Log Before-tax Gini	1.031***	1.011***	1.031***
	(0.0825)	(0.0937)	(0.0830)
Fin Dev	0.0973***	0.125***	0.0762***
	(0.0274)	(0.0437)	(0.0206)
GDP	0.000456	0.00338	-0.000550
	(0.00217)	(0.00254)	(0.00249)
lCPI	0.0120**	0.00626	0.0150**
	(0.00590)	(0.00604)	(0.00644)
Trade_op	-0.00534	-0.00957	-0.00109
	(0.00491)	(0.00707)	(0.00431)
LogGov	-0.00450	-0.0100	0.00510
	(0.0139)	(0.0157)	(0.0139)
L1.Log-education	-0.0546**	-0.0784**	-0.0446**
	(0.0210)	(0.0305)	(0.0203)
Constant	0.0869	0.0877	0.0971
	(0.0697)	(0.0820)	(0.0741)
Observations	1,508	1,508	1,508
Number of ccode	120	120	120
AR 2 test (p-value)	0.082	0.175	**0.040**
Sargan test(p-value)	0.000	0.001	0.112
Hansen test(p-value)	0.009	0.136	0.003

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2. 5.1 Impacts of overall financial sector development on before-tax income inequality (Subsample results).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
		FM						FI						FD				
	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC
L1. Log Before-tax Gini	0.652***	1.461*	-0.0222	0.709***	1.551	-0.0498	0.816**	1.353*	-0.0125	0.534***	1.381*	-0.0219	0.709***	1.345**	0.0229	0.703***	1.333*	0.0268
	(0.156)	(0.787)	(0.510)	(0.195)	(0.972)	(0.397)	(0.305)	(0.695)	(0.571)	(0.151)	(0.795)	(0.532)	(0.148)	(0.670)	(0.543)	(0.210)	(0.705)	(0.562)
Findev	0.0176	-0.00163	-0.0284	0.129	0.0549	-0.128	-0.0599	0.0433	-0.114	0.370	0.0148	-0.0937	0.00876	0.0110	-0.171	0.488	0.0666	-0.365
	(0.0468)	(0.0416)	(0.291)	(0.179)	(0.302)	(0.782)	(0.0468)	(0.0758)	(0.181)	(0.639)	(0.302)	(0.741)	(0.0581)	(0.0501)	(0.274)	(0.610)	(0.340)	(1.533)
Findev^2				-0.0885	-0.0832	0.536				-0.278	0.0434	-0.0349				-0.378	-0.0838	0.604
				(0.118)	(0.464)	(4.263)				(0.428)	(0.437)	(1.178)				(0.434)	(0.516)	(4.646)
GDP	-0.00634	0.00747	-0.109	-0.00552	0.00830	-0.111	-4.82e-05	0.00493	-0.128	-0.00550	0.00504	-0.128	-0.00382	0.00657	-0.114	-0.000382	0.00688	-0.116
	(0.0100)	(0.0214)	(0.0735)	(0.00959)	(0.0195)	(0.0660)	(0.00486)	(0.0218)	(0.0950)	(0.00832)	(0.0229)	(0.0896)	(0.00798)	(0.0201)	(0.0921)	(0.00689)	(0.0192)	(0.0876)
lCPI	0.112	0.00242	-0.0320	0.123*	0.000574	-0.0320	0.136*	-0.00678	-0.0409	0.151**	-0.00698	-0.0409	0.109	0.00242	-0.0385	0.174**	0.00151	-0.0385
	(0.0694)	(0.0456)	(0.0456)	(0.0658)	(0.0444)	(0.0467)	(0.0671)	(0.0319)	(0.0628)	(0.0629)	(0.0343)	(0.0630)	(0.0734)	(0.0387)	(0.0489)	(0.0668)	(0.0358)	(0.0507)
Trade_op	-0.00910	-0.0426	0.00709	-0.0125	-0.0411	0.00775	-0.0176	-0.0385	0.0268	-0.0172	-0.0381	0.0262	-0.0105	-0.0409	0.0211	-0.0255*	-0.0416	0.0245
	(0.0152)	(0.0422)	(0.0175)	(0.0139)	(0.0486)	(0.0201)	(0.0105)	(0.0416)	(0.0415)	(0.0116)	(0.0424)	(0.0472)	(0.0150)	(0.0383)	(0.0266)	(0.0134)	(0.0372)	(0.0426)
LogGov	-0.00647	-0.0369	-0.0106	-0.0176	-0.0314	-0.0110	-0.0141	-0.0384	-0.00437	-0.0193	-0.0382	-0.00464	-0.00571	-0.0379	-0.00619	-0.0365	-0.0372	-0.00523
	(0.0325)	(0.0343)	(0.0312)	(0.0320)	(0.0376)	(0.0307)	(0.0342)	(0.0313)	(0.0391)	(0.0346)	(0.0333)	(0.0378)	(0.0331)	(0.0308)	(0.0283)	(0.0389)	(0.0301)	(0.0320)
L1.Log-education	-0.162	0.0892	0.0784	-0.200	0.111	0.0786	-0.330**	0.0858	0.130	-0.243	0.0876	0.129	-0.195	0.0635	0.119	-0.355**	0.0631	0.125
	(0.238)	(0.212)	(0.112)	(0.219)	(0.203)	(0.116)	(0.131)	(0.186)	(0.195)	(0.207)	(0.196)	(0.203)	(0.231)	(0.193)	(0.132)	(0.167)	(0.190)	(0.163)
Observations	446	655	287	446	655	287	446	655	287	446	655	287	446	655	287	446	655	287
Number of countrycodes	34	53	32	34	53	32	34	53	32	34	53	32	34	53	32	34	53	32
AR 2 test (p-value)	0.450	0.820	0.083	0.647	0.971	0.084	0.604	0.482	0.160	0.179	0.543	0.173	0.511	0.480	0.115	0.700	0.460	0.136
Sergan test (p-value)	0.182	0.691	0.577	0.133	0.800	0.671	0.247	0.570	0.837	0.075	0.683	0.865	0.211	0.601	0.635	0.124	0.473	0.741
Hansen test (p-value)	0.942	0.291	0.597	0.942	0.234	0.389	0.663	0.233	0.512	0.067	0.171	0.677	0.973	0.250	0.446	0.951	0.214	0.754

Robust standard errors in parenthesis

*** p<0.01, ** p<0.05, **p<0.1

Table 2. 6. (A): Impacts of access to financial institutions and markets on before-tax income inequality-1st difference GMM full sample results.

	(1)	(2)	(3)	(4)	(5)	(6)
	FIA	ATM	FMA	FIA	ATM	FMA
L1. Log Before-tax Gini	1.082***	0.829***	1.017***	0.806***	0.365	0.674***
	(0.120)	(0.137)	(0.106)	(0.125)	(0.630)	(0.203)
Financial Access	0.107***	0.0686*	0.0651**	-0.261**	-0.0667	0.468*
	(0.0364)	(0.0348)	(0.0296)	(0.107)	(0.110)	(0.261)
Financial Access2				0.291***	0.0849	-0.379*
				(0.108)	(0.0973)	(0.205)
GDP	0.00526	0.00688	0.00151	0.00129	0.00806	0.00570
	(0.00340)	(0.00431)	(0.00264)	(0.00323)	(0.0101)	(0.00507)
lCPI	-0.00168	-0.0163	0.0161	0.00105	-0.0290	0.0114
	(0.00619)	(0.0117)	(0.0101)	(0.00843)	(0.0338)	(0.0173)
Trade_op	-0.0236*	-0.00604	0.0121	-0.00133	0.00562	-0.00651
	(0.0126)	(0.00811)	(0.00735)	(0.00715)	(0.00882)	(0.00968)
LogGov	-0.0321	0.0149	0.0321	0.0148	0.0583	0.0210
	(0.0227)	(0.0199)	(0.0199)	(0.0144)	(0.0558)	(0.0297)
L1.Log-education	-0.0541**	-0.0964*	-0.0774**	0.0181	-0.0756	-0.109
	(0.0237)	(0.0510)	(0.0363)	(0.0306)	(0.116)	(0.0838)
Constant	0.0746	0.0529	0.195	-0.129	-0.248	-0.0774
	(0.0858)	(0.128)	(0.118)	(0.123)	(0.423)	(0.144)
Observations	1,508	1,416	1,508	1,508	1,416	1,508
Number of ccode	120	119	120	120	119	120
AR 2 test (p-value)	0.236	0.826	0.009	0.962	0.614	0.948
Sargan test(p-value)	0.180	0.266	0.432	0.534	0.559	0.763
Hansen test(p-value)	0.017	0.243	0.069	0.257	0.499	0.184

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2. 6. 1 Impacts of access to financial institutions and markets on before-tax income inequality (Subsamples).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	FIA						FMA						ATM					
	AM	EM	LIC	AM	EM	LIC	AM	LIC	AM	EM	LIC		AM	EM	LIC	AM	EM	LIC
L1. Log Before-tax Gini	0.412	1.241*	-0.0407	0.520**	0.721	-0.0167	0.735***	0.872	-0.171	0.728***	0.842	-0.253	0.885*	1.203***	1.258	0.710***	1.299**	1.325**
	(0.254)	(0.697)	(0.530)	(0.246)	(1.282)	(0.547)	(0.260)	(1.003)	(0.496)	(0.261)	(1.168)	(0.521)	(0.475)	(0.428)	(0.766)	(0.238)	(0.504)	(0.575)
FIA	0.0660	-0.0477	-0.0384	0.413	0.121	0.00249	-0.00266	0.0562	0.0777	0.0472	0.151	0.253	-0.0270	-0.0165	0.138	0.0704	-0.0583	0.0130
	(0.105)	(0.0393)	(0.266)	(0.449)	(0.269)	(0.431)	(0.0200)	(0.0637)	(0.300)	(0.0731)	(0.202)	(0.369)	(0.0443)	(0.0258)	(0.179)	(0.149)	(0.0481)	(0.133)
Sq_FIA				-0.315	-0.286	-0.0700				-0.0430	-0.0908	-0.486				-0.0341	0.0437	0.220
				(0.310)	(0.543)	(0.336)				(0.0598)	(0.159)	(1.142)				(0.0651)	(0.0602)	(0.192)
GDP	-0.0123	0.0138	-0.106	0.000218	0.0158	-0.106	-0.00274	0.0154	-0.137*	-0.00225	0.0203	-0.142*	0.00360	0.00438	0.00485	-0.00322	0.0144	-0.00411
	(0.0150)	(0.0176)	(0.0756)	(0.00973)	(0.0143)	(0.0759)	(0.00433)	(0.0156)	(0.0763)	(0.00448)	(0.0167)	(0.0821)	(0.0111)	(0.0150)	(0.0637)	(0.00817)	(0.0142)	(0.0476)
lCPI	0.0949	0.0120	-0.0332	0.125	0.00856	-0.0308	0.107*	0.00801	-0.0353	0.0959*	-0.000595	-0.0417	0.157**	0.0113	0.00553	0.154**	-0.00411	0.00398
	(0.0966)	(0.0354)	(0.0389)	(0.0830)	(0.0529)	(0.0294)	(0.0534)	(0.0413)	(0.0603)	(0.0525)	(0.0408)	(0.0628)	(0.0636)	(0.0239)	(0.0211)	(0.0621)	(0.0304)	(0.0153)
Trade_op	-0.00874	-0.0351	0.0110	-0.0158	-0.0236	0.0100	-0.0110	-0.0565	0.0106	-0.0103	-0.0670	0.0117	-0.0181	-0.0368	-0.0185	-0.0152	-0.0407	-0.00992
	(0.0147)	(0.0368)	(0.0221)	(0.0120)	(0.0361)	(0.0243)	(0.00962)	(0.0429)	(0.0269)	(0.00971)	(0.0501)	(0.0280)	(0.0113)	(0.0277)	(0.0237)	(0.0110)	(0.0329)	(0.0170)
LogGov	-0.0235	-0.0136	-0.00537	0.000908	0.00144	-0.00895	-0.00493	-0.0373	-0.0121	-0.00188	-0.0381	-0.0114	-0.00347	-0.0404	-0.0492	-0.0155	-0.0225	-0.0268
	(0.0303)	(0.0243)	(0.0326)	(0.0348)	(0.0260)	(0.0397)	(0.0279)	(0.0352)	(0.0312)	(0.0277)	(0.0390)	(0.0325)	(0.0406)	(0.0288)	(0.0569)	(0.0364)	(0.0341)	(0.0363)
L1.Log-education	0.0354	0.0144	0.0877	-0.214	-0.0465	0.0754	-0.208	-0.107	0.0874	-0.186	-0.0968	0.106	-0.397	0.0437	-0.0464	-0.266	0.0648	-0.00313
	(0.491)	(0.178)	(0.0684)	(0.388)	(0.309)	(0.0655)	(0.131)	(0.335)	(0.159)	(0.124)	(0.370)	(0.163)	(0.263)	(0.116)	(0.0753)	(0.186)	(0.124)	(0.0609)
Observations	446	655	287	446	655	287	446	655	287	446	655	287	442	620	235	442	620	235
Number of countrycodes	34	53	32	34	53	32	34	53	32	34	53	32	34	53	31	34	53	31
AR 2 test (p-value)	0.154	0.183	0.017	0.099	0.933	0.022	0.602	0.603	0.205	0.549	0.471	0.162	0.299	0.294	0.511	0.470	0.275	0.740
Sergan test (p-value)	0.096	0.663	0.727	0.097	0.700	0.825	0.281	0.819	0.805	0.225	0.880	0.862	0.146	0.461	0.373	0.085	0.616	0.233
Hansen test (p-value)	0.741	0.170	0.450	0.925	0.225	0.573	0.777	0.476	0.807	0.791	0.911	0.863	0.792	0.045	0.065	0.284	0.160	0.065

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2. 7. (A). Impacts of financial institutions and markets depth on before-tax income inequality-1st difference GMM full sample results.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dom_Credit % of GDP	FID	FMD	Dom_Credit % of GDP	FID	FMD
L1. Log Before-tax Gini	0.762***	0.842***	0.916***	0.760***	0.963***	0.997***
	(0.151)	(0.107)	(0.0816)	(0.171)	(0.0880)	(0.0945)
Financial Access	0.0534**	0.130*	0.0600***	0.0425	0.312*	0.179**
	(0.0219)	(0.0780)	(0.0229)	(0.0384)	(0.178)	(0.0694)
Financial Access2				0.00527	-0.159	-0.129**
				(0.0170)	(0.104)	(0.0562)
GDP	0.00769	0.00406	0.00379	0.00769	0.00350	0.00202
	(0.00524)	(0.00402)	(0.00329)	(0.00520)	(0.00426)	(0.00286)
lCPI	-0.00535	0.0120	0.00966	-0.00520	0.0196	0.0127
	(0.0108)	(0.0131)	(0.00770)	(0.0119)	(0.0159)	(0.00798)
Trade_op	-0.0122	0.00565	0.00863	-0.0119	-0.00206	0.00327
	(0.00837)	(0.00572)	(0.00558)	(0.00855)	(0.00577)	(0.00501)
LogGov	-0.00689	0.00791	0.0232	-0.00568	-0.0119	0.00909
	(0.0180)	(0.0148)	(0.0167)	(0.0167)	(0.0156)	(0.0171)
L1.Log-education	-0.0627	-0.121	-0.0768**	-0.0608	-0.142	-0.0657**
	(0.0470)	(0.0796)	(0.0381)	(0.0479)	(0.0950)	(0.0311)
Constant	-0.112	0.0770	0.0992	-0.112	0.152	0.107
	(0.147)	(0.130)	(0.0934)	(0.161)	(0.152)	(0.0889)
Observations	1,383	1,508	1,508	1,383	1,508	1,508
Number of ccode	119	120	120	119	120	120
AR 2 test (p-value)	0.572	0.480	0.061	0.587	0.418	0.009

Sargan test(p-value)	0.429	0.334	0.210	0.365	0.423	0.120
Hansen test(p-value)	0.393	0.285	0.149	0.365	0.167	0.054

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2. 7. 1 Impacts of financial institutions and markets depth on before-tax income inequality-Subsample results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	FMD						**FID**						**Dom_Credit % of GDP**					
	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC	AM	EM	LIC
L1. Log Before-tax Gini	0.772***	1.255*	-0.0601	0.830***	1.778	-0.0484	0.720**	1.427*	-0.0278	0.570***	1.264*	-0.212	0.859***	1.119**	0.0577	0.468**	1.255*	0.305
	(0.269)	(0.638)	(0.524)	(0.301)	(1.417)	(0.734)	(0.284)	(0.742)	(0.430)	(0.155)	(0.662)	(0.437)	(0.284)	(0.497)	(0.394)	(0.211)	(0.708)	(0.564)
Financial Depth	-0.00725	0.0114	-0.0527	0.416	0.169	-0.0739	-0.0362	0.0360	-0.0221	0.227	0.0967	0.244	-0.00165	-0.0406	-0.0904	0.104	-0.0819	-0.182
	(0.0145)	(0.0186)	(0.132)	(0.351)	(0.330)	(0.790)	(0.0477)	(0.112)	(0.613)	(0.426)	(0.148)	(0.925)	(0.0241)	(0.0570)	(0.131)	(0.0758)	(0.124)	(0.199)
Financial Depth2				-0.336	-0.257	0.105				-0.173	-0.108	-1.896				-0.0285	0.103	0.221
				(0.274)	(0.492)	(4.109)				(0.308)	(0.226)	(4.155)				(0.0262)	(0.164)	(0.292)
GDP	-0.00160	0.00399	-0.112	-0.000440	0.0177	-0.112	-0.00356	0.00621	-0.113	-0.00548	0.00412	-0.121	0.00370	0.00286	-0.135	-0.0104	0.0208	-0.120*
	(0.00492)	(0.0209)	(0.0875)	(0.00644)	(0.0313)	(0.0828)	(0.00457)	(0.0230)	(0.0947)	(0.00694)	(0.0203)	(0.113)	(0.00907)	(0.0211)	(0.0958)	(0.00968)	(0.0234)	(0.0678)
lCPI	0.120*	0.00562	-0.0341	0.123	-0.0162	-0.0336	0.134**	0.00138	-0.0331	0.129**	-0.00184	-0.0412	0.0955*	0.0265	-0.0152	0.0528	-0.0344	-0.00919
	(0.0604)	(0.0353)	(0.0453)	(0.0792)	(0.0577)	(0.0333)	(0.0552)	(0.0409)	(0.0296)	(0.0587)	(0.0314)	(0.0325)	(0.0471)	(0.0510)	(0.0376)	(0.0571)	(0.0599)	(0.0350)

Trade_op	-0.0147	-0.0320	0.00688	-0.0173	-0.0553	0.00684	-0.0174*	-0.0381	0.00880	-0.0106	-0.0349	0.0115	-0.0103	-0.0377	0.00818	-0.00369	-0.0498	0.00865
	(0.0105)	(0.0376)	(0.0162)	(0.0154)	(0.0747)	(0.0156)	(0.0101)	(0.0448)	(0.0304)	(0.0143)	(0.0402)	(0.0365)	(0.00737)	(0.0382)	(0.0158)	(0.00854)	(0.0741)	(0.0128)
LogGov	-0.0112	-0.0359	-0.00909	-0.00997	-0.0325	-0.00896	-0.0167	-0.0383	-0.00937	-0.0105	-0.0370	-0.00685	0.0133	-0.0330	0.00211	-0.0312	-0.0523	0.00290
	(0.0302)	(0.0266)	(0.0284)	(0.0394)	(0.0462)	(0.0304)	(0.0288)	(0.0348)	(0.0202)	(0.0313)	(0.0289)	(0.0211)	(0.0404)	(0.0331)	(0.0291)	(0.0370)	(0.0716)	(0.0269)
L1.Log-education	-0.255*	0.0414	0.0870	-0.234	0.205	0.0871	-0.241	0.0806	0.0838	-0.193	0.0663	0.102	-0.249	-0.0369	0.0757	0.0670	0.0921	0.0623
	(0.128)	(0.189)	(0.111)	(0.191)	(0.353)	(0.114)	(0.143)	(0.206)	(0.111)	(0.189)	(0.167)	(0.128)	(0.211)	(0.180)	(0.0702)	(0.187)	(0.235)	(0.0646)
Observations	446	655	287	446	655	287	446	655	287	446	655	287	413	590	261	413	590	261
Number of countrycodes	34	53	32	34	53	32	34	53	32	34	53	32	34	53	31	34	53	31
AR 2 test (p-value)	0.670	0.312	0.030	0.430	0.888	0.022	0.693	0.642	0.056	0.262	0.325	0.030	0.802	0.458	0.063	0.177	0.308	0.216
Sergan test (p-value)	0.174	0.514	0.417	0.092	0.945	0.317	0.164	0.706	0.376	0.084	0.550	0.768	0.181	0.673	0.289	0.134	0.778	0.793
Hansen test (p-value)	0.806	0.093	0.458	0.942	0.358	0.408	0.621	0.177	0.073	0.414	0.130	0.253	0.610	0.130	0.292	0.445	0.498	0.423

Robust standard errors in parenthesis
*** p<0.01, ** p<0.05, **p<0.1

Table 4.2.1: Descriptive statistics of the main dependent variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
financial transactions	10378	.735	.441	0	1
formal	10378	.443	.497	0	1
informal	10378	.332	.471	0	1
borrowed	10378	.556	.497	0	1
borrowed formal	10378	.184	.387	0	1
borrowed informal	10378	.295	.456	0	1
saved	10378	.485	.5	0	1
save formal	10378	.342	.474	0	1
save informal	10378	.081	.273	0	1
gender	10378	1.49	.5	1	2
age	10378	37.62	13.98	15	99
primary	10378	.251	.434	0	1
tertiary	10378	.277	.447	0	1
richest	10378	.247	.431	0	1
richest2nd	10378	.225	.418	0	1
middle	10378	.194	.395	0	1
poorest2nd	10378	.177	.381	0	1
receive wage	10378	.44	.496	0	1

APPENDIX B

Meta-analysis data: 24 studies

Author	Year	Title	Published Journal	Number of Citations[6]
Kapingura	2017	Financial sector development and income inequality in South Africa	African Journal of Economic and Management Studies	20
Beck et al	2004	Finance, Inequality, and Poverty: Cross-Country Evidence	NBER Working Papers 10979,	923
Clarke et al	2006	Finance and Income Inequality: What Do the Data Tell Us?	Southern Economic Journal	770
Liang	2006	Financial Development and Income Inequality in Rural China 1991-2000	UNU-WIDER paper	8
Prete	2013	Economic literacy, inequality, and financial development	Economics Letters	37
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
Wahid et al	2012	Does Financial Sector Development Increase Income Inequality? Some Econometric Evidence from Bangladesh	Indian Economic Review	29
Jaumotte et al	2008	Rising income inequality: technology, or trade and financial globalization?	IMF Economic review	865
Seven and Coskun	2016	Does financial development reduce income inequality and poverty? Evidence from emerging countries.	Emerging Market Review	272

[6] Citation based on google scholar.

Shahbaz and Islam	2011	Financial development and income inequality in Pakistan: An application of ARDL approach.	Journal of Economic Development	219
Shahbaz et al	2014	Financial development and income inequality: is there any financial Kuznets curve in Iran?	Social Indicators Research	149
de Haan and Sturm	2017	Finance and income inequality: A review and new evidence	European Journal of Political Economy	465
Kim and Lin	2011	Nonlinearity in the financial development–income inequality nexus	Journal of Comparative Economics	263
Tan and Law	2011	Nonlinear dynamics of the finance-inequality nexus in developing countries	The Journal of Economic Inequality	154
Weychert	2020	Financial development and income inequality.	Central European economic Journal	16
Le and Nguyen	2019	Financial development and income inequality in emerging markets: a new approach	Journal of Risk and Financial Management	32
Olohunlana and Dauda	2019	Financial development and economic growth in Africa: Lessons and prospects.	Business and Economic Research,	38
Nasreddine and Mensi	2016	Financial development and income inequality: The linear versus the nonlinear hypothesis.	Economics Bulletin	16
Majeed ,Tariq	2013	Inequality, Financial Development and Government: Evidence from Low-Income Developing Countries.	Munich Personal RePEc Archive	4
Rosemy and Masih	2017	What is the link between financial development and income inequality? evidence from Malaysia.	Munich Personal RePEc Archive	22

Serafim	2021	Financial deepening, stock market, inequality and poverty: some african evidence	REM Working paper; number 0177 – 2021	
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
Zhang and Naceur	2019	Financial development, inequality, and poverty: Some international evidence	International Review of Economics and Finance	318
Hsieh et al	2019	Financial structure, bank competition and income inequality.	The North American Journal of Economics and Finance	32

Meta-data

How to read Appendix B: From 1st row is study ID number 1, a study by Kapingura (2017); from this study, I took 3 econometric estimates from table 6: model 1,2 & table 7, model 1. This study used only one method, the ARDL, using time series data from South Africa and used the Gini index as the dependent variable, while study id 2 used the growth of Gini as the dependent variable. Thus, in the multivariate analysis, the transformation done on Gini is also modelled using dummies from the transformed Gini column. Furthermore, footnotes are available at the end of the table with descriptions of the below column headings, allowing the reader to follow through on the analysis done, the data used in this study, and the abbreviation used in the methodology column.

Study_id[7]	**Sample period start - end date of data sample**[8]		**Number of regression estimate**[9]	**Reference for the econometric estimates for each study**[4]	**The methodology used in the econometric models**[10]	**Data type**	**Geographic location of the study**[11]	**Transformation on Gini**[12]	**Number of control variables in the econometric models**[13]
1	1990	2012	3	Table 6; Model 1, 2 & Table 7	ARDL	Time series	South Africa	Gini	6; 5; 5
2	1960	1999	5	Table 4, model 1,2,3,4,5	OLS & IV	Panel	Developed & developing countries	Growth Gini	2;2;3;3;3
3	1960	1995	6	Table 2, 3, & 4: model 1 & 5	OLS, 2SLS, RE, &IV	Cross-Sectional Panel	Developed & developing countries	Log Gini	7;7;5;5;7;7
4	1991	2000	4	Table 3, Model 1-4	GMM	Panel	Chine’s province	Log Gini	3;4;4;5
5	1980	2005	6	Table 2, Model 1, -6	OLS	Panel	Mixed	Growth Gini	1;4;5;4;5;6
6	1997	2017	1	Table 3, model F	GMM	Panel	Asian countries	Gini	6

7	1985	2006	2	Table 4 &Table 5 model 1	ARDL	Time series	Bangladeshi	Gini	4; 5
8	1981	2003	6	Table 1, model 1-7	SUR & IV	Panel	20 Developed and 31 developing	Log Gini	9; 13; 8; 10;8;8
9	1987	2011	7	Table 2, model 1-7	OLS & GMM	Panel	Emerging countries	Growth Gini	1;5;6;7; 1;5;6
10	1971	2005	2	Table 4 & 5, model 1	ARDL & ECM	Time series	Pakistan	Log Gini	6; 6;
11	1965	2011	2	Table 5 & 6, model 1	ECM ARDL	Time series	Iran	Log Gini, Change in log of Gini	3; 4
12	1975	2005	7	Table 1, model 2, 4-9	GMM, FE	Panel	Mixed	Gini	0; 2; 3; 4; 56
13	1960	2005	6	Table 1 & 2, model 1-2	IV Threshold	Panel	Mixed	Growth Gini	0; 0; 1; 0; 0; 5
14	1980	2000	2	Table 1, model 1 and table 3 model 1	GMM	Panel	Mixed/ EM	Gini	4; 4
15	2003	2014	3	Table 1, model 1 & 6	FE	Panel	Mixed	GINI	4; 8; 3
16	2002	2016	2	Table 2, model 1	GMM	Panel	Vietnam provinces	Gini	9; 10
17	1996	2017	2	Table 6 & 7	ARDL	Time series	Nigeria	Gini	6; 6
18	1980	2012	5	Table 3, 4,5,6 & 7 model 1	GLS & RE	Panel	138 countries grouped by income level	Gini	7; 7; 7; 7; 7;
19	1970	2008	4	Table 5.1 model 2,3,4 & 6	OLS	Panel	Low-income developing countries	Log Gini	2; 4; 6; 7
20	1970	2007	2	Table 4.2 & 4.3, model 1	ARDL	Time series	Malaysia	Gini	2; 2
21	1992	2018	4	Table 5, model 1, 2, 3 & 4	PMG-ARDL	Panel	9 African countries	Gini	4; 5; 4;4
22	1991	2015	1	Table 4.2, model 1	FE	Panel	32 Advanced & 41 EME countries	Gini	10
23	1961	2011	3	Table 4, model 1 & 2, Table 8, model 3	OLS & IV	Panel	143 Developing and developed countries	Gini	4; 4; 8
24	1989	2014	2	Table 2, model 1 & 2	CUP-FM	Panel	86 Developed and developing countries	Gini	2; 3

[2] The study id in Appendix B corresponds with the study id in Appendix A. 24 studies were used for the meta-analysis and meta-variate analysis.
[3] These two columns show the sample period for the respective study used in the analysis.
[4] In running the meta-analysis, I used coefficients from 87 estimates. This column shows how many regression coefficients were taken from each study. While the next column gives the reader a reference to the taken econometric estimates from the respective papers. Thus, allowing readers to identify exactly which models were taken from which tables.
[5] Different methodologies are applied in the analysis of financial depth and income inequality. Thus, I create dummies for this column and model them in the multivariate analysis. The methodology used in the collected studies are: ARDL: Autoregressive distributed lag, GMM: Generalized Method of Moments, OLS: Ordinary Least Squares; IV: Instrumented Variable model;

RE: Random Effect model, FE: Fixed Effect model, 2SLS: Two-stage least-squares regression uses instrumental variables; SUR: Seemingly Unrelated Regressions, ECM: Error Correction Model; GLS: Generalized Least Squares; PMG: Pooled Mean Group

[6] For time series studies we have a clear geographic point of the county of analysis in the study. While other studies took homogenous countries in terms of development levels or income levels others used a mix of heterogeneous countries.

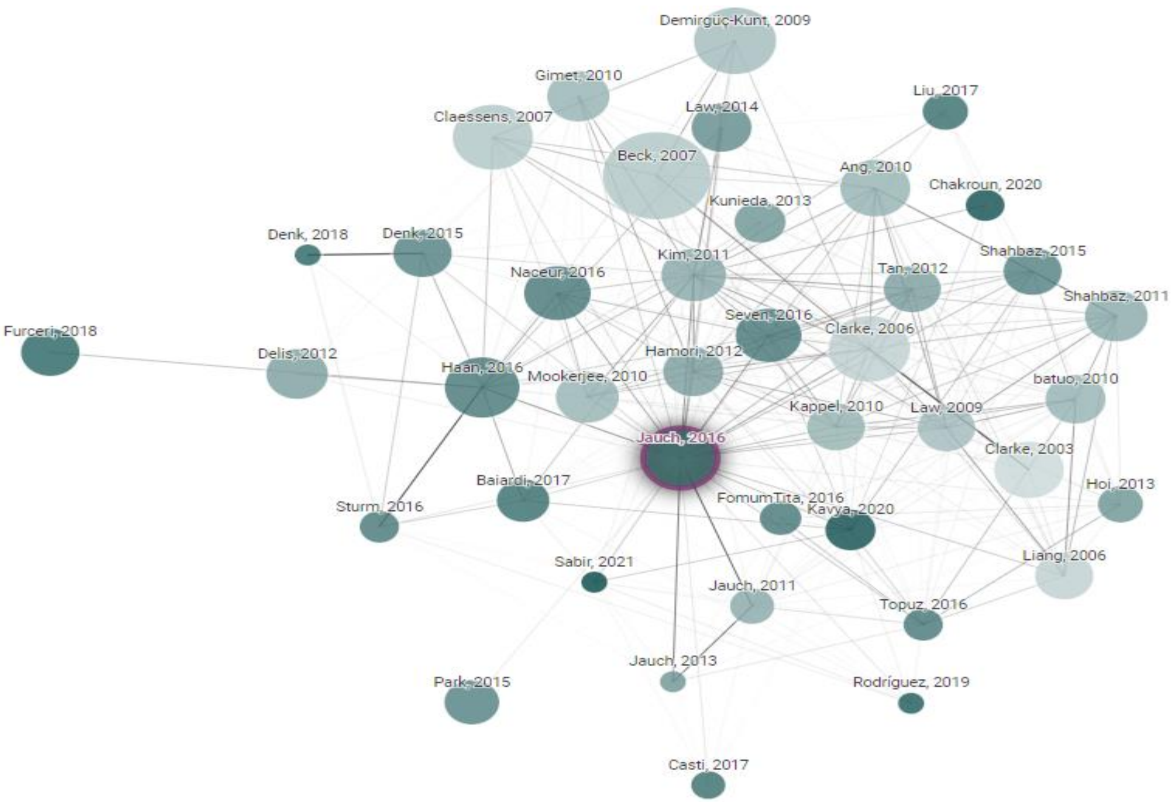
[7] Gini is the dependent variable in all the chosen 87 econometric models, but some studies used the Gini index as it is and others used transformed Gini index to logs or growth rates.

[8] In each model, the number of control variables ranges from 2 to 7. Depending on the number of regressions used from that paper, the number of control variables is listed by table separated by a semicolon (;). Thus the number of control variables matches with the table and models mentioned in column 4. Readers wishing to read more / replicate or expand the data/ this study are encouraged to download the full data set and Stata codes used in the analysis from the author's GitHub, under the meta-analysis folder.

APPENDIX C

Studies on financial sector development and income inequality

The figure presented in this appendix is from connected papers, derived by searching the topic: financial sector development and income inequality. This study only focused on one measure of financial sector development (FSD) namely depth (domestic credit). As a result, not to all the studies in the diagram below were selected for the analysis mainly because the measurements for financial sector depth and income inequality. However, almost half of the studies in this diagram are included in this meta-analysis study.


Demirgüç-Kunt, 2009
Gimet, 2010
Law, 2014
Liu, 2017
Claessens, 2007
Beck, 2007
Ang, 2010
Chakroun, 2020
Kunieda, 2013
Denk, 2018
Denk, 2015
Kim, 2011
Shahbaz, 2015
Naceur, 2016
Tan, 2012
Shahbaz, 2011
Seven, 2016
Furceri, 2018
Clarke, 2006
Delis, 2012
Hamori, 2012
Haan, 2016
Mookerjee, 2010
batuo, 2010
Kappel, 2010
Law, 2009
Jauch, 2016
Clarke, 2003
Baiardi, 2017
Hoi, 2013
Sturm, 2016
FomumTita, 2016
Kavya, 2020
Liang, 2006
Sabir, 2021
Jauch, 2011
Topuz, 2016
Jauch, 2013
Park, 2015
Rodríguez, 2019
Casti, 2017

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

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

Author	Year	Study_id	i_regression_estimate	Coefficient	Sample_size	No_countries	Data_type	Geographic	Methodology	Dependent_Var
		9	3	0.007	168	45	Panel	Emerging countries	OLS	Growth Gini
		9	4	0.003	168	45	Panel	Emerging countries	OLS	Growth Gini
		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

Author	Year	Study_id	i_regression_estimate	Coefficient	Sample_size	No_countries	Data_type	Geographic	Methodology	Dependent_Var
		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
		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/ Clasiffied 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

Author	Year	Study_id	i_regression_estimate	Coefficient	Sample_size	No_countries	Data_type	Geographic	Methodology	Dependent_Var
		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
		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