# *Essays on Financialization, Income Inequality and Household Debt*

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# Essays on Financialization, Income Inequality, and Household Debt

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# Abstract

This thesis contributes to the growing literature of financialization by investigating the relationship between financialization and income inequality, which constitutes the focus of the first chapter. The second chapter makes a contribution to the current body of literature by examining the relationship between financial structure and income inequality. Finally, the third chapter contributes to the existing literature by analyzing the relationship between household debt and income inequality.

The first chapter empirically examines the relationship between financialization and income inequality using the panel ARDL approach for OECD countries data in the 1980-2019 period. The panel ARDL results suggest that financialization variables are associated with an increase in the Gini coefficient in the long run. The existence of the long relationship between financialization and income inequality is also confirmed by the CS-ARDL estimators which account for potential cross sectional dependence and induced feedback effects among the variables. Moreover, the results are robust to different financialization and income inequality measures considered. Thus, the empirical findings provide strong evidence that financialization is one of the leading causes of growing income inequality in addition to technological progress, globalization, and the weakening of labour market institutions which are well documented in the literature. Finally, the DOLS method is used as an alternative approach to the panel ARDL estimation and the results also confirm that financialization variables widen income inequality in the long run.

The second chapter conducts an empirical analysis of the relationship between financial structure and income inequality using the panel ARDL method on data from OECD countries over the period 1980-2019. The panel ARDL results suggest that there is a cointegrating relationship between income inequality and financial structure measures. The negative and significant error correction term in all specifications confirms that financial institutions index and financial market index jointly Granger cause income inequality measures in the long run. The PMG, MG and DFE estimations indicate that a more bank based financial system is associated with lower income inequality, while a more market based financial system tends to increase inequality over time. The CS-ARDL results also support the presence of a long run equilibrium relationship between financial structure and income inequality measures, thereby confirming the reliability and validity of the empirical findings. Moreover, the results are robust to dif-

ferent inequality measures considered. Lastly, the DOLS estimation, applied as an alternative robustness check, further supports the existence of a stable long run relationship between financial structure and income inequality.

The third chapter examines the long-run relationship between income inequality and household debt in advanced OECD countries for the period 1980-2019. Based on the current body of literature, the paper hypothesizes that an increase in income inequality is associated with higher household debt at both the per-capita and aggregate levels. To investigate the existence and direction of the causal relationship between income inequality and household debt, the study applies the panel vector error correction model (VECM). The panel VECM results suggest that there is a positive, long run relationship between income inequality and household debt. The results also show that there is a bidirectional long-run causality between household debt and income inequality. The long run relationship between income inequality and household debt remains robust to different measures of household debt and income inequality. Moreover, the DOLS estimation results confirm that income inequality measures increase household debt in the long run.

# Declaration

I hereby declare that none of the materials in this thesis have been submitted elsewhere for another degree or qualification. This thesis is the result of my original work, conducted under the supervision of Dr. Bibhas Saha and Dr. Cem Cakmakli of Durham University Business School, Durham University.

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# Dedication

*To my mother, Muyassar, my brother, Zokhid and my children, Sulaymon shokh and Yakhyo*

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# Chapter 1

# Essays on Financialization, Financial Structure, Income Inequality and Household Debt

## 1.1 Introduction

Over the past four decades, rising income inequality has emerged as a persistent and defining characteristic of most advanced economies. The empirical evidence shows that in many OECD countries, the wage inequality has increased significantly since the early 1980s, while the labor share of income has steadily declined (Piketty and Saez, 2003; OECD, 2011; Alvaredo et al., 2013). The existing body of literature attributes this trend to a combination of structural forces, including globalization, skill-biased technological change, and the weakening of labor market institutions (Jaumotte et al., 2013; IMF, 2007; ILO, 2013). The globalization has contributed to wage inequality by increasing competition and offshoring low-skilled jobs to lower-wage economies, thereby exerting downward pressure on wages in advanced economies (ILO, 2008). The skill-biased technological change has disproportionately benefited high-skilled workers, widening the earnings gap between skilled and unskilled labor (Acemoglu, 2011). Simultaneously, the declining unionization rates, erosion of minimum wage protections, and labor market deregulation have reduced workers' bargaining power, further exacerbating wage dispersion in many advanced OECD countries.

While the above explanations focus primarily on wage inequality, a growing body of research highlights the importance of non-wage income inequality, particularly income derived from capital, property, and financial assets, as a key driver of overall income inequality. In this context, the role of financial markets and institutions has become increasingly prominent. The phenomenon of *financialization*, broadly understood as the growing influence of financial motives, actors, and institutions on the economy, has recently emerged as a critical factor in debates on inequality among academics, policymakers, and practitioners (Stiglitz, 2012; ILO, 2013; Stockhammer, 2017; Alexiou et al., 2022). Despite growing theoretical interest, empirical analysis of the various channels through which financialization influences income distribution remains relatively underdeveloped (Jerzmanowski and Nabar, 2013; ILO, 2013; Kumhof et al, 2015; Shin and Lee, 2019). This thesis contributes to the evolving literature by providing a comprehensive empirical investigation of the relationship between financialization, financial structure, and income inequality across 20 advanced OECD countries over the period 1980–2019. In addition, it examines whether the rise in income inequality has been a contributing factor to the surge in household debt observed over the same period.

The thesis is organized into three core chapters, each addressing a distinct question as part of the overall theme of financialization. The first chapter examines the short run dynamics and long run equilibrium relationship between financialization and income inequality. In this analysis, financialization is represented by three principal indicators: the financial development index, financial globalization and financial liberalization, while income inequality is captured by the Gini coefficient alongside alternative measures. These measures are chosen for their comprehensive representation of the financialization process and their widespread recognition in the literature. Although further dimensions of financialization such as measures of securitization, financial payments, capital market depth, financial innovation, etc. could enrich the analysis, consistent and comparable cross country data over the period of study are limited. The study therefore focuses on the most widely available and reliable indicators in order to maintain analytical rigor and comparability across countries.

In examining the relationship between financialization and income inequality, the choice of econometric methodology is crucial. Previous studies on the finance-inequality nexus have relied on static panel models, such as pooled OLS, fixed effects, or random effects, as well as dynamic approaches such as GMM estimators. However, in this regard, static panel methods are limited in their ability to distinguish between short-run and long-run effects and often suffer from low statistical power and potential bias arising from unobserved heterogeneity (Wooldrige, 2010; Samargandi et al., 2015). Likewise, dynamic GMM estimators face well-documented econometric challenges including weak instruments, instrument proliferation, poor finite-sample properties, and sensitivity to cross-sectional dependence, all of which can undermine the validity and reliability of their estimates (Bound et al., 1995; Stock et al., 2002; Roodman, 2006; Guggenberger, 2012). To address these issues and effectively capture both short-run and long-run dynamics, this study adopts the panel autoregressive distributed lag framework, complemented by the cross-sectionally augmented ARDL (CS-ARDL) estimator to account for cross-sectional dependence and induced feedback effects between the variables. Since the main interest of this study lies in understanding the long run impact of financialization on income inequality, the capacity of panel ARDL to estimate equilibrium relationships directly is of particular importance. Moreover, Pesaran, Shin, and Smith (1999) demonstrate that an ARDL model provides consistent coefficients despite the possible presence of endogeneity given appropriate lags of dependent and independent variables without the need for external instruments. This method is also particularly reliable in small samples of this nature where the time dimension exceeds the cross-sectional dimension (Chudik et al., 2016). Overall, the panel ARDL along with CS-ARDL estimators should provide a comprehensive and robust framework for exploring the short- and long-run dynamics between financialization and income inequality.

Given the methodological merits, the research questions and the characteristics of the given data set, the panel ARDL model emerges as a more suitable approach for this study. The panel ARDL results suggest that financialization variables are associated with an increase in the Gini coefficient. The results are also robust to different financialization and income inequality measures considered. The estimations include controls for globalization, technological progress, labor market institutions and education which ensure that the long run influence of financialization is identified alongside these widely recognized determinants of inequality. The empirical findings support the hypothesis that in the long run, financialization is one of the leading causes of rising income inequality in addition to the globalization, technological progress and weakening of labor market institutions, which is consistent with the broad literature. The results also remain robust under CS-ARDL and DOLS estimation methods. The long run positive relationship that has been established here between income inequality and financialization is supported by a growing body of literature (Stiglitz, 2012; ILO, 2013; Jerzmanowski and Nabar, 2013; Leopold, 2015; Makhlouf et al., 2020).

The contribution of the first chapter is threefold. First, it demonstrates that financialization exerts a significant and persistent long-run effect on income inequality. Second, it shows that employing the CS-ARDL framework enhances the reliability of results by addressing concerns related to endogeneity and cross-sectional dependence. Third, it advances the literature by integrating a broad set of financialization indicators and inequality measures, thereby offering a more comprehensive assessment of the finance–inequality nexus than has typically been provided in prior studies. Taken together, the evidence suggests that financialization emerges as another important factor behind rising income inequality. The current results also open up the possibility that the impact of finance may have been underestimated in many of the previous studies and suggest that overlooking the role of financialization may have serious implications for our understanding of the causes of rising income inequality.

Continuing on the theme of financialization, the second chapter investigates how the structure of the financial system affects the relationship between finance and inequality. More specifically, it explores whether the bank-dominated or the market-dominated financial systems have differential effects on income distribution. While the empirical literature has long debated the growth implications of financial structure (Luintel et al., 2008; Gole and Sun, 2013; Gambacorta et al., 2014; Chu, 2020), its distributional consequences have received less empirical attention. A growing body of evidence suggests that deep and developed financial systems are closely linked to rising top incomes and rent extraction within the financial sector (Brei et al., 2023). Philippon and Reshef (2012) provide evidence that labour compensation in the financial sector rose substantially during periods of financial expansion. This pattern was evident both in the early twentieth century and in the decades preceding the 2008 global financial crisis, when the financial industry experienced rapid growth and increasing profitability. Several explanations have been proposed for this phenomenon. Greenwood and Scharfstein (2013) argue that it stems from the expansion of asset management and household credit markets, which have generated substantial fee-based revenues and commission-driven profits. Axelson and Bond (2015) suggest that elevated pay levels reflect compensation for the greater risks inherent in the financial industry, while Bolton et al. (2016) emphasize the role of information asymmetries that facilitate rent extraction by financial intermediaries. In a similar vein, Kalyta (2009) and Stiglitz (2016) contend that the growing complexity, opacity, and systemic dominance of financial markets have expanded opportunities for managerial self-enrichment and rent-seeking behaviour. At a more critical level, financial innovation and the deepening of financial markets have been described as exploitative or even predatory, contributing to inequality through mechanisms that disproportionately benefit high income groups (Allen, 2012).

Using the IMF's financial institutions and financial markets indices as proxies for bank-based and market-based systems, the second chapter also applies the panel ARDL model to examine the short run dynamics and long run relationship between income inequality and financial structure. The results suggest that in the long run, a greater reliance on bank-based finance is associated with lower income inequality, whereas a stronger orientation toward market-based finance contributes to greater inequality. The CS-ARDL and DOLS estimations also confirm that the financial structure measures are statistically significant in relation to income inequality variables in the long run. The differing impact of bank based and market based financial systems on income inequality in the long run is consistent with the findings of Morado et al. (2016), Maldonado (2017), Makhlouf et al. (2023) and Brei et al. (2023). The results of this panel study show that more market-based financial systems, represented by the financial markets index, tend to concentrate wealth among those who are already well-off, while bank-based systems are more likely to support broad-based economic participation. This result is consistent with the existing literature (Maldonado, 2017; Brei et al. 2023; Makhlouf et al. 2023) suggesting that market-based systems often favor wealthier individuals and bigger corporations that have greater access to capital markets (Stiglitz, 2012; ILO, 2013).

The contribution of this chapter lies in demonstrating that the composition of financial systems, whether bank dominated or market dominated, has significant and divergent implications for income inequality. Despite limitations in data availability, the use of the IMF's financial institutions index and financial markets index as proxies for bank based and market based systems provides robust evidence that financial structure plays a crucial role in shaping inequality outcomes. Moreover, the application of advanced panel time series techniques, including CS-ARDL methodology, addresses endogeneity and cross sectional dependence concerns, thereby enhancing the reliability and validity of the empirical results. This chapter therefore extends the existing literature by shifting the focus from the growth effects of financial structure to its distributional consequences, an area that has so far received limited empirical attention.

The results are also consistent with the expanding body of literature, which has highlighted the different channels through which financial structures affect inequality. Previous studies suggest that in market dominated systems, the benefits of financial deepening and innovation, such as stock market growth and increased investment opportunities, are captured disproportionately by higher income groups who are more likely to own financial assets (Stiglitz, 2012; ILO 2013; Maldonado, 2017; Brei et al., 2023). By contrast, bank dominated systems appear to exert an inequality reducing effect by promoting more inclusive economic growth (Makhlouf et al., 2023). Through mechanisms such as relationship banking and wider access to credit, bank dominated systems can assume a more redistributive role, helping to mitigate income disparities and foster more equitable patterns of growth. Collectively, these findings reinforce the conclusion that financial structure has also been a crucial determinant of inequality trajectories across OECD countries during the period 1980–2019.

The third core chapter turns to the household-level consequences of income inequality, focusing on the dynamic relationship between income inequality and household debt. There is a growing consensus that an increase in income inequality over the last decades has fuelled household debt which in turn has been an important driver of banking and financial crisis (Kumhof et al., 2015; Bartscher et al., 2020). As a result of the recent global financial crisis, the evolution of household indebtedness and its roots have been on the agenda of economic discussions and they have raised the question as to why households generally take on debt and what role income inequality plays in relation to surging household debt. Based on the current body of literature, this chapter will empirically examine the relationship between income inequality and household debt in the advanced OECD countries over the period 1980-2019. Using a panel vector error correction model (VECM), the analysis confirms the existence of a long-run, bidirectional causal relationship between income inequality and household debt. The results suggest that not only does rising inequality lead to greater household indebtedness, but increased debt also contributes to the persistence and deepening of inequality over time. However, the evidence is particularly strong in support of the hypothesis that rising income inequality acts as a key driver of household indebtedness in advanced economies. These findings are consistent with the broader empirical literature (Malinen, 2013;

Klein, 2015; Kumhof et al., 2015; Bartscher et al., 2020 and Bazillier et al., 2021).

A key contribution of this chapter lies in its methodological and empirical approach. First, it extends the empirical analysis of the relationship between household debt and income inequality by employing the panel VECM, a method not previously applied in this context to examine both the existence and direction of causality between the two variables. The panel VECM allows for a more comprehensive understanding of the short run and long run dynamics between household debt and income inequality. This represents an important advancement over much of the existing literature, which has often relied on more limited techniques that overlook dynamic interdependence. Second, the study incorporates more accurate and comprehensive measures of both household debt and income inequality, thereby addressing data and measurement limitations present in earlier research and enhancing the robustness and reliability of the empirical findings. By examining a broad period spanning 1980–2019, the study provides substantive evidence that distributional developments are integral to understanding the evolution of household indebtedness and its implications for financial stability.

This thesis advances the empirical understanding of how financialization and financial structure measures contribute to rising income inequality and its relationship with household debt in developed countries. By combining different strands of the literature on financialization, financial systems, and debt dynamics, it provides an integrated perspective on the complex and evolving finance–inequality nexus. The findings underscore the importance of rethinking the role of finance beyond its conventional function as a growth-enabling mechanism, emphasizing instead its distributional implications and its central role in the long-term trajectory of inequality in advanced economies.

The remainder of the thesis is organized as follows. Chapter 2 presents the full details of the first paper, titled *Financialization and Income Inequality: The evidence from advanced OECD countries in 1980-2019.* Chapter 3 provides the full content of my second paper, titled *Financial structure and Income Inequality: The bank vs. market dominated financial systems and Inequality, the evidence from OECD countries in 1980-2019.* Chapter 4 details my third paper, titled *Household debt and Income Inequality: The evidence from advanced OECD countries in 1980-2019.* Chapter 5 concludes the thesis by summarizing the key findings across all three papers.

# Chapter 2

# Financialization and Income Inequality

## 2.1 Introduction

Over the past few decades, OECD countries have been characterized by significant changes in the distribution of income and increased financialization of the economy. According to Stiglitz (2012), the process of financialization can be defined as the growing size of the financial sector, and the increasing influence of financial institutions, markets and investors on the local as well as the global economy. However, in the current body of literature, there is no one standard definition for this phenomenon. The issues of both income distribution and financialization have generated considerable literature in recent years. As a result of the global financial crisis in 2008, a number of empirical studies have been conducted to find out whether financialization is another major factor behind growing income inequality. However, there is still a considerable debate on the relationship between financialization and income distribution. Philippon (2016) argues that over the last decades, high wages in the financial sector and sophisticated high return financial products being only accessible to wealthy households have led to an increase in income inequality in advanced OECD countries. The study by Kus (2012) indicates that financialization includes several concomitant processes which can be put as follows: 1) increasing share of the financial sector in the economy, 2) financial deregulation, 3) securitization, 4) increasing reliance of non-financial firms' on financial markets as a source of revenue, 5) shareholder value maximization, and 6) rising household debt. Most studies so far have analysed the implications of financialization on firms investment decisions (Stockhammer, 2004; Orhangazi, 2008; Demir, 2009; Onaran and Tori, 2018), the effects of financial deregulation on financial stability (Mishkin and Edwards, 1995; Jayaratne and Strahan, 1996) and the increasing household debt and its distributional consequences (Iacoviello, 2008; Coibion et al., 2016; Berisha et al., 2018). Thus, there is still a limited empirical literature regarding the channels through which financialization affects income distribution. Among the few studies, Palley (2007) and Mukunda (2014) argue that financialization is one of the main contributing factors for the decline in the wage share of income. However, they fail to provide empirical evidence due to lack of the clear mechanisms linking financialization with income distribution. There have been recent studies by Stiglitz (2012), Jerzmanowski and Nabar (2013), Philippon (2015) which provide theoretical and empirical support regarding the impact of financialization on income inequality and wage share of the income respectively. In this regard, the research by Jerzmanowski and Nabar (2013) also offers the most detailed theoretical examination on how financial development can increase income inequality by presenting an endogenous growth model. Moreover, Matsuyama (2004), Jaumotte et al. (2013), Korinek and Kreamer (2014), Azzimonti et al. (2014), Berisha et al. (2018) provide studies that analyze the relationship between particular channel of financialization (e.g. financial globalization, financial deregulation, etc.) and wage inequality.

According to Prasad (2005), the extensive literature on the relationship between economic downturns and inequality triggered by the global 2008 financial crisis is regarded as being nurtured by a deregulated financial markets starting from the 1980s. The process of financialization, involving substantial shifts of funds towards the financial sector from various economic sectors, including taxpayers (Tomaskovic-Devey and Lin, 2011), appears to be linked to rising income inequality in advanced countries. Tomaskovic-Devey et al. (2015) argue that the business cycles in developed economies is considered to be prompted by the inherent contradictions and volatility present in deregulated and highly leveraged financial markets, subsequently leading to disruptions in income distribution. Further research on the link between banking regulations and wages demonstrates that changes in institutions and deregulations across industries have a significant influence on wage inequality (Fortin and Lemieux, 1997). In spite of the growing evidence regarding the impact of financialization on increasing income inequality (e.g. Zalewski and Whalen, 2010; Assa 2012; Van

Arnum and Naples, 2013), Epstein (2015) claims that a number of questions still remain to be answered about this relationship and underlying factors that require further research in the future.

As explained by Kus (2012), the concept of financialization is multifaceted in a way that encompasses the activities of the financial sector, the rapid expansion of the financial sector or the increasing use of financial instruments by non financial firms. Stiglitz (2012) asserts that financialization has certainly contributed to widening income inequality through different channels, including macroeconomic policies. In this regard, the policies of continuous quantitative easing resulting in zero low bound and even negative interest rates can be considered as driving forces behind formation of bubbles in different industries. On the other hand, austerity policies in some advanced economies post 2008 financial crisis has severely affected low income households, contributing to rising income inequality. The other channels through which financialization has affected income inequality is the increased security trading by financial as well as non financial firms in the financial markets. Epstein (2015) argues that the financialization-inequality channels range from a weakening of certain policies and institutions that assist to reduce inequality to a shift from the traditional 'retain and reinvest' policy of non financial corporations to a new profit model that prioritizes the shareholders' interests over other stakeholders. Moreover, the evolution of capitalism as an economic system has altered power dynamics between capital and labour. Consequently, income distribution has increasingly favoured capital, making it challenging for working class households to sustain their consumption levels and thereby reducing domestic demand. A lack of conclusive evidence on the relationship between financialization and income inequality has provided the impetus to explore deeper the role of financialization in relation to rising inequality.

This study will empirically investigate whether financialization has contributed to the increase in income inequality based on the panel data of 20 advanced OECD countries over the period 1980-2019. The research will critically assess the major empirical studies regarding the linkages between financialization and income distribution. Having analysed the current body of literature, it is important to note that several studies have been conducted so far to examine the impact of globalization, technological progress, and transformations in the labour market institutions on wage inequality and labour's share of income using time series, cross sectional and panel regressions. However, there seems to be a dearth of empirical studies analysing the direct effect of financialization on the wage share and income inequality across countries and over time. Thus, this thesis will attempt to close the gap in empirical literature through examination of the measures financialization affects income distribution and how financialization variables interact with the determinants of income inequality, using the panel data analysis techniques. In addressing this gap, this chapter contributes to the literature in three important ways. First, it demonstrates that financialization exerts a significant and persistent long-run effect on income inequality. Second, it shows that employing the CS-ARDL framework enhances the reliability and validity of results by addressing the limitations of panel ARDL regarding the issues of endogeneity and cross sectional dependence. Third, it advances the literature by integrating a broad set of financialization indicators and inequality measures, thereby offering a more comprehensive assessment of the finance–inequality nexus than has typically been provided in prior studies.

## 2.2 Literature review

### 2.2.1 Background to financialization

According to Epstein (2005), financialization is a relatively new concept which is referred to as the increasing role of financial motives, financial actors and financial institutions on both domestic and global economies. The institutional framework of financialization has mostly developed within a system characterized by deregulated financial and labour markets (Gemzik-Salwach and Opolski, 2017). The economic liberalization seen in many developed countries in 1980s and 1990s has facilitated the transition from industrial capitalism to financial capitalism. The recent academic literature has attempted to offer more theoretical and empirical evidence regarding the impact of financialization on rising income inequality. One of the early studies by Hilferding (1981) argues that there has been a rapid development and expansion of financial markets and institutions following the deregulation policies in 1980s which later have affected income distribution among households across many advanced economies. Argitis and Pitelis (2008) provide evidence that the conflict between industrial and financial capital has harmed real economic activity. In this regard, Alexis and Nellis (2016) claim that the financialization of big firms, in particular non financial firms have negatively affected their long term investment strategies with the allocation of profits between industry and finance playing a critical role in capital accumulation. Similarly, Minsky (1986) asserts that the financial operations of the non financial firms can have a considerable effect on an economic system that is inherently fragile and unstable. Harcourt and Sardoni (1995) claim that more resource allocation towards financial capital at the expense of industrial capital has lately led to higher market volatility which results in reduction of private sector liquidity, thus stifling investment.

It is also important to note that financial capitalism is to some extent characterised by the financial practices of rentiers, private bankers, currency speculators, portfolio investors as well as central bankers and their business operations. Epstein (2001) and Crotty (2009) examine the effect of financial capital on income distribution and show how it is influenced by contractionary monetary policy and inflation targeting . According to Alexiou and Nellis (2016), advances in financial sector have enabled more free movement of capital. Moreover, they assert that the financial innovation and advancements in information and communication technologies have facilitated the globalization of finance and global integration of financial markets and institutions, especially in countries where the government intervention is limited. However, the report by ILO (2009) shows that financial capital has dominated industrial capital due to its exploitative nature which allows for abnormal short term profitability and financial capital accounts for a significant share of total profits in a number of developed countries.

The empirical evidence regarding the effect of financialization on wage inequality is inconclusive. There is also no general consensus through what channels financialization affects income inequality. Greenwood and Jovanovic (1990) argue that more advanced financial markets have mainly benefited the rich households and established firms. However, Beck et al. (2007) find that financial development has reduced income inequality based on their panel study of 72 countries over the period 1960-2005. Delis et al. (2014) suggest that financial liberalization has exacerbated income inequality with varying degrees in many advanced economies due to the nature of deregulation policies implemented. Claessens and Perotti (2007) assert that the deregulation of financial sector has led to the inherently unstable financial system through allowing for excessive supply of credit which later triggered the financial crisis in 2008. Agnello and Sousa (2012) claim that financial liberalization policies in the US have enabled banks to take excessive risk and be more speculative with their customers' deposits for abnormal profit and provided bail out insurance to failing banks. In this regard, Alexiou and Nellis (2016) argue that increased credit issuance, which leads to the accumulation of corporate debt, have negatively impacted long terms investment activities and consequently employment. According to Wright and Rogers (2015), due to the decline in the non financial sector and increased profitability in the financial sector, there has been a significant pressure on wages of labour in the real sector which in turn have contributed to rising inequality. Their study shows that the real wages in the non financial sector have been stagnant or even declined in numerous advanced OECD countries despite significant increase in labour productivity since 1980s. In recent research, Kwon and Roberts (2015) find that financialization measures are positively associated with income inequality based on a panel study of 18 advanced economies over the period 1988-2008.

Dunhaupt (2013) suggests that financialization can be broadly defined as the growing size and influence of financial sector which in turn has implications on allocation between wages and profit whereas retained earnings and financial income are kept in the form of dividends and interests. Bertoli and Farina (2007) argue that the increase in labour share of income in continental Europe during the 1970s can be mostly explained by institutional reforms and rises in real income greater than labour productivity. Blanchard (1997) claims that as a result, to maintain profitability firms in different industries responded to this change by switching from labour production to more capital intensive production. According to Tomaskovic-Devey and Lin (2011), financialization has significantly increased income for workers in the financial sector while limiting real income growth for employees in the non financial sector. Their study also demonstrates that a dramatic increase in the financial wages in the US during 1970-2008 had a significant and negative impact on the labour share of income. In this regard, Alvarez (2015) provides evidence that firms' increased reliance on financial profits in the non financial sector led to decrease in the labour share of income during 2004-2013. Moreover, the adverse impact of financialization on labour share of income is also confirmed by the study of Kohler et al. (2018). According to Van Arnum and Naples (2013), financialization has negatively impacted job creation and bargaining power of workers which in turn has increased wage inequality based on their study of the relationship between financial sector growth and inequality.

There is also an argument in the current body of literature emphasizing the notion of financial vulnerability which is defined as households being financially unable to maintain a basic level of consumption and cover health care expenses along with other unforeseen expenses. In this regard, Anderloni et al. (2012) using a survey data for 3102 Italian households investigate household financial distress. They develop a financial vulnerability index in order to study different dimensions of household financial distress and its implications. Their findings indicate that the cost of debt servicing has a robust positive effect on financial vulnerability. They also show that the households exposed to unsecured debt suffer even more from financial vulnerability. However, their study does not address the impact of financial vulnerability on the bargaining power of workers. Stiglitz (2012) argues that if working class are concerned about their access to loans and the consequences of their personal bankruptcy, then they can get more financially vulnerable, thus undermining their bargaining power in terms of wages. The idea is that debt makes workers more financially insecure and it can have a negative impact on the wage negotiations given the limited exit options. At this point, the empirical literature have not yet provided the study of the effect of increasing household debt on the wage share of income. However, as long as increasing household debt reflects financial vulnerability, its effect on the wage is expected to be negative.

### 2.2.2 Capital exit options

The existence of bargaining power is one of the important assumptions of political economy theory in explaining market relations. The idea is that the allocation of income between profits and wages is the result of a bargaining process rather than a simple market clearing mechanism. The study by Blanchard and Giavazzi (2003) indicates that the relative bargaining power being influenced by the labour market regulations determines the distribution of income between firms and workers given the assumption of oligopoly in formal bargaining models. Depending on the external options of both parties, the output is split between firm and workers. The factors like unemployment benefits, the elasticity of substitution between capital and labour influence the terms of bargaining power between workers and firms. If the change in these factors improve the bargaining power of workers, then real wages would increase. In search and matching models the wage share is always the result of a Nash bargaining equilibrium that depends on the relative bargaining power between firms and workers. Therefore, bargaining power is a theory that is associated with the non-clearing market models of mainstream economics. However, bargaining models of neoclassical economics also assume that more firms can enter the market in the long run which will gradually decrease their profits. As a result, the wage share would eventually go back to its original level (Blanchard and Giavazzi, 2003). The assumption here is that there is a fully elastic supply of firms in the long run. However, this view is not consistent with the heterodox theory of bargaining models where imperfect competition is assumed to be inherent in the functioning of capitalist economies.

Although models explaining bargaining power initially examined labour market institutions (LMI hereafter), a number of recent studies associate firms' increasing bargaining power with globalization (Feenstra and Hanson, 1996; OECD 2011). They assert that the globalization has been one of the main factors behind widening wage gap between high skilled and low skilled workers in developed countries. The argument here is that increased trade integration has increased the relative wages for skilled workers whereas it has lowered the wages for low skilled workers due to the effects of international trade. However, it is important to note that empirical studies analysing the impact of globalization on the wage share have so far given mixed results (Khadria 2001; Rudra, 2004; Strauss-Khan, 2004; OECD, 2011). The past research findings appear to differ due to the choice of sample size, countries and the time period considered in the analysis.

Choi (2001) using bargaining models studies the link between unionized workers and international firm that can move its production line via foreign direct investment (FDI) to a country where the cost of labour is very low. Applying the Nash bargaining model, his research findings indicate that there is a negative relationship between FDI and wages. Harrison (2002) conducting a panel study of over 100 countries (1967-1997) analyses the relationship between labour's share of income and measures of globalization. However, she finds that outward FDI does not have a statistically significant effect on the wage share. In this regard, the recent study by Onaran (2012) documents that outward FDI has a negative impact on the wage share and it is also negatively related to employment in Austria between 1996 and 2005. There is now a growing literature discussing the adverse effect of financialization on labour market institutions. According to the study by Jaumotte and Buitron (2015), financialization is one of the main factors behind the erosion of trade union density, employment protection legislation and bargaining coverage. They argue that more deregulated and less unionized labour market has reduced the bargaining power of workers which in turn contributed to the decline in the wage share of income.

A number of studies have attempted to incorporate the financialization among the variables that affect bargaining power of workers and wage inequality. As mentioned above, financial deregulation is one of key aspects of financialization which has led to increased capital mobility over the last decades starting in 1980s (Jayadev, 2007; ILO 2008; Stiglitz, 2012; Korinek and Kreamer, 2014). The research by Jayadev (2007) conducts a panel study based on 100 countries over the period 1972-1995. His results based on an Ordinary Least Squares (OLS) regression indicate that financial openness has a robust negative impact on the labour's share of income. According to the ILO (2008), financial globalization being defined as foreign assets plus foreign liabilities has contributed to a falling labour's share of income through the weakening of labour's bargaining power. The study associates the weakening of labour's bargaining power with firms pursuing shareholder interests and short term goals due to the pressures of financial markets. A number of authors including Stockhammer (2009) and the ILO (2011) have attempted to provide empirical examination of this hypothesis. In this regard, the research by Stockhammer (2009) studies the impact of trade globalization, financial globalization, technological progress and LMI variables on the wage share for 15 OECD countries between 1982 and 2003. According to the findings of the paper based on fixed effects estimation and other techniques of panel data analysis, financial globalization has a robust negative impact on the labour's share of income (Stockhammer, 2009). Moreover, ILO (2011) conducts a panel study based on 16 developed countries for the period of 1981-2005. This study by ILO (2011) applies Generalized Least Squares (GLS) method by employing similar independent variables and documents the robust negative impact of financial globalization on the labour's share of income.

The current body of literature provides numerous theoretical and empirical studies of financial globalization and financial deregulation in relation to income inequality. In this regard, the study by Matsuyama (2004) analyzes the theoretical relationship between financial market globalization and wage inequality. Based on the diamond overlapping generations model, his findings indicate that the financial market integration has a robust negative impact on income inequality. Similarly, Jaumotte et al. (2013) examine the relationship between financial globalization and wage inequality by conducting a panel study of 51 countries over the period of 1981-2003. They document that the measures of financial globalization are associated with an increase in wage inequality. Moreover, the study by Azzimonti et al. (2014) using the multi country theoretical model with incomplete markets indicates that the financial market integration is negatively related to income inequality.

### 2.2.3 Financial payments and revenues of non-financial firms

According to heterodox economic thought, firms charge prices depending on unit costs plus a mark-up. The idea is that interest payments, dividends and other financial payments are considered as overhead costs (Hein, 2015). As firms have market power, higher financial payments (interest and dividend payments) required by shareholders and rentiers might therefore encourage firms to increase prices. This reasoning is consistent with the Kaleckian theory where firms charge a mark-up that varies with their market power (Kalecki, 1969). Given the assumption of oligopolistic markets where a few firms dominate the market, an increase in the mark-up will lead to a rise in prices which in turn drive down real wages and raise the firm's profit level. In other words, if the elasticity of mark-up with respect to overhead costs is more than one, an increase in interest and dividend payments will reduce the labour's share of income. This reasoning is also shared by mark-up pricing theories in mainstream economics. In this regard, Hein (2015) argues that there has been a rise in financial payments (dividends and interest) for firms over the last decades due to the increased priority given to shareholder interests. Thus, increased pay-out ratios have reduced unit labour costs in light of financial deregulation and increased market integration where prices tend to be sticky upward (Stockhammer 2004; Hein, 2015; UNCTAD, 2017). Alvarez (2015) asserts that maximizing shareholder value strategies have also made firms pay high remuneration packages to senior management by aligning their interests with shareholders in the form of stock options and other ways. Consequently, firms are under constant pressure to ensure financial profitability at the expense of wage share in order to meet the demands of shareholders and rentiers.

There have been a few econometric studies so far to analyse the impact of financial payments on the labour's share of income. Hein and Schoder (2011) carry out an empirical study of the USA and Germany for the period of 1963-2007 by applying the applications of an autoregressive distributed lag model. Their findings indicate that interest payments have a weakly significant positive effect on the profit share. Dunhaupt (2013) conducts a panel study of 13 OECD countries between 1986 and 2007 by regressing the labour' share of income on net financial payments (dividends and interest) of non-financial firms as a percentage of their total primary income. Controlling for international trade, FDI inflows and outflows, import, government activity and LMI measures, she applies different panel data techniques and documents the robust negative impact of financial payments on the labour's share of income. Similarly, Alvarez (2015) empirically studies the impact of interest payments and dividends on the wage share using firm level data for France over the period 2004-2013. Interestingly, his findings indicate that interest payments have the second largest effect on the wage share among the explanatory variables. Thus, it is plausible to claim that as non-financial firms make more financial payments to meet the demands of their shareholders and rentiers along with their growing reliance on the financial markets as a source of revenue, the relative share of labour's income has declined. This hypothesis reinforces the claims of shareholders and managers (Mukunda, 2014).

### 2.2.4 Shareholder value maximization and real investment

The shareholder value orientation and its implications on firm's investment behaviour have been comprehensively studied in the empirical literature (Lazonick and O'Sullivan, 2000; Jensen, 2001; Stockhammer, 2004; Demir, 2009; Onaran and Tori, 2018) . However, there is no general consensus in the current body of literature regarding the impact of shareholder value orientation on firm's investment decisions. For instance, Lazonick and O'Sullivan (2000) assert that over the last decades, firms have given an increasing priority to their shareholders' interests at the expense of other stakeholders. According to their argument, as a result of shareholder value orientation, there has been a change in firms' strategies from 'retain and reinvest' to 'downsize and distribute' (Lazonick and O'Sullivan, 2000). The idea is that firm's increased reliance on financial markets have made them reduce their real investment in their core businesses and pursue short term interests in order to make a financial profit. In this regard, there have been interesting studies by Stockhammer (2004) and Onaran and Tori (2018) which examine the implications of financialization on non-financial firms' long term investment. There are also arguments put by Jensen and Meckling (1976) and Jensen (2001) in the literature with regard to the distributional changes encouraging more profitability for shareholders.

Overall, it is important to note that there are no empirical studies in the current body of literature which provide economic evidence regarding the implications of maximizing shareholder interests on the labour's share of income and wage inequality. In this regard, the non-mainstream versions of the argument emphasizing the negative impact of shareholder value orientation is not adequate.

### 2.2.5 The established literature

The current body of literature mainly supports the idea that the wage share has decreased due to technological change, globalization and transformations in labour market institutions (LMI). In this regard, technological advancements are frequently identified as the primary driver, often characterized as "capital augmenting" rather than "labor augmenting." This shift has increased demand for capital and complementary high-skilled labor while decreasing demand for lower-skilled workers (IMF, 2007; European Commission, 2007; OECD, 2012b; IILS, 2012). A prevalent hypothesis posits that the spread of information and communication technologies (ICT) has enabled greater automation, enhancing productivity but replacing low-skilled labor. According to recent OECD findings, technological change and capital accumulation collectively contributed an average of 80% to intra-industry shifts in the labor share within advanced economies from 1990 to 2007 (OECD, 2012b). According to neoclassical economists, technological change plays an important role in understanding the declining wage shares. They argue that wages have fallen mainly due to a skill biased technical change. According to their explanation, technological progress has increased the demand for high skilled workers as it has been more skill biased. However, technological development has reduced the demand for low skilled workers, thus causing significant job losses in certain industries. This hypothesis has been extensively investigated by a number of studies (Berman et al., 1998; Card and DiNardo, 2002; IMF, 2007), however a control variable for financialization has not yet been provided.

Globalization has also been discussed in the empirical literature as another major factor for understanding changes in the distribution of income. The main argument of the literature is that the more mobile factor, usually capital will benefit from international trade (OECD, 2011). A number of empirical studies confirm that skilled workers gain from international trade as their wages have gone up over the last decades. However, increased trade integration have lowered the wages for unskilled workers, thus widening the wage gap (Kremer and Maskin, 2006; OECD, 2011). According to ILO (2008) globalization exerts negative but modest effects on the labor share of income. This may be attributed to heightened competition and the integration of labor-abundant countries into the global market, which likely contributes to wage moderation. Bacchetta and

Jansen (2011) conduct a firm level study and indicate that trade liberalization often drives firms in both advanced and emerging economies to boost productivity via "industry rationalization." This process entails phasing out the least efficient firms and reducing the workforce in those that remain. Additionally, Epstein and Burke (2001) argue that a shift from labor to capital could be occurring through offshoring or "threat effects," where firms may leverage the potential to relocate production without actually doing so.

The third factor is usually associated with the weakening of labour market institutions (LMI) as one of the contributing factors behind declining wage share. The labor market institutions and welfare state dimensions are widely discussed variables in the existing literature. These institutional factors encompass elements including union density, minimum wage laws, unemployment benefits and their coverage, severance pay, and government consumption. In many advanced economies, the weakening of LMIs has been associated with diminished bargaining power for workers, limiting their ability to secure a greater share of compensation (IMF, 2007; ILO 2013). According to OECD (2012), institutional factors like the minimum wage, employment protection laws, the coverage of unemployment benefits, and other fiscal policies frequently appear in the empirical literature. The coverage of unemployment benefits, in particular, may impact the labor share of income by influencing workers' "reservation wages"—the minimum pay they are willing to accept. Overall, the analysis of the empirical studies shows that the wage share is the result of bargaining power between firms and workers and the LMI plays a key role here in understanding the changes of income distribution (Jaumotte and Buitron, 2015). In this regard, Jaumotte and Buitron (2015) argue that the labour market deregulations over the last decades have reduced the bargaining power of workers in advanced countries. Although workers' bargaining power can be a difficult measure to capture in an empirical study, the union density, employment protection legislation and other relevant LMI variables should be taken into consideration so as to analyze its impact on the income distribution.

Figure 1.5 below presents an illustration of the leading causes behind growing income inequality (ILO, 2013). The usual suspects documented in the global wage report by ILO (2013) include globalization, technological progress, financialization, labour market institutions and the bargaining power of workers. The illustration shows that the circle for financialization overlaps with the circle of globalization meaning the issues in isolating their effects at both theoretical and empirical levels. The figure also shows that the bargaining power of workers derives directly from labour market institutions but it is also affected by financialization and globalization which provide companies more opportunities for investment in financial assets and in real assets at home as well as abroad (Kremer and Maskin, 2006; ILO, 2013).

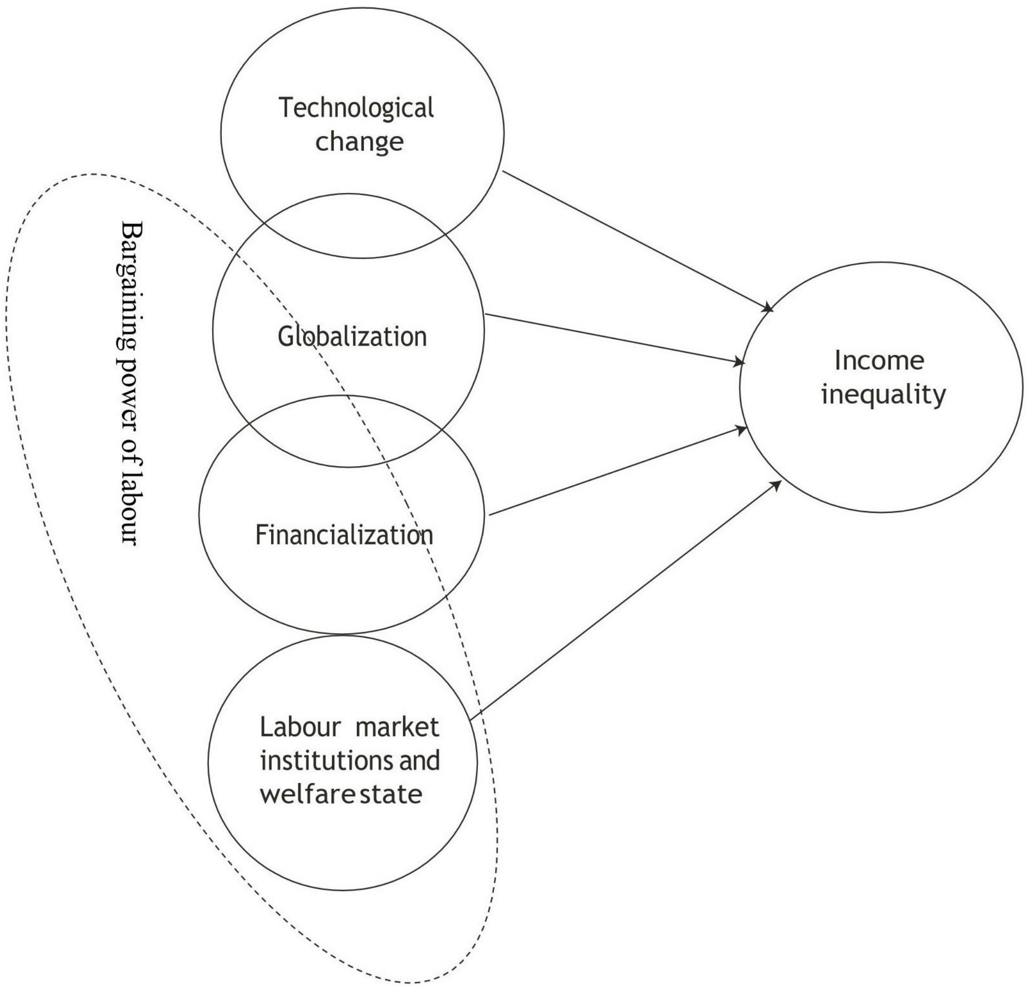


Figure 2.1: Factors influencing the income inequality (ILO, 2013, p. 49)

Although a number of empirical studies have been conducted so far to analyse the effects of globalization and technological progress on income distribution for OECD countries, in recent years, there have been interesting studies from some authors (Stiglitz, 2012; Jerzmanowski and Nabar, 2013; Stockhammer, 2015; Alexiou et al., 2022) regarding the impact of financialization. According to their empirical studies, the evolution of wage share cannot be robustly explained by the analysis of globalization and technological change factors alone. Authors like Jayadev (2007), Stiglitz (2012), Jerzmanowski and Nabar (2013) argue that financialization is one of the key factors for understanding changes in the bargaining position of workers and its impact might be even stronger on the wage inequality and labour's share of income comparing to technological change and globalization.

## 2.3 Theoretical motivation

This thesis draws on the endogenous growth model with imperfect capital markets developed by Jerzmanowski and Nabar (2013) to explain how financialization affects wage inequality through the channel of financial deregulation. Financial deregulation is understood as a combination of policy changes and financial innovations that facilitate easier access to finance for firms. In their framework, financial market frictions are modelled in reduced form as a search and matching process between entrepreneurs with new ideas and financial intermediaries with capital. The model shows that financial deregulation amplifies inequality both across and within skill groups.

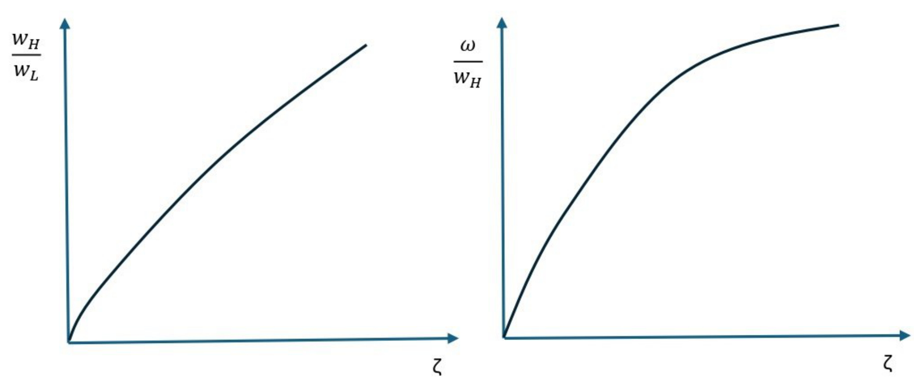


Figure 2.2: Financial deregulation and Wage Inequality (Jermanowski and Nabar, 2013, p. 224)

First, advances in financial markets significantly depress the wages of unskilled workers, who constitute the majority of the labour force. This downward pressure on wages widens overall income disparities and lowers the labour share of income. Second, financial development generates residual or within-group inequality by raising the wages of skilled workers employed in the innovation sector relative to their counterparts in the manufacturing sector. The underlying mechanism is that when the bargaining power of skilled workers in the innovation sector is positive, their relative wages increase, reinforcing disparities within the skilled labour group.

The numerical simulations provided by Jerzmanowski and Nabar (2013) further illustrate these dynamics which can be seen from the graphs above. Figure 2.2 shows that as financial deregulation, $\zeta$ intensifies, the ratio of high-skilled to low-skilled wages, $\frac{w_H}{w_L}$ rises over time, demonstrating an increase in between-group inequality. At the same time, figure 2.2 also indicates that the ratio of skilled wages in the innovation sector to skilled wages in the traditional sector, $\frac{\omega}{w_H}$ also rises, reflecting the persistence of within-group inequality. In this way, financial deregulation fosters organisational change by reallocating workers across sectors according to skill levels, ultimately widening the wage distribution.

Overall, the model highlights that financial deregulation contributes to a greater skilled–unskilled wage gap and simultaneously accentuates disparities within the skilled labour force. Jerzmanowski and Nabar (2013) argue that financial development, often overlooked in previous studies, may have been an important driver of distributional changes observed in recent decades. Their insights are directly relevant to the current study, which examines financialization as a determinant of income inequality. In particular, the channel of financial deregulation in their model provides theoretical support for the hypothesis advanced in this study that financialization exacerbates income inequality by raising both between-group and within-group wage disparities.

## 2.4 Data description

This chapter examines the relationship between financialization and income distribution in 20 advanced OECD countries for the period of 1980-2019. The selection of countries is driven by considerations of data consistency and availability across key financial and income inequality indicators. In this section, the data and its properties are discussed prior to detailing the empirical methodology. This section defines all the financialization variables and control variables along with the income inequality measures. Due to data availability constraints, this study focuses on three key measures of financialization: the financial development index, financial globalization and financial liberalization. These measures are chosen for their comprehensive representation of the financialization process and their widespread recognition in the empirical literature (ILO, 2013; Stiglitz, 2012; UN Trade and Development Report, 2017; Makhlouf et al., 2020; Alexiou et al. 2022). Based on the existing literature, these variables have been identified as distinct channels through which financialization can affect income inequality. Using one representative variable per channel mitigates the risk of multicollinearity while preserving the conceptual breadth of financialization.

### 2.4.1 Financialization variables

**Financial globalization (FG)** is defined as foreign assets plus foreign liabilities as a share of GDP. Lane and Milesi-Ferretti (2007) assembled a comprehensive and up-to-date dataset on the foreign assets of advanced, emerging and developing countries for the period 1970-2011. Financial globalization reflects the extent of cross-border financial integration, which is crucial for understanding global capital flows' impact on domestic inequality.

**Financial development index (FD)** is a relative ranking of countries on the depth, access and efficiency of their financial institutions and financial markets, providing a broad measure of financial sector growth. It is an aggregate of the Financial Institutions index and the Financial Markets index. The data developed by Svirydzenka (2016) is available from the IMF database.

**Financial liberalization (FL)** is based on several sub indices mostly pertaining to banking regulatory practices and it is developed by Abiad et al., (2010). The database recognizes the multi-faceted nature of financial reforms and records financial policy changes along seven different dimensions: credit controls and reserve requirements, interest rate controls, entry barriers, state ownership, policies on securities markets, banking regulations, and restrictions on the capital account. Liberalization scores for each category are then combined in a graded index that is normalized between zero and one. This contrasts with most existing measures, which code financial liberalization using binary dummy variables. Hence, the database provides a much better measure of the magnitude and timing of financial policy changes than was previously possible.

### 2.4.2 Control variables

**Labour market institutions (LMI)** is represented by trade union density which is based on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS) and the database was developed by Prof. Jelle Visser at the University of Amsterdam. The ICTWSS database combined data from various sources and projects with a main focus on trade union in EU and OECD countries, collective bargaining and employment relations in Europe, and social pacts.

**Trade globalization (GLOB)** is defined as exports plus imports as a share of GDP and it is based on the World Bank national accounts and OECD National Accounts data files. The data for this variable is available from the World Bank database.

**Technological progress (TECH)** is represented by research and development (R&D) spending as a share of GDP. R&D comprises creative work undertaken on a systematic basis in order to increase the stock of human knowledge and to devise new applications based upon it. This indicator includes R&D carried out by all resident companies, research institutes, university, and government laboratories. It also includes R&D funded from abroad but excludes domestic funds for R&D performed outside the domestic economy. This measure is widely used in the empirical research as a proxy for technological innovation. The data can be accessed from the OECD database.

**Education (EDU)** is the fraction of the school age population that is enrolled in primary, secondary and tertiary schooling and the source of the data is Madsen, Islam, and Doucouliagos (2018). Education is used to control for financial literacy. Education is a critical control variable as it directly affects income inequality, influences financial market participation and interacts with the broader socio-economic consequences of financialization. The data is available from the World Bank database.

**Real GDP growth rate (RGDPG)** rate measures economic growth adjusted for the inflation rates and it is included to control for cyclic and structural changes and might affect the secular trend of the share of functional income. Real GDP growth captures within country heterogeneity that varies deterministically over time. The source is World Economic Outlook (2024), IMF. The data is available from the Our World in Data.

### 2.4.3 Income inequality variables

**GINI index (GINI)** is the main measure of income inequality in this study and it represents the measure of the distribution of income across population. The GINI index is based on gross income which is the sum of market income and transfer payments and it is defined as pre-tax and post transfer income. The data is available from the Standardized World Income Inequality Database (SWIID) and it is developed by Solt (2020).

**Labour share of income (LSI)** is defined as the compensation per employee as a share of GDP at factor costs per person employed. The labour share of income includes both employed and self-employed and it does not include taxes. Since income inequality can be analyzed through the lens of functional distribution, a declining labor share often reflects a shift in income from workers to capital owners, which exacerbates income inequality. This is particularly relevant in the context of financialization, as it tends to benefit capital more than labor. The data for the adjusted wage share variable is available from the AMECO database.

**Top 1%** is the income share held by highest 1% earners of the population and the data can be accessed from the World Inequality database (WID). WID develops the data based on different sources including national accounts, surveys, fiscal data and wealth rankings.

**Top 10%** is the income share that accounts for top 10% earners of the population and the data can be obtained from the World Inequality database. WID develops the data based on different sources including national accounts, surveys, fiscal data and wealth rankings.

As highlighted in both theoretical and empirical studies, financialization can influence income inequality through several channels. However, due to data constraints, further dimensions of financialization such as measures of securitization, financial payments, capital market depth, stock market turnover ratio, etc. were unavailable for most of the countries in the sample during 1980–2019.

The variables used in this study were therefore compiled from multiple reputable databases to ensure adequate coverage and consistency across countries and time. Every effort has been made to verify the accuracy of the data and ensure that all sources are reliable and drawn from internationally recognized institutions, with careful cross-checks undertaken to harmonize information across databases and enhance the credibility and reliability of the empirical results.

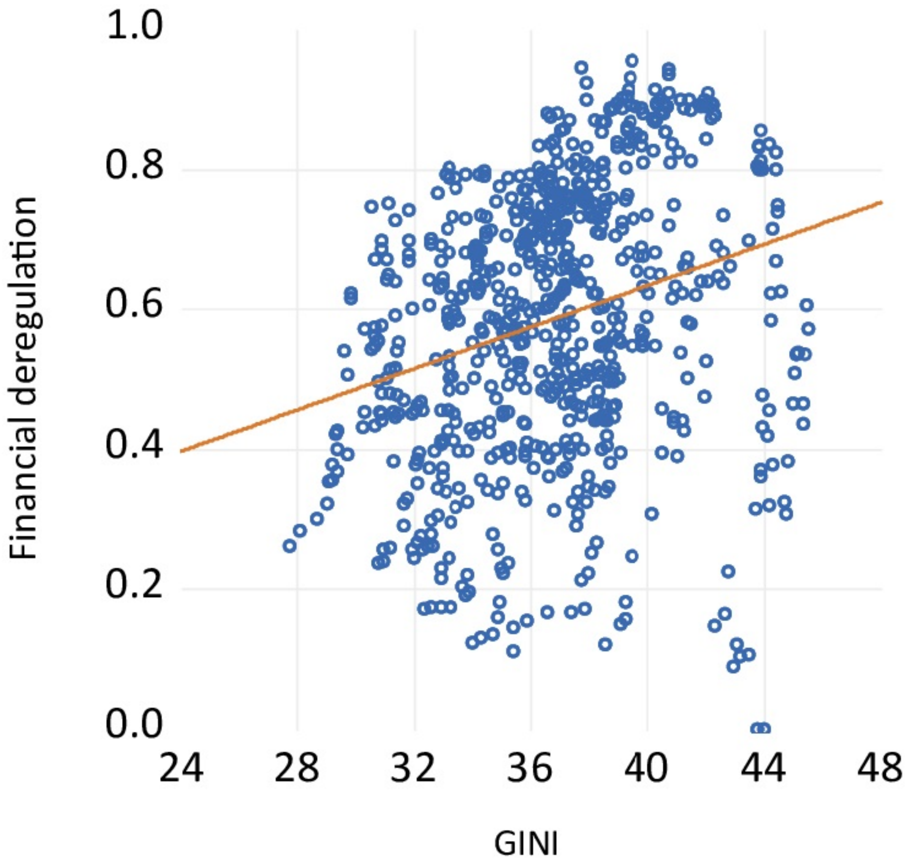


Figure 2.3: Financial deregulation and GINI, 1980-2019

Figure 2.3 shows a positive correlation between income inequality measured by gini index and financial deregulation for 20 advanced OECD countries over the period 1980-2019. It is evident from the graph that deregulation of financial markets and institutions coincided with rising income inequality during this period. The empirical literature suggests that financial deregulation contributed to higher income inequality through easing access to credit, rapid expansion of financial activities, wage polarization, speculative investments in real estate and stock markets (Stiglitz, 2012).

Figure 2.4 demonstrates that there is a steep positive correlation between financial deregulation and another income inequality measure represented by top 1% income share. This positive relationship can be explained by Waldenstrom and Tanndal (2018) who argue that deregulations of financial markets and institutions have significantly boosted the incomes of top 1% wealthy households with financial assets and other investments in the financial sector during the period 1980-2019.

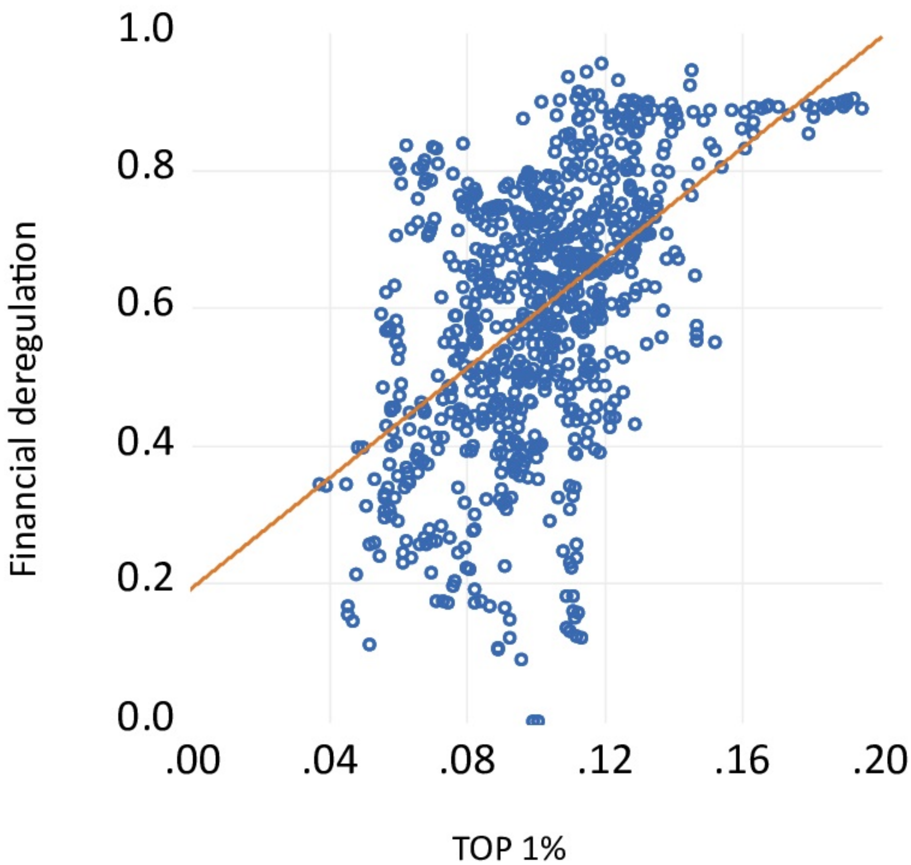


Figure 2.4: Financial deregulation and Top 1% income share, 1980-2019

Thus, the substantial increase in the incomes of top 1% wealthy households who own a wide range of financial products has exacerbated income inequality over this period.

Figure 2.5 also reveals a pronounced positive correlation between financial deregulation and the income share of the top 10%. The illustration confirms that the strong positive relationship between financial deregulation and income inequality is robust to different inequality measures considered. This observation aligns with the findings of Fligstein and Goldstein (2015), ILO (2013), and Waldenstrom and Tanndal (2018) who argue that deregulations of financial markets and banks have subsequently contributed to higher income inequality in most of the advanced OECD economies.

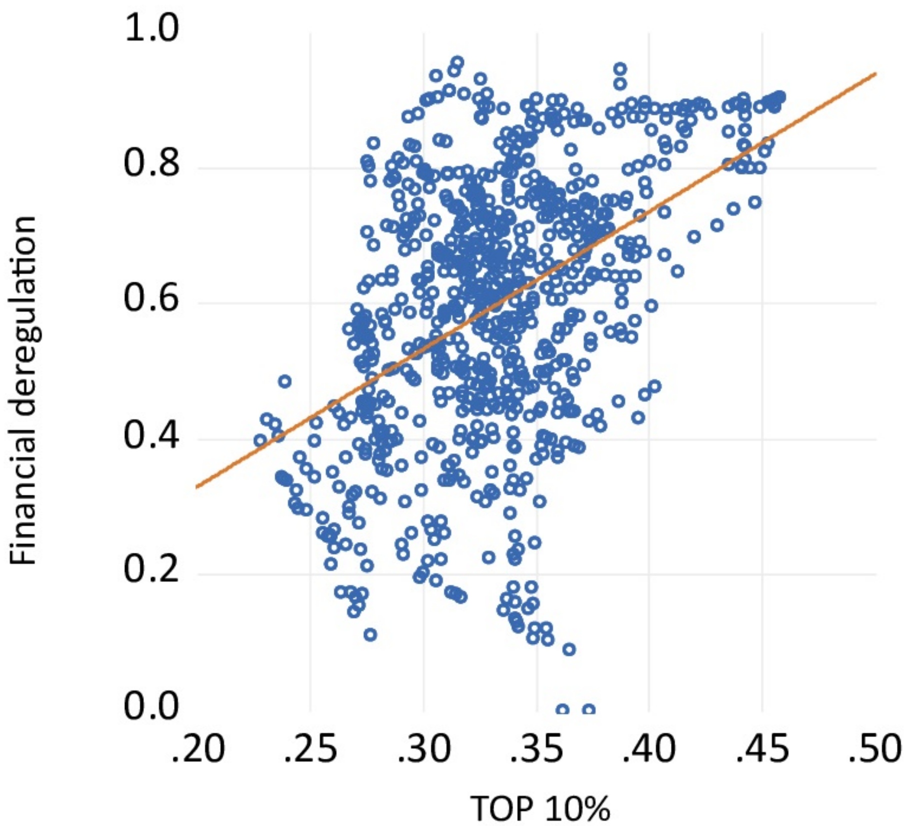


Figure 2.5: Financial deregulation and Top 10% income share, 1980-2019

Finally, figure 2.6 illustrates that there is a strong negative correlation between financial deregulation and labour share of income. This observation is consistent with the long-term decline in the labour share of income that accompanied financial deregulation over the period 1980–2019. This finding is also well documented in the empirical literature (Jerzmanowski and Nabar, 2013; ILO, 2013) which shows that the shift in economic dynamics due to deregulations of financial markets and institutions allowed capital to capture a larger share of income while reducing labour share of income due to profit maximising strategies of firms (e.g. short term profits, shareholder value prioritization, etc.) and lower bargaining power of workers resulting from the weakening of labour market institutions and other factors. Overall, the graphical evidence based on different income inequality measures indicates that financial deregulation has been associated with rising income inequality over the period 1980–2019.

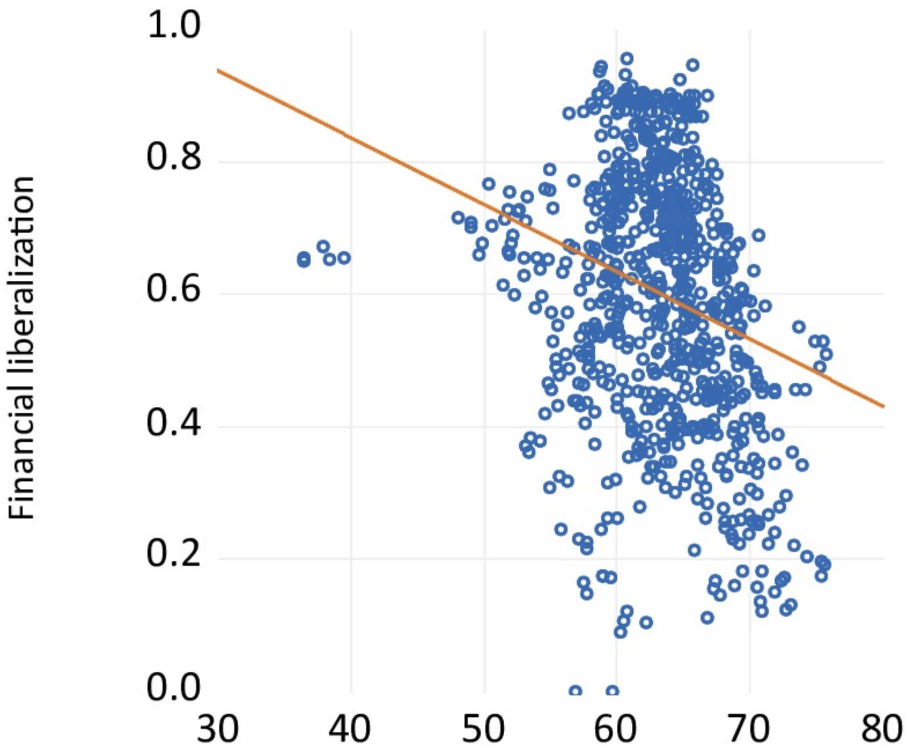


Figure 2.6: Financial deregulation and Labour share of income, 1980-2019

Building on the growing empirical literature and the panel dataset used in this research, this study empirically will test the following hypotheses:

**H1. Financialization is associated with rising income inequality in advanced OECD countries.**

**H2. Financialization is associated with declining labour share of income in advanced OECD countries.**

## 2.5 Econometric methodology

This section outlines the empirical methodology employed to examine the relationship between income inequality and financialization across 20 OECD countries from 1980 to 2019. Previous studies on the finance–inequality nexus have predominantly applied static panel estimators such as pooled OLS, fixed effects, and random effects models, as well as dynamic approaches like the GMM estimators. However, in this regard, static panel methods are limited in their ability to distinguish between short-run and long-run effects and often suffer from low statistical power and potential bias arising from unobserved heterogeneity. Likewise, dynamic GMM estimators face well-documented econometric challenges, including weak instruments, instrument proliferation, poor finite-sample properties, and sensitivity to cross-sectional dependence, all of which can undermine the validity and reliability of their estimates. To address these issues and effectively capture both short-run and long-run dynamics, this study adopts the panel autoregressive distributed lag framework, complemented by the cross-sectionally augmented ARDL (CS-ARDL) estimator to account for cross-sectional dependence and induced feedback effects between the variables. The panel ARDL model, through the PMG, MG, and DFE estimators proposed by Pesaran, Shin, and Smith (1999), offers a robust and flexible approach that accommodates country-specific heterogeneity while ensuring consistent long-run estimation. Before assessing the suitability and implementation of the panel ARDL and CS-ARDL models, the following sections first discuss the panel unit root and panel cointegration tests which are essential for establishing the order of integration and determining the existence of long-run relationships among the variables.

### 2.5.1 Panel unit root test

In panel data econometrics, establishing the stationarity properties of the underlying series is a crucial preliminary step before estimating long-run relationships.

This is particularly relevant in the context of this study, which examines the relationship between financialization and income inequality across 20 advanced OECD countries from 1980 to 2019, where panel unit root tests are essential to assess stationarity across time and countries. Given the 40-year time span and the moderate cross-sectional size of 20 countries, the choice of tests should account for both the structural features of the data and the econometric challenges involved. This study applies the methodologies of Breitung (2000), Levin, Lin and Chu (2002), and Im, Pesaran and Shin (2003), which are among the most widely accepted first-generation tests in the literature. These tests provide a well-established framework for assessing stationarity but rely on restrictive assumptions regarding cross-sectional independence. To address potential cross sectional dependence, the second-generation CIPS test of Pesaran (2007) is also employed, offering a more robust assessment of unit roots in macro panels of this nature.

Before proceeding with the panel setting, it is useful to briefly revisit the unit root process in the time-series context, since panel unit root tests are largely extensions of the univariate framework. Consider the following autoregressive process of order one:

$$y_t = \rho y_{t-1} + u_t,\ -1 < \rho < 1 \tag{2.1}$$

where $u_t$ is a white noise error term. Testing for a unit root amounts to examining whether $\rho = 1$. Direct estimation of this equation using OLS is problematic, however, since the usual $t$ test for $\rho = 1$ is biased in the presence of a unit root. To address this, the model can be reparameterized by subtracting $y_{t-1}$ from both sides of the equation:

$$y_t - y_{t-1} = \rho y_{t-1} - y_{t-1} + u_t \tag{2.2}$$

which can be alternatively written as:

$$\Delta y_t = \delta y_{t-1} + u_t,\ \delta = (\rho - 1) \tag{2.3}$$

where $\Delta$ denotes the first difference operator. Dickey and Fuller (1979, 1981) showed that under the null hypothesis of a unit root ($\delta = 0$) the $t$ test for $y_{t-1}$ does not follow the standard normal distribution, but instead converges to a nonstandard distribution, denoted by the $\tau$ statistic. The corresponding regression can also include a constant and deterministic trend:

$$\Delta y_t = \beta_1 + \beta_2 t + \delta y_{t-1} + u_t \tag{2.4}$$

allowing for a random walk with drift or with drift around a deterministic trend. In this setting, the null hypothesis ($\delta = 0$)indicates non-stationarity (unit root), while the alternative indicates ($\delta < 0$) implies stationarity. A key assumption of these DF regressions is that the error term $u_t$ is uncorrelated. When serial correlation is present, the Augmented Dickey-Fuller (ADF) test extends the framework by including lagged differences of $y_t$ to absorb residual autocorrelation:

$$\Delta y_t = \beta_1 + \beta_2 t + \delta y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta y_{t-i} + \epsilon_t \tag{2.5}$$

This specification ensures that the error term $\epsilon_t$ is a white noise, yielding consistent estimation of $\delta$. Importantly, the ADF test retains the same limiting distribution as the DF test, so critical values remain unchanged.

Panel unit root tests, such as those proposed by Breitung (2000), Levin, Lin and Chu (2002), and Im, Pesaran and Shin (2003), build directly on the DF and ADF foundation by extending the univariate framework across multiple cross-sectional units. Among these, the Breitung (2000) test is designed to enhance the power of panel-based testing while reducing the finite-sample bias associated with earlier methods. The test begins by specifying the observed series as:

$$y_{it} = \mu_i + \beta_i t + x_{it}, t = 1, 2, ....T, \tag{2.6}$$

where $y_{it}$ is the observed series for unit $i$ at time $t$, $\mu_i$ captures the individual fixed effect, $\beta_i t$ allows for individual-specific deterministic trends and $x_{it}$ is generated by the following autoregressive process:

$$x_{it} = \sum_{k=1}^{p+1} \phi_{ik} x_{i,t-k} + \epsilon_{it} \tag{2.7}$$

where $x_{it}$ is the unobserved error term and $\epsilon_{it}$ is assumed to be independent and identically distributed with zero mean and constant variance ($\epsilon_{it} \sim iid.(0, \sigma^2)$). The null hypothesis is that $y_{it}$ is difference stationary with $\sum_{k=1}^{p+1} \phi_{ik} - 1 = 0$ for all $i$ and the alternative hypothesis is that the process is trend stationary with $\sum_{k=1}^{p+1} \phi_{ik} - 1 < 0$ for all $i$. In other words, Breitung (2000) test accounts for heterogeneity in panel data, with the null hypothesis that all cross-sectional units contain a unit root and the alternative that all units are stationary. Breitung's method is a pooled test but uses a different pre-processing step that effectively "neutralizes" the heterogeneity before testing, making the pooled test valid without assuming identical $\rho$. To see the connection with the familiar DF/ADF-type regression, consider the following simple AR(1) case:

$$x_{it} = \phi_i x_{i,t-1} + \epsilon_{it} \tag{2.8}$$

Taking first differences yields:

$$\Delta x_{it} = x_{it} - x_{i,t-1} = (\phi_i - 1)x_{i,t-1} + \epsilon_{it} \tag{2.9}$$

which is the classic DF regression form with autoregressive parameter $\rho_i = \phi_i - 1$.Substituting back $x_{it} = y_{it} - \mu_i - \beta_i t$ gives:

$$\Delta y_{it} = (\phi_i - 1)y_{i,t-1} + \beta_i + (1 - \phi_i)(\mu_i + \beta_i(t-1)) + \epsilon_{it} \tag{2.10}$$

where $\beta_i + (1 - \phi_i)(\mu_i + \beta_i(t-1))$ is the deterministic component representing intercept and trend. Testing the unit root null ($\phi_i = 1$) therefore amounts to testing whether the coefficient on $y_{i,t-1}$ is zero, directly paralleling the DF/ADF approach.

The main contribution of Breitung (2000) is methodological. By applying a data transformation that removes individual effects and deterministic components prior to estimation, the test avoids the loss of power typically observed in earlier approaches and eliminates the need for bias corrections. This transformation produces a relatively efficient test statistic, particularly in panels with a longer time dimension, such as the one considered in this study. As a result, the Breitung test achieves better finite sample performance and greater power against stationary alternatives, while remaining firmly grounded in the DF/ADF tradition. At the same time, it is important to note that empirical applications and Monte Carlo simulations have shown that the Breitung test can be oversized in finite samples, which implies a tendency to over-reject the null hypothesis of non-stationarity. This raises the possibility of spurious conclusions about stationarity, although the relatively long time span of the present dataset helps to mitigate this risk. Nevertheless, the test remains vulnerable to cross-sectional dependence, an issue that is particularly relevant in panels of OECD economies given their high degree of economic integration and synchronized financial cycles.

Levin, Lin, and Chu (2002) propose a panel unit root test based on the following augmented Dickey–Fuller (ADF)-type regression:

$$\Delta y_{it} = \delta y_{it-1} + \sum_{j=1}^{p_i} \theta_{ij} \Delta y_{it-j} + \alpha_{mi} d_{mt} + \epsilon_{it},\ m = 1, 2, 3 \tag{2.11}$$

where $y_{it}$ denotes the series of interest for cross-sectional unit $i$ at time $t$, $\delta$ is the autoregressive parameter common across individuals, $p_i$ is the lag order which may vary across units, $\alpha_{mi} d_{mt}$ captures deterministic components, and $\epsilon_{it}$ is the error term. The deterministic components $d_{mt}$ correspond to three alternative model specifications: i) $d_{1t} = \emptyset$ ( the empty set), a specification without individual effects; ii) $d_{2t} = \{1\}$, which allows for an individual-specific intercept but excludes a time trend; iii) $d_{3t} = \{1, t\}$, which incorporates both an individual intercept and a linear time trend. The test examines the null hypothesis of unit root, $H_0 : \delta = 0$ for all $i$, against the alternative hypothesis $H_1 : \delta < 0$ for all $i$. A distinctive feature of Levin, Lin and Chu (2002) test is the imposition of a common autoregressive parameter $\delta$ across all cross-sectional units, while still allowing heterogeneity in the lag order $p_i$ and the coefficients on lagged differences $\theta_{ij}$. The lag order is typically determined using standard information criteria within the ADF framework, denoted by $\hat{p_i}$. For the asymptotic properties of the test to hold, it is required that $\frac{\sqrt{N}}{T} \to 0$ as $T \to \infty$ where $N$ is the number of cross-sectional units and $T$ is the time dimension of the panel. This condition ensures that the time dimension grows sufficiently fast relative to the cross-sectional dimension. The error terms $\epsilon_{it}$ are assumed to be independently and identically distributed with zero mean and variance $\sigma_i^2$, implying no contemporaneous correlation across units. Under these assumptions, Levin, Lin, and Chu (2002) demonstrate that the appropriately normalized t-statistic for $\delta$ converges to the standard normal distribution, thereby enabling conventional inference. In the discussion that follows, the work is cited as 'Levin, Lin, and Chu (2002)' when emphasizing the authorship and as 'LLC' when referring to the test itself.

Levin, Lin and Chu (2002) sought to address some of the limitations of earlier panel unit root tests by improving size control and statistical efficiency. Although the LLC test assumes a common autoregressive parameter across panel units, the test allows for individual-specific intercepts and time trends. Compared with Breitung (2000), the LLC test demonstrates better control over Type I errors, particularly in moderate-sized panels, making it well-suited to the current panel structure in terms of maintaining nominal significance levels. However, the Breitung (2000) test accounts for heterogeneity in panel data through a pre-processing step that effectively 'neutralizes' individual differences before testing, thereby ensuring the validity of the pooled procedure without assuming identical, $\rho$. Moreover, the LLC test remains sensitive to cross-sectional correlation in the residuals, which can distort both size and power in the presence of global shocks or common factors affecting all units.

Im, Pesaran, and Shin (2003) extend the panel unit root testing framework by allowing for heterogeneity in the autoregressive coefficients across cross-sectional units. In what follows, the work is cited as 'Im, Pesaran and Shin (2003)' when drawing attention to the authors, and as 'IPS' when referring to the test itself. Their test is based on the following augmented Dickey–Fuller (ADF)-type regression:

$$\Delta y_{it} = \delta_i y_{it-1} + \sum_{j=1}^{p_i} \theta_{ij} \Delta y_{it-j} + \alpha_{mi} d_{mt} + \epsilon_{it},\ m = 1, 2, 3 \qquad (2.12)$$

where $\delta_i$ is the autoregressive coefficient, which may vary across individuals, $\theta_{ij}$ are the lag parameters, and $\alpha_{mi} d_{mt}$ represents the deterministic components. As in the Levin, Lin, and Chu (2002) framework, three specifications are considered for the deterministic terms: i) no individual effects ($d_{1t} = \emptyset$) ii) an individual-specific intercept ($d_{2t} = \{1\}$), and (iii) an intercept and linear trend $d_{3t} = \{1, t\}$. The null hypothesis is that all series contain a unit root, $H_0 : \delta_i = 0$ for all $i$ while the alternative allows for heterogeneity: $H_1 : \delta_i < 0$ for $i = 1, 2, ..., N_1$, $\delta_i = 0$ for $i = N_1 + 1, ..., N$. Thus, under the alternative, at least a nonzero fraction of the series are stationary, with the limiting proportion given by $lim_{N\to\infty} \frac{N_1}{N} = \eta \in (0, 1]$. To operationalize the test, Im, Pesaran and Shin (2003) construct their statistic as the average of individual ADF t-statistics across cross-sectional units. This statistic is then standardized using simulated mean and variance values under the null, enabling inference based on its asymptotic convergence to the standard normal distribution. The lag length $p_i$ is selected using the same criteria as in the Levin, Lin, and Chu (2002) test. A key distinction between the IPS and LLC tests is that while LLC imposes a homogeneous autoregressive parameter across all units, IPS allows for heterogeneity in $\delta_i$, thereby permitting some series to be stationary while others remain non-stationary under the alternative hypothesis. Moreover, similar to extensions of the LLC framework, the IPS test can be generalized to allow for weak cross-sectional dependence by incorporating time-specific common factors.

Im, Pesaran and Shin (2003) panel unit root test relaxes the homogeneity assumption by allowing for individual-specific autoregressive coefficients. This feature makes it particularly appropriate for panels comprising heterogeneous countries including the dataset examined in this study. The IPS test is designed to provide both size accuracy and high power in panels with moderate to large cross-sections and time dimensions. Given the structure of the current panel, the IPS test performs well in terms of correctly identifying non-stationarity under heterogeneity. However, the test still assumes cross-sectional independence, which may not be tenable in the case of OECD countries that are closely linked through trade, capital flows, and policy coordination. While the IPS test is more robust to heterogeneity than the Breitung (2000) and LLC (2002) tests, it remains susceptible to distortions in the presence of cross-sectional dependence.

The reliance on first-generation panel unit root tests, therefore, presents a trade-off. These tests are widely used and facilitate comparability across empirical studies. Yet they may yield misleading results if the assumption of cross-sectional independence is violated. Given the interconnectedness of advanced economies, it is essential to supplement these tests with second-generation panel unit root tests that explicitly account for such dependence. Among these, the Cross-sectionally Augmented Im, Pesaran and Shin (CIPS) test of Pesaran (2007) is particularly relevant. The CIPS test extends the IPS framework by augmenting the standard ADF regression with cross-sectional averages of the dependent variable and its lagged differences. For each unit $i$ in the panel, the test estimates a cross sectionally augmented ADF (CADF) regression:

$$\Delta y_{it} = a_i + \delta_i y_{i,t-1} + b_i \bar{y}_{t-1} + c_i \Delta \bar{y}_t + \sum_{j=1}^{p} \theta_{ij} \Delta y_{i,t-j} + \epsilon_{it} \quad (2.13)$$

where $y_{it}$ is the variable for country/firm $i$ at time $t$, $\bar{y}_{t-1}$ is the cross sectional average of lagged levels, $\Delta \bar{y}_t$ is the cross sectional average of first differences. The additional terms $\bar{y}_{t-1}$ and $\Delta \bar{y}_t$ capture common global dynamics and thereby filter out cross-sectional dependence. The null hypothesis $H_0 : \delta_i = 0$ implies the presence of a unit root, while the alternative hypothesis allows for at least some cross-sectional units to be stationary. The test statistic for each unit is the CADF $t$-statistic associated with $\delta_i$. Pesaran (2007) then constructs the panel-level statistic, the CIPS statistic, as the average of these individual

CADF statistics across all units:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} t_i(\delta_i), \tag{2.14}$$

where $t_i(\delta_i)$ denotes the CADF statistic for unit $i$. Since the asymptotic distribution of the CIPS statistic is non-standard, Pesaran (2007) provides simulated critical values that depend on both the time dimension $T$ and the cross sectional dimension $N$. The intuition behind the CIPS test is that, by augmenting the standard ADF regression with cross-sectional averages, one controls for the influence of unobserved global shocks that otherwise induce strong correlations across units. As a result, the CIPS test distinguishes genuine unit-root behaviour from co-movement induced by common factors such as financial crisis, economic downturn, etc., making it a more robust approach than first-generation tests when applied to panels of countries or firms exposed to shared shocks. This approach captures the influence of unobserved common factors, thereby mitigating the effects of cross-sectional dependence. The CIPS test allows for heterogeneity in autoregressive dynamics and performs well in panels where global shocks or spillover effects are likely to induce correlation across units. In the context of this study, where financialization and inequality are shaped by global capital flows, shared regulatory trends, and synchronized macroeconomic conditions, the CIPS test offers a robust alternative to traditional unit root tests.

In summary, while the Breitung (2000), Levin et al. (2002), and Im et al. (2003) panel unit root tests provide a useful benchmark for assessing stationarity, their underlying assumptions regarding homogeneity and cross-sectional independence limit their reliability in macro panels characterized by interdependence and heterogeneity. These limitations may lead to size distortions, inflating the risk of Type I errors (incorrectly rejecting the null of a unit root), or to low power, increasing the likelihood of Type II errors (failing to detect stationarity when it exists). Given the nature of the panel data used in this study, the application of second-generation tests such as Pesaran's CIPS is necessary to ensure robust inferences. These tests not only accommodate the heterogeneity and cross-sectional dependence inherent in macroeconomic data, thereby reducing the risks of both Type I and Type II errors, but also strengthen the empirical foundation of the long-run relationships being investigated in this study.

### 2.5.2 Panel cointegration tests

The panel cointegration tests are widely used in the empirical literature to examine the existence of long-run relationships among integrated variables (Pedroni, 2004). If the variables are non-stationary, the cointegration tests are conducted to determine whether a stable long-run equilibrium exists between income inequality and financialization variables. In this study, the first-generation panel cointegration tests of Fischer (1999), Kao (1999), and Pedroni (1999, 2004) are employed, all of which test the null hypothesis of no cointegration among $I(1)$ variables against the alternative of cointegration. These tests provide an important benchmark for establishing long-run relationships, but to reinforce their findings and ensure the robustness of the results, the second-generation panel cointegration test of Westerlund (2007) is also applied. Unlike the residual-based first-generation tests, Westerlund (2007) is built on error-correction dynamics and accommodates cross-sectional dependence through robust bootstrapping techniques. Incorporating this test therefore not only complements the evidence obtained from the first-generation approaches but also enhances the reliability of the analysis in panels where interdependencies across countries may be present.

Before moving to the panel context, it is useful to briefly revisit the concept of cointegration and the error correction mechanism in a time-series framework. Panel cointegration tests are essentially extensions of these time-series methods, adapting residual-based and error-correction approaches to the longitudinal data. Consider the following simple model:

$$y_t = \beta_1 + \beta_2 x_t + u_t \tag{2.15}$$

which can be rewritten as:

$$u_t = y_t - \beta_1 - \beta_2 x_t \tag{2.16}$$

If both $y_t$ and $x_t$ are I(1), but $u_t$ are stationary, I(0), then $y_t$ and $x_t$ are said to be cointegrated. In economic terms, two variables will be cointegrated if they have a long-term, or equilibrium, relationship between them. In the language of cointegration theory, the equation (2.15) is known as a cointegration regression and the slope parameter $\beta_2$ is known as the cointegrating parameter. The concept of cointegration can be extended to a regression model containing $k$ regressors. Testing for cointegration in a time-series setting typically involves applying the Dickey–Fuller (DF) or Augmented Dickey–Fuller (ADF) unit root tests to the residuals obtained from a cointegrating regression (Engle and Granger, 1987). Since the estimated $u_t$ are based on the estimated cointegrating parameter $\beta_2$, the DF and ADF critical significance values are not quite appropriate. Therefore, the DF and ADF tests in the present context are known as Engle–Granger (EG) and augmented Engle–Granger (AEG) tests. Although straightforward, this approach underscores the key insight that if the residuals are stationary, then a valid long-run relationship exists between non-stationary variables.

The concept of cointegration naturally leads to the error correction mechanism (ECM), which links long-run equilibrium with short-run dynamics. Suppose the residuals from the cointegration regression are denoted by $u_t$:

$$u_t = y_t - \beta_1 - \beta_2 x_t - \beta_3 t \tag{2.17}$$

Then an ECM can be expressed as follows:

$$\Delta y_t = \alpha_0 + \alpha_1 \Delta x_t + \alpha_2 u_{t-1} + \varepsilon_t \tag{2.18}$$

where $\varepsilon_t$ is a white noise disturbance term. Here, the lagged equilibrium error $u_{t-1}$ captures the extent of disequilibrium in the previous period, while the coefficient $\alpha_2$ measures the speed of adjustment back to equilibrium. A negative and statistically significant $\alpha_2$ indicates that deviations from the long-run path are corrected over time. This is consistent with the Granger representation theorem, which states that if two or more variables are cointegrated, their relationship can be represented as an ECM (Engle and Granger, 1987). The ECM thus provides a dynamic framework that reconciles short-run fluctuations with long-run equilibrium forces.

**Kao test**

The Kao (1999) panel cointegration test extends the residual-based methodology of Engle and Granger (1987) to panel data settings. The idea is straightforward: if a group of non-stationary variables are cointegrated, then the residuals from their long-run regression should themselves be stationary. Consider the following model with cross-sectional unit $i = 1, ..., N$ and time period $t = 1, ..., T$:

$$y_{it} = \alpha_i + x_{it}\beta + u_{it} \tag{2.19}$$

where $y_{it}$ and $x_{it}$ are I(1) processes, $\alpha_i$ denotes an individual-specific intercept, and $u_{it}$ is the disturbance term. After estimating the equation above, Kao (1999) examines the residuals $\hat{u_{it}}$ If these residuals still behave like a unit root process, then no cointegration is present. If instead the residuals are stationary, this indicates that $y_{it}$ and $x_{it}$ move together in the long run. To test this, Kao (1999) proposes running auxiliary regressions of the following form:

$$\hat{u}_{it} = \rho \hat{u}_{it-1} + \sum_{j=1}^{p} \phi_j \Delta \hat{u}_{it-j} + v_{it} \tag{2.20}$$

and tests $H_0 : \rho = 1$ against $H_1 : \rho < 1$. Kao (1999) proposes five panel cointegration test statistics: four based on the Dickey–Fuller (DF) approach and one based on the Augmented Dickey–Fuller (ADF) framework. The idea is each DF statistic is designed to handle a different aspect of the problem, addressing different forms of heterogeneity or misspecification in the simple DF framework. The DF-type statistics differ in how the residuals are normalized, but all assume no serial correlation in the error term. By contrast, the ADF statistic augments the regression with lagged differences of the residuals, thereby addressing possible serial correlation. In all cases, the autoregressive coefficient $\rho$ is estimated by pooling residuals across cross-sectional units, which imposes a common speed of adjustment to the long-run equilibrium. This pooling enhances the test's power but also makes it restrictive, since it assumes homogeneous residual dynamics across cross sectional units. This homogeneity assumption later motivated the development of Pedroni (1999, 2004) test, which allows for heterogeneity in the autoregressive coefficient, $\rho_i$.

**Pedroni test**

Pedroni (1999, 2004) extends the Engle–Granger residual-based approach to the panel setting but introduces considerably more flexibility than Kao (1999). The general cointegrating equation under Pedroni (1999, 2004) is specified as:

$$y_{it} = \alpha_i + \delta_i t + \beta_i x_{it} + u_{it}, \tag{2.21}$$

where the parameters $\alpha_i$ and $\delta_i$ capture unit-specific intercepts and time trends, and $\beta_i$ is allowed to vary across units, thereby accommodating slope heterogeneity. The residuals $u_{it}$ are then used in auxiliary ADF-type regressions:

$$\hat{u}_{it} = \rho_i \hat{u}_{i,t-1} + \sum_{j=1}^{p_i} \phi_{ij} \Delta \hat{u}_{i,t-j} + v_{it}, \tag{2.22}$$

where $\hat{u}_{it}$ are the residuals from the cointegrating regression, $\rho_i$ captures the persistence of the residual process, $\phi_{ij}$ are the coefficients of the lagged differences, and $v_{it}$ is the error term. Pedroni (1999, 2004) proposes seven statistics derived from the residuals of the cointegrating regression in order to test the null hypothesis of no cointegration, $H_0 : \rho_i = 1$. Four of these are based on the assumption of a common autoregressive coefficient, $\rho$ across cross-sectional units. In this case, the null $H_0 : \rho_i = 1$ is tested against the alternative $H_1^p : \rho_i = \rho < 1$ for all $i$. These are referred to as the within-dimension, or panel cointegration statistics test. Intuitively, the within-dimension test checks if every single member of the panel follows the same long-run equilibrium relationship. The four statistics in this category include a non-parametric panel variance ratio statistic, a panel $\rho$-statistic that is analogous to the PP $\rho$-statistic developed by Phillips and Perron (1988) and Phillips and Ouliaris (1990), the non-parametric panel $t$-statistic in the spirit by Phillips and Perron (1988) and a parametric panel $t$-statistic that is based on the augmented DF test of Dickey and Fuller (1979). The remaining three statistics relax this restriction by allowing the autoregressive parameters, $\rho_i$ to vary across cross-sections. Here, the null $H_0 : \rho_i = 1$ for all $i$ is tested against the alternative $H_1^g : \rho_i < 1$ for each $i$. These are termed the between-dimension, or group-mean panel cointegration statistics tests. Conceptually, the group-mean tests examine whether a cointegrating relationship exists on average across the panel, even if the strength of the relationship varies across units. By accommodating heterogeneity in autoregressive coefficients, $\rho_i$ the group-mean statistics take one additional source of potential heterogeneity across individual members of the panel into consideration. The three statistics in this category consist of a group-mean rho-statistic of the PP type, a group-mean non-parametric $t$-statistic of the PP type, and a group-mean parametric $t$-statistic of the ADF type. Overall, Pedroni (1999, 2004)'s seven statistics draw upon both DF or ADF type tests, which are parametric, and PP type tests, which are non-parametric. The distinction between these approaches lies in how they deal with the serial correlation. The ADF method addresses serial correlation by including lagged difference terms directly in the regression model, whereas the PP method employs a simple DF regression without such lagged terms but adjusts the test statistic after estimation to correct for the presence of serial correlation in the error term.

The asymptotic distribution of Pedroni's (1999, 2004) test statistics similar to Kao (1999) test is derived under the assumption of cross-sectional independence, which may lead to bias when unobserved common factors are present. Taken together, both Kao (1999) and Pedroni (1999, 2004) extend the Engle–Granger framework to panels, but they differ in scope and robustness. Kao (1999) offers a straightforward residual-based test that is relatively easy to implement but restrictive due to the homogeneity assumption of autoregressive coefficient, $\rho$ and more limited correction for endogeneity. By contrast, Pedroni (1999, 2004) provides a richer set of statistics that explicitly accommodate the heterogeneity of autoregressive parameters, $\rho_i$ and incorporate variance corrections to mitigate endogeneity and serial correlation, thereby offering greater flexibility for empirical applications.

**Fischer test**

The Fisher (1999) panel cointegration test, developed by Maddala and Wu (1999) building on Johansen's (1988, 1991) methodology, provides a system-based approach to testing for cointegration in panel data. The null hypothesis is that no cointegration exists in any of the cross-sectional units, while the alternative allows at least some units to exhibit cointegration.
For each unit $i$, Johansen's framework begins with a vector autoregressive (VAR) model of order $p$:

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + \varepsilon_t, \tag{2.23}$$

where $y_t$ is a $k \times 1$ vector of I(1) variables. This VAR can be rewritten in error-correction form as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{j=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t, \tag{2.24}$$

$$\Pi = A_1 + A_2 + ... + A_p - I = \sum_{i=1}^{p} A_i - I, \; \Gamma_i = -(A_{i+1} + A_{i+2} + ... + A_p) = -\sum_{j=i+1}^{p} A_j \tag{2.25}$$

where $\Pi$ is the crucial long run impact matrix and $\Gamma_i$ are the matrices of short-run coefficients. The rank of $\Pi$ determines the number of cointegrating vectors. If rank($\Pi$) = 0, there is no cointegration; if the coefficient matrix $\Pi$ has reduced rank $r < k$, then there exist $k \times r$ matrices $\alpha$ and $\beta$, each of rank r, such that $\Pi = \alpha\beta'$. In this case, $\beta' y_t$ represents stationary linear combinations of the variables, with $r$ denoting the number of cointegrating relationships. The columns of $\beta$ correspond to the cointegrating vectors, whereas the coefficients in $\alpha$ are interpreted as adjustment parameters governing how deviations from long-run equilibrium feed back into the system. For a given rank $r$, the maximum likelihood estimator of $\beta$ identifies the linear combinations of $y_{t-1}$ that maximize the $r$ largest canonical correlations between $\Delta y_t$ and $y_{t-1}$ after accounting for lagged differences and deterministic components. Canonical correlation analysis provides the optimal linear combinations of two sets of variables that are most highly correlated with each other. In the Johansen (1991) framework, this leads to solving a generalized eigenvalue problem of the form:

$$|\lambda S_{11} - S_{10} S_{00}^{-1} S_{01}| = 0, \tag{2.26}$$

where $S_{00}$ is the covariance matrix of the residuals from regressing $\Delta y_t$ on lagged differences, $S_{11}$ is the covariance matrix of the residuals from regressing $y_{t-1}$ on the same regressors, and $S_{01}$ is the cross-covariance matrix between them. Solving this equation yields the eigenvalues $\hat{\lambda}_1 > \hat{\lambda}_2 > ... > \hat{\lambda}_k$, which are the squared canonical correlations. Each eigenvalue measures the strength of a potential stationary linear combination of the variables, with larger values indicating stronger evidence of cointegration. On the basis of these eigenvalues, Johansen (1991) derives two likelihood ratio (LR) test statistics for determining the number of cointegrating relationships in the system and thereby the reduced rank of the $\Pi$ matrix: the trace test and maximum eigenvalue test as shown in equations (2.27) and (2.28).

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{k} ln(1 - \hat{\lambda}_i), \tag{2.27}$$

where the trace statistic tests the null of at most $r$ cointegrating vectors against the alternative of more than $r$. The statistic accumulates evidence from all eigenvalues beyond the $r$-th, and thus provides a joint test for whether additional cointegrating relationships exist. While the maximum eigenvalue statistic tests the null of exactly $r$ cointegrating vectors against the alternative of $r+1$. Unlike the trace test, this statistic is based solely on the next eigenvalue, focusing on whether a single additional cointegrating relationship is significant:

$$\lambda_{max}(r, r+1) = -Tln(1 - \hat{\lambda}_{r+1}), \tag{2.28}$$

where $T$ is the sample size, $k$ is the number of variables, and $\hat{\lambda}_i$ are the estimated eigenvalues obtained from the canonical correlations between $\Delta y_t$ and $y_{t-1}$ after correcting for lagged differences. These eigenvalues measure the strength of the long-run relationships.
Each Johansen (1991) test yields a p-value, $\pi_i$, for unit $i$. Fisher (1999)'s method then combines the evidence across all $N$ cross-sectional units:

$$\chi^2_{2N} = -2\sum_{i=1}^{N} log(\pi_i) \tag{2.29}$$

where $\chi^2_{2N}$ follows a chi-squared distribution with $2N$ degrees of freedom and $N$ is the number of cross sectional units. $\pi_i$ is the p-value from the cointegration test for unit $i$. To check for the cointegration, the combined test statistic $\chi^2_{2N}$ is calculated and compared with the critical value from the chi-square distribution with $2N$ degrees of freedom. If the test statistic exceeds the critical value, the null hypothesis of no cointegration is rejected for the variables of interest. The Fisher-type method does not impose homogeneity of the cointegration vectors across cross-sectional units. Each unit may exhibit different long-run relationships, and the combined statistic simply aggregates their individual evidence. However, the standard distributional result of the test relies on the assumption that the p-values from individual Johansen (1991) tests are independent across units.

The test combines the trace and maximum eigenvalue statistics from individual Johansen cointegration tests across cross-sections using Johansen's (1991) method, thereby increasing statistical power while accommodating heterogeneity in country-specific dynamics. Johansen (1999) test treats all variables as jointly endogenous within the system, thus it mitigates concerns about endogeneity that affects single-equation residual-based methods. However, this joint system approach is designed to identify the cointegrating space rather than individual coefficients, so caution is required when interpreting specific parameter estimates. In addition, by incorporating lagged dynamics directly into the estimation process, the test corrects for serial correlation in the data, although its reliability depends on the careful selection of lag length. Like other first-generation panel cointegration tests, however, it assumes cross-sectional independence, which can limit its robustness in macroeconomic panels with strong interdependencies. Overall, the Fisher (1999) test offers a rigorous alternative to residual-based procedures, with particular strengths in addressing issues of endogeneity and autocorrelation in the assessment of long-run relationships.

**Westerlund test**

Westerlund (2007) develops an error correction-based cointegration test for panel data. Unlike other panel cointegration tests such as Pedroni (1999, 2004) and Kao (1999), which typically rely on residual-based approaches, the Westerlund (2007) test focuses on the error correction mechanism and is designed to better accommodate cross-sectional dependence and heterogeneity. The core idea of the Westerlund (2007) approach is to test the null hypothesis that the error correction term in a conditional panel error-correction model is equal to zero. Westerlund (2007) employs a bootstrap procedure to address potential cross sectional dependence. Therefore, the test inference is valid in the presence of cross sectional correlation in the panel dataset. Moreover, as simulation results in Westerlund (2007) indicate, the test has robust finite-sample properties. The error correction test proposed by Westerlund (2007) can be represented by the following equation:

$$\Delta y_{it} = \delta' d_t + \alpha_i (y_{i,t-1} - \beta_i x_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + e_{it}, \quad (2.30)$$

The equation (2.30) can be re-expressed as follows:

$$\Delta y_{it} = \delta' d_t + \alpha_i y_{i,t-1} + \lambda_i' x_{i,t-1} + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + e_{it}, \quad (2.31)$$

where $d_t$ contains the deterministic components as discussed above and $\lambda_i' = -\alpha_i \beta_i'$. The equilibrium relationship of the equation is represented by $y_{i,t-1} - \beta_i' x_{i,t-1}$, with $\alpha_i$ measuring the speed at which deviations from equilibrium are corrected following an exogenous shock. A positive value of $\alpha_i$ ($\alpha_i > 0$) indicates the presence of error correction, confirming a cointegrating relationship between $y_{it}$ and $x_{it}$. Conversely, if $\alpha_i = 0$, it indicates that no long-run cointegrating relationship exists between the variables. In Westerlund's (2007) framework, the null hypothesis is defined as the absence of cointegration, expressed as $\alpha_i = 0$

for all cross-sectional units. The form of the alternative hypothesis depends on whether homogeneity of the adjustment parameter $\alpha_i$ is assumed. When no such restriction is imposed, the null is tested against the alternative that at least one unit exhibits a negative adjustment coefficient ($\alpha_i < 0$), which is evaluated using the so-called group-mean tests. In contrast, the panel tests impose the condition that $\alpha_i$ is identical across units, and therefore assess the null against the alternative that all cross-sectional units display error-correcting behavior. This distinction between group-mean and panel tests closely parallels the separation found in Pedroni (1999, 2004)'s and Westerlund (2007)'s respective test statistics.

Westerlund (2007) offers distinct improvements over traditional panel cointegration tests, particularly in its ability to model error-correction dynamics while allowing for heterogeneity across cross-sections and accommodating cross-sectional dependence. Unlike residual-based tests such as those of Pedroni (1999, 2004) and Kao (1999), Westerlund's (2007) approach directly tests for the existence of cointegration by examining the significance of the error correction term in a conditional error-correction model. Another advantage of the test over residual-based cointegration tests is what is referred to as common factor restriction (Kremers et al. 1992; Banerjee et al. 1998). Residual-based tests impose the condition that the long-run cointegration vector among the level variables must correspond to the short-run error correction mechanism of the differenced variables (Westerlund, 2007). As highlighted by Kremers et al. (1992) and Banerjee et al. (1998), this restriction can substantially reduce the statistical power of residual-based cointegration tests. Although the test is robust in finite samples and flexible in its structure, it is computationally intensive and requires careful specification of lag lengths and deterministic components. Nonetheless, given the characteristics of the dataset and the potential for cross-country heterogeneity and interdependence, Westerlund (2007) should provide a more robust cointegration test.

### 2.5.3 Panel ARDL model

The panel Autoregressive Distributed Lag (ARDL) model is a widely applied econometric method for analyzing panel data, particularly when the objective is to capture both short-run dynamics and long-run equilibrium relationships among variables. This model has gained popularity due to its flexibility in accommodating different types of panel data and its ability to handle mixed integration orders among variables (Lombardi et al., 2022). In other words, this method is superior regardless of whether the underlying explanatory variables at level are stationary, non-stationary or both and it allows us to differentiate between short run and long run effects. Previous studies use different econometric models to analyse the underlying relationship between finance and income inequality. A first strand relies on static panel estimators such as pooled OLS, fixed effects, and random effects models (Kappel, 2010; Jaumotte et al., 2013; Denk and Cournede, 2015), while another uses dynamic panel approaches such as GMM estimators (Beck et al., 2007; Jeanneney and Kpodar, 2011; Hamori and Hashiguchi, 2012). In this regard, Samargandi et al. (2015) provide a useful overview of the limitations associated with static panel estimators, such as pooled OLS, fixed effects, and random effects models, as well as GMM type approaches. Although the static models are used as alternative approach in this study, mainly for comparison purposes, they do not allow us to examine how financialization variables interact with income inequality measures in the short run and in the long run.

While Instrumental Variable (IV) and GMM estimators are common methods in empirical research, their practical implementation is often constrained by econometric issues including weak instruments, instrument proliferation, poor finite-sample properties, and sensitivity to cross-sectional dependence. These methods are typically employed to address endogeneity problems that arise when regressors are correlated with the error term, most commonly due to simultaneity bias or omitted variable bias. In this regard, the GMM is designed to handle endogeneity through instrument variables which are prone to weak instrumental problems, especially in finite samples (Roodman, 2006; Chudik and Pesaran, 2015). According to Stock et al. (2002), the issue of weak instruments remains a persistent challenge in empirical economics, undermining the reliability of both standard instrumental variable (IV) and generalized method of moments (GMM) estimators. Bound et al. (1995) demonstrate that weak instruments can result in substantial bias and inconsistency in IV estimates, even when the instruments exhibit only a minor correlation with the error term of the structural equation. Likewise, Guggenberger (2012) highlights that the finite-sample performance of IV estimators deteriorates when instruments lack strict exogeneity, further compromising the validity of the estimates. Roodman (2006) argues that in the small $N$ (cross sectional units) and large $T$ (time dimension) case, the GMM estimators are likely to produce spurious results for two reasons. First, small $N$ might lead to unreliable autocorrelation test. Second, as the time dimension increases, so does the number of instruments, potentially inflating the instrument count and compromising the validity of the Sargan test for overidentifying restrictions. This situation increases the risk of incorrectly rejecting the null hypothesis of instrument exogeneity. Consequently, the use of GMM under such conditions raises concerns regarding the reliability and validity of its estimates (Samargandi et al., 2015; Roodman, 2006). Another important limitation of the GMM estimation approach relates to the assumption of slope homogeneity across cross-sectional units. As emphasized by Kiviet (1995) and further discussed in Bond (2002), imposing homogeneity on the coefficients of lagged dependent variables can introduce substantial bias if, in reality, these coefficients differ across units. This concern is echoed by Pesaran (1997), Pesaran and Shin (1999), and Pesaran and Smith (1995), who argue that heterogeneous dynamics across countries or units are often the norm rather than the exception in macroeconomic panels. Therefore, unless the assumption of identical slope coefficients is empirically justified, GMM estimators risk producing inconsistent or misleading results, particularly in heterogeneous panel settings. Furthermore, Sarafidis and Robertson (2006) demonstrate that in short dynamic panel data models, the presence of cross-sectional dependence in the error terms undermines the consistency of estimators that rely on instrumental variables and the generalized method of moments (GMM), including those proposed by Anderson and Hsiao (1981), Arellano and Bond (1991), and Blundell and Bond (1998). This is particularly problematic given that cross-sectional correlation in the residuals is a realistic feature in macroeconomic data.

The panel ARDL framework offers clear methodological advantages over traditional static and GMM-type approaches, particularly in the context of this study, which focuses on the long-run impact of financialization on income inequality. Unlike GMM estimators that depend heavily on the validity and strength of instruments and their poor finite-sample performance, the panel ARDL model provides a more robust and flexible approach for handling dynamic relationships in small samples of this nature where the time dimension exceeds the cross-sectional dimension ($T > N$). Its ability to accommodate variables of mixed integration orders, estimate both short- and long-run coefficients directly, and incorporate an error-correction mechanism makes it especially suitable for the current panel dataset. Moreover, Pesaran, Shin, and Smith (1999) demonstrate that an ARDL model provides consistent coefficients despite the possible presence of endogeneity given appropriate lags of dependent and independent variables, thereby avoiding the complexities of internal instrumentation required by GMM methods. To further strengthen the empirical analysis, this study complements the panel ARDL estimation with the cross-sectional ARDL (CS-ARDL) approach developed by Chudik and Pesaran (2015), which explicitly addresses cross-sectional dependence and unobserved common shocks through the inclusion of cross-sectional averages of both dependent and independent variables and their lags. This augmentation not only captures unobserved common shocks that may affect all units in the panel but also mitigates the bias arising from omitted variables and simultaneity, thereby offering a more robust mechanism for addressing endogeneity. As discussed above, the GMM-type methods are inherently limited in their ability to account for cross-sectional dependence and parameter heterogeneity which can lead to biased or inconsistent estimates. Overall, the panel ARDL along with CS-ARDL estimators should provide a comprehensive and robust framework for exploring the short- and long-run dynamics between financialization and income inequality.

Before turning to the panel ARDL framework, it is useful to begin with a discussion of the ARDL model in a time series setting. This method serves as a widely accepted approach for examining long-run relationships, as it effectively mitigates endogeneity concerns while distinguishing between short-run and long-run effects of financialization. The concept of cointegration, as introduced by Engle and Granger (1987), remains the most widely used econometric tool for assessing long-run relationships. Among the various approaches to cointegration, the ARDL method, initially developed by Pesaran and Smith (1995), is particularly well suited for applications involving panel data. An illustration following the methodology of Chudik et al. (2016) is presented below.
Consider the aim is to investigate the long-run association between $y_t$ and $x_t$, where their joint behaviour is characterized by the following VAR(1) specification:

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} e_t^y \\ e_t^x \end{bmatrix} \tag{2.32}$$

In this system, the error terms $e_t^y$ and $e_t^x$ are generally correlated, implying a contemporaneous relationship between $y_t$ and $x_t$. As a result, estimating $y_t$ on $x_t$ using ordinary least squares (OLS) would suffer from endogeneity issues. Nonetheless, these error terms can be decomposed into their orthogonal components, allowing the endogenous part to be separated out. Specifically:

$$e_t^y = E(e_t^y | e_t^x) + u_t = \omega e_t^x + u_t, \tag{2.33}$$

where $\omega = cov(e_t^y, e_t^x)/var(e_t^x)$. This decomposition indicates that the error term in the $y_t$ equation consists of two parts, with one component ($u_t$) being orthogonal to the error term in $x_t$. Inserting this expression (2.33) back into the system (2.32) yields:

$$y_t = \phi_{11} y_{t-1} + \phi_{12} x_{t-1} + \omega e_t^x + u_t, \tag{2.34}$$

and from the $x_t$ equation:

$$e_t^x = x_t - \phi_{21} y_{t-1} - \phi_{22} x_{t-1} \tag{2.35}$$

Substituting (2.35) into (2.34) leads to the following ARDL specification:

$$y_t = \varphi y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + u_t, \tag{2.36}$$

with parameter definitions:

$$\varphi = \phi_{11} - \omega\phi_{21},\ \beta_0 = \omega,\ \beta_1 = \phi_{12} - \omega\phi_{22} \tag{2.37}$$

The equation (2.36) provides a basic ARDL model. Given that $u_t$ is inherently orthogonal to both $x_t$ and its lagged values, the specification (2.36) deals with the endogeneity arising from the contemporaneous correlation, allowing for consistent estimation through OLS. This demonstrates that the ARDL model can be derived directly from a VAR representation where the inclusion of lagged terms effectively captures the interdependence between $y_t$ and $x_t$. In a broader sense, this mechanism also explains how the ARDL model mitigates other forms of endogeneity, such as those arising from omitted variables. When an omitted variable follows an autoregressive process, its lagged influence becomes embedded in the past values of $x_t$ and $y_t$. By including these lagged terms, the ARDL specification absorbs the dynamic effects of the omitted factor, reducing its correlation with the contemporaneous error term. Therefore, whether the endogeneity stems from the contemporaneous correlation or from the persistent influence of omitted variables, the ARDL framework addresses both by exploiting the information contained in lagged observations to produce consistent long-run estimates. Moreover, Pesaran et al.(1999) demonstrate that the OLS estimates of the equation (2.36) remain consistent regardless of whether those variables are integrated of order one or zero.

The equation (2.36) from the time series context can be naturally extended to a panel setting. Denoting by $i$ the cross-sectional unit (country), the general ARDL$(p, q)$ specification for panel data can be written as:

$$y_{it} = \alpha_i + \sum_{j=1}^{p} \eta_{ij} y_{i,t-j} + \sum_{k=0}^{q} \beta_{ik} x_{i,t-k} + u_{it} \tag{2.38}$$

where $p$ and $q$ denote the lag orders of the dependent and explanatory variables, respectively. The associated error correction representation of the model can be written as:

$$\Delta y_{it} = \alpha_i + \phi_i (y_{i,t-1} - \psi_i x_{i,t-1}) + \sum_{j=1}^{p-1} \eta^*_{ij} \Delta y_{i,t-j} + \sum_{k=0}^{q-1} \beta^*_{ik} \Delta x_{i,t-k} + u_{it} \tag{2.39}$$

where $\phi_i$ is the error-correction coefficient, $\psi_i$ is the vector of long-run parameters, and $\eta^*_{ij}$, $\beta^*_{ik}$ denote short-run coefficients.

In the context of this study, which examines the relationship between financialization and income inequality across countries, the panel ARDL framework provides a particularly useful tool. It allows both the long-run equilibrium relationship and short-run adjustments to be modeled simultaneously, while accommodating heterogeneity in the coefficients across countries. Given the methodological strengths discussed above, as well as the characteristics of the dataset ($T > N$) and the objectives of this research, the panel ARDL is deemed appropriate for the analysis. Accordingly, this study follows the panel ARDL approach proposed by Pesaran et al. (1999) in the literature and applies Mean Group (MG), Pooled Mean Group (PMG) and Dynamic Fixed effects (DFE) in order to analyse how financialization variables influence income inequality measures in the long run. The dynamic heterogeneous panel regressions are introduced by Pesaran et al. (1999) in an error correction term of ARDL estimators. The baseline panel ARDL specification employed in this chapter is given by:

$$GINI_{it} = \alpha_i + \sum_{k=1}^{p} \beta_{ik} GINI_{i,t-k} + \sum_{k=0}^{q} \gamma'_{ik} FIN_{i,t-k} + \sum_{k=0}^{q} \delta'_{ik} X_{i,t-k} + u_{it} \tag{2.40}$$

The panel ARDL equation (2.40) in error correction form is re-parameterized as:

$$
\begin{aligned}
\Delta GINI_{it} = \alpha_i + \phi_i(GINI_{i,t-1} - \theta_i' FIN_{i,t-1} - \lambda_i' X_{i,t-1}) + \\
\sum_{k=1}^{p-1} \beta_{ik}^* \Delta GINI_{i,t-k} + \sum_{k=0}^{q-1} \gamma_{ik}^{*'} \Delta FIN_{i,t-k} + \sum_{k=0}^{q-1} \delta_{ik}^{*'} \Delta X_{i,t-k} + u_{it}
\end{aligned}
\tag{2.41}
$$

where $i$ and $t$ represent country and time respectively, $GINI$ is the income inequality measure, $FIN$ is the vector of financialization variables and $X$ is the vector of control variables. In this specification, the coefficients on the differenced terms, namely $\beta^*$, $\gamma^{*'}$ and $\delta^{*'}$ capture the short run dynamics of income inequality, financialization variables, and control variables, respectively. The parameters $\theta_i'$ and $\lambda_i'$ represent the long run coefficients associated with financialization and the control variables, while $\phi_i$ denotes the speed of adjustment towards the long run equilibrium following short run disturbances. A negative and statistically significant $\phi_i$ indicates the existence of a stable long run relationship, implying that any short run deviations from equilibrium are gradually corrected over time. The empirical literature generally suggests that financialization tends to reduce income inequality in the short run, as the expansion of financial access initially benefits a broader segment of the population, reflected in negative short run coefficients ($\gamma^{*'} < 0$). However, over the long run, the deepening of financialization is often associated with widening income disparities, captured by positive long run coefficients ($\theta_i' > 0$) (Kus, 2012; Stiglitz, 2012; ILO, 2013; Stockhammer, 2017; Makhlouf et al. 2020). This finding aligns with the hypothesis proposed by Makhlouf et al. (2020), which argues that in the short run the extensive margin of financial development dominates, leading to reductions in inequality, whereas in the long run the intensive margin becomes more influential, resulting in increases in inequality.

The MG estimator proposed by Pesaran and Smith (1995) allows all coefficients to vary freely across countries in both the short- and long-run relationships. This estimator provides consistent estimates when both the time dimension ($T$) and the cross-sectional dimension ($N$) of the panel are sufficiently large. However, it can be sensitive to outliers and small model variations, which may reduce its efficiency in relatively small samples (Samargandi et al., 2015). In contrast, the DFE estimator imposes homogeneity on the speed of adjustment, slope coefficients, and short-run dynamics across countries. This assumption implies that all countries respond identically to shocks in both the short and long run. While this restriction simplifies estimation, it may be unrealistic in the context of heterogeneous economies, as it overlooks potential differences in adjustment processes. Moreover, the DFE estimator can be susceptible to simultaneity bias in small samples due to the potential endogeneity between the disturbance term and lagged regressors (Baltagi et al., 2000). Finally, the PMG estimator, developed by Pesaran, Shin, and Smith (1999), offers a middle ground between the MG and DFE approaches. It constrains the long-run coefficients to be homogeneous across countries while allowing the short-run coefficients, intercepts, speeds of adjustment, and error variances to differ. This flexibility enables the model to account for country-specific short-run dynamics while maintaining a common long-run equilibrium relationship. Such an assumption is particularly appropriate when countries are expected to share similar long-run structural relationship while exhibiting distinct short-run responses to internal and external shocks. As long as the homogeneity assumption holds in the long run, the PMG estimator is more efficient than the MG estimator. Furthermore, Pesaran, Shin, and Smith (1999) demonstrate that the PMG estimator yields consistent and asymptotically normal estimates regardless of whether the underlying variables are I(0) or I(1). Overall, the PMG estimator can thus be regarded as an intermediate and efficient approach between the two extremes of MG and DFE estimators.

Following the recommendations of the existing literature, this study employs the PMG and MG estimators within the panel ARDL framework and applies the Hausman test to determine the most appropriate estimator. The Hausman test examines whether the difference between the PMG and MG estimators is statistically significant. Under the null hypothesis, the PMG estimator is both efficient and consistent, implying that the difference between the two estimators is not statistically significant at the 5% level. In addition, the panel ARDL lag structure is specified as ($p = q = 1$) and selected according to the Schwarz Bayesian Criterion (SBC). This specification is consistent with prior empirical studies employing ARDL models to investigate macroeconomic relationships and it ensures a parsimonious yet robust dynamic structure for analyzing the relationship between financialization and income inequality (Li et al., 2016; Makhlouf et al., 2020).

### 2.5.4 CS-ARDL methodology

This section presents an alternative approach as opposed to standard panel ARDL estimators in order to tackle the problems of endogeneity. This approach has been proposed by Chudik and Pesaran (2015) which is based on a standard method to examine a long run relationship in panel data. Chudik and Pesaran (2015) shows that this technique not only solves the issues of endogeneity but also gives a useful tool to isolate the short run and long run effects of financialization on income inequality measures. A possible issue with the ARDL model is that the disturbance terms might have correlation which leads to inconsistency in the estimated values of long run coefficients. Chudik and Pesaran (2015) demonstrate that one solution to tackle this issue is to augment the equation (47) with cross section averages of the dependent and independent variables, as well as their lags which should account for a common unobserved factor in the disturbance term. This technique is called the cross section augmented ARDL (CS-ARDL) model. To illustrate the CS-ARDL, let's consider the panel ARDL model and its error correction representation as shown in the equations (2.38) and (2.39). If the residuals contain unobserved common factors $f_t$:

$$u_{it} = \gamma_i f_t + \epsilon_{it} \tag{2.42}$$

then augmenting the model with cross-sectional averages $\bar{z}_{t-l} = (\bar{y}_{t-l}, \bar{x}_{t-l})'$ provides a proxy for these factors.
As a result, the CS-ARDL specification extends the error-correction form by including these cross-sectional averages and their lags. This ensures that the influence of unobserved common shocks is properly captured and that the estimated long-run coefficients are not biased by cross-sectional dependence. The model can be written as:

$$\Delta y_{it} = \alpha_i + \phi(y_{i,t-1} - \psi_i x_{i,t-1}) + \sum_{j=1}^{p-1} \eta_{ij}^* \Delta y_{i,t-j} + \sum_{k=0}^{q-1} \beta_{ik}^* \Delta x_{i,t-k} + \sum_{l=0}^{s} \omega_{il} \bar{z}_{t-l} + \epsilon_{it} \tag{2.43}$$

Overall, the CS-ARDL approach proposed by Chudik and Pesaran (2015) provides a robust and flexible framework for estimating long-run relationships in dynamic panel data models while addressing key econometric challenges such as endogeneity, cross-sectional dependence, and unobserved common factors. By augmenting traditional ARDL models with cross-sectional averages of both dependent and independent variables, the CS-ARDL estimator mitigates biases arising from omitted variables and correlated disturbances. Moreover, its error correction representation enables a clear distinction between short-run dynamics and long-run equilibrium effects. Given these advantages, the CS-ARDL model offers a valuable alternative to standard panel ARDL estimators.

### 2.5.5 Dynamic Ordinary Least Squares

This study employs the Dynamic Ordinary Least Squares (DOLS) estimator as a robustness check. Originally developed by Stock and Watson (1993) for time-series analysis and later extended to panel data by Kao and Chiang (2000), the DOLS is widely recognized for its efficiency and reliability in estimating cointegrating relationships. Wagner and Hlouskova (2010) further show that the estimator performs well in panel settings in the presence of cross-sectional dependence and endogeneity and often outperforms alternative methods for estimating long-run coefficients. The DOLS can be expressed as follows:

$$y_{it} = \delta_i' d_t + \varphi_i' x_{it} + \gamma_i' z_{it} + \sum_{j=-k_i}^{k_i} \psi_{ij}' \Delta x_{i,t-j} + \sum_{j=-k_i}^{k_i} \omega_{ij}' \Delta z_{i,t-j} + e_{it}, \quad (2.44)$$

where $d_t$ denotes deterministic components such as fixed effects or time trends. The paramaters $\varphi_i$ and $\gamma_i$ capture the long-run coefficients associated with the main explanatory variables and the control variables, respectively. The vectors $\psi$ and $\omega$ contain the coefficients on the leads and lags of the first differences of the regressors, which serve to correct for possible endogeneity and serial correlation. Allowing the number of leads and lags ($k_i$) to vary across units introduces flexibility and accommodates heterogeneity in short-run dynamics. When a valid cointegrating relationship exists, the panel DOLS estimator is $\sqrt{N}$-consistent and asymptotically normal. This means that the estimate of the average long-run effect $\varphi_i$ converges to its true value at a rate proportional to the square root of the number of cross-sectional units, $N$.

## 2.6 Empirical results and discussion

This section presents the empirical results of the panel unit root, panel cointegration and panel ARDL tests conducted to examine the relationship between income inequality and financialization across 20 advanced OECD countries. The analysis also includes the results of the CS-ARDL estimation, which accounts for potential cross sectional dependence and induced feedback effects among the variables, thereby improving the reliability and validity of the empirical findings. To address potential multicollinearity among the financialization indicators, each financialization variable is examined separately in relation to the income inequality measures and the relevant control variables within the ARDL framework. In addition, the panel DOLS estimator is employed as a robustness check to confirm the existence and stability of the long run relationship between financialization and income inequality, ensuring that the results are consistent across alternative estimation techniques.

Table 2.1: Descriptive statistics

| Variables | Obs. | Mean | Std. dev. | Min. | Max. |
|---|---|---|---|---|---|
| Gini | 800 | 36.86 | 3.58 | 27.77 | 45.51 |
| Top 1% income share | 800 | 0.10 | 0.026 | 0.03 | 0.19 |
| Top 10% income share | 800 | 0.33 | 0.04 | 0.22 | 0.45 |
| Labour share of income | 800 | 63.28 | 5.02 | 36.52 | 75.86 |
| Financial development | 800 | 0.60 | 0.19 | 0.06 | 0.95 |
| Financial liberalization | 700 | 0.77 | 0.22 | 0.09 | 1.00 |
| Financial globalization | 800 | 3.90 | 5.46 | 0.27 | 40.28 |
| Labour market institutions | 800 | 36.91 | 20.30 | 9.91 | 86.62 |
| Technological progress | 702 | 1.84 | 0.79 | 0.15 | 3.87 |
| Globalization | 800 | 68.26 | 35.59 | 15.81 | 252.33 |
| Real GDP growth | 800 | 2.22 | 2.41 | -10.15 | 25.17 |
| Education | 800 | 54.63 | 23.35 | 11.41 | 148.53 |

Table 2.1 reports descriptive statistics for 20 advanced OECD countries over the period 1980–2019. The income inequality indicators are measured as continuous variables with different bounds. The Gini index is a bounded measure reported on a 0–100 scale. The top 1% and top 10% income shares are continuous variables bounded between 0 and 1, representing the proportion of total national income accruing to the respective top income groups. The labour share of income is a continuous percentage variable reflecting the share of GDP accruing to labour.

Financialization is measured using several continuous indicators. The financial development index is a normalized composite index bounded between 0 and 1, capturing the depth, access, and efficiency of financial institutions and markets. The financial liberalization index is also continuous and normalized between 0 and 1, aggregating multiple dimensions of financial reform into a graded measure rather than a set of discrete or binary indicators. Financial globalization is measured as foreign assets plus foreign liabilities relative to GDP and is a continuous, unbounded variable that can exceed 100% of GDP. Labour market institutions are proxied by trade union density, defined as the percentage of employees who are union members. Technological progress is measured by research and development expenditure as a share of GDP whereas trade globalization is proxied by trade openness, defined as exports plus imports as a share of GDP, expressed in percentage terms. Real GDP growth is measured as the annual percentage change in real output. Finally, education is captured by the gross enrollment rate, a continuous percentage variable that may exceed 100% due to the inclusion of over-aged or under-aged students. Overall, the dataset consists of continuous variables with varying degrees of normalization and boundedness, which is taken into account in the econometric analysis.

### 2.6.1 Panel unit root test

A variety of panel unit root tests have been developed in the empirical literature to assess the stationarity properties of panel data, including those by Maddala and Wu (1999), Breitung (2000), Hadri (2000), Levin, Lin, and Chu (2002), and Im, Pesaran, and Shin (2003). As discussed above, while these first-generation tests are widely applied, they are based on the assumption of cross-sectional independence, which may not always hold in macroeconomic panels where interdependencies across countries are common. Ignoring cross-sectional dependence can lead to biased inferences regarding the underlying integration properties of the series.

Table 2.2: Panel unit root tests

| | **Levin, Lin and Chu** | | **Breitung t-test** | | **Im, Pesaran and Shin** | |
|---|---|---|---|---|---|---|
| | I(0) | I(1) | I(0) | I(1) | I(0) | I(1) |
| GINI | -3.21 | -24.5*** | -2.31 | -16.3*** | -3.89 | -23.6*** |
| LSI | -2.53 | -20.2*** | -0.25 | -14.1*** | -2.69 | -19.4*** |
| Top 1% | -2.13 | -19.3** | -4.14 | -13.9*** | -1.63 | -20.6** |
| Top 10% | -1.16 | -18.55*** | -2.54 | -12.92*** | -1.33 | -20.37*** |
| FD | 2.20 | -21.1*** | 3.97 | -17.5*** | 5.27 | -21.4*** |
| FG | 114.52 | 30.93*** | -1.22 | -4.95*** | -3.96 | -15.09*** |
| FL | 0.70 | -9.10*** | 1.57 | -7.13*** | -0.42 | -13.14*** |
| RGDPG | -11.11*** | -25.42 | -9.26*** | -17.10 | -10.56*** | -26.32 |
| EDU | 2.39 | -8.01*** | 2.95 | -5.31*** | 3.11 | -44.43*** |
| LMI | -2.47*** | -14.9 | -1.97*** | -11.7 | -1.27** | -12.9 |
| GLOB | -4.56*** | -23.97 | -2.52*** | -15.9 | -1.79** | -20.6 |
| TECH | 2.23 | -16.4*** | 3.48 | -6.75*** | 5.63 | -14.4*** |

Panel unit root tests were performed with individual trends and intercepts for each series. *, **, *** represent statistical significance at 10%, 5% and 1% respectively.

Table 2.3: Panel unit root tests

| | **Levin, Lin and Chu** | | **Breitung t-test** | | **Im, Pesaran and Shin** | |
|---|---|---|---|---|---|---|
| | I(0) | I(1) | I(0) | I(1) | I(0) | I(1) |
| GINI | -2.31 | -26.69*** | | | -0.34 | -25.51*** |
| LSI | -3.95 | -22.41*** | | | -2.19 | -20.32*** |
| Top 1% | -3.790 | -22.82*** | | | -2.64 | -23.33*** |
| Top 10% | -3.23 | -22.54*** | | | -1.25 | -22.99*** |
| FD | -7.31 | -21.62*** | | | -2.50 | -21.29*** |
| FG | 58.04 | 28.68*** | | | -7.33 | -12.98*** |
| FL | -5.74 | -11.37*** | | | -4.57 | -13.31*** |
| RGDPG | -13.19*** | -28.06 | | | -13.19*** | -28.44 |
| EDU | -0.65 | -8.24*** | | | 4.89 | -7.63*** |
| LMI | -6.85*** | -14.66 | | | -1.49*** | -14.14 |
| GLOB | 0.81*** | -25.34 | | | 3.37*** | -22.19 |
| TECH | -6.81 | -16.61*** | | | -0.12 | -14.45*** |

Panel unit root tests were performed without trend for each series. *, **, *** represent statistical significance at 10%, 5% and 1% respectively.

To address this concern, the analysis also employs Pesaran's (2007) second-generation CIPS test, which explicitly accounts for cross-sectional dependence. The results from these tests are reported and discussed below. The results of the Levin, Lin and Chu (2002), Breitung (2000) and Im, Pesaran and Shin (2003) panel unit root tests for the variables of interest are reported in Table 2.2 and Table 2.3. The panel unit root tests in Table 2.2 include individual constants and time trends following the empirical evidence (Klein, 2015; Makhlouf et al., 2020; etc.). As can be seen from the Table 2.2, the test results are provided at the level as well as the first difference against each variable. Table 2.1 shows that the variables of interest have both stationary and non-stationary characteristics. The test statistics for Gini index, top 1% income share, labour share of income, financial development index, financial globalization, financial liberalization, education and technological progress contain unit root at level. When the first differences are applied based on the panel unit root tests of Levin et al.,(2002), Breitung (2000) and Pesaran et al., (2003), the null hypothesis of unit root is rejected for all of these variables at 1% significance level. However, the test statistics for the real GDP growth rate, labour market institutions and globalization are significant implying that each of these variables are stationary at level. Overall, the panel unit root tests generate mixed results as the variables considered contain both stationary and non stationary characteristics at level.

The panel unit root tests without trend are reported in Table 2.3 to indicate whether the stationary results of the variables considered remain unchanged. As can be seen from the Table 2.3, Levin, Lin and Chu (2002), Breitung (2000) and Im, Pesaran and Shin (2003) test once again confirm that all the variables except for the real GDP growth rate, labour market institutions, and trade globalization contain unit root at level. Thus, the panel unit test results do not change for the variables of interest even after excluding the trend.

Table 2.4: Pesaran's CIPS test results

| | CIPS Statistics | 10% CV | 5% CV | 1% CV | Order of Integration |
|---|---|---|---|---|---|
| GINI | –1.440 | –2.110 | –2.200 | –2.360 | I(1) |
| LSI | -1.969 | -2.110 | -2.200 | -2.360 | I(1) |
| Top 1% | -1.863 | -2.110 | -2.200 | -2.360 | I(1) |
| Top 10% | -2.026 | -2.110 | -2.200 | -2.360 | I(1) |
| FD | -1.981 | -2.110 | -2.200 | -2.360 | I(1) |
| FG | -2.017 | -2.110 | -2.200 | -2.360 | I(1) |
| FL | -1.913 | -2.110 | -2.200 | -2.360 | I(1) |
| RGDPG | -3.771 | -2.110 | -2.200 | -2.360 | I(0) |
| EDU | -1.563 | -2.110 | -2.200 | -2.360 | I(1) |
| LMI | -2.729 | -2.110 | -2.200 | -2.360 | I(0) |
| GLOB | -3.247 | -2.110 | -2.200 | -2.360 | I(0) |
| TECH | -2.873 | -2.110 | -2.200 | -2.360 | I(1) |

Finally, the results of the Pesaran's (2007) Cross-Sectionally Augmented IPS (CIPS) panel unit root test, presented in Table 2.4 also indicate that all the variables under investigation are non-stationary in levels, with the exception of the real GDP growth rate, globalization and labour market institutions, which are found to be stationary. These findings suggest that the variables of interest in the dataset follow an integrated process of order one, I(1), and thus require first differencing to achieve stationarity. Establishing that the variables under consideration are integrated order of one, I(1) is an essential prerequisite for conducting panel cointegration test in the subsequent section. Importantly, the CIPS test results are consistent with those obtained from the first-generation panel unit root tests, including Breitung (2000), Levin et al. (2002), and Im et al. (2003). Overall, the confirmation of non-stationarity in levels for the variables of interest validates the application of panel cointegration and panel ARDL techniques used in later parts of this study.

### 2.6.2 Panel cointegration tests

To examine the existence of a long-run equilibrium relationship between income inequality and financialization variables, the Fisher (1999), Kao (1999), and Pedroni (1999, 2004) tests were applied and their results are reported in Table 2.5. The Fisher–Johansen results indicate strong evidence of cointegration,

Table 2.5: Panel coingteration tests

| | **Test statistic** | **P-value** |
|---|---|---|
| **Johansen Fischer test** | | |
| Fischer statistics from trace test | 80.79 | 0.000 |
| Fischer statistics from max-Eigen value test | 64.05 | 0.000 |
| **Kao test** | | |
| ADF t-statistic | -0.922 | 0.018 |
| **Pedroni test** | | |
| Panel v-statistic | 1.636 | 0.061 |
| Panel rho-statistic | -2.491 | 0.006 |
| Panel PP-statistic | -4.321 | 0.000 |
| Panel ADF-statistic | -4.728 | 0.000 |
| Group rho-statistic | -1.731 | 0.042 |
| Group PP-statistic | -4.819 | 0.000 |
| Group ADF-statistic | -5.128 | 0.000 |

with both the trace and maximum eigenvalue statistics being highly significant suggesting that the null hypothesis of no cointegration can be rejected for the panel as a whole. Similarly, the Kao (1999) test also rejects the hypothesis of no cointegration at the 5% level, providing support for a stable long-run association between the Gini index and the financialization variables. Furthermore, the Pedroni cointegration test shows that six out of the seven test statistics accept the alternative hypothesis of long run relationship between the Gini index and the financialization variables. However, the hypothesis of no cointegration between the variables under consideration can only be accepted for the panel v-statistics where the corresponding p-value is still below 10% significance threshold. Taken together, the convergence of evidence across all three cointegration approaches confirms the presence of a long-run equilibrium relationship between income inequality and the financial development index, financial liberalization, financial globalization. This outcome provides a robust justification for the application of panel ARDL estimators discussed in the next section.

To further verify the existence of a long-run equilibrium between income inequality and financialization variables, the Westerlund (2007) error-correction-based panel cointegration test was also employed and its results are reported in Table 2.6. The Westerlund results indicate that both the group-mean $G_t$ statistic (p = 0.013) and the panel-mean $P_t$ statistic (p = 0.038) reject the null hypothesis of no cointegration at the 5 % significance level, suggesting that at least some individual countries, as well as the panel as a whole, exhibit a stable long-run relationship between the Gini index and the financialization variables.

Table 2.6: Westerlund test statistics

| Statistic | Value | Z-value | P-value |
|---|---|---|---|
| $G_t$ | -2.769 | -2.217 | 0.013 |
| $G_a$ | -11.948 | 0.042 | 0.052 |
| $P_t$ | -10.997 | -1.772 | 0.038 |
| $P_a$ | -9.411 | -0.349 | 0.036 |

The remaining statistics, $G_a$ and $P_a$, display p-values of 0.052 and 0.036, respectively; while $P_a$ is significant at the 5% level, $G_a$ is marginally insignificant, which may reflect heterogeneity in the adjustment dynamics across countries rather than a genuine absence of cointegration. Given that the t-type statistics ($G_t$ and $P_t$) are generally considered more reliable indicators in the presence of cross-sectional dependence, the results provide strong overall evidence in favour of cointegration. Overall, these findings reinforce the evidence of a long-run equilibrium between income inequality and the financialization indicators, thereby further supporting the use of the panel ARDL estimations in the following section.

### 2.6.3 Panel ARDL estimation results

The panel ARDL approach is employed in this study to examine the relationship between income inequality and financialization variables across 20 advanced OECD countries over the period 1980–2019. This method is particularly advantageous as it remains valid regardless of whether the underlying series are integrated of order zero, one, or a combination of both (Pesaran and Shin, 1998). Table 2.7 indicates the results of PMG, MG and DFE estimators based on the panel ARDL specification. The upper part of the table shows the long run coefficients whereas the lower part indicates the short run coefficients. The Hausman test is used to determine whether the PMG method is significantly different from the MG estimator. The p-value of 0.89 shows that the null hypothesis can not be rejected even at 1% significance level, suggesting the PMG estimator is the more efficient and consistent choice. The error-correction term, $\phi$ is negative and highly significant across all specifications, confirming the existence of a long-run equilibrium relationship between income inequality and financialization measures. The magnitude and significance of this coefficient imply that deviations from the long-run equilibrium are corrected over time, supporting the presence of cointegration among the variables. Furthermore, the negative and significant adjustment term also confirms that financial development, financial globalization, and financial liberalization, together with the control variables, jointly Granger-cause the Gini index in the long run. The long-run coefficients reported under the PMG, MG, and DFE estimators show that financialization variables exert statistically significant and theoretically consistent effects on income inequality. These findings are broadly aligned with the growing empirical literature, which suggests that financialization contributes to widening income disparities in advanced economies (Kus, 2012; ILO, 2013; Dünhaupt, 2014; Stockhammer, 2017; Makhlouf et al., 2020).

In contrast, the short-run results reveal that the coefficients of financial globalization and financial liberalization are not statistically significant with respect to the Gini index, while financial development remains significant. This indicates that in the short run, financial development helps to reduce income inequality, possibly by improving access to credit and financial services for a broader segment of the population. The control variables, however, do not exhibit statistical significance in the short-run dynamics, suggesting that their effects on inequality materialize primarily over longer horizons.

The opposing short- and long-run effects of financialization can be explained by the different mechanisms that dominate at various stages of financial sector evolution. Initially, financialization may alleviate income inequality by expanding access to financial resources and relaxing credit constraints, thereby benefiting lower- and middle-income households. Over time, however, the nature of financialization changes. As financial markets deepen and become more complex, the benefits increasingly accrue to wealthier individuals and firms who possess greater financial information, knowledge and access to sophisticated instruments. Makhlouf et al. (2020) conceptualize this dynamic through the extensive and intensive margins of financialization. In the short run, the extensive margin dominates by representing the expansion of financial services to previously underserved or excluded populations.

Table 2.7: ARDL estimation results for Income Inequality and Financialization

| | **PMG** | **MG** | **DFE** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FD_{it-1}$ | 0.048*** | 0.016** | 0.052*** |
| | (0.016) | (0.012) | (0.061) |
| $FG_{it-1}$ | 0.019*** | 0.018* | 0.024** |
| | (0.053) | (0.009) | (0.017) |
| $FL_{it-1}$ | 0.042*** | 0.014** | 0.021*** |
| | (0.064) | (0.011) | (0.016) |
| $RGDPG_{it-1}$ | -0.241*** | -0.012* | -0.219** |
| | (0.033) | (0.035) | (0.105) |
| $EDU_{it-1}$ | -0.041** | -0.053** | -0.032* |
| | (0.032) | (0.026) | (0.017) |
| $TECH_{it-1}$ | 0.167*** | 0.123*** | 0.064* |
| | (0.019) | (0.071) | (0.037) |
| $GLOB_{it-1}$ | 0.026** | 0.022* | 0.067* |
| | (0.010) | (0.037) | (0.021) |
| $LMI_{it-1}$ | -0.074*** | -0.034*** | -0.048** |
| | (0.017) | (0.104) | (0.032) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.366*** | -1.113*** | -0.206*** |
| | (0.079) | (0.101) | (0.029) |
| $\Delta FD_{it}$ | -0.004*** | -0.017** | 0.003** |
| | (0.089) | (0.003) | (0.008) |
| $\Delta FG_{it}$ | 0.015 | 0.027 | 0.001 |
| | (0.012) | (0.012) | (0.004) |
| $\Delta FL_{it}$ | -0.005* | 0.002 | 0.006 |
| | (0.069) | (0.007) | (0.002) |
| $\Delta EDU_{it}$ | 0.028 | 0.031 | 0.017 |
| | (0.013) | (0.027) | (0.014) |
| $\Delta RGDPG_{it}$ | 0.034 | 0.003 | 0.019 |
| | (0.018) | (0.036) | (0.018) |
| $\Delta TECH_{it}$ | -0.065 | -0.051 | -0.081 |
| | (0.066) | (0.091) | (0.051) |
| $\Delta GLOB_{it}$ | -0.025 | -0.038 | -0.018 |
| | (0.017) | (0.030) | (0.008) |
| $\Delta LMI_{it}$ | -0.034 | -0.251 | -0.021 |
| | (0.077) | (0.226) | (0.028) |
| Constant | -0.089*** | -0.345*** | -0.075*** |
| | (0.043) | (0.079) | (0.016) |
| *Hausman test* | 1.55 | | |
| *P-value* | 0.89 | | |

*Notes:* standard errors are presented in parantheses. The income inequality denotes Gini index. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). PMG is more efficient estimation than MG under the null hypothesis. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

In the long run, the intensive margin prevails, characterized by the deepening of financial markets and the proliferation of complex instruments that primarily benefit affluent groups. This shift from inclusivity to exclusivity has been noted by Stiglitz (2012), who argues that while the initial phases of financialization may promote inclusive growth, over time the process becomes increasingly regressive. The rich, who are better positioned to navigate and capitalize on complex financial systems, gain disproportionate advantages, whereas the poor and middle class are left behind, reinforcing structural inequalities.

Turning to the control variables, it is important to note that most of them are statistically insignificant in the short run despite displaying their expected signs. This outcome is consistent with the notion that structural and institutional factors such as technological progress, labour market institutions, and globalization affect income distribution primarily through long-term mechanisms rather than short-term fluctuations. It is well documented in the current body of literature that technological progress, labour market institutions and globalization are regarded as the main causes behind growing income inequality. These variables are therefore incorporated in the ARDL estimation to control for their influence when examining the relationship between financialization and income inequality. The PMG, MG and DFE estimator results show that in the long run, the technological progress, labour market institutions and globalization are highly statistically significant whereas in the short run these variables are statistically insignificant in relation to income inequality. As expected, technological progress and globalization are positively associated with the Gini index while the labour market institutions are negatively related with the Gini index. In this regard, technological progress can widen inequality by increasing the skill premium which in turn raises the wage gap between skilled and unskilled labour (Jerzmanowski and Nabar, 2013). Similarly, the positive long-run effect of globalization on income inequality aligns with the evidence presented in previous studies, as greater trade and market integration often favour high-skilled and capital-intensive sectors (Strauss-Khan, 2004; OECD, 2011). Conversely, the weakening of labour market institutions contributes to rising wage inequality by influencing the terms of bargaining power between workers and firms (Giavazzi, 2003). The results also indicate that education is statistically significant and, as expected, negatively associated with income inequality in the long run. This finding suggests that higher educational attainment contributes to reducing inequality by enhancing financial literacy and enabling individuals to make more informed and effective use of financial services (Lusardi and Mitchell, 2014; Gill and Prowse, 2015). Real GDP growth also exhibits a statistically significant and negative effect on income inequality in the long run, implying that sustained economic growth can reduce disparities by generating employment opportunities and increasing income levels across a broader segment of the population.

Overall, the panel ARDL estimation results provide strong evidence that financialization exerts a positive and statistically significant impact on income inequality, indicating that financialization contributes to rising income inequality in the long run. In other words, the results from the PMG, MG, and DFE estimators consistently support the hypothesis that financialization is an important long-run determinant of inequality among advanced OECD countries. Although financialization may yield short-term distributional benefits by expanding access to credit and financial opportunities, its long-term effects appear to be inequality-enhancing as financial gains become increasingly concentrated among wealthier segments of the population. The robustness of these findings is further confirmed by the statistically significant and negative error correction terms across all specifications, which validate the presence of a stable long-run equilibrium relationship between financialization and income inequality, as reported in Table 2.7. Taken together, these findings substantiate the hypothesis that financialization represents a significant driver of rising income inequality in advanced OECD countries, consistent with the expanding body of literature (Onaran, 2011; ILO, 2013; Shin and Lee, 2018; Makhlouf et al., 2020).

Although the Gini index remains the primary measure of income inequality widely used in previous studies, this study also employs alternative inequality indicators to test the robustness of the relationship between financialization and income inequality. Specifically, the top 1% income share, the top 10% income share, and the labour share of income are used as alternative dependent variables to assess whether the relationship remains consistent across different measures of inequality. Table 2.8 presents the panel ARDL estimation results where the labour share of income serves as the measure of income inequality. The negative and statistically significant error correction coefficients across all estimators indicate that the null hypothesis of no long-run relationship can be rejected, confirming the existence of a stable long-run equilibrium between financialization and the labour share of income. The Hausman test p-value indicates that the null hypothesis cannot be rejected even at the 1% significance level, implying that the PMG estimator is both consistent and more efficient than the MG estimator.

Table 2.8: ARDL estimation results for Labour Share of Income and Financialization

| | **PMG** | **MG** | **DFE** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FD_{it-1}$ | -0.091*** | -0.334* | -0.094** |
| | (0.072) | (0.094) | (0.071) |
| $FG_{it-1}$ | -0.052*** | -0.036* | -0.049** |
| | (0.021) | (0.058) | (0.063) |
| $FL_{it-1}$ | -0.029*** | -0.179** | -0.129*** |
| | (0.038) | (0.073) | 0.096 |
| $RGDPG_{it-1}$ | 0.234*** | 0.171 | 0.918** |
| | (0.062) | (0.027) | (0.221) |
| $EDU_{it-1}$ | 0.042* | 0.028* | 0.038* |
| | (0.023) | (0.012) | (0.018) |
| $TECH_{it-1}$ | -0.410*** | -0.126* | -0.393** |
| | (0.086) | (0.034) | (0.086) |
| $GLOB_{it-1}$ | -0.032* | -0.301* | -0.008** |
| | (0.022) | (0.029) | (0.047) |
| $LMI_{it-1}$ | 0.119** | 1.291* | 0.011** |
| | (0.019) | (0.025) | (0.072) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.205*** | -0.726*** | -0.169*** |
| | (0.073) | (0.097) | (0.025) |
| $\Delta FD_{it}$ | 0.051 | 0.022 | 0.012 |
| | (0.008) | (0.088) | (0.046) |
| $\Delta FD_{it}$ | 0.041 | 0.022 | -0.001 |
| | (0.003) | (0.059) | (0.089) |
| $\Delta FL_{it}$ | 0.038** | 0.027 | 0.007* |
| | (0.025) | (0.021) | (0.021) |
| $\Delta EDU_{it}$ | 0.013 | 0.011 | 0.012 |
| | (0.002) | (0.001) | (0.004) |
| $\Delta RGDPG_{it}$ | -0.169* | -0.149*** | -0.193* |
| | (0.041) | (0.056) | (0.032) |
| $\Delta TECH_{it}$ | 0.297 | 0.352 | 0.292 |
| | (0.02) | (0.027) | (0.091) |
| $\Delta GLOB_{it}$ | 0.027 | 0.008 | 0.076 |
| | (0.041) | (0.045) | (0.015) |
| $\Delta LMI_{it}$ | 0.043 | 0.211 | 0.079 |
| | (0.011) | (0.025) | (0.051) |
| Constant | -0.159*** | -0.581*** | -0.143*** |
| | 0.064 | 0.017 | (0.019) |
| *Hausman test* | 1.64 | | |
| *P-value* | 0.54 | | |
| *Observations* | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

The estimated coefficients for financialization variables display the expected signs and are statistically significant in the long run across all specifications. The results reveal that financial development, financial globalization, and financial liberalization are all negatively associated with the labour share of income in the long run. This suggests that increased financialization leads to a declining share of income accruing to labour. The negative and significant error correction term further confirms that financialization variables, together with the control variables, jointly Granger-cause the labour share of income in the long run.

In contrast, the short-run results show that financialization variables are not statistically significant, although they maintain their expected signs. This finding implies that while financialization influences income distribution primarily through long-term structural mechanisms, its short-term effects on the labour share are limited. Similarly, the control variables including education, globalization, technological progress, and labour market institutions exhibit the expected signs but are statistically insignificant in the short run. The only exception is real GDP growth, which is statistically significant and negatively associated with the labour share of income in the short run.

Table 2.9 presents the panel ARDL estimation results using the top 1% income share as an alternative measure of income inequality. The negative and statistically significant error correction coefficient confirms that the null hypothesis of no long-run relationship can be rejected, indicating the presence of a stable long-run equilibrium between financialization variables and the top 1% income share. The estimated long-run coefficients for financialization variables exhibit the expected positive signs and remain statistically significant, consistent with the results reported in Table 2.7. Specifically, the financial development index, financial globalization, and financial liberalization are all positively associated with the top 1% income share, suggesting that higher levels of financialization disproportionately benefit top income earners and thereby contribute to widening income disparities. The control variables are also statistically significant and display the expected signs in relation to income inequality. In line with the existing literature, technological progress and globalization are positively related to the top 1% income share, while labour market institutions exert a statistically significant negative effect, implying that stronger labour market institutions help to mitigate income concentration at the top (Jerzmanowski and Nabar, 2013; Strauss-Khan, 2004; OECD, 2011; Giavazzi, 2003).

Table 2.9: ARDL estimation results for Top 1% Income Share and Financialization

| | **PMG** | **MG** | **DFE** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FD_{it-1}$ | 0.045*** | 0.035* | 0.041*** |
| | (0.012) | (0.028) | (0.021) |
| $FG_{it-1}$ | 0.004* | 0.029** | 0.006* |
| | (0.009) | (0.029) | (0.012) |
| $FL_{it-1}$ | 0.014*** | 0.083* | 0.019** |
| | (0.011) | (0.039) | (0.017) |
| $RGDPG_{it-1}$ | -0.076* | -0.037** | -0.016* |
| | (0.004) | (0.005) | (0.009) |
| $EDU_{it-1}$ | -0.023* | -0.065* | 0.037** |
| | (0.012) | (0.024) | (0.015) |
| $TECH_{it-1}$ | 0.093* | 0.017** | 0.051* |
| | (0.002) | (0.001) | (0.003) |
| $GLOB_{it-1}$ | 0.135* | 0.019 | 0.003* |
| | (0.001) | (0.005) | (0.002) |
| $LMI_{it-1}$ | -0.045*** | -0.064** | -0.093** |
| | (0.005) | (0.001) | (0.003) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.246*** | -0.964*** | -0.204*** |
| | (0.068) | (0.109) | (0.028) |
| $\Delta FD_{it}$ | -0.021* | -0.001* | -0.023 |
| | (0.015) | (0.021) | (0.008) |
| $\Delta FG_{it}$ | 0.002 | 0.014 | -0.002 |
| | (0.013) | (0.026) | (0.005) |
| $\Delta FL_{it}$ | 0.013* | 0.027 | 0.002* |
| | (0.007) | (0.028) | (0.006) |
| $\Delta EDU_{it}$ | -0.012 | -0.011 | -0.023 |
| | (0.009) | (0.012) | (0.018) |
| $\Delta RGDPG_{it}$ | 0.059** | 0.051* | 0.079* |
| | (0.002) | (0.002) | (0.002) |
| $\Delta TECH_{it}$ | -0.071 | -0.219 | -0.021 |
| | (0.007) | (0.002) | 0.051 |
| $\Delta GLOB_{it}$ | -0.021 | -0.022 | -0.004 |
| | (0.001) | (0.029) | (0.008) |
| $\Delta LMI_{it}$ | -0.083 | -0.195 | -0.018 |
| | (0.005) | (0.018) | (0.003) |
| Constant | 0.003*** | 0.011*** | -0.021*** |
| | (0.003) | (0.081) | (0.006) |
| *Hausman test* | 2.33 | | |
| *P-value* | 0.26 | | |
| *Observations* | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

In the short run, the effects are comparatively weaker. While the coefficients for financial development and financial globalization have the expected positive signs, they are not statistically significant. Only financial liberalization exhibits a significant positive impact on the top 1% income share, suggesting that short-term liberalization shocks tend to amplify top-end income gains. Among the control variables, real GDP growth is the only factor that is statistically significant and positively associated with the top 1% income share, whereas the others remain insignificant.

Table 2.10 presents the ARDL estimation results using the top 10% income share as the measure of income inequality. The negative and statistically significant error correction coefficient indicates the rejection of the null hypothesis of no long-run relationship, confirming that financialization variables, together with the control variables, jointly Granger-cause the top 10% income share over the long term. The long-run coefficients show that financial development, financial globalization, and financial liberalization have the expected positive signs and exert statistically significant effects on the top 10% income share, suggesting that financialization continues to reinforce top-end income concentration. Likewise, the control variables are statistically significant and maintain their expected signs in the long run. In contrast, the short-run coefficients indicate that financial globalization and most control variables are not statistically significant despite their anticipated directions. Overall, the PMG, MG, and DFE estimators consistently confirm the existence of a stable long-run causal relationship between financialization and income inequality.

To address potential multicollinearity among the financial development index, financial liberalization, and financial globalization, each financialization variable is examined separately alongside the control variables using the PMG estimator. Table 2.11 reports the corresponding estimation results. Across all regressions, the error correction term remains negative and statistically significant, reaffirming the existence of a long-run equilibrium relationship between financialization variables and income inequality. The long-run coefficients further reveal that financial development, financial liberalization, and financial globalization each exert a positive and statistically significant effect on the Gini index. This finding implies that, over the long term, all dimensions of financialization contribute to widening income inequality among advanced OECD countries. Overall, the robustness of the panel ARDL estimates is confirmed, as the positive long-run association between financialization and income inequality persists even when each financialization variable is considered independently.

Table 2.10: ARDL estimation results for Top 10% Income Share and Financialization

| | **PMG** | **MG** | **DFE** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FD_{it-1}$ | 0.037*** | 0.026** | 0.038*** |
| | (0.009) | (0.076) | (0.029) |
| $FG_{it-1}$ | 0.026* | 0.087** | 0.017* |
| | (0.007) | (0.029) | (0.016) |
| $FL_{it-1}$ | 0.047*** | 0.054** | 0.036*** |
| | (0.008) | (0.033) | (0.025) |
| $RGDPG_{it-1}$ | -0.032** | -0.071*** | -0.023* |
| | (0.003) | (0.013) | (0.013) |
| $EDU_{it-1}$ | -0.023** | -0.012* | -0.014** |
| | (0.002) | (0.002) | (0.003) |
| $TECH_{it-1}$ | 0.025** | 0.026* | 0.011* |
| | (0.001) | (0.028) | (0.005) |
| $GLOB_{it-1}$ | 0.021** | 0.027** | 0.019* |
| | (0.006) | (0.005) | (0.003) |
| $LMI_{it-1}$ | -0.027*** | -0.022** | -0.017** |
| | (0.007) | (0.002) | (0.004) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.345*** | -0.298*** | -0.186*** |
| | (0.105) | (0.106) | (0.028) |
| $\Delta FD_{it}$ | -0.016** | -0.022* | -0.026 |
| | (0.015) | (0.026) | (0.011) |
| $\Delta FG_{it}$ | 0.020 | 0.033 | 0.008 |
| | (0.011) | (0.022) | (0.006) |
| $\Delta FL_{it}$ | 0.007* | 0.002* | 0.002 |
| | (0.006) | (0.021) | (0.008) |
| $\Delta EDU_{it}$ | -0.012 | -0.016 | -0.018 |
| | (0.001) | (0.002) | (0.007) |
| $\Delta RGDPG_{it}$ | 0.008 | 0.005 | 0.007 |
| | (0.002) | (0.004) | (0.002) |
| $\Delta TECH_{it}$ | -0.011 | -0.007 | -0.002 |
| | (0.009) | (0.017) | (0.006) |
| $\Delta GLOB_{it}$ | -0.002 | -0.012 | -0.007 |
| | (0.005) | (0.003) | (0.001) |
| $\Delta LMI_{it}$ | -0.011 | -0.017 | -0.005 |
| | (0.006) | (0.016) | (0.004)) |
| Constant | -0.147*** | -0.336*** | -0.065*** |
| | (0.045) | (0.010) | (0.011) |
| *Hausman test* | 2.72 | | |
| *P-value* | 0.34 | | |
| *Observations* | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Table 2.11: PMG sensitivity analysis

| | **FD** | **FL** | **FG** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FD_{it-1}$ | 0.247*** | | |
| | (0.088) | | |
| $FL_{it-1}$ | | 0.142*** | |
| | | (0.052) | |
| $FG_{it-1}$ | | | 0.089** |
| | | | (0.047) |
| $RGDPG_{it-1}$ | -0.151*** | -0.124*** | -0.148** |
| | (0.044) | (0.037) | (0.043) |
| $EDU_{it-1}$ | -0.082*** | -0.076** | -0.068** |
| | (0.023) | (0.035) | (0.028) |
| $TECH_{it-1}$ | 0.107*** | 0.163*** | 0.106*** |
| | (0.016) | (0.024) | (0.012) |
| $GLOB_{it-1}$ | 0.299*** | 0.144** | 0.228** |
| | (0.007) | (0.014) | (0.008) |
| $LMI_{it-1}$ | -0.121** | -0.101*** | -0.048*** |
| | (0.021) | (0.021) | (0.022) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.321*** | -0.326*** | -0.342*** |
| | (0.058) | (0.069) | (0.065) |
| $\Delta FD_{it}$ | -0.012* | | |
| | (0.094) | | |
| $\Delta FL_{it}$ | | 0.039** | |
| | | (0.057) | |
| $\Delta FG_{it}$ | | | 0.005* |
| | | | (0.085) |
| $\Delta EDU_{it}$ | 0.023 | 0.013 | 0.017 |
| | (0.012) | (0.014) | (0.019) |
| $\Delta RGDPG_{it}$ | 0.017 | 0.072 | 0.011 |
| | (0.016) | (0.015) | (0.011) |
| $\Delta TECH_{it}$ | -0.038 | -0.091 | -0.029 |
| | (0.050) | (0.053) | (0.052) |
| $\Delta GLOB_{it}$ | -0.031 | 0.014 | -0.013 |
| | (0.014) | (0.013) | (0.009) |
| $\Delta LMI_{it}$ | -0.015 | -0.086 | -0.061 |
| | (0.041) | (0.087) | (0.039) |
| Constant | -0.108*** | -0.089*** | -0.106*** |
| | (0.091) | (0.088) | (0.057) |
| *Observations* | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Table 2.12 illustrates the results of employing 5-year observations. The idea behind this procedure is to remedy the potential effect of business cycle fluctuations and allow us to focus on longer term effects of financialization variables on income inequality. This method mitigates the potential effect of business cycle fluctuations including global financial crisis in 2008 and enables us to focus on longer term impact of financialization. In other words, this approach smooths out the volatility associated with business cycles, ensuring that the analysis captures the underlying structural relationship between financialization and income inequality.

Table 2.12: Financialization and Income Inequality (ARDL 5-year intervals)

| | **PMG** | **MG** | **DFE** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FD_{it-1}$ | 0.054*** | 0.037*** | 0.094** |
| | (0.009) | (0.025) | (0.049) |
| $FG_{it-1}$ | 0.017** | 0.014* | 0.013** |
| | (0.012) | (0.007) | (0.008) |
| $FL_{it-1}$ | 0.034*** | 0.028*** | 0.024*** |
| | (0.015) | (0.012) | (0.016) |
| $Controls_{it-1}$ | Yes | Yes | Yes |
| | | | |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.130*** | -0.272*** | -0.082*** |
| | (0.034) | (0.056) | (0.013) |
| $\Delta FD_{it}$ | 0.006** | 0.003* | 0.007** |
| | (0.002) | (0.004) | (0.006) |
| $\Delta FG_{it}$ | 0.008 | 0.006 | 0.009 |
| | (0.003) | (0.004) | (0.001) |
| $\Delta FL_{it}$ | 0.005* | 0.009* | 0.008 |
| | (0.046) | (0.007) | (0.002) |
| $\Delta Controls_{it}$ | Yes | Yes | Yes |
| Constant | Yes | Yes | Yes |
| *Observations* | 160 | 160 | 160 |
| *Hausman test* | 8.9 | | |
| *P-value* | 0.45 | | |

*Notes:* standard errors are presented in parantheses. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). Based on the p-value of Hausman test, PMG is more efficient than MG under the null hypothesis. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Table 2.13: CS-ARDL estimation results for Income Inequality and Financialization

| | **GINI** | **Top 10%** | **Top 1%** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FD_{it-1}$ | 0.056*** | 0.051*** | 0.040*** |
| | (0.018) | (0.013) | (0.031) |
| $FL_{it-1}$ | 0.043*** | 0.034** | 0.105*** |
| | (0.028) | (0.026) | (0.096) |
| $FG_{it-1}$ | 0.034*** | 0.014** | 0.041** |
| | (0.021) | (0.016) | (0.025) |
| $RGDPG_{it-1}$ | -0.231*** | -0.034*** | -0.021*** |
| | (0.036) | (0.012) | (0.019) |
| $EDU_{it-1}$ | -0.017*** | -0.025*** | -0.023** |
| | (0.012) | (0.015) | (0.014) |
| $TECH_{it-1}$ | 0.154*** | 0.024*** | 0.052*** |
| | (0.064) | (0.013) | (0.041) |
| $GLOB_{it-1}$ | 0.031*** | 0.006** | 0.008*** |
| | (0.022) | (0.010) | (0.012) |
| $LMI_{it-1}$ | -0.054*** | -0.027*** | -0.031*** |
| | (0.013) | (0.007) | (0.005) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.313*** | -0.254*** | -0.295*** |
| | (0.028 | (0.012) | (0.013) |
| $\Delta FD_{it}$ | -0.007** | -0.009* | -0.023* |
| | (0.021) | (0.023) | (0.019) |
| $\Delta FL_{it}$ | 0.026* | 0.047* | 0.036 |
| | (0.018) | (0.048) | (0.040) |
| $\Delta FG_{it}$ | 0.017 | 0.026 | 0.042 |
| | (0.014) | (0.031) | (0.026) |
| $\Delta RGDPG_{it}$ | 0.036* | 0.007* | 0.004 |
| | (0.023) | (0.002) | (0.003) |
| $\Delta EDU_{it}$ | 0.004 | 0.006 | 0.003 |
| | (0.002) | (0.007) | (0.008) |
| $\Delta TECH_{it}$ | 0.059 | 0.021 | 0.025 |
| | (0.022) | (0.018) | (0.013) |
| $\Delta GLOB_{it}$ | -0.031 | -0.005 | -0.007 |
| | (0.013) | (0.006) | (0.004) |
| $\Delta LMI_{it}$ | 0.025 | 0.018 | 0.024 |
| | (0.019) | (0.012) | (0.011) |
| *Observations* | 777 | 777 | 777 |

*Notes:* standard errors are presented in parantheses. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

By re-estimating the panel ARDL model with these 5-year averages, this study also strengthens the robustness of our findings, demonstrating that the observed effects are not merely due to short-term variations but reflect persistent trends. The results of the PMG estimator, the efficient estimator as suggested by the Hausman test, confirm our previous results, particularly the positive impact of financialization on income inequality in the long run. However, in the short run financialization measures have a statistically significant negative impact on income inequality which is proxied by the Gini measure. The results confirm that even after moderating the effect of business cycle fluctuations including financial crisis in 2008 by applying 5-year intervals, the financialization variables lead to higher income inequality in the long run.

Table 2.13 presents the results of CS-ARDL estimation which is intended to account for cross sectional dependence and induced feedback effects between the variables. As expected, the long run coefficients for financialization variables are statistically significant in relation to income inequality measures. In other words, financial development, financial liberalization and financial globalization have a statistically significant positive impact on income inequality meaning all the financialization variables widen income inequality in the long run. It is also important to note that the control variables have the expected signs and are statistically significant with respect to income inequality measures. However, as expected, in the short run financial development is negatively associated with income inequality whereas other financialization variables are either weakly significant or not significant despite their expected signs. The CS-ARDL estimation results suggest that the long run relationship between financialization variables and income inequality remains robust and it is in line with the ARDL results analysed above. To summarize, the panel ARDL and CS-ARDL estimations show that there is a positive long run relationship between financialization and income inequality measures. Thus, the results confirm that financialization is another important driver behind rising income inequality which is consistent with a growing body of literature (Stiglitz, 2012; Kus, 2012; ILO, 2013; Leopold, 2015; Stockhammer, 2017; Makhlouf et al., 2020; Alexiou et al., 2022).

### 2.6.4 Robustness tests

Table 2.14: DOLS estimates

| | **GINI** | **Top 1%** | **Top 10%** | **LSI** |
|---|---|---|---|---|
| Financial development | 0.042*** | 0.038*** | 0.034*** | -0.086*** |
| | (0.014) | (0.016) | (0.012) | (0.028) |
| Financial liberalization | 0.046*** | 0.018*** | 0.044*** | -0.032*** |
| | (0.016) | (0.008) | (0.016) | (0.014) |
| Financial globalization | 0.018*** | 0.006** | 0.025* | -0.054*** |
| | (0.006) | (0.004) | (0.013) | (0.020) |
| Real GDP growth | -0.264*** | -0.072* | -0.034** | 0.256*** |
| | (0.022) | (0.004) | (0.006) | (0.046) |
| Education | -0.045** | -0.018* | -0.021** | 0.044* |
| | (0.036) | (0.010) | (0.007) | (0.021) |
| Technological progress | 0.156*** | 0.087* | 0.028** | -0.432*** |
| | (0.015) | (0.004) | (0.004) | (0.076) |
| Globalization | 0.024** | 0.128* | 0.026*** | -0.034*** |
| | (0.014) | (0.012) | (0.014) | (0.018) |
| Labour market institutions | -0.082*** | -0.046*** | -0.022*** | 0.124*** |
| | (0.012) | (0.016) | (0.008) | (0.032) |

*Notes:* standard errors are presented in parenthesis. Lag and lead lengths were determined by the Schwarz Information Criterion. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Table 2.14 reports the results of the panel DOLS estimations for the coefficients of the financialization variables in relation to different measures of income inequality. All estimations include individual constants and trends. The results show that all financialization variables are statistically significant and display the expected signs across the income inequality measures. Specifically, financial development, financial liberalization and financial globalization are positively associated with the Gini index, the top 1% income share and the top 10% income share in the long run. This implies that an increase in the level of financialization is linked to a rise in income inequality over time. In contrast, financial development, financial liberalization and financial globalization are negatively related to the labour share of income, indicating that financialization tends to reduce the proportion of income accruing to labour. These results confirm the existence of a long run relationship between financialization and various measures of income inequality. Moreover, the findings are consistent with the panel ARDL results discussed earlier, providing additional evidence that the relationship between financialization and inequality remains robust across alternative estimation methods.

Table 2.15 presents the results of pooled OLS, fixed effects and random effects with cluster-robust standard errors which are used as alternative approach to estimating the panel ARDL model. These estimators are applied with cluster-robust standard errors at the country level to control for an autocorrelation and heteroscedasticity. As can be seen from the regression results, the estimated coefficients for financialization and control variables are statistically significant at conventional levels. In particular, the financial development index, financial liberalization and financial globalization have the expected signs and they are statistically significant in relation to the Gini index.

Table 2.15: Financialization and Income Inequality: Static Models

| | **OLS** | **FE** | **RE** |
|---|---|---|---|
| Financial development | 0.091*** | 0.025*** | 0.026*** |
| | (0.122) | (0.063) | (0.063) |
| Financial liberalization | 0.052*** | 0.031*** | 0.031*** |
| | (0.108) | (0.053) | (0.052) |
| Financial globalization | 0.028 | 0.029** | 0.030** |
| | (0.074) | (0.036) | (0.037) |
| Real GDP growth | -0.074* | -0.073*** | -0.076*** |
| | ((0.062) | (0.025) | (0.025) |
| Education | -0.035* | -0.024** | -0.028** |
| | (0.014) | (0.011) | (0.011) |
| Technological progress | -0.003 | 0.083*** | 0.079*** |
| | (0.012) | (0.012) | (0.012) |
| Labour market institutions | -0.096 | -0.028*** | -0.033*** |
| | (0.007) | (0.010) | (0.010) |
| Globalization | -0.003 | 0.043** | 0.042** |
| | (0.005) | (0.007) | (0.006) |
| Constant | 0.402*** | 0.353*** | 0.357*** |
| | (0.611) | (0.756) | (0.986) |
| *Observations* | 800 | 800 | 800 |
| *R-squared* | 0.409 | 0.921 | 0.847 |

*Notes:* standard errors are presented in parenthesis. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively. The income inequality denotes Gini index.

The R-squared of the FE regression shows that 92% of the variations in income inequality can be explained by the financialization and control variables. Overall, the fixed effects and random effects estimations consistently indicate that financialization constitutes a significant structural determinant of rising income inequality in advanced OECD countries over the post-1980 period. In addition to financialization, technological progress, the weakening of labour market institutions, and globalization are confirmed as contributing factors of income inequality, in line with the established literature. The positive and statistically significant relationship between financialization and income inequality remains robust across different model specifications, further reinforcing the stability of the estimated effect. These findings corroborate the evidence obtained from the panel ARDL estimations presented above, confirming that financialization represents a key driver of increasing income inequality in advanced economies.

## 2.7 Concluding remarks

The phenomenon of financialization and its implications on income inequality have been recently an important topic of debate among academics, practitioners and policymakers. This research contributes to the financialization-inequality literature by focusing on a selection of advanced OECD countries where income inequality has increased considerably along with financialization, particularly post 1980s. The aim of this paper is to empirically examine the long run relationship between income inequality and financialization based on the panel study of 20 developed OECD countries between 1980 and 2019. First, the study conducts panel unit root tests so as to assess the stationarity properties of the variables under consideration. Second, the panel cointegration tests are performed to determine the existence of a stable long run relationship among the variables of interest. The panel ARDL approach is then employed to analyse both the short-run dynamics and long-run equilibrium relationship between financialization and income inequality. The study also uses CS-ARDL method developed by Chudik and Pesaran (2015) in order to account for cross sectional dependence and induced feedback effects between the variables. Furthermore, the DOLS estimator is used as a robustness check to validate the stability of the long-run relationship between financialization and income inequality measures. By explicitly correcting for potential endogeneity and serial correlation, the DOLS approach complements the panel ARDL estimations and reinforces the credibility and reliability of the empirical findings.

The panel ARDL results suggest that financialization variables are associated with an increase in the Gini coefficient. The results are also robust to different financialization and income inequality measures considered. The estimations include controls for globalization, technological progress, labor market institutions and education which ensure that the long run influence of financialization is identified alongside these widely recognized determinants of inequality. The negative and significant error correction term in the PMG, MG and DFE estimations shows that financialization variables jointly Granger cause income inequality measures in the long run. In contrast, the short-run estimates reveal that financialization tends to reduce income inequality, although most short-run coefficients are statistically insignificant across different specifications. The main income inequality variable under consideration is Gini index so that top 1% income share, top 10% income share and labour share of income are used as alternative inequality measures in order to deal with the limitations of Gini index. Overall, the empirical findings support the hypothesis that in the long run, financialization is one of the leading causes of rising income inequality in addition to the globalization, technological progress and weakening of labor market institutions, which is consistent with the broad literature. The results also remain robust under CS-ARDL and DOLS estimation methods. The long run positive relationship that has been established here between income inequality and financialization is supported by a growing body of literature (Stiglitz, 2012; ILO, 2013; Jerzmanowski and Nabar, 2013; Leopold, 2015; Makhlouf et al., 2020).

This chapter has attempted to contribute to the current body of literature in three important ways. First, it demonstrates that financialization exerts a significant and persistent long-run effect on income inequality, a relationship that has been relatively underexplored in the post-1980s period when financial deregulation accelerated across most advanced OECD economies. Second, it shows that employing the CS-ARDL framework enhances the reliability and validity of results by addressing the limitations of panel ARDL regarding the issues of endogeneity and cross sectional dependence. Third, despite the data availability constraints, it advances the literature by integrating a broad set of financialization indicators and inequality measures, thereby offering a more comprehensive assessment of the finance–inequality nexus than has typically been provided in prior studies.

This research suggests that the impact of financialization on income inequality has policy implications for governments to promote a more equitable and inclusive economic system. Our findings highlight the importance of considering the long-term relationship between financialization and income distribution.

The key message for policymakers is that while policies promoting credit expansion might reduce inequality in the short term, they could have negative effects in the long term (Rajan, 2010; Stiglitz, 2012). To prevent this, additional measures, such as fiscal redistribution through progressive income tax, financial regulation and financial education to help households avoid excessive debt, may be necessary following credit expansion. There is growing but still inconclusive evidence linking economic growth, globalization, financialization, regulation, and the fluctuations of the business cycle, alongside frequent financial crises, especially in advanced economies. Policymakers should develop policies that promote real economic activity, support trade, and create employment opportunities to reduce income inequality (ILO, 2013). Simultaneously, regulators need to implement measures that connect finance meaningfully to the real economy while curbing speculative behavior in financial markets. Moreover, increasing income inequality is closely connected to rising volatility and uncertainty in financial markets. As financial asset prices continue to climb without adding significant value to the real economy, inequality is likely to worsen, leading to a more precarious economic environment (Stiglitz, 2012; Brei et al., 2023). The global financial crisis and numerous studies have demonstrated that financialization has exacerbated inequality globally, especially in advanced economies. However, this study has not included all the relevant financialization measures due to data unavailability. Yet the study has attempted to capture the impact of multidimensional financialization on income inequality measures. As more data becomes available on all relevant measures of financialization discussed in the literature above, further research should provide more comprehensive analysis and robust evidence on how different financialization variables interact with income inequality in the short and long run.

A growing body of literature makes clear that labour market policies alone will not suffice to rebalance income distribution. The recent empirical studies demonstrate that one of the driving factors behind rising income inequality since 1980s and 1990s is the policies that have led to rapid expansion of financial sector without its meaningful contribution to the real economy (ILO, 2013; Leopold, 2015; Makhlouf et al., 2020; Alexiou et al. 2022). According to Epstein (2015), financialization has spurred incentives for corporations to shift their internal resources from real, productive investment towards high-risk speculative activities focused on maximizing short-term profits. This lack of regulation in financial markets has not only deepened inequality but has also led to economically unstable and suboptimal outcomes. Therefore, “rebalancing" requires more robust financial sector regulation and restoring their role in channelling resources into productive and sustainable investments.

Nevertheless, the current results open up the possibility that the impact of finance may have been underestimated in many of the previous studies and suggest that overlooking the role of financialization may have serious implications for our understanding of the causes of rising income inequality. The long run positive relationship that has been established here between income inequality and financialization is an important finding given the limited literature in this area. Although this study has not included all the relevant financialization measures due to data unavailability, the impact of financialization has become evident in relation to rising inequality based on the panel study of advanced OECD economies. The panel data analysis contributes to the broader debate concerning the role of financialization and shows how the subject relationship is critical for addressing the root causes of rising income inequality and requires further investigation.

## Appendix 2.A Theoretical Model

Jerzmanowski and Nabar (2013: pp. 211-234) shows that competitive firms can produce final output using two forms of production technologies. In the old economy, firms produce output using both high skilled workers and low skilled workers whereas in the new economy, output is produced only by high skilled workers with an increasing variety of intermediate product. Economic agents use this final output for consumption, investment and production of inputs. The model also includes the innovation sector which is composed of high-skilled workers with ideas for new intermediate goods, who require external finance to start production. Thus, Jerzmanowski and Nabar (2013) show that the production function in the new economy can be expressed as follows:

$$Y_{Nt} = H_{Nt}^{1-\alpha} \int_0^{At} x_{jt}^{\alpha} dj,\ 0 < \alpha < 1.\ where\ x_j, j \in [0, A] \tag{2.45}$$

However, comptetitive firms in the old economy produce output characterized by a constant elasticity substitution (CES) production function:

$$Y_{Ot} = B_t[H_{Ot}^p + L^p]^{1/p},\ p < 1, \tag{2.46}$$

where $B_t$ is a technology measure which gains from the realized innovative projects in the new economy. Thus, the assumption is that $B_t < A_t$ for all t.

Financial market frictions are modelled here in a reduced form as a search and matching process. Every time a successful match is formed between skilled workers with innovative ideas and financial intermediaries, a new entrepreneurial firm is set up in the new economy. The following equation represents the matching process:

$$M_t = \zeta F_t^{\phi}(H - N_t)^{1-\phi} \tag{2.47}$$

where $F_t$ is defined as the number of financial firms searching for skilled workers, $(H-N_t)$ denotes the total number of skilled workers searching for finance. In the equation (2.47), $\zeta$ measuring the efficiency of the matching process represents financial deregulation and it is defined as a mix of changes in regulatory policy and financial innovation that allows easier access to finance for firms. Successful matches lead to growth in the variety of intermediate goods:

$$\dot{A} = \eta\delta A_t N_t = \eta\delta A_t(H - H_{Ot} - H_{Nt}) \tag{2.48}$$

The wages for high-skilled workers in the old and new economy are equalized in equilibrium. In the new economy, high-skilled wages increase with the number of intermediate goods:

$$w_{Ht} = (1-\alpha)\alpha^{\frac{2\alpha}{1-\alpha}} A_t. \tag{2.49}$$

As $A_t$ rises with financial deregulation, high-skilled labor shifts from the old to the new economy, raising their wages. In turn, this reallocation reduces the productivity and wages of low-skilled workers, who are complements in the old economy:

$$\tilde{w}_{Lt} = \frac{B_t}{A_t}[H_{Ot}^p + L^p]^{(1-p)/p} L^{p-1} \tag{2.50}$$

Moreover, high-skilled workers who obtain funding and move to the innovation sector earn even higher wages due to Nash bargaining with financial intermediaries. Their wage is:

$$\tilde{\omega} = \beta\left(\frac{\eta\delta\pi}{p} + \frac{\kappa}{\theta}\right) + (1-\beta)\tilde{w}_H. \tag{2.51}$$

where $\beta$ is the worker's bargaining power, $\pi$ the profit from innovation, and $\theta$ defined as the ratio of unmatched skilled labour to financial intermediaries. Since $\tilde{\omega} > \tilde{w}_H$, this creates within-group inequality among high-skilled workers.

The model shows that financial deregulation raises the skill premium, defined as the ratio of high-skilled to low-skilled wages. In the old economy:

$$\frac{\tilde{w}_{Ht}}{\tilde{w}_{Lt}} = \left(\frac{H_{Ot}}{L}\right)^{p-1} \tag{2.52}$$

As high-skilled workers exit the old economy, $H_{Ot}$ falls, and the skill premium rises. The average skill premium also increases as more high-skilled labor enters the high-wage innovation sector:

$$Average\ Skill\ Premium = \frac{N}{H}\frac{\tilde{\omega}}{\tilde{w}_L} + \left(1 - \frac{N}{H}\right)\frac{\tilde{w}_H}{\tilde{w}_L} \tag{2.53}$$

Over time, as financial deregulation continues and the number of innovative firms ($N$) grows, the economy shifts to a higher balanced growth path. While this fosters long-run growth, it also widens both between-group (skilled vs. unskilled) and within-group (among skilled) income inequality.

## Appendix 2.B List of sampled countries studied in this research

| List of sampled countries | | | |
|---|---|---|---|
| United Kingdom | France | Portugal | Ireland |
| Sweden | Austria | Norway | Japan |
| Greece | Belgium | United States | Australia |
| Finland | Netherlands | Italy | New Zealand |
| Spain | Denmark | Germany | Canada |

# Chapter 3

# Financial structure and income inequality

## 3.1 Introduction

The issues of both income distribution and financial systems have generated a considerable debate in recent years. As a result, there has been a growing interest among academics, practitioners and policymakers to study the relationship of financial structure with income inequality. The global financial crisis of 2008 has demonstrated that the financial structure has had different implications on income inequality depending on whether an economy has a more market dominated or bank dominated financial system. In this context, the financial structure refers to the relative importance of banks versus financial markets (such as stock markets, bond markets, etc.) in providing financial services, including lending, investment, and risk management. There are ongoing studies that analyze the interplay between bank based and market based financial systems in advanced economies, exploring their mixed presence and their relationship with indicators of income inequality.

Despite increasing interest and theoretical debate regarding the role of financial systems in relation to rising income inequality, the empirical literature remains limited. This study will empirically examine the relationship between financial structure and income inequality based on the panel data of 20 advanced OECD countries for the period 1980-2019 and aim to contribute to the literature in three different ways. First, it addresses a research gap in the literature by applying the panel ARDL model so as to examine both the short term dynamics and the long term equilibrium relationship between income inequality and financial structure, specifically comparing bank-based and market-based financial systems. Second, despite limitations in data availability, this chapter employs the financial institutions index and financial markets index to represent bank based and market based systems respectively in order to fully capture the composition of financial system. Third, the use of CS-ARDL and DOLS estimation methods along with different inequality measures helps to test the robustness of the long run relationship between income inequality and financial structure and enhances the credibility and reliability of our findings.

The current body of literature mainly focuses on the finance-inequality nexus by considering financial systems in general as a whole and ignoring differences between bank dominated and market dominated financial systems. Distinguishing these differences is important to our understanding of how and when financial systems may help reduce income inequality (Cournede et al., 2015). Thus, this chapter aims to provide insight on the relationship between financial structure and income inequality as contribution to the ongoing debate on real effects of financial systems. This study will examine the financial system, defined as the relative share of financial markets and banks in the country's financial structure.

## 3.2 Literature review

The existing empirical literature examines how financial systems influence income inequality, primarily through measures of financial development (Chakroun, 2020; Selim and Gungor, 2021; Shi et al., 2022). Financial development can decrease inequality as limited access to financial services is a major factor driving poverty and unequal opportunities (Levine, 2008). Moreover, financial development helps to reduce inequality by broadening the economic opportunities of business owners and households (Stiglitz, 1974; Atkinson and Stiglitz, 1980). Gimet and Lagoarde-Segot (2011) argues that financial development is also associated with lower inequality through promoting economic growth and stabilizing household expenditure and savings decisions. Makhlouf et al. (2020) show that the inequality reducing impact of financial development is limited to the short term, when financial expansion is at the extensive margin, making access to finance and financial services available to more individuals and businesses. However, in the long run financial growth shifts to the intensive margin, whereby more sophisticated services may be provided to high income clients and this is where financial development starts to raise inequality. Although the relationship between financial development and inequality is well studied in the existing literature, the role of financial structure remains to be investigated in terms of its implications on income inequality. Among the limited studies, Kpodar and Singh (2011) and Seven and Coskun (2015) look into the impact of bank and market finance on poverty and inequality in the sample of developing countries and their findings turn out to be inconclusive in relation to the differing effects of financial structure. Kpodar and Singh (2011) document that more bank based financial system is correlated with lower inequality, particularly in the presence of weak institutional quality whereas more advanced financial markets are associated with higher inequality. However, their findings indicate that the financial structure measures are not statistically significant in relation to income inequality indicators. In this regard, Seven and Coskun (2016) demonstrate that even though the financial development has no impact on income inequality, analysis of the financial structure on the basis of financial institutions development and financial market development gives contradictory results with respect to income inequality.

Although the theoretical literature is limited on the finance-inequality relationship, Banerjee and Newman (1993) and Galor and Zeira (1993), Greenwood and Jovanovic (1990) have developed theoretical models to demonstrate how the finance is linked with income inequality. While the first two studies suggest that more advanced financial markets can help reduce income inequality, the latter posits an inverted U-shaped relationship between financial development and inequality. According to this view, in the initial stages of financial development—when only a limited segment of society gains access—income inequality tends to rise. However, as financial development progresses and reaches a certain threshold, increased access to finance begins to reduce inequality. Although the theoretical pathways remain somewhat ambiguous, the main reason that higher levels of financial development ultimately reduce income inequality is improved credit access, which allows households to make choices and manage expenditures more effectively over time, independently of inherited wealth.

The recent theoretical studies begin examining the channels through which finance may contribute to rising income inequality by expanding opportunities for rent extraction. Korinek and Kreamer (2014) argue that rent can be extracted in different ways and they present a model showing how financial deregulation induced rent seeking behavior in the financial sector which in turn contributed to rising inequality. Gennaioli et al., (2012), Thakor (2012) and Bolton et al. (2016) examine the negative effects of harmful or inefficient financial innovation which enables agents to extract rents and leads to a more uneven distribution of income and wealth. Additionally, Ehrlich and Siedel (2019) assert that income inequality has exacerbated when employees benefit from rent-sharing agreements within big exporting companies, especially, if they have expanded through improved access to external financing.

The early empirical literature generally shows that financial development tends to improve income levels for the low income households, particularly in developing economies (Burgess and Pande, 2005; Demirguc-Kunt and Levine, 2009). In the early stages of development, bank-based finance often proves more effective than market-based finance due to inadequate institutional structures that are insufficient to support market activity (Gerschenkorn, 1962). However, the growth of a monopolistic banking sector can also lead to distortions (Stiglitz, 2012). In such cases, financial markets may provide alternative funding sources that improve efficiency and encourage economic growth (Boyd and Smith, 1998). Yet, excessive growth in markets can lead to complexities that may also cause inefficiencies. Clarke et al. (2006) and Beck et al. (2007), using data from numerous countries, test these theories and confirm a linear, inequality-reducing effect of financial development. However, as noted by Kim and Lin (2011) in line with the theoretical model of Greenwood and Jovanovic (1990), financial depth only begins to yield benefits once a country reaches a certain level of financial development.

Income inequality is a multifaceted issue influenced by a number of factors documented in the empirical literature and the financial system being one such critical factor has recently become an area of research interest among academic circles. Understanding the connection between different financial systems and income distribution is important due to its implications for policymakers in addressing the root causes of rising income inequality. This chapter aims to explore the existing literature on financial system-inequality nexus and examine the relationship between financial structure and income inequality. Income inequality is shaped by various economic, social, and political factors, including globalization, the deregulation of financial markets and institutions, the weakening of labor market institutions, and the increasing financialization of economies (Keeley, 2015). Denk and Cazenave-Lacroutz (2015) argue that the rise in income inequality in advanced OECD countries post 1980 has been mainly associated with financial development, technological progress, tax and social reforms and education. As a result, Piketty (2014) claims that given the importance of income inequality and its implications, it is important to examine the dynamics of inequality in terms of its components, labour share of income relative to capital share of income.

A financial system encompasses all financial institutions and markets and their relations with regard to the movement of funds among households, governments, business firms and foreigners as well as the financial infrastructure (De Haan et al., 2009). Its primary role is to lower information and transaction costs while facilitating the trade, diversification, and management of risk (Domanski et al., 2016). Generally, financial systems allocate resources by channeling savings to borrowers, enabling the smoothing of consumption over time and the sharing of risk (Beck, 2011). As previously mentioned, financial systems are categorized into two main types: bank-based and market-based systems. According to De Haan et al. (2009), the US and the UK are the most market-oriented economies, Japan occupies a middle position, France leans more towards a bank-based system, and Germany represents an extreme example of a bank-based system. Therefore, economies typically display characteristics of both bank-based and market-based systems (Beck, 2011). The financial system is continuously evolving, shaped by historical, legal, political, and economic changes. In recent decades, many countries have begun shifting towards market-based systems (De Haan et al., 2009). Notably, OECD countries have seen a significant expansion of their financial sectors, particularly in stock markets, driven by the deregulation of financial markets and institutions since the 1980s (Cournede et al., 2015). Allen and Gale (2001) suggest that financial markets are more efficient than banks in resource allocation, risk management, and diversification. Despite the growing emphasis on developing financial markets, substantial differences in financial systems across countries persist (IMF, 2006).

Although numerous European countries have followed the global trend of disintermediation, their financial markets remain underdeveloped compared to their banking sector and overall economic growth (Veron and Wolff, 2015). During the 1980s, several advanced OECD economies, such as the US and the UK, rapidly transitioned to more market-based systems. However, in the 2000s, a notable shift back toward banking occurred, particularly in most advanced European nations (European Systemic Risk Board, 2014). It's important to highlight that the total assets of the European banking sector have recently grown to nearly three times their GDP, whereas in countries like the US and the UK, bank assets are less than the size of their GDP. Despite some common trends, the financial structure across Europe still vary considerably in terms of the size of financial markets and the role of both financial institutions and markets (Beck, 2011).

A growing body of literature shows that it is difficult to compare financial systems due to the distinct advantages and disadvantages of both bank-based and market-based systems. Assessing different financial systems requires navigating through complex trade-offs between economic growth and stability (De Haan et al., 2009). Allen and Gale (2001) suggest that bank-based systems offer benefits such as insurance, stability, private information, and independence from free-riding, whereas market-based systems promote competition, efficiency, public information, and external oversight. Although there is limited research on how different financial systems affect inequality, many studies have explored the relationship between financial development and inequality. The empirical literature suggests that beyond a certain threshold, financial markets and institutions may negatively impact income inequality (Beck, 2011). In this context, Cournede et al. (2015) argue that financial development is advantageous when the financial sector is relatively small, but excessive finance in already well-developed financial sectors can be detrimental. Their findings indicate that an overgrown financial sector can eventually slow down economic growth and increase vulnerability to crises, which can, in turn, exacerbate income inequality (Keeley, 2015). Due to the limited literature on the financial structure-inequality nexus, it is not clear to what extent having more banked based or market based system makes difference in relation to rising inequality.

There is growing evidence suggesting that more mature and sophisticated financial systems have been linked to significant increases in the earnings and rents within the financial sector. Philippon and Reshef (2012) provide empirical evidence that high wages in the financial sector is associated with the rapid development of financial industry which occurred in the early 20th century and again in the years leading up to the global financial crisis in 2008. However, Greenwood and Scharfstein (2013) argue that high labour compensation in the financial sector is attributed to increasing fees in asset management and the expansion of household credit. Axelson and Bond (2015) claim that higher renumeration stems from risky trading and transactions in the financial industry or the exploitation of information asymmetries that facilitate rent extraction. Moreover, according to Stiglitz (2016), lower transparency and systemic significance of financial institutions and markets have amplified opportunities for managerial rent extraction. Beck et al. (2009) assert that financial intermediaries and financial markets cater to distinct customer bases and function in different areas of the financial sector. Due to their closer relationships with their clients, banks generally experience less information asymmetry and have fewer incentives for rent-seeking compared to entities in financial markets. This is especially true for stakeholder-oriented banks, where clients are also shareholders and are involved in the bank's decision-making processes (Cornée and Szafarz, 2014). Allen (2012) claims that in some cases financial innovations aimed at advancing financial markets have been exploitative and predatory.

Beck et al. (2004) carry out a comprehensive cross-country analysis on the impact of finance, specifically private credit, on income growth among the lowest income quintile and the gini index, using data from 52 emerging and advanced countries spanning 1960 to 1999. Their findings suggest that financial development positively influences income inequality and reduces poverty. Denk and Cazenave-Lacroutz (2015) explore the link between income distribution and financial depth, represented by household credit relative to GDP and intermediated credit. However, they discover that expanding intermediated credit does not serve as a pro-poor mechanism. Guiso et al. (2003) employ a probit model to assess stock market participation and portfolio allocation to stocks, based on classical portfolio theory with participation costs. Their study, conducted across six European countries and the US in 1998, reveals that stock market participation increases when entry barriers such as transaction costs, management fees, and information costs are lower. Furthermore, Guiso et al. (2003) demonstrate that stock market participation rises with higher income, wealth, and education levels. Similarly, Arrondel et al. (2014) utilize probit and tobit regressions to examine asset participation in a panel study of 15 eurozone countries, finding that investment in risky assets is positively associated with wealth, and both the extensive and intensive margins for risky assets increase with educational level. Tanndal and Waldenström (2016) use an innovative approach involving synthetic control groups to generate counterfactual time series for the UK and Japan. Their results indicate that financial liberalization significantly boosts the income of rich households, attributing this effect to high wages within the financial services industry.

Greenwood ad Jovanovic (1990) argue that there is a non-linear relationship between financial development and income inequality where the impact on the distribution of income changes with the level of economic growth. In this regard, Clarke et al. (2006) tests the U-shaped relationship between financial development and inequality based on a panel data over the period 1960-1995. However,

their findings conclude that financial development decreases income inequality at all stages of financial development. Moradi et al. (2016) conduct a panel study of 15 developed and developing countries and examine the effect of bank-based and market-based financial systems on income inequality using FMOLS method. They find out that market based financial system reduces income inequality in advanced economies whereas bank-based financial system leads to lower inequality in emerging economies. However, the study uses a small sample and estimates the type of financial system with a dummy variable which does not fully capture different dimensions of bank based vs. market based systems. De Haan and Sturm (2016) conduct a panel study of 121 countries to analyse the effect of financial development, financial deregulation and financial crises on income inequality for the period 1975-2005. Their results indicate that all three finance measures are positively associated with the gini index where the impact of financial deregulation on inequality is conditional upon the level of financial development and the quality of political institutions.
Cournede et al. (2015) examine the impact of intermediated credit and stock market capitalization across OECD economies controlling for country and time fixed effects and financial crises. They conclude that intermediated credit is negatively related to inequality measures whereas stock market capitalisation is positively correlated with household disposable income growth and GDP growth. Similarly, Denk and Cournede (2015) conduct a panel study of advanced OECD economies for the period 1974-2011 to analyze the relationship between finance and inequality measures. They apply a novel empirical methodology and find that more finance leads to higher income inequality where finance is represented by the value added of finance, intermediated credit and stock market capitalisation. Using a simulation exercise, Denk and Cournede (2015) also show that more finance is associated with the rapid income growth of high income households relative to middle and low income households.

A growing body of literature highlights the importance of distinguishing between the extensive and intensive margins of financial sector expansion. The intensive margin typically involves wealthier households with higher incomes and well-established firms (Greenwood and Jovanovic, 1990; Allen and Gale, 2004; Kokas et al., 2020). This distinction links the two margins of financial development to income distribution within a population; financial development on the extensive margin tends to reduce inequality, whereas the intensive margin tends to increase it (Antzoulatos et al., 2016). On the extensive margin, financial markets can enhance income distribution by shifting funds from creditors to debtors

(Aghion and Bolton, 1997). However, broad and relatively unrestricted market access is necessary to involve a larger number of people and businesses in market dynamics. In practice, financial markets predominantly operate on the intensive margin, serving clients who already have market access. Well-developed financial markets stimulate investment by providing the real sector with a wide range of financing sources, facilitating risk management, enabling performance monitoring, and providing information to investors by aggregating individual signals (Beck and Levine, 2002). Aggarwal and Goodell (2009) demonstrate that large corporations and high-income households significantly benefit from stock market development, which, in turn, leads to increased income inequality. Moreover, financial markets can shield individuals from external shocks to their incomes and opportunities (Levine, 1991). Kumhof et al. (2015) argue that low-income households suffer disproportionately during recessions and adverse shocks, whereas high-income households are more adaptable in adjusting their consumption during economic downturns. Borensztein et al. (2013) show that well-functioning financial markets provide protection from shocks through diversification and act as a source of funding when other options are unavailable. However, only well-established firms and investors have access to these services. As a result, the shock-absorbing role of financial markets primarily benefits high-income households, who are less vulnerable to recessions, thereby contributing to greater income inequality (Kumhof et al., 2015).

In general, financial institutions are seen as intermediaries at the extensive margin that provide access to finance and savings opportunities for low-income households, who otherwise face challenges in accessing the market (Levine, 1991). In this context, Vinogradov (2012) argues that financial intermediaries also mitigate risk and provide higher liquidity for low-income households and entrepreneurs, who seek to minimize the risks of renewing and renegotiating loan contracts and require mechanisms to ensure credibility. According to Paulson and Townsend (2004), low-income households and start-up businesses face difficulties accessing financial markets due to credit constraints, limited savings, and inadequate internal funds, making external financing essential for income generation and business growth. Galor and Maov (2004) demonstrate that improving access to financial services expands opportunities for low-income households, such as the opening of new bank branches, which primarily affects the borrowing capacity of the poorer segments of society. Consequently, Makhlouf et al. (2020) underscore the importance of access to and efficiency of financial services in reducing income inequality.

However, financial intermediation is often associated with costs and inefficiencies, such as credit rationing, interest rate manipulation, and customer selection processes (Petersen and Rajan, 1994; Burgess and Pande, 2005; Galor and Moav, 2004; Vinogradov, 2012). Allen and Gale (1997) suggest that banks operating through the intensive margin can exacerbate income inequality unless government intervention is implemented to manage this effect. Burgess and Pande (2005) found that bank expansion supported by the government helped reduce income inequality in India during the period from 1977 to 1990. Agarwal et al. (2018) argue that financial intermediaries help mitigate the impact of external shocks over time by distributing their effects across different periods. Bolton et al. (2016) show that financial intermediaries continue to extend loans to existing clients during recessions, which supports businesses and promotes economic growth. However, when banks are unable to provide loans, emergency funding from financial markets plays a crucial role (Levine et al., 2016). As a result, it is reasonable to conclude that financial intermediaries are more likely to assist low-income households that are vulnerable to recessions and economic downturns.

The finance-inequality nexus is well documented in the literature with the effect of finance on inequality being conditional upon a number of factors including the level of economic development, economic stability, the quality of institutions, time period, etc (Gimet and Lagoarde-Segot, 2011; Denk and Cournede, 2015; De Haan and Sturm, 2017). However, the lending scheme of financial intermediaries is significantly affected by their competitiveness. Martinez-Miera and Repullo (2010) argue that high market power makes banks riskier and consequently more conservative in their lending practices since high interest rates shift borrower selection towards riskier loans. In contrast, Bolton et al. (2016) suggest that market competition decreases bank profitability and encourages them to provide more loans and keep lower reserves. The empirical literature shows that high market power and competition make banks choose borrowers with lower risks (Jimenez et al., 2013; Braggion et al., 2017; Liebersohn, 2017). Kpodar and Singh (2011) suggest that high market power and competition enable financial intermediaries to absorb deposit shocks without affecting their lending. According to Vinogradov (2012), it is difficult for banks to withstand recessions and recover afterwards due to their low profitability in highly competitive markets, thus making their shock smoothing role weaker. Fonseca and Gonzalez (2010) demonstrate that higher market power is associated with higher bank reserves. Whilst competitive financial institutions don't have the flexibility and the internal funding of monopolists, they can issue new liabilities, conduct share buybacks and adjust dividend policy to achieve better outcomes. Mavrotas and Vinogradov (2007) argue that high competition makes it difficult for banks to survive and recover from recessions or crises, especially if a few powerful banks dominate the market, thus contributing to higher inequality.

To summarise, the above arguments suggest that a more market-based financial system tends to exacerbate income inequality, whereas a more bank-based financial system appears to mitigate it. In light of the limited empirical evidence on the nexus between financial systems and income inequality, this study hypothesizes that market-dominated financial structures are associated with higher levels of income inequality, while bank-dominated systems are more conducive to reducing inequality in advanced economies.

## 3.3 Data description

This study focuses on 20 advanced OECD countries over the period 1980 to 2019 to investigate the relationship between the financial system and income inequality. This section provides a detailed description of the data and variable definitions before presenting the empirical model. The selection of countries is based on the need for consistency and availability of data across indicators of financial structure and income inequality. The existing literature generally classifies financial systems into two main types, namely bank dominated and market dominated systems. Accordingly, this study employs the financial institutions index and the financial markets index developed by Svirydzenka (2016) to represent the bank based and market based systems respectively. These indicators are selected for their comprehensive coverage and their ability to capture the depth, access, and efficiency dimensions of both banking institutions and financial markets. The control variables are selected based on insights from the established literature, as they play a crucial role in isolating and clarifying the specific influence of bank based and market based financial systems on the evolution of income inequality.

### 3.3.1 Financial system indicators

**Financial institutions index (FI)** is an aggregate of the depth (FID), access (FIA), and efficiency (FIE) of financial institutions. This index is an effective proxy for a bank-based financial system because it comprehensively measures the attributes essential to the functioning and influence of banks within a financial system. The index directly captures the extent and effectiveness of banks in mobilizing savings, allocating capital, and supporting economic activities. The data developed by Svirydzenka (2016) is available from the IMF database.

**Financial markets index (FM)** is an aggregate of the depth (FMD), access (FMA) and efficiency (FME) of financial markets. This index is designed to capture the capacity of market-based financial systems, where markets play a pivotal role in financial intermediation, often facilitating risk-sharing and enabling corporate financing through securities rather than bank loans. Therefore, this index aligns closely with the market-based financial system by measuring how well-developed and accessible financial markets are, thus serving as a robust proxy for market-based financial structures. The data developed by Svirydzenka (2016) and can be obtained from the IMF database.

### 3.3.2 Income inequality indicators

**GINI index (GINI)** is the main measure of income inequality in this study and it represents the measure of the distribution of income across population. It is widely used in the empirical research in relation to inequality. The GINI index is based on gross income which is the sum of market income and transfer payments and it is defined as pre-tax and post transfer income. The data is available from the Standardized World Income Inequality Database (SWIID) and it is developed by Solt (2020).

**Labour share of income (LSI)** is defined as the compensation per employee as a share of GDP at factor costs per person employed. The labour share of income includes both employed and self-employed and it does not include taxes. The data is available from the AMECO database.

**Top 1%** represents the share of income that accounts for top 1 % of the population as a share of GDP and the data comes from the World Top Incomes Database.

**Top 10%** is the share of income that accounts for top 10% of the population as a share of GDP and the data is available from the World Inequality

Database.

### 3.3.3 Control variables

**Real GDP growth rate (RGDPG)** rate measures economic growth adjusted for the inflation rates and it is included to control for cyclic and structural changes and might affect the secular trend of the share of functional income. Real GDP growth captures within country heterogeneity that varies deterministically over time. The source is World Economic Outlook (2024), IMF. The data is available from the Our World in Data.

**Education (EDU)** is the fraction of the school age population that is enrolled in primary, secondary and tertiary schooling. This variable is used to control for financial literacy. The data is available from the World Bank database.

**Globalization (GLOB)** is defined as exports plus imports as a share of GDP and as suggested by the literature, it is considered to have a positive effect on the income inequality. The data for this variable is available from the World Bank database.

**Labour market institutions (LMI)** is represented by trade union density which is based on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS) and the database was developed by Prof. Jelle Visser at the University of Amsterdam. The ICTWSS database combined data from various sources and projects with a main focus on trade union in EU and OECD countries, collective bargaining and employment relations in Europe, and social pacts.

**Technological progress (TECH)** is represented by research and development (R&D) spending as a share of GDP. R&D comprises creative work undertaken on a systematic basis in order to increase the stock of human knowledge and to devise new applications based upon it. The R&D mainly covers three activities: basic research, applied research and experimental development. It is widely used in the empirical research as a proxy for technological innovation. The data can be accessed from the OECD database.

**Population growth (PG)** for year t is the exponential rate of growth of midyear population from year t-1 to t, expressed as a percentage. Population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship. The data is available from the World Bank database.

**Government expenditure (GE)** includes all government current expenditures for purchases of goods and services (including compensation of employees). It also includes most expenditures on national defence and security, but excludes government military expenditures that are part of government capital formation. The data is from the World Bank database.

**Inflation (INF)** is measured by the consumer price index which is the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals. The laspeyres formula is generally used. The data can be obtained from the International Monetary Fund (IMF) database.

**Regime corruption index (RCI)** measures the level of corruption within a country's political and administrative systems. It typically assesses the extent to which public officials abuse their power for private gain, such as through bribery, embezzlement, or favoritism, and how deeply corruption is embedded in the political regime. Controlling for corruption is necessary as it directly affects inequality through the distribution of wealth and limiting opportunities for low income groups. The corruption weakens institutional quality, misallocates public resources, and fosters tax evasion, which reduces the ability of governments to implement redistributive policies. Due to limited data availability, it is only used in robustness check tests. The dataset is available from V-Dem database.

These data sources are selected for their broad coverage and widespread use in previous empirical research. The databases of international institutions and organizations are regarded as credible and consistent, providing reliable data across countries and over time, which is essential for the panel data analysis in this study. The period from 1980 to 2019 is chosen to capture the major developments in financial systems and the evolution of income inequality over the past four decades. The data are collected annually, allowing for the examination of long term trends and structural relationships while minimizing short term fluctuations. Since no single database contains all the required variables, the data on financial system indicators, income inequality, and control variables are compiled from multiple reputable sources. Careful attention has been paid to ensure accuracy, consistency, and comparability across all datasets. Overall, the use of well established databases and rigorous data validation enhances the credibility of the empirical analysis and strengthens the reliability of the study's findings.

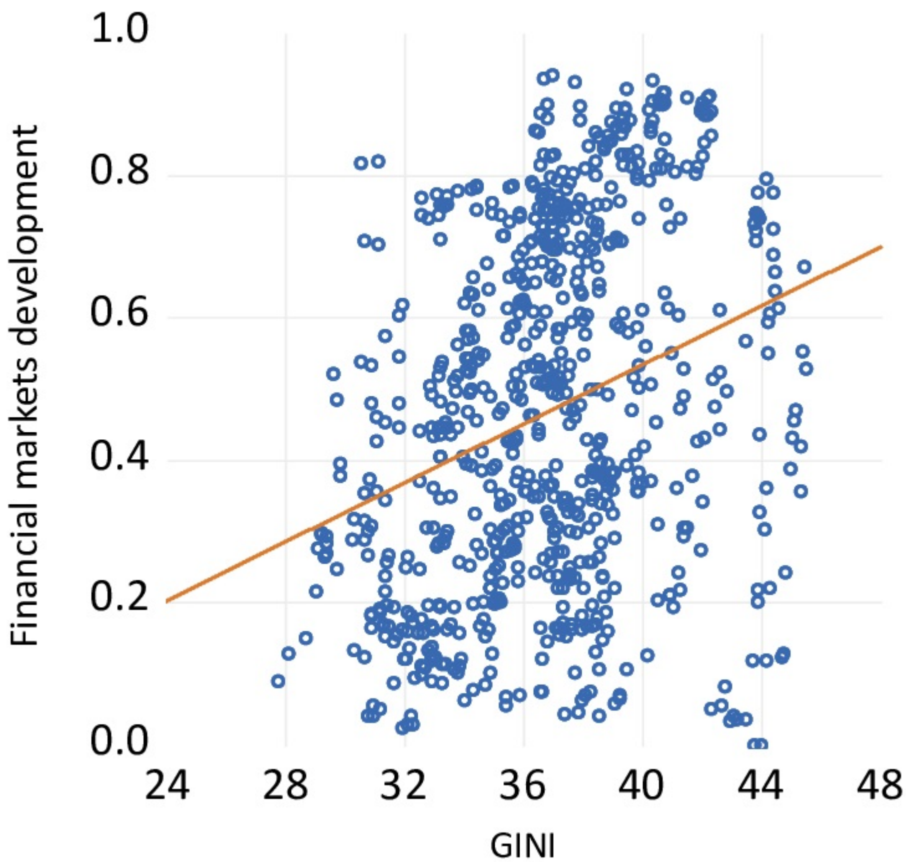


Figure 3.1: Financial markets development and GINI index, 1980-2019

Figure 3.1 shows a strong positive correlation between financial markets development and Gini index based on the panel data of 20 advanced OECD countries over the period 1980-2019. It is clear from the graph that financial markets advancement coincided with rising income inequality over this period. This is consistent with the empirical literature which suggests that financial markets development has contributed to higher income inequality due to unequal access to financial services, asset price appreciation in the form of stock markets boom and the growth of other financial assets, and higher earnings in the financial sector. Although financial markets development can spur economic growth, it has disproportionately benefited the wealthier segments of society, leading to higher income inequality in most of the advanced economies over the period 1980-2019.

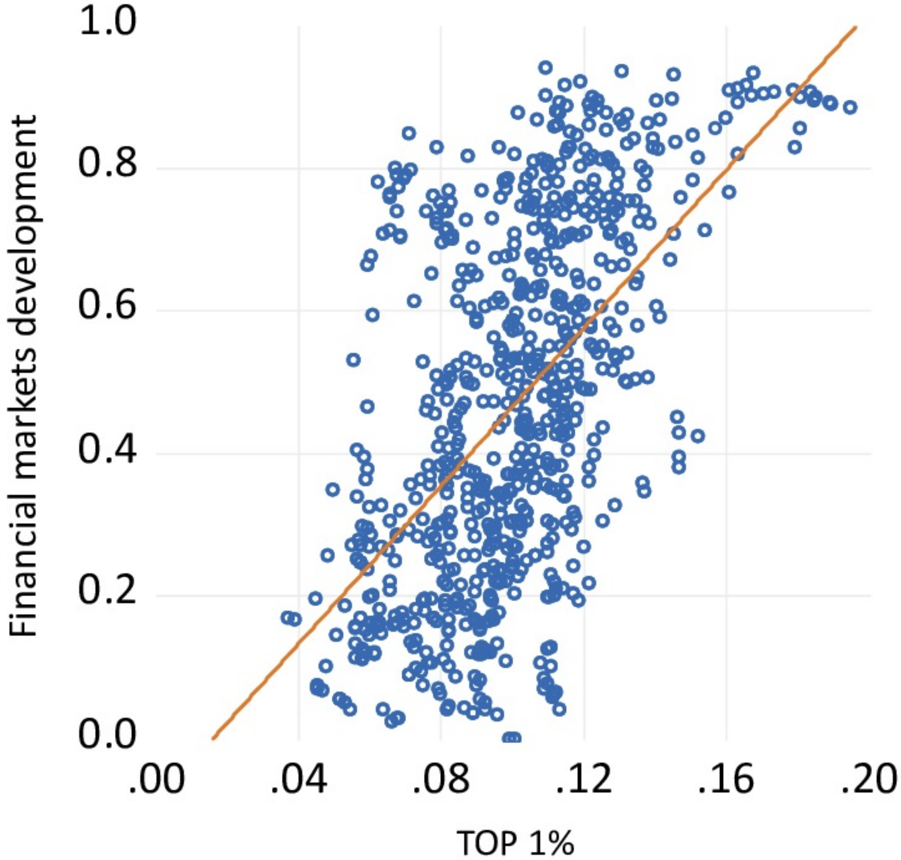


Figure 3.2: Financial markets development and Top 1% income share, 1980-2019

Figures 3.2 and 3.3 also indicate that the steep positive correlation between financial markets development and income inequality is robust to different income inequality measures considered. The previous studies suggest that as financial markets advanced, high income households had better access to financial instruments, credit, and investment opportunities which in turn allowed for their substantial wealth accumulation over time.

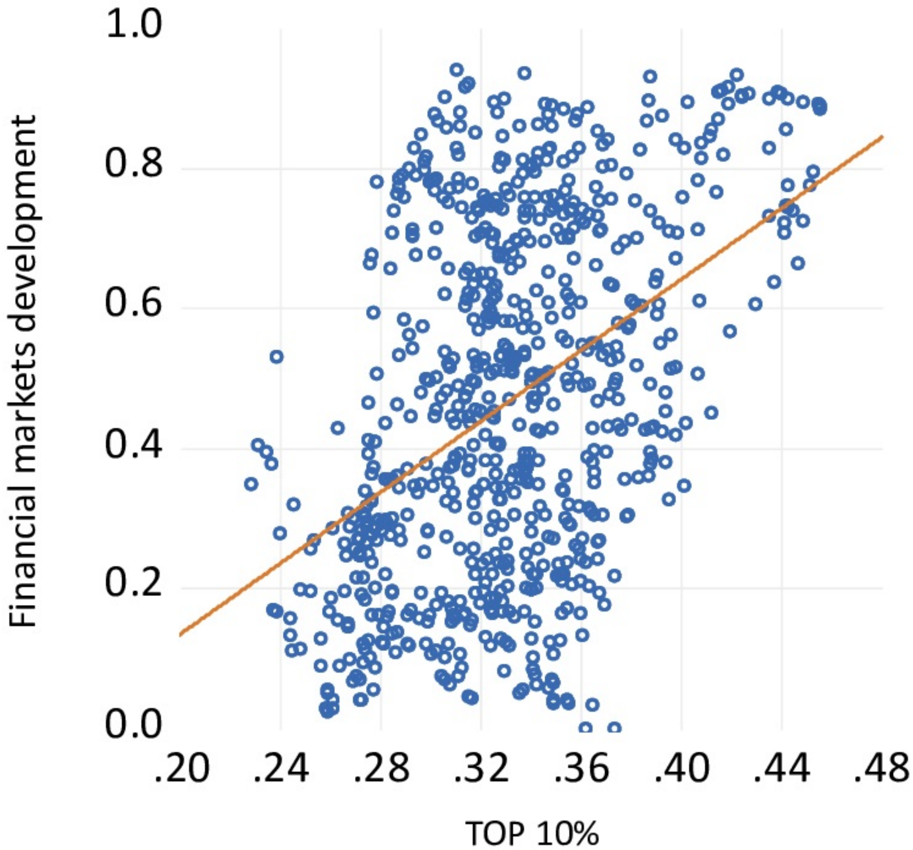


Figure 3.3: Financial markets development and Top 10% income share, 1980-2019

As can be seen from the graphs above, stock markets boom and the growth of other financial assets disproportionately benefited top income households who are more likely to own stocks, bonds and real estate. Overall, the graphs confirm that financial markets development are associated with rising income inequality over the period 1980-2019. Building on the empirical literature and the panel dataset used in this research, this study empirically will test the following hypothesis:

**H1. A more market dominated financial system increases income inequality as opposed to more bank dominated financial system which tends to reduce inequality in advanced economies.**

## 3.4 Econometric methodology

This section outlines the empirical methodology employed to investigate the relationship between financial structure, distinguishing between bank-dominated and market-dominated financial systems, and income inequality across 20 OECD countries over the period 1980-2019. Building on the methodological discussion presented in the first chapter, this chapter similarly adopts the panel ARDL framework as the most suitable approach for analyzing both the short-run dynamics and long-run equilibrium relationship between the variables under consideration. The panel ARDL method is particularly well suited for this analysis given the characteristics of the current dataset where time dimension exceeds cross sectional units ($T > N$) and its ability to accommodate variables that are integrated of different orders. Furthermore, the framework effectively captures heterogeneous country-specific effects and addresses potential endogeneity arising from contemporaneous correlation between financial structure and income inequality. To enhance robustness and account for cross-sectional dependence, the analysis also employs the CS-ARDL estimator, which incorporates common factors and induced feedback effects that may influence the estimates. Together, these approaches provide a consistent and comprehensive means of examining the long run relationship between financial structure and income inequality within a panel setting.

### 3.4.1 Panel unit root tests

Conducting panel unit root tests is an essential preliminary step before estimating the panel ARDL model, as it verifies the integration properties of the variables and ensures their suitability for the analysis. In this regard, the panel ARDL framework offers a particular advantage, as it can accommodate variables with mixed orders of integration, making it well suited for this study. To establish the stationarity properties of the data, the analysis employs a set of widely recognized tests developed by Breitung (2000), Levin, Lin, and Chu (2002), Im, Pesaran, and Shin (2003), as well as the cross-sectionally augmented IPS (CIPS) test proposed by Pesaran (2007). These tests collectively offer complementary strengths in addressing heterogeneity and cross-sectional dependence across countries. The theoretical background and empirical advantages of these tests have been discussed comprehensively in the first chapter, and they are applied here to ensure the robustness and reliability of the empirical framework used in this chapter.

### 3.4.2 Panel cointegration tests

To examine the existence of a stable long-run relationship among the variables, panel cointegration tests are employed prior to the estimation of the panel ARDL model. Consistent with the approach adopted in the first chapter, this analysis applies both first- and second-generation panel cointegration tests to ensure the robustness of the results. The first-generation tests provide the initial evidence of cointegration, while the second-generation Westerlund (2007) test offers a more rigorous framework by accounting for cross-sectional dependence and incorporating error-correction dynamics. The detailed discussion of the theoretical foundations and empirical advantages of these tests has been presented in the first chapter, and their application here serves to confirm the presence of a long-run equilibrium relationship between financial structure and income inequality measures before proceeding with the panel ARDL estimation.

### 3.4.3 Panel ARDL model

Given that the panel ARDL methodology and its advantages over alternative approaches such as GMM methods have been discussed in the first chapter, this chapter applies the same framework to analyse the short-run dynamics and long-run relationship between financial structure and income inequality. Considering the methodological strengths of the ARDL approach, the characteristics of the dataset, and the objectives of this study, it remains the most appropriate method for the analysis. Following the specification proposed by Pesaran, Shin, and Smith (1999), the study employs the MG, PMG and DFE estimators to account for country-specific heterogeneity while examining the long-run equilibrium relationship between bank-based vs. market-based financial systems and income inequality. These estimators incorporate an error-correction mechanism that captures the speed at which deviations from the long-run equilibrium are adjusted following short-run fluctuations. The baseline panel ARDL specification employed in this chapter is presented as follows:

$$GINI_{it} = \alpha_i + \sum_{k=1}^{p} \beta_{ik} GINI_{i,t-k} + \sum_{k=0}^{q} \gamma_{ik} FI_{i,t-k} + \sum_{k=0}^{q} \delta_{ik} FM_{i,t-k} \sum_{k=0}^{q} \lambda'_{ik} Z_{i,t-k} + u_{it} \tag{3.1}$$

The panel ARDL equation (3.1) in error correction form is re-parameterized as:

$$\Delta GINI_{it} = \alpha_i + \phi_i(GINI_{i,t-k} - \theta_i FI_{i,t-k} - \mu_i FM_{i,t-k} - \psi'_i Z_{i,t-k}) + \sum_{k=1}^{p-1} \beta^*_{ik} \Delta GINI_{i,t-k} + \sum_{k=0}^{q-1} \gamma^*_{ik} \Delta FI_{i,t-k} + \sum_{k=0}^{q-1} \delta^*_{ik} \Delta FM_{i,t-k} + \sum_{k=0}^{q-1} \lambda^{*}_{ik}{}' \Delta Z_{i,t-k} + u_{it} \tag{3.2}$$

where $i$ and $t$ denote country and time respectively, $GINI$ is the income inequality measure, $FI$ is the financial institutions index, $FM$ is the financial markets index, and $Z$ is a vector of control variables. In this specification, $\beta^*$, $\gamma^*$, $\delta^*$, $\lambda^{*\prime}$ represent the short-run dynamic coefficients associated with changes in income inequality, financial institutions, financial markets, and control variables, respectively. The parameters $\theta_i$, $\mu_i$ and $\psi'_i$ capture the long-run equilibrium relationships between income inequality and the explanatory variables, while $\phi_i$ denotes the error-correction term that measures the speed at which short-run deviations adjust toward the long-run equilibrium. A negative and statistically significant $\phi_i$ indicates the presence of a stable long-run relationship, implying that any short-run disequilibrium in income inequality converges back to its long-run equilibrium level over time.

In line with the established empirical practice, this chapter employs the MG and PMG estimators within the panel ARDL framework to examine the long run relationship between financial structure and income inequality (Li et al., 2016; Asteriou et al., 2020; Makhlouf et al., 2020). The Hausman test is used to identify the preferred estimator, with the null hypothesis indicating no significant difference between PMG and MG estimates. Based on the Schwarz Bayesian Criterion and consistency with previous empirical studies, the lag structure is set to $p = q = 1$, ensuring a parsimonious and comparable model specification.

## 3.5 Empirical results and discussion

This section presents the empirical results from the analysis of the relationship between income inequality and financial structure measures across 20 advanced OECD countries over the period 1980-2019. The results are obtained from panel unit root and panel cointegration tests, which examine the stationarity properties of the series and the existence of a long run equilibrium relationship among the variables under consideration. The panel ARDL approach is then applied to estimate the long run and short run dynamics between income inequality and financial structure. The analysis further employs the CS-ARDL estimator to obtain more reliable and valid results by addressing potential cross sectional dependence and induced feedback effects among the variables. In addition, the panel DOLS method is used as a robustness check to verify the stability and consistency of the long run relationship. Overall, the empirical results aim to determine whether bank dominated or market dominated financial systems contribute to an increase or a reduction in income inequality measures across advanced OECD economies.

Table 3.1: Descriptive statistics

| Variables | Obs. | Mean | Std. dev. | Min. | Max. |
|---|---|---|---|---|---|
| Financial institutions | 800 | 0.71 | 0.17 | 0.16 | 0.96 |
| Financial Markets | 800 | 0.49 | 0.25 | 0.022 | 0.94 |
| Gini | 800 | 36.86 | 3.58 | 27.77 | 45.51 |
| Top 1% income share | 800 | 0.10 | 0.026 | 0.03 | 0.19 |
| Top 10% income share | 800 | 0.33 | 0.04 | 0.22 | 0.45 |
| Labour share of income | 800 | 63.28 | 5.02 | 36.52 | 75.86 |
| Labour market institutions | 800 | 36.91 | 20.30 | 9.91 | 86.62 |
| Technological progress | 702 | 1.84 | 0.79 | 0.15 | 3.87 |
| Globalization | 800 | 68.26 | 35.59 | 15.81 | 252.33 |
| Real GDP growth | 800 | 2.22 | 2.41 | -10.15 | 25.17 |
| Population growth | 800 | 0.57 | 0.49 | -0.59 | 3.09 |
| Government expenditure | 800 | 45.49 | 8.12 | 16.33 | 69.41 |
| Inflation | 800 | 3.98 | 4.38 | -4.48 | 28.38 |

Table 3.1 reports descriptive statistics for 20 advanced OECD countries over the period 1980–2019. The key explanatory variables, financial institutions and financial markets, are continuous normalized composite indices bounded between 0 and 1, capturing the depth, access, and efficiency of the respective segments of the financial system. The income inequality measures and the main control variables follow the same definitions and data structure as discussed in the previous chapter and are all continuous indicators expressed either as bounded indices, proportions, or percentage shares. Additional controls include population growth, measured as an annual percentage change, govern-

ment expenditure expressed as a percentage of GDP, and inflation measured as the annual percentage change in the consumer price index. Overall, the dataset consists of continuous macroeconomic variables with differing degrees of boundedness and normalization, which are accounted for in the subsequent econometric analysis.

### 3.5.1 Panel unit root test

The results of the Levin, Lin and Chu (2002), Breitung (2000), and Im, Pesaran and Shin (2003) panel unit root tests for the variables considered in this study are reported in Tables 3.2 and 3.3. Table 3.2 presents the results that include individual constants and time trends. The tests are conducted at both the level and first-difference forms of each variable. The statistics for the Gini index, top 1% income share, top 10% income share, labour share of income, financial markets index, financial institutions index, technological progress, population growth, and inflation indicate that these variables are non-stationary at level. However, when tested in first differences, the null hypothesis of non-stationarity is rejected for all these variables at the 1% significance level according to the Levin, Lin and Chu (2002), Breitung (2000), and Im, Pesaran and Shin (2003) tests.

Table 3.2: Panel unit root tests

| | **Levin, Lin and Chu** | | **Breitung t-test** | | **Im, Pesaran and Shin** | |
|---|---|---|---|---|---|---|
| | I(0) | I(1) | I(0) | I(1) | I(0) | I(1) |
| GINI | -3.21 | -24.5*** | -2.31 | -16.3*** | -3.89 | -23.6*** |
| LSI | -2.53 | -20.2*** | -0.25 | -14.1*** | -2.69 | -19.4*** |
| Top 1% | -2.13 | -19.3** | -4.14 | -13.9*** | -1.63 | -20.6** |
| Top 10% | -1.16 | -18.55*** | -2.54 | -12.92*** | -1.33 | -20.37*** |
| FM | 0.834 | -21.09*** | -0.487 | -18.36*** | 1.406 | -22.09*** |
| FI | -1.304 | -19.91*** | 4.512 | -14.13*** | 2.126 | -18.26*** |
| RGDPG | -11.11*** | -25.42 | -9.26*** | -17.10 | -10.56*** | -26.32 |
| GLOB | -4.56*** | -23.97 | -2.52*** | -15.9 | -1.79** | -20.6 |
| LMI | -2.47*** | -14.9 | -1.97*** | -11.7 | -1.27** | -12.9 |
| TECH | 2.23 | -16.4*** | 3.48 | -6.75*** | 5.63 | -14.4*** |
| PG | 0.47 | -14.46*** | -0.24 | -8.224*** | 0.15 | -14.13*** |
| INF | -7.47 | -19.89*** | -1.33 | -11.06*** | -5.94 | -19.14*** |
| GE | -2.86*** | -18.22 | -3.04*** | -11.72 | -3.54*** | -17.62 |

Panel unit root tests were performed with individual trends and intercepts for each series. *, **, *** represent statistical significance at 10%, 5% and 1% respectively.

In contrast, the results show that real GDP growth, globalization, labour market institutions, and government expenditure are stationary at level. Overall, these findings suggest that all variables except real GDP growth, globalization, labour market institutions, and government expenditure exhibit unit roots in their level form but become stationary after first differencing.

Table 3.3 reports the panel unit root test results without time trends in order to verify the robustness of the stationarity properties. The Levin, Lin and Chu (2002), Breitung (2000), and Im, Pesaran and Shin (2003) tests in Table 3.3 confirm that, consistent with the earlier results, all variables except globalization, real GDP growth, labour market institutions, and government expenditure contain unit roots at level. Therefore, the overall conclusion remains unchanged, indicating that the stationarity characteristics of the variables are robust to the inclusion or exclusion of trend components.

Table 3.3: Panel unit root tests

| | **Levin, Lin and Chu** | | **Breitung t-test** | | **Im, Pesaran and Shin** | |
|---|---|---|---|---|---|---|
| | I(0) | I(1) | I(0) | I(1) | I(0) | I(1) |
| GINI | -2.31 | -26.69*** | | | -0.34 | -25.51*** |
| LSI | -3.95 | -22.41*** | | | -2.19 | -20.32*** |
| Top 1% | -3.790 | -22.82*** | | | -2.64 | -23.33*** |
| Top 10% | -3.23 | -22.54*** | | | -1.25 | -22.99*** |
| FM | -2.73 | -21.20*** | | | 0.85 | -21.22*** |
| FI | -6.41 | -14.98*** | | | -4.21 | -15.29*** |
| RGDPG | -13.19*** | -28.06 | | | -13.19*** | -28.44 |
| GLOB | 0.81*** | -25.34 | | | 3.37*** | -22.19 |
| LMI | -6.85*** | -14.66 | | | -1.49*** | -14.14 |
| TECH | -6.81 | -16.61*** | | | -0.12 | -14.45*** |
| PG | 0.29 | -12.52*** | | | -0.16 | -13.63*** |
| INF | -10.71 | -21.26*** | | | -9.19 | -20.66*** |
| GE | -3.57*** | -19.86 | | | -3.56*** | -19.54 |

Panel unit root tests were performed without trend for each series. *, **, *** represent statistical significance at 10%, 5% and 1% respectively.

Finally, the results of Pesaran's CIPS panel unit root test, presented in Table 3.4, confirm that all variables under investigation are non-stationary in levels, except for the real GDP growth, globalization, and labour market institutions, which are found to be stationary. These results indicate that the variables of interest follow an integrated process of order one, I(1), and therefore require first differencing to achieve stationarity. Establishing that the variables are integrated of order one is a necessary step before conducting the panel cointegration tests in the following section. Moreover, the CIPS results are consistent with those obtained from the first generation panel unit root tests developed by Breitung (2000), Levin et al. (2002) and Im et al. (2003), supporting the robustness of the unit root properties of the data. Overall, the confirmation of non-stationarity in levels for the variables under consideration validates the use of panel cointegration and panel ARDL estimation techniques in the subsequent empirical analysis.

Table 3.4: Pesaran's CIPS test results

| | CIPS Statistics | 10% CV | 5% CV | 1% CV | Order of Integration |
|---|---|---|---|---|---|
| GINI | –1.440 | –2.110 | –2.200 | –2.360 | I(1) |
| LSI | -1.969 | -2.110 | -2.200 | -2.360 | I(1) |
| Top 1% | -1.863 | -2.110 | -2.200 | -2.360 | I(1) |
| Top 10% | -2.026 | -2.110 | -2.200 | -2.360 | I(1) |
| FI | -1.862 | -2.110 | -2.200 | -2.360 | I(1) |
| FM | -1.971 | -2.110 | -2.200 | -2.360 | I(1) |
| RGDPG | -3.771 | -2.110 | -2.200 | -2.360 | I(0) |
| LMI | -2.729 | -2.110 | -2.200 | -2.360 | I(0) |
| GLOB | -3.247 | -2.110 | -2.200 | -2.360 | I(0) |
| TECH | -2.873 | -2.110 | -2.200 | -2.360 | I(1) |
| PG | -1.626 | -2.110 | -2.200 | -2.360 | I(1) |
| INF | -1.891 | -2.110 | -2.200 | -2.360 | I(1) |
| GE | -1.745 | -2.110 | -2.200 | -2.360 | I(1) |

### 3.5.2 Panel cointegration tests

To examine the existence of a long run equilibrium relationship between income inequality and financial structure variables, the Fisher (1999), Kao (1999), Pedroni (1999, 2004), and Westerlund (2007) panel cointegration tests were conducted, and their results are presented in Table 3.5. The Fisher–Johansen (1999) test provides strong evidence of cointegration, as both the trace and maximum eigenvalue statistics are highly significant, leading to the rejection of the null hypothesis of no cointegration for the panel as a whole. Consistently, the Kao (1999) test also rejects the null hypothesis at the 1% significance level, confirming a stable long run association between the Gini index and financial structure indicators. The Pedroni test further supports these findings, with six out of seven statistics rejecting the null of no cointegration, indicating a long run relationship between the Gini index and the financial institutions and financial markets indices, while only the panel v-statistic fails to reject the null. Overall, the convergence of results across all three cointegration tests provides strong and consistent evidence of a long run equilibrium relationship between income inequality and financial structure, thereby validating the application of panel ARDL estimators in the subsequent section.

Table 3.5: Panel cointegration tests

| | **Test statistic** | **P-value** |
|---|---|---|
| **Johansen Fischer test** | | |
| Fischer statistics from trace test | 95.87 | 0.000 |
| Fischer statistics from max-Eigen value test | 71.70 | 0.000 |
| **Kao test** | | |
| ADF t-statistic | -5.544 | 0.000 |
| **Pedroni test** | | |
| Panel v-statistic | 1.171 | 0.121 |
| Panel rho-statistic | -0.316 | 0.038 |
| Panel PP-statistic | -1.825 | 0.034 |
| Panel ADF-statistic | -2.147 | 0.016 |
| Group rho-statistic | 0.786 | 0.007 |
| Group PP-statistic | -1.131 | 0.012 |
| Group ADF-statistic | -1.311 | 0.009 |

To further verify the existence of a long-run equilibrium between income inequality and financial structure variables, the Westerlund (2007) panel cointegration test was also employed and its results are reported in Table 3.6. The findings indicate that both the group-mean $G_t$ and the panel-mean $P_t$ statistic reject the null hypothesis of no cointegration at the 1% significance level, suggesting that at least some individual countries, as well as the panel as a whole, display a stable long run relationship between the Gini index and financial structure indicators. The remaining statistics, $G_a$ and $P_a$, yield p-values of 0.245 and 0.001, respectively.

Table 3.6: Westerlund test statistics

| Statistic | Value | Z-value | P-value |
|---|---|---|---|
| $G_t$ | -2.797 | -3.699 | 0.000 |
| $G_a$ | -10.093 | -0.690 | 0.245 |
| $P_t$ | -10.646 | -2.890 | 0.002 |
| $P_a$ | -9.625 | -3.008 | 0.001 |

While $P_a$ is statistically significant at the 1% level, $G_a$ is not, possibly reflecting heterogeneity in the speed of adjustment and long run dynamics across countries. As the t-type statistics ($G_t$ and $P_t$) are generally considered more robust in the presence of cross-sectional dependence, the results provide strong overall support for the existence of cointegration. Taken together, these findings reinforce the presence of a stable long run equilibrium relationship between income inequality and financial structure measures, thereby providing further justification for the application of panel ARDL estimators in the next section.

### 3.5.3 Panel ARDL estimation results

This study employs the panel ARDL approach to analyze the relationship between income inequality and financial structure across 20 advanced OECD countries from 1980 to 2019. This method is advantageous as it can be applied regardless of whether the variables are stationary, non-stationary, or a combination of both (Pesaran and Shin, 1998). Table 3.6 presents the outcomes of the PMG, MG and DFE estimations based on the ARDL model. The upper part of the table displays the long-term coefficients, while the lower section shows the short-term coefficients. The Hausman test is used to determine whether the PMG method is significantly different from the MG estimator. The p-value of 0.99 indicates that the null hypothesis cannot be rejected even at the 1% significance level, suggesting that the PMG estimator is more efficient than the MG method. The results reveal that the error correction term, known as the speed of adjustment is negative and highly significant across all model specifications. This finding suggests that deviations from the long run equilibrium are corrected over time and provides strong evidence of a stable long run relationship between income inequality and financial structure. The significant and negative error correction term also confirms that the financial institutions index and financial markets index, together with the control variables, Granger cause the Gini index in the long run. The results from the PMG, MG, and DFE estimations indicate that the financial structure variables display the expected signs and exert a statistically significant influence on income inequality in the long run, consistent with the existing literature (Maldonado, 2017; Brei et al., 2023; Makhlouf et al., 2023).

However, in the short run, table 3.7 shows that the coefficients of financial institutions and financial markets, although exhibiting the expected signs, are not statistically significant.

Table 3.7: ARDL estimation for Income Inequality and Financial Structure

| | **PMG** | **MG** | **DFE** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FI_{it-1}$ | -0.279*** | -0.493** | -0.509*** |
| | (0.078) | (0.024) | (0.016) |
| $FM_{it-1}$ | 0.266*** | 0.425*** | 0.571*** |
| | (0.040) | (0.016) | (0.021) |
| $RGDPG_{it-1}$ | -0.117*** | -0.049*** | -0.199*** |
| | (0.052) | (0.075) | (0.087) |
| $GLOB_{it-1}$ | 0.042*** | 0.025*** | 0.013*** |
| | (0.007) | (0.029) | (0.014) |
| $TECH_{it-1}$ | 0.124*** | 0.120*** | 0.121*** |
| | (0.016) | (0.010) | (0.027) |
| $LMI_{it-1}$ | -0.097*** | -0.096*** | -0.057*** |
| | (0.018) | (0.011) | (0.028) |
| $PG_{it-1}$ | 0.221*** | 0.121*** | 0.549** |
| | (0.019) | (0.018) | (0.043) |
| $GE_{it-1}$ | -0.036*** | -0.027** | 0.059** |
| | (0.017) | (0.016) | (0.036) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.353*** | -0.854*** | -0.234*** |
| | (0.060) | (0.068) | (0.024) |
| $\Delta FI_{it}$ | -0.041 | -0.040 | -0.079 |
| | (0.014) | (0.028) | (0.089) |
| $\Delta FM_{it}$ | 0.034 | 0.023 | 0.041 |
| | (0.009)) | (0.006) | (0.045) |
| $\Delta RGDPG_{it}$ | 0.044*** | 0.029 | 0.044*** |
| | (0.021) | (0.020) | (0.016) |
| $\Delta GLOB_{it}$ | -0.013 | -0.035 | -0.008 |
| | (0.011) | (0.021) | (0.007) |
| $\Delta TECH_{it}$ | -0.035 | -0.051 | -0.011 |
| | (0.073) | (0.011) | (0.036) |
| $\Delta LMI_{it}$ | -0.037 | -0.028 | -0.011 |
| | (0.058) | (0.092) | (0.029) |
| $\Delta PG_{it}$ | 0.034 | 0.025 | 0.087 |
| | (0.006) | (0.007) | (0.015) |
| $\Delta GE_{it}$ | -0.087** | -0.078 | -0.005 |
| | (0.037) | (0.040) | (0.013) |
| Constant | 11.772*** | 24.329*** | 7.179*** |
| | (0.018) | (0.017) | (0.094) |
| *Hausman test* | 1.24 | | |
| *P-value* | 0.99 | | |

*Notes:* standard errors are presented in parantheses. The income inequality is measured by the Gini index and financial structure is represented by financial institutions index and financial markets index. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). PMG is more efficient estimation than MG under the null hypothesis. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Similarly, most control variables do not show a significant short run relationship with income inequality, with the exception of real GDP growth and government expenditure. In the long run, however, both financial institutions and financial markets exert a statistically significant impact on the Gini coefficient. As expected, the financial institutions index is negatively associated with the Gini measure, while the financial markets index is positively associated with it. The differing impacts of market-based and bank-based financial systems on income inequality stem from how these systems allocate resources and who benefits from financial growth. Market-based systems tend to concentrate wealth among those who are already well-off, while bank-based systems are more likely to support broad-based economic participation. Therefore, while advances in financial markets can exacerbate income inequality, the development of financial institutions can play a role in reducing it by promoting more inclusive economic growth in the long run. This finding is consistent with the findings of Maldonado (2017), Brei et al. (2023), and Makhlouf et al. (2023).

Turning to the control variables, the government expenditure is statistically significant and as expected, it is negatively associated with income inequality in the long run. The empirical evidence generally supports the view that government expenditure on social welfare, education, healthcare, and public goods should reduce income inequality. In particular, countries with well-designed and adequately funded social programs tend to see significant reductions in income inequality (ILO, 2013). Another control variable, the real GDP growth has a statistically significant and negative impact on income inequality in the long run. The negative long run relationship between the real GDP growth rate and Gini measure is expected as long as the economic growth is inclusive and accompanied by effective redistribution policies (Kuznets, 1955). However, the population growth is statistically significant and positively related to income inequality in the long run. The empirical literature provides several mechanisms (e.g. labour market dynamics, urbanization, strain on public services, demographic pressures, etc.) through which population growth can lead to an increase in income inequality, as measured by the Gini index. These mechanisms highlight how rapid population growth can exacerbate disparities in income distribution, particularly in contexts where economic and social structures are unable to accommodate the growing population effectively. It is also important to note that most control variables are not statistically significant in the short run despite displaying the expected signs.

As discussed in the previous chapter, the empirical literature widely recognizes globalization, technological progress, and weakening labour market institutions as key drivers of rising income inequality.As can be seen from the table, these variables are controlled in the panel ARDL estimation in order to examine the relationship between financial structure and income inequality measures. The PMG, MG, and DFE estimation results show that in the long run, globalization, technological progress, and labour market institutions have the expected signs and statistically significant effects on income inequality. However, in the short run, most of these variables remain statistically insignificant with respect to the Gini index. As anticipated, globalization and technological progress are positively correlated with the Gini index, while labor market institutions show a negative correlation with the Gini index in the long run. The globalization tends to widen income inequality through various channels including labour market effects, the shift in income from labour to capital, sectoral shifts and regional disparities (OECD, 2011). As discussed in the previous chapter, technological progress can increase income inequality through the change in skill premium, the shift from labour to capital income and the technological transformations in work places. The weakening of labor market institutions has been identified in the empirical literature as another factor contributing to the rise in income inequality. According to ILO (2013), the weakening of labor market institutions in the form of unions, minimum wage laws, and employment protections has been strongly associated with rising income inequality post 1980 in most of advanced OECD countries.

While the Gini index is the primary measure of income inequality employed in this study, alternative inequality measures are utilized to test the robustness of the relationship between income inequality and financial structure. Accordingly, the labour share of income, as well as the top 1% and top 10% income shares, are used to examine whether the established relationship remains consistent across different measures of inequality. Table 3.8 presents the ARDL estimation results where the labour share of income is used as the dependent variable. The Hausman test p-value indicates that the null hypothesis cannot be rejected even at the 1% significance level, implying that the PMG estimator is both consistent and more efficient than the MG estimator. The estimated coefficients for the financial institutions index and financial markets index display the expected signs and are statistically significant in the long run.

Table 3.8: ARDL estimation for Labour share of income and Financial structure

| | **PMG** | **MG** | **DFE** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FI_{it-1}$ | 0.037*** | 0.031** | 0.054*** |
| | (0.053) | (0.098) | (0.042) |
| $FM_{it-1}$ | -0.051*** | -0.023*** | -0.031*** |
| | (0.087) | (0.017) | (0.027) |
| $RGDPG_{it-1}$ | 0.091*** | 0.010*** | 0.028*** |
| | (0.044) | (0.028) | (0.022) |
| $GLOB_{it-1}$ | -0.059*** | -0.130*** | -0.010*** |
| | (0.026) | (0.051) | (0.004) |
| $TECH_{it-1}$ | -0.035*** | -0.109*** | -0.039*** |
| | (0.023) | (0.019) | (0.077) |
| $LMI_{it-1}$ | 0.039*** | 0.083*** | -0.071** |
| | (0.019) | (0.024) | (0.067) |
| $PG_{it-1}$ | -0.069** | -0.043** | -0.023** |
| | (0.027) | (0.021) | (0.014) |
| $GE_{it-1}$ | 0.068*** | 0.013** | 0.014** |
| | (0.028) | (0.012) | (0.007) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.301*** | -0.437*** | -0.129*** |
| | (0.012) | (0.047) | (0.018) |
| $\Delta FI_{it}$ | 0.011** | 0.028** | 0.005*** |
| | (0.005) | (0.017) | (0.004) |
| $\Delta FM_{it}$ | -0.019 | -0.005 | -0.008 |
| | (0.009) | (0.008) | (0.007) |
| $\Delta RGDPG_{it}$ | 0.016*** | 0.046** | 0.012*** |
| | (0.002) | (0.031) | (0.003) |
| $\Delta GLOB_{it}$ | -0.005*** | -0.010** | -0.040*** |
| | (0.002) | (0.021) | (0.011) |
| $\Delta TECH_{it}$ | -0.035 | -0.030 | -0.038 |
| | (0.013) | (0.011) | (0.005) |
| $\Delta LMI_{it}$ | 0.009 | 0.008 | -0.024 |
| | (0.008) | (0.006) | (0.004) |
| $\Delta PG_{it}$ | -0.046 | -0.008 | -0.043 |
| | (0.055) | (0.007) | (0.001) |
| $\Delta GE_{it}$ | 0.015*** | 0.014*** | 0.011*** |
| | (0.005) | (0.004) | (0.002) |
| Constant | 8.202*** | 30.438*** | 9.796*** |
| | (2.488) | (4.569) | (1.605) |
| *Hausman test* | 2.06 | | |
| *P-value* | 0.40 | | |
| *Observations* | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

The findings indicate that, over the long run, the financial institutions index—representing a bank-based financial system—is positively associated with the labour share of income, while the financial markets index—representing a market-based financial system—is negatively associated with it. This result suggests that the expansion of bank-based financial systems tends to support a higher labour share of income by promoting broader access to credit and fostering investment in productive sectors, which benefits workers and enhances wage growth. In contrast, greater reliance on market-based financial systems tends to lower the labour share, as financial market activities often concentrate income among capital owners and high-income groups, thereby shifting income from labour to capital. Furthermore, the negative and statistically significant error correction term confirms the existence of a stable long run equilibrium relationship between the variables. This indicates that financial structure measures, together with the control variables, jointly Granger-cause the labour share of income in the long run, supporting the evidence of a robust relationship between financial structure and income distribution.

Table 3.9 reports the ARDL estimation results where the top 1% income share is used as an alternative measure of income inequality. The negative and statistically significant error correction coefficient across all estimators confirms the rejection of the null hypothesis of no long run relationship, thereby supporting the presence of a stable long run equilibrium between financial structure and income inequality. As expected, both the financial institutions index and the financial markets index exhibit the anticipated signs and are statistically significant in explaining variations in the top 1% income share. The long run results indicate that financial institutions development is associated with a reduction in top income concentration, while financial market development tends to increase it. This finding suggests that bank-based financial systems contribute to a more equitable income distribution by facilitating access to finance and promoting inclusive growth, whereas market-based systems primarily benefit high-income earners and investors, thereby widening the income gap at the top. Moreover, the control variables display the expected signs and are statistically significant in the long run, indicating that macroeconomic and structural factors also play an important role in shaping the income distribution at the top end. In contrast, in the short run, most control variables are not statistically significant, even though their coefficients generally align with theoretical expectations.

Table 3.9: ARDL estimation for Top 1% Income Share and Financial Structure

| | PMG | MG | DFE |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FI_{it-1}$ | -0.063*** | -0.056*** | -0.051*** |
| | (0.006) | (0.004) | (0.016) |
| $FM_{it-1}$ | 0.075*** | 0.062*** | 0.046*** |
| | (0.004) | (0.002) | (0.011) |
| $RGDPG_{it-1}$ | -0.022*** | -0.015*** | -0.050*** |
| | (0.004) | (0.008) | (0.001) |
| $GLOB_{it-1}$ | 0.031*** | 0.025*** | 0.039*** |
| | (0.001) | (0.003) | (0.002) |
| $TECH_{it-1}$ | 0.078*** | 0.012*** | 0.010*** |
| | (0.002) | (0.006) | (0.002) |
| $LMI_{it-1}$ | -0.010*** | -0.003*** | -0.033** |
| | (0.003) | (0.001) | (0.003) |
| $PG_{it-1}$ | 0.009** | 0.014** | 0.003** |
| | (0.002) | (0.016) | (0.005) |
| $GE_{it-1}$ | -0.016* | -0.019** | -0.067* |
| | (0.001) | (0.001) | (0.004) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.369*** | -0.929** | -0.222*** |
| | (0.061) | (0.080) | (0.025) |
| $\Delta FI_{it}$ | -0.007 | -0.022 | -0.003 |
| | (0.009) | (0.021) | (0.008) |
| $\Delta FM_{it}$ | 0.003 | 0.014 | 0.005 |
| | (0.004) | (0.009) | (0.004) |
| $\Delta RGDPG_{it}$ | 0.002 | 0.005 | 0.002 |
| | (0.001) | (0.003) | (0.001) |
| $\Delta GLOB_{it}$ | 0.0023 | 0.004 | 0.009 |
| | (0.002) | (0.002) | (0.007) |
| $\Delta TECH_{it}$ | -0.0024 | -0.016 | -0.008 |
| | (0.001) | (0.001) | (0.004) |
| $\Delta LMI_{it}$ | -0.004 | -0.003 | -0.002 |
| | (0.003) | (0.006) | (0.003) |
| $\Delta PG_{it}$ | 0.001 | 0.005 | 0.002 |
| | (0.006) | (0.007) | (0.001) |
| $\Delta GE_{it}$ | -0.009** | -0.0027* | -0.003* |
| | (0.002) | (0.004) | (0.001) |
| Constant | 0.035*** | 0.074*** | 0.022*** |
| | (0.062) | (0.041) | (0.006) |
| *Hausman test* | 3.74 | | |
| *P-value* | 0.29 | | |
| *Observations* | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Overall, these findings are consistent with the previous ARDL results where the Gini index is employed as the income inequality measure.

Table 3.10 presents the ARDL estimation results where the top 10% income share is used as the measure of income inequality. The negative and statistically significant error correction coefficient across all estimations confirms the rejection of the null hypothesis of no long run relationship, indicating that the financial institutions index and the financial markets index jointly Granger cause the top 10% income share over time. The long run coefficients for the control variables show the expected signs and are statistically significant, consistent with the results reported earlier in Table 3.5. As expected, the financial institutions index is negatively associated with the top 10% income share, while the financial markets index is positively associated with it. This suggests that bank-based financial systems tend to support a more balanced income distribution, whereas market-based systems contribute to higher income concentration among top earners. Furthermore, the control variables including real GDP growth, globalization, technological progress, labour market institutions, population growth and government expenditure are all significant in the long run, highlighting their important role in shaping income inequality. The negative and significant error correction term further confirms the presence of a stable long run equilibrium, showing that financial structure and control variables are cointegrated and jointly influence the top 10% income share.

In the short run, however, most coefficients for financial structure and control variables are not statistically significant, except for government expenditure, which continues to exert a meaningful effect on income inequality. Overall, the PMG, MG, and DFE estimation results provide strong evidence of a long run causal relationship between financial structure and income inequality. The confirmation of cointegration across all measures of inequality demonstrates that the relationship between financial structure and income distribution remains robust and is not undermined by the inclusion of control variables.

To further verify our results, this study divides time into non-overlapping 5-year intervals and replaces all variables with their 5-year averages on these intervals. This method mitigates the potential effect of business cycle fluctuations including global financial crisis in 2008 and enables us to focus on longer term impact of financial systems. In other words, this approach smooths out the volatility associated with business cycles, ensuring that the analysis captures the underlying relationship between financial systems and income inequality.

Table 3.10: ARDL estimation for Top 10% Income Share and Financial Structure

| | **PMG** | **MG** | **DFE** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FI_{it-1}$ | -0.021*** | -0.052*** | -0.078*** |
| | (0.009) | (0.038) | (0.024) |
| $FM_{it-1}$ | 0.034*** | 0.021*** | 0.047*** |
| | (0.006) | (0.015) | (0.016) |
| $RGDPG_{it-1}$ | -0.010*** | -0.042*** | -0.022*** |
| | (0.008) | (0.009) | (0.012) |
| $GLOB_{it-1}$ | 0.026*** | 0.022*** | 0.072*** |
| | (0.008) | (0.003) | (0.004) |
| $TECH_{it-1}$ | 0.022*** | 0.018*** | 0.016*** |
| | (0.003) | 0.010) | (0.004) |
| $LMI_{it-1}$ | -0.016*** | -0.054*** | -0.030*** |
| | (0.002) | (0.011) | (0.043) |
| $PG_{it-1}$ | 0.011*** | 0.037*** | 0.011*** |
| | (0.004) | (0.082) | (0.007) |
| $GE_{it-1}$ | -0.008*** | -0.012*** | -0.008*** |
| | (0.003) | (0.005) | (0.006) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.256*** | -0.829*** | -0.187*** |
| | (0.044) | (0.066) | (0.022) |
| $\Delta FI_{it}$ | -0.014 | -0.005 | -0.002 |
| | (0.010) | (0.019) | (0.011) |
| $\Delta FM_{it}$ | 0.015** | 0.0036 | 0.008 |
| | (0.006) | (0.010) | (0.005) |
| $\Delta RGDPG_{it}$ | 0.0024 | 0.0015 | 0.003 |
| | (0.002) | (0.002) | (0.002) |
| $\Delta GLOB_{it}$ | 0.0019 | -0.004 | -0.002 |
| | (0.001) | (0.003) | (0.001) |
| $\Delta TECH_{it}$ | 0.0016 | 0.005 | 0.0015 |
| | (0.001) | (0.001) | (0.004) |
| $\Delta LMI_{it}$ | -0.006 | -0.008 | -0.004 |
| | (0.005) | (0.007) | (0.003) |
| $\Delta PG_{it}$ | -0.004 | 0.0018 | 0.0036* |
| | (0.003) | (0.0068) | (0.0019) |
| $\Delta GE_{it}$ | -0.008*** | -0.005 | -0.004*** |
| | (0.004) | (0.004) | (0.001) |
| Constant | 0.104*** | 0.227*** | 0.068*** |
| | (0.017) | (0.065) | (0.011) |
| *Hausman test* | 4.58 | | |
| *P-value* | 0.18 | | |
| *Observations* | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

By re-estimating the panel ARDL model with these 5-year averages, this study also strengthens the robustness of our findings, demonstrating that the observed effects are not merely due to short-term variations but reflect persistent trends. Additionally, this method reduces data noise and accounts for different phases of economic cycles, providing a more comprehensive view of how bank based and market based financial systems influence inequality measures across varying economic conditions. Table 3.11 presents the estimation results based on five-year averaged observations. The results from the PMG estimator, identified as the most efficient according to the Hausman test, reinforce the previous findings regarding the differing effects of bank-based and market-based financial systems on income inequality in the long run. The negative and statistically significant error correction coefficient confirms the existence of a stable long run relationship, indicating that the financial institutions index and financial markets index, together with the control variables, jointly Granger cause income inequality over time. These results demonstrate that even after accounting for business cycle fluctuations through the use of five-year intervals, the long run relationship between financial structure and income inequality remains robust. Specifically, the financial institutions index, representing the bank-based financial system, continues to be associated with a reduction in income inequality, while the financial markets index, representing the market-based system, is linked to an increase in inequality. This outcome highlights the persistent structural differences in how the two types of financial systems influence income distribution across advanced economies. In the short run, however, both the financial institutions index and the financial markets index remain statistically insignificant, despite exhibiting the expected signs. This suggests that the influence of financial structure on income inequality materializes primarily over the long term rather than through short-term adjustments.

Table 3.12 presents the results of the CS-ARDL estimation, which accounts for pontential cross-sectional linkages and feedback effects among the variables. The findings confirm a robust long run relationship between financial structure and income inequality across all specifications. The financial institutions index exerts a statistically significant negative influence on income inequality, while the financial markets index has a significant positive effect, reinforcing the differing impact of bank-based and market-based systems. The control variables generally display the expected signs and remain statistically significant in explaining variations in income inequality. In the short run, however, most financial structure and control variables are statistically insignificant, except for the real GDP growth rate, suggesting that the adjustment dynamics primarily operate over the long term.

Table 3.11: Income Inequality and Financial Structure (5-year observations)

| | **PMG** | **MG** | **DFE** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FI_{it-1}$ | -0.027**** | -0.015 | -0.013*** |
| | (0.006) | (0.004) | (0.003) |
| $FM_{it-1}$ | 0.058*** | 0.061*** | 0.042*** |
| | (0.026) | (0.022) | (0.025) |
| $RGDPG_{it-1}$ | -0.091*** | -0.064*** | -0.037*** |
| | (0.032) | (0.035) | (0.029) |
| $GLOB_{it-1}$ | 0.021*** | 0.029*** | 0.012*** |
| | (0.013) | (0.016) | (0.006) |
| $TECH_{it-1}$ | 0.018*** | 0.014*** | 0.016*** |
| | (0.008) | (0.006) | (0.007) |
| $LMI_{it-1}$ | -0.012*** | -0.015*** | -0.011*** |
| | (0.007) | (0.012) | (0.006) |
| $PG_{it-1}$ | 0.014*** | 0.035*** | 0.019*** |
| | (0.019) | (0.018) | (0.015) |
| $GE_{it-1}$ | -0.036*** | -0.024*** | -0.025*** |
| | (0.008) | (0.007) | (0.006) |
| $INF_{it-1}$ | 0.028* | 0.024* | 0.013* |
| | (0.014) | (0.011) | (0.009) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.475*** | -0.756*** | -0.124*** |
| | (0.024) | (0.052) | (0.016) |
| $\Delta FI_{it}$ | -0.012 | -0.009 | -0.007 |
| | (0.006) | (0.003) | (0.002) |
| $\Delta FM_{it}$ | 0.016 | 0.011 | 0.014 |
| | (0.008) | (0.004) | (0.005) |
| $\Delta Controls_{it}$ | Yes | Yes | Yes |
| Constant | Yes | Yes | Yes |
| *Observations* | 160 | 160 | 160 |
| *Hausman test* | 8.9 | | |
| *P-value* | 0.45 | | |

*Notes:* standard errors are presented in parantheses. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Table 3.12: CS-ARDL estimation for Income Inequality and Financial Structure

| | **GINI** | **Top 10 %** | **Top 1 %** |
|---|---|---|---|
| *Long run coefficients* | | | |
| $FI_{it-1}$ | -0.571*** | -0.120*** | -0.086*** |
| | (0.036) | (0.012) | (0.014) |
| $FM_{it-1}$ | 0.119*** | 0.112*** | 0.011*** |
| | (0.089) | (0.010) | (0.009) |
| $RGDPG_{it-1}$ | -0.059*** | -0.076*** | -0.087*** |
| | (0.042) | (0.039) | (0.035) |
| $GLOB_{it-1}$ | 0.029*** | 0.057*** | 0.051*** |
| | (0.028) | (0.025) | (0.029) |
| $TECH_{it-1}$ | 0.115*** | 0.027*** | 0.033*** |
| | (0.087) | (0.012) | (0.005) |
| $LMI_{it-1}$ | -0.120*** | -0.051*** | -0.078*** |
| | (0.086) | (0.056) | (0.057) |
| $PG_{it-1}$ | 0.043*** | 0.087*** | 0.059*** |
| | (0.099) | (0.050) | (0.060) |
| $GE_{it-1}$ | -0.058*** | -0.012*** | -0.009*** |
| | (0.027) | (0.006) | (0.006) |
| *Short run coefficients* | | | |
| $ECT_{it-1}$ | -0.906*** | -0.412*** | -0.257*** |
| | | | (0.084) |
| $\Delta FI_{it}$ | -0.055* | -0.065* | -0.041 |
| | (0.011) | 0.015 | (0.012) |
| $\Delta FM_{it}$ | 0.022 | 0.054*** | 0.013 |
| | (0.008) | (0.014) | (0.007) |
| $\Delta RGDPG_{it}$ | 0.052** | 0.083*** | 0.006** |
| | (0.030) | (0.029) | (0.002) |
| $\Delta GLOB_{it}$ | -0.017 | -0.019 | -0.027 |
| | (0.023) | (0.031) | (0.003) |
| $\Delta TECH_{it}$ | -0.096 | -0.027 | -0.004 |
| | (0.072) | (0.009) | (0.002) |
| $\Delta LMI_{it}$ | -0.083 | -0.014 | -0.008 |
| | (0.070) | (0.009) | (0.005) |
| $\Delta PG_{it}$ | 0.028 | 0.075 | 0.0021 |
| | (0.007 | (0.006) | (0.005) |
| $\Delta GE_{it}$ | -0.049 | -0.011 | -0.002 |
| | (0.026) | (0.004) | (0.003) |
| *Observations* | 777 | 777 | 777 |

*Notes:* standard errors are presented in parantheses. The lag structure is p=1 and q=1 based on Schwarz-Bayesian Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Overall, the CS-ARDL estimation results are consistent with the panel ARDL results above and confirm the differing effects of financial institutions index and financial markets index on income inequality measures in the long run.

### 3.5.4 Robustness tests

Table 3.13 presents the results of the DOLS estimation, which is employed to examine the long-run impact of bank-based and market-based financial systems on income inequality. In this specification, income inequality measures are regressed on financial structure indicators and a set of control variables to assess the extent to which the composition of the financial system influences inequality outcomes. The estimated coefficients for the financial structure variables are statistically significant and exhibit the expected signs across all model specifications.

Table 3.13: DOLS estimates

| | **GINI** | **Top 1%** | **Top 10%** |
|---|---|---|---|
| Financial institutions | -0.295*** | -0.074*** | -0.028*** |
| | (0.086) | (0.007) | (0.008) |
| Financial markets | 0.281*** | 0.067*** | 0.032*** |
| | (0.052) | (0.006) | (0.008) |
| Real GDP growth | -0.123*** | -0.028*** | -0.012*** |
| | (0.046) | (0.004) | (0.006) |
| Globalization | 0.054*** | -0.042*** | -0.024*** |
| | (0.008) | (0.002) | (0.004) |
| Technological progress | 0.132*** | 0.072*** | 0.021*** |
| | (0.021) | (0.008) | (0.003) |
| Labour market institutions | -0.087*** | -0.012*** | -0.014*** |
| | (0.014) | (0.003) | (0.004) |
| Population growth | 0.214*** | 0.008*** | 0.016*** |
| | (0.016) | (0.002) | (0.008) |
| Government expenditure | -0.042*** | -0.014*** | -0.007*** |
| | (0.014) | (0.001) | (0.003) |
| Inflation | 0.104 | 0.007 | 0.012 |
| | (0.025) | (0.001) | (0.005) |

*Notes:* Standard errors are presented in parenthesis. Lag and lead lengths were determined by the Schwarz information criterion. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

The findings indicate that the financial institutions index is negatively associated with the Gini coefficient, the top 1%, and the top 10% income shares, suggesting that more developed financial institutions contribute to reducing income inequality in the long run. In contrast, the financial markets index is positively and significantly related to the same inequality measures, implying that more advanced financial markets tend to exacerbate income disparities over time. These results remain robust across alternative inequality measures, reinforcing the reliability of the estimates.

Table 3.14: Financial Structure and Income Inequality with extended controls, 1980-2019

| | **Gini** | **Top 1%** | **Top 10%** |
|---|---|---|---|
| Financial Institutions | -0.042*** | -0.022** | -0.048** |
| | (0.056) | (0.007) | (0.007) |
| Financial Markets | 0.061** | 0.037*** | 0.053*** |
| | (0.036) | (0.005) | (0005) |
| Real GDP growth | -0.045*** | -0.011** | -0.012** |
| | (0.020) | (0.001 | (0.003) |
| Globalization | 0.021** | 0.034*** | 0.058*** |
| | (0.005) | (0.004) | (0.006) |
| Technological progress | 0.116** | 0.012* | 0.014* |
| | (0.010) | (0.002) | (0.002 |
| Labour market institutions | -0.060*** | -0.003* | -0.004 |
| | (0.009) | (0.0006) | (0.0008 |
| Population growth | 0.051 | 0.005 | 0.0037 |
| | (0.017) | (0.002) | (0.0016) |
| Government expenditure | -0.069** | -0.003 | -0.005 |
| | (0.011) | (0.001) | (0.002) |
| Inflation | 0.012 | 0.001** | 0.001** |
| | (0.022) | (0.0003) | (0.0021) |
| Education | -0.027** | -0.016 | -0.018 |
| | (0.008) | (0.004) | (0.006) |
| Regime corruption | 0.021*** | 0.017* | 0.012* |
| | (0.004) | (0.002) | (0.003) |
| Constant | 32.704*** | 0.105*** | 0.352*** |
| | (0.814) | (0.008) | (0.011) |
| *Countries* | 20 | 20 | 20 |
| *R-squared* | 0.90 | 0.833 | 0.882 |
| *F-statistic* | 215.61*** | 121.98*** | 183.67*** |

*Notes:* Standard errors are presented in parenthesis. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Overall, the DOLS estimation provides strong evidence of a stable long-run relationship between financial structure and income inequality. The results are broadly consistent with those obtained from the panel ARDL estimations discussed earlier, thereby confirming the robustness of the long-run link between financial structure and income inequality across OECD countries.

Table 3.14 reports the results of the fixed effects regression estimated with cluster-robust standard errors, which account for any potential autocorrelation and heteroskedasticity. The results indicate that both financial institutions and financial markets exert a statistically significant influence on income inequality measures. Specifically, a more market-based financial system, captured by the financial markets index, is positively associated with income inequality, whereas a stronger bank-based system, represented by the financial institutions index, is negatively related to inequality across all specifications. Importantly, these relationships remain robust even after controlling for a comprehensive set of variables commonly associated with inequality in the empirical literature (Levine, 2002; Beck et al., 2007; Zhang and Naceur, 2019). These findings are consistent with the long-run results obtained from the panel ARDL and DOLS estimations, thereby supporting the robustness and stability of the established relationship between financial structure and income inequality across advanced OECD economies.

## 3.6 Concluding remarks

The financial system and its implications on income inequality have been recently an important topic of debate among academics, practitioners and policymakers. This study contributes to the financial structure-inequality literature based on the panel study of 20 advanced OECD countries where income inequality has increased considerably along with the rapid development of financial institutions and markets over the period 1980-2019. Thus, the aim of this research is to examine the long run relationship between financial systems and income inequality using the panel ARDL estimation method. First, the study conducts panel unit root tests in order to determine whether the variables of interest contain unit root at level. Second, the panel cointegration tests are performed to determine the existence of a stable long run relationship among the variables under consideration. Then, the panel ARDL method is applied to analyze the short-run dynamics and long run equilibrium relationship between income inequality and financial structure variables with particular attention to whether bank-based and market-based systems exert differential effects on inequality. To account for potential cross sectional dependence and induced feedback effects among the variables, this study further employs CS-ARDL method developed by Chudik and Pesaran (2015). In addition, the DOLS approach is used as a robustness test to ensure the stability and reliability of the estimated relationships between financial structure and income inequality.

The panel ARDL estimation results indicate the existence of a cointegrating relationship between income inequality and financial structure variables. The negative and statistically significant error correction term across all specifications confirms a long-run equilibrium in which financial institutions and financial markets jointly Granger cause income inequality. Across the PMG, MG, and DFE estimators, the results consistently indicate that a more bank-based financial system mitigates inequality, whereas a more market-based financial system exacerbates it. This is reflected in the statistically significant negative long-run coefficients of the financial institutions index and the positive long-run coefficients of the financial markets index. The CS-ARDL estimation results are consistent with the panel ARDL results, thereby confirming the reliability and validity of the long run relationship between income inequality and financial structure measures. Although the short-run coefficients of financial structure variables are generally insignificant, the long-run relationships remain stable and robust. Simlarly, the DOLS results further corroborate these findings, confirming a statistically significant long-run impact of both financial institutions and financial markets on income inequality. Overall, the findings provide strong empirical support for the hypothesis that a bank-dominated financial system helps reduce income inequality, whereas a market-dominated financial system amplifies it in the long run. These results underscore the importance of financial system composition in influencing distributional outcomes and align with the growing empirical evidence that financial structures play a crucial role in shaping inequality dynamics (Morado et al., 2016; Maldonado, 2017; Makhlouf et al., 2023; Brei et al., 2023).

This chapter aims to contribute to the existing literature in three main ways. First, it addresses a gap in the literature by demonstrating that financial structure significantly influences income inequality in the long run. The results show that the financial institutions index, which reflects the banking system, is associated with lower levels of income inequality, whereas the financial markets index, which reflects the market-oriented system, is linked to higher inequality. Second, despite constraints in data availability, this study provides robust empirical evidence on the importance of financial system composition for long-term inequality dynamics. By employing the financial institutions and financial markets indices to represent the two dominant financial structures, the analysis highlights how differences in financial system orientation can shape income distribution across advanced economies. Third, the application of the CS-ARDL approach strengthens the reliability and validity of the panel ARDL results by addressing potential cross-sectional dependence and feedback effects among the variables. The consistency of findings across alternative income inequality measures further supports the robustness of the established long-run relationship between financial structure and income inequality.

The impact of financial structure on income inequality have significant policy implications, both from the perspective of economic stability and social equity. The findings of this study, alongside existing literature, suggest that policymakers need to carefully consider the structure of their financial systems when designing strategies to address income inequality. The findings of this research demonstrates that more bank-dominated financial systems, as captured by the financial institutions index, are associated with a reduction in income inequality. This finding aligns with some strands of the literature (Maldonado 2017; Brei et al. 2023; Makhlouf et al. 2023) that argue bank-dominated systems tend to be more inclusive, offering wider access to financial services across different segments of society. Banks, through their intermediation role, can provide credit to a broader range of borrowers, including small and medium-sized enterprises (SMEs) and lower-income individuals, who might otherwise be excluded from capital markets. By facilitating access to credit and financial services, bank-dominated systems can help reduce income disparities by supporting economic activities that generate income for lower-income groups. Policy implications include the need to strengthen and expand banking systems, particularly in ways that enhance access to financial services for underrepresented segments of the population. This could involve promoting microfinance, enhancing regulatory frameworks to ensure fair lending practices, and incentivizing banks to extend credit to SMEs and individuals in lower-income brackets. Additionally, policies that ensure financial stability in banking, such as prudent regulation and oversight, are crucial to maintaining the inclusiveness of bank-dominated systems, which can, in turn, help mitigate income inequality.

Conversely, the results of this panel study show that more market-dominated financial systems, represented by the financial markets index, tend to increase income inequality. This result is consistent with the existing literature (Maldonado, 2017; Brei et al. 2023; Makhlouf et al. 2023) suggesting that market-dominated systems often favor wealthier individuals and bigger corporations that have greater access to capital markets. In market-dominated systems, the benefits of financial deepening and innovation, such as stock market growth and increased investment opportunities, tend to be captured disproportionately by higher-income groups who are more likely to own financial assets. This can lead to a concentration of wealth among the rich households and exacerbate existing income inequalities. While market-dominated systems can drive economic growth and innovation, there is a need for policies that mitigate their unequal effects (Maldonado, 2017). These could include progressive taxation on capital gains, measures to broaden access to capital markets (e.g., through financial education and inclusion programs), and initiatives to ensure that financial market developments benefit a wider population. Additionally, policymakers should be aware of the possibility of financial crises and economic downturns in market-dominated systems, which can disproportionately impact lower-income groups and thus worsen inequality.

Given the differing effects of bank-dominated and market-dominated financial systems, a balanced approach to financial system development is essential. Policymakers should aim to harness the strengths of both systems while addressing their weaknesses. For instance, while promoting the inclusiveness of bank-based systems, it is also important to ensure that the benefits of financial markets are more broadly distributed. This might involve regulatory reforms that encourage more equitable access to financial markets or policies that promote broader asset ownership among the population. In transitioning or mixed financial systems, where both banks and markets play significant roles, a coordinated policy approach is necessary. This could involve regulatory frameworks that ensure both sectors contribute to inclusive growth, such as regulations that promote responsible lending in banking and equitable practices in capital markets. Policymakers could also consider developing complementary financial products and services that leverage the strengths of both systems, ensuring that financial development contributes to reducing inequality. Moreover, policymakers should be cautious of feedback loops where inequality itself may influence the development and structure of financial systems, potentially reinforcing existing disparities. For instance, high levels of inequality could lead to a financial system that is more market-based and exclusive, further exacerbating inequality. To counteract such dynamics, policies should aim to create a virtuous cycle where financial system development supports broad-based economic growth and reduced inequality. This could involve targeted interventions in both banking and financial markets to ensure that financial development benefits the wider economy rather than just the affluent.

This study provides compelling evidence that the type of financial system has a statistically significant impact on income inequality in the long run. These findings carry profound implications for policymakers, suggesting that a greater reliance on bank-based financial systems may be instrumental in mitigating income disparities, whereas market-based systems may contribute to widening inequality. Policymakers should strive to create a balanced financial system that leverages the inclusivity of banking while ensuring that the benefits of market-based systems are more widely distributed. This requires a combination of regulatory oversight, financial inclusion initiatives, and policies that promote equitable access to both banking services and financial markets. By doing so, financial systems can be developed in a way that supports sustainable and inclusive economic growth, ultimately contributing to a reduction in income inequality. The current results suggest that the impact of financial structure may have been underestimated in many of the previous studies and the main idea advocated in this research is that the way a country's financial system grows towards more market dominated vs. bank dominated systems has implications for income inequality. The long term term relationship that has been established here between the composition of financial system and income inequality is an important finding given the limited literature in this area. The differing effects of bank dominated and market dominated financial systems on income inequality based on the panel study of advanced OECD countries demonstrates that the composition of financial systems has implications for income inequality in the long run. Thus, the findings from this study have contributed to the broader debate regarding the role of financial structure in relation to rising income inequality in advanced economies.

# Chapter 4

# Household Debt and Income Inequality

## 4.1 Introduction

The rising income inequality and its implications on household debt have been recently an important topic of debate among academics, practitioners and policymakers. There is a growing consensus that an increase in income inequality over the last decades has fuelled household debt which in turn has been an important driver of banking and financial crisis (Kumhof et al., 2015; Bartscher et al., 2020). Kumhof et al., (2015), Bartscher et al., (2020) and Bazillier et al., (2021) point out that a significant increase in household leverage coincided with rising income inequality over the past 40 years. Mian and Sufi (2018) argue that households increased their debt considerably in some advanced OECD countries and confirm the importance of household leverage behind the 2008 financial crisis in the US. As a result of the recent global financial crisis, the evolution of household indebtedness and its roots have been on the agenda of economic discussions and they have raised the question as to why households generally take on debt and what role income inequality plays in relation to surging household debt.

Although there is a growing theoretical discourse on the role of income inequality in driving household indebtedness, empirical evidence remains comparatively scarce, particularly for advanced economies. This chapter seeks to fill this gap by examining the dynamic relationship between income inequality and household debt across advanced OECD countries from 1980 to 2019. The study contributes to the literature in two primary respects. First, it employs a panel Vector Error Correction Model (VECM) to jointly assess short run adjustments and long run cointegrating relationships, thereby enabling a more rigorous evaluation of both the direction and persistence of causality between the variables. This approach offers a superior framework for identifying long run equilibrium conditions that previous studies often overlook. Second, the study uses enhanced and more comprehensive measures of both household debt and income inequality, helping to address measurement limitations that may have contributed to inconclusive or inconsistent findings in the existing literature. The incorporation of multiple inequality indicators further strengthens the robustness of the empirical findings and enables a more comprehensive assessment of how distributional dynamics shape the evolution of household indebtedness over time.

The novelty of this research arises from its combined methodological and data enhancements relative to the existing literature. Previous empirical studies on the inequality–debt nexus (Bordo and Meissner, 2012; Malinen, 2013; Bazillier et al., 2021) have typically relied on broad bank credit indicators such as those developed by Schularick and Taylor (2012) as proxies for household debt, while employing a single distributional metric such as the Gini coefficient or top income shares to capture inequality. Such approaches may disguise important heterogeneity within both financial and inequality dynamics. This study addresses these limitations by utilizing household debt measures sourced directly from the Bank for International Settlements, including household debt as a share of GDP and real household debt per capita, which more accurately reflect indebtedness at the household level. In addition, four distinct income inequality indicators are incorporated to capture a wider set of distributional dimensions and ensure greater robustness in the empirical results. As a result, this research can be regarded as a more precise and comprehensive approach for examining the existence and direction of a causal relationship between income inequality and household debt hypothesized in Rajan (2010) and formalized in the theoretical framework of Kumhof, Ranciere and Winant (2015).

The current body of literature generally distinguishes household income inequalities of three types which are market income, gross income and disposable income. The market income is a relatively new concept among these terms and it is based on a distinction between private and welfare state based income sources including state pensions, unemployment benefits, social security, etc.

The Gini based on the market income tends to indicate high inequalities for developed countries due to the concentration of capital incomes and the existence of many households with zero market income (e.g. retirees, unemployed, etc.) in developed welfare states. Thus, the market income is not a good measure of a highly unequal state. The disposable income can be more accurate for analysing the distribution of economic welfare across households. However, the limitation of this method is that it would not always differentiate the countries with more effective re-distributive tax systems from the countries with less effective tax system for the distribution of economic welfare. As a result, this study uses the Gini measure based on the gross income which will be best indicator of pre-tax inequality across nations and through time.

This research has important policy implications for governments on how to prevent financial crisis. In fact, the findings of this paper indicate that income inequality dynamics play a paramount role in the build-up of household leverage bubbles. To be more specific, the reduction of wealth for middle class relative to top income households is found to be a significant driver behind destabilizing credit bubbles. Mian and Sufi (2018) argue that the business cycle following the household leverage driven by excessive supply of credit is a consequence of positive shocks to the wealth of top income households at the expense of middle and lower class households. Therefore, government programs and policies intended to tackle growing income inequality, especially those affecting the middle class, could help reduce the risk of financial crisis.

The rest of the paper is organized as follows. The next section provides a review of the relevant literature on the relationship between household debt and income inequality. The section 4.3 provides theoretical motivation to analyse the channels through which income inequality influences household debt. The econometric methodology of the study and data selection procedures are explained in the sections 4.4 and 4.5. The remaining sections discuss the empirical test results and key findings along with the robustness tests. The last section gives concluding remarks and suggestions.

## 4.2 Literature review

The economic implications of income inequality have been one of the main topics of the academic literature over the past decades. A number of studies have attributed the recent financial crisis in 2008 to a significant increase in wage inequality and household leverage (e.g. Kumhof, et al 2015; Rajan, 2010; Atkinson and Morelli, 2011). In this regard, Mian and Sufi (2010) point out the role of increasing household debt leading up to the financial crisis in 2008. They conclude that a more thorough study of household finance can explain the sources of macroeconomic fluctuations (Mian and Sufi, 2010). Mian and Sufi (2010) state that the credit-driven household demand channel has been an important factor behind business cycles and can elucidate the occurrence of many economic cycles in advanced countries over the last four decades. Bazillier et al.(2021) also indicate the importance of household leverage in relation to the economic downturn in eurozone countries. Thus, this paper will concentrate on a specific dynamic that might impact this household credit channel, specifically the role of income inequality. Rajan (2010) argues that there is a close association between the income inequality and the crisis and highlights the role of governments in pursuing easy credit policy as a solution to rising inequality instead of addressing it's root causes. Rajan (2010) concludes that a growing inequality in advanced countries led to redistribution of income in the form of subsidized housing finance which resulted in a housing bubble and subsequently contributed to the financial crisis with severe consequences. However, Acemoglu (2011) and Johnson (2015) argue that Rajan's hypothesis is not consistent with the timing of rising inequality and the subsequent crisis by pointing out that deregulation of financial sector and mortgage industry being critical factors behind the recent crisis occurred mainly as a result of the lobbying of the financial industry rather than inequality.

Following the financial crisis in 2008, there have been quite a few number of empirical studies that look into the relationship between income inequality and household debt. Kumhof and Ranciere (2010) were one of the first to examine the relationship between wage inequality, household debt and crises using the DSGE model. They develop a model that comprises two representative households. One type of households who own all of the capital, earn only capital income which is used for saving, investment and consumption. However, another type of households, referred to as workers, earn only labour income and use it entirely for consumption. The model shows that negative shocks on the bargaining power of low income households and positive shocks to the income of high income households lead to a rise in income differences between these households. Due to an increase in inequality, low income households take on more debt to maintain their basic standard of living and it is included as a minimum level of consumption in their utility function. As a result of more borrowing on the part of low income households to maintain their desired level of consumption, household debt will increase in the economy. As Kumhof and Ranciere (2010) assume that there is a convex relationship between household debt and the probability of an economic crisis, they attempted to relate growing inequality to a rising leverage and how they lead to a higher probability of an economic crisis.The crisis arises from a deliberate and reasoned decision by low-income earners to default on their debts, weighing the advantages of reducing their increasing debt burden against the drawbacks of reduced productivity and satisfaction associated with defaulting. Lenders anticipate and factor in this behavior when setting loan terms. This crisis is marked by partial defaults on household debts and a sudden decline in economic output, a pattern observed in studies by Philippon and Midrigan (2011) and Gärtner (2013) during the Great Recession and the Great Depression respectively. While a rational decision to default can alleviate financial strain for low-income earners, the severe economic downturn disproportionately affects them and leads to higher interest rates after the crisis. Consequently, any improvement in their debt-to-income ratios is minimal, and unless income inequality changes, their debt levels rebound swiftly. Kumhof and Benes (2012) later continued this study by extending it to an open economy model.

The existing literature shows that the historically low levels of interest rates and increased availability of credit have also been critical factors behind the significant growth of household debt, especially before the financial crisis in 2008 (Taylor, 2009; Justiniano et al., 2015). Moreover, there are other studies that relate the increase in household debt to the housing market conditions, demographic factors, stagnant real wages and cutbacks in the welfare state (Moore and Stockhammer, 2018; Magri, 2007; Barba and Pivetti, 2009; and Leicht, 2012). However, it is important to highlight the role of advances in financial services industry where improvements in loan production technology (e.g. risk management innovations, reductions in distribution costs, etc.) have made the access to loans considerably easier, thus fuelling the household debt in developed OECD economies.

Berisha et al. (2018) argue that the evolution of household debt since the 1980s has played a significant role in driving redistribution in advanced OECD countries. Their empirical study shows that growing household debt among lower income families are coincident with low interest rate environment, infrequent business cycle fluctuations and the increase in wealth of top earners. In particular, advances in the financial services industries have enabled top earners to gain more wealth in the form of financial assets that are claims on loans to the rest of the population. The income inequality is further exacerbated by relatively stable economic environment and the decreased costs of financial leveraging which induced middle and lower income families to maintain their consumption through more borrowing. Moreover, Saez (2017) asserts that significant increases in the borrowing of bottom 90 percent earners show that these households have not been able to save at all over the last three decades. In contrast, top earners have accumulated even bigger wealth through their savings during this period. As a result, this has fuelled income and wealth inequalities in some of the advanced OECD countries.

Fitoussi and Saraceno (2010) demonstrate that widening income inequality tends to suppress aggregate demand, prompting central banks to lower interest rates. Concurrently, households that accumulate substantial wealth at the expense of growing inequality often pursue high-yield investment opportunities, which can contribute to asset bubbles through the expansion of private debt. They propose a transmission mechanism whereby rising concentration of income at the top of the distribution increases the availability of household credit. Similarly, Milanovic (2009) argues that increasing inequality in the United States has generated significant wealth accumulation among the top earners, producing an excess of funds seeking profitable outlets. Confronted with a surplus of investment-seeking capital and limited opportunities in the productive sector, the financial industry became increasingly inventive and, at times, reckless, effectively "throwing money at anyone who would take it." On the household side, rising inequality compels those with declining incomes to borrow more in order to sustain their consumption levels. This observation aligns with earlier research on the link between income inequality and household debt by Iacoviello (2008), Blundell et al. (2008), and Krueger and Perri (2006). A central debate, however, concerns whether the observed increases in measured income inequality reflect greater dispersion in permanent income or transitory income, as only changes in the latter would drive higher borrowing according to permanent income and life-cycle theories (Friedman, 1957; Modigliani and Brumberg, 1954). Empirical findings indicate that the rise in inequality over recent decades has been primarily driven by increasing dispersion in permanent income (Kopczuk et al., 2010; DeBacker et al., 2013). Stockhammer (2013) argues that income inequality encourages affluent households to take excessive risk and leverage in advanced countries with developed financial systems. Stiglitz (2012) studying the implications of increasing inequality points out that stagnant real wages have made poorer households to take on more debt in order to sustain their rising standard of living.

Iacoviello (2008) proposes a quantitative dynamic model to replicate the observed contemporaneous relationship between the evolution of inequalities and household debt. His study offers explanations as to why growing income inequality is the driving factor behind the increase in household debt post 1980. Iacoviello (2008) argues that the permanent increase in income inequality has fuelled the household debt since 1980. The study by Krusell and Smith (1998) shows that the rise in household debt is attributed to growing income inequality whereas business cycle fluctuations can account for the short run changes in household debt. They set up a model where agents face aggregate and idiosyncratic income shocks while accumulating real and financial assets in their life cycle. Their model indicates that there are two types of agents with one being defined as patient agents and other one as impatient agents. Patient agents do not face borrowing constraints given their access to loans at low interest rates whereas impatient agents have limited access to loans given their collateral constraints with high discount rates. The implications of negative idiosyncratic income shocks are that agents without borrowing constraints decrease their consumption by a little amount but increase their debt more. However, agents with collateral constraints reduce their consumption and borrowing. The model indicates how the observed income inequality interacts with household debt data.

The current body of literature indicates that there are theoretical studies by Kumhof and Ranciere (2010), Iacoviello (2008) and others who model the channels through which rising income inequality affects household debt. However, the empirical literature examining the relationship between income inequality and household debt appears to be limited. For instance, Atkinson and Morelli (2011) look into a dataset covering 25 countries in order to analyze whether increasing wage inequality leads to economic crises. Their study concludes that changes in income inequality do not increase the probability of banking crises. However, the study by Bellettini and Delbono (2013) shows that most of banking crises during the period of 1982-2008 were preceded by growing income inequality. However, the empirical research by Atkinson and Morelli (2011) and Bellettini and Delbono (2013) does not examine the link between household debt and inequality as both of the studies test the relationship between inequality and the probability of crises.

Bordo and Meissner (2012) examine the empirical relationship between wage inequality and credit growth which they define as the amount of outstanding bank loans to the private sector and use it as a proxy for household debt. The top 1% share of the income is used as a measure for inequality. They study 14 developed countries between 1920 and 2000 and find out that there is no significant relationship between growing inequality and credit changes. According to their results, interest rates and GDP per capita growth are the main driving factors behind credit boom. Nonetheless, the study by Bordo and Meissner (2012) has a number of shortcomings in terms of testing the link between inequality and household debt. One of the limitations is that total loans to the private sector used as dependent variable also include credit to businesses which is not the direct measure of household debt as defined in Rajan (2010), Iacoviello (2008) and others. Another issue is that the authors do not use other income inequality measures along with the top 1% share of the income to fully capture the relationship between household debt and inequality. As discussed above, Rajan (2010) first developed the hypothesis that growing inequality affects household debt and this relationship was later modeled theoretically in Iacoviello (2008) and Kumhof and Ranciere (2010).

Based on quarterly US data from 1980 to 2003, Christen and Morgan (2005) conclude that there is a positive correlation between income inequality and household indebtedness, in relation to an increase in credit demand from individuals. Similarly, Coibon et al. (2020) using data on individual mortgage applications find out that low income households in high inequality regions borrowed relatively less than similar households in low inequality regions. However, their study shows that the level of income inequality has a big impact on debt accumulation in both regions. Perugini et al. (2016) examine panel data of 18 OECD countries for the period 1970-2007 and find out that widening income inequality has a positive influence on household debt. El Herradi and Leroy (2020) also show a positive association between top incomes and credit growth based on a panel study of 12 developed countries over the period 1948-2015. These empirical studies stress the difficulties inherent to the identification of a causal relationship between income inequality and household debt due to endogeneity issues. Drawing from these studies, it is possible that income inequality and household debt are likely to be simultaneously determined by common shocks, and reverse causality from credit to inequality is also very likely.

Piao et al. (2023) employ a VAR model in examining the relationship between household deb and income inequality. Their findings show that widening income inequality increases household debt and this relationship is also supported by Jestl (2023) based on a panel study of European Union countries. Hake and Poyntner (2022) analyse the underlying link between determinants of household debt and income inequality measures. Their results suggest an increase in credit to high income earners and decrease in credit for low income earners in response to income inequality shocks. A growing body of research has shown that the rise in inequality over the past several decades primarily reflects a redistribution of permanent income across social groups (Piketty and Saez, 2013), a pattern supported by evidence from multiple countries. According to permanent income theory, permanent shocks should lead to a proportional adjustment in consumption, without inducing lasting changes in savings or borrowing. Consequently, to explain why households might increase their debt in response to persistently stagnant incomes, it is necessary to move beyond the predictions of this framework.

What unites basically most of the above studies is that widening income inequality affects household debt through different channels and it is one of the critical factors behind growing household debt in financially advanced countries. This finding has recently been also shown by Klein (2015) who documents that there is a long run relationship between household debt and income inequality. Malinen (2013) also gives useful insights into the relationship between household debt and inequality based on the panel study of 9 countries. The author applies co-integration test in order to find out whether growing income inequality is associated with household debt in the long run. Based on the panel cointegration tests, Malinen (2013) accepts the null hypothesis that the household debt does not have a long term relationship with wage inequality. However, their study also suffers from similar limitations in that Malinen (2013) also uses total bank loans to the private sector and the top 1% income as proxies for household and income inequality. Thus, this panel study will attempt to contribute to the current literature by using the household debt without including credit to businesses and employing four different income inequality measures. In this research, the theoretical framework which links household debt with inequality is motivated by the studies of Iacoviello (2008), Rajan (2010) and Kumohof and Ranciere (2010). To summarize, the above arguments suggest that income inequality measures are associated with growing household debt. The empirical literature shows that there are a number of channels through which income inequality affects household debt in countries with developed financial systems. Given the limited empirical evidence on the relationship between household debt and income inequality, this study proposes two testable hypotheses. First, increases in income inequality are expected to generate upward pressure on household debt at both the per capita and aggregate levels, as lower and middle income households rely more heavily on borrowing to sustain consumption in the face of widening income disparities. Second, a rise in the income share of high income households is anticipated to be associated with greater expansion in household credit, reflecting the role of wealthier households in supplying funds to the financial system and stimulating lending activity.

## 4.3 Theoretical motivation

This study is primarily motivated by the dynamic stochastic general equilibrium model developed by Kumhof, Rancière, and Winant (2015), who demonstrate that persistent increases in income inequality can lead to rising household indebtedness through interactions between heterogeneous households in a credit market setting. Their core mechanism is identified as the credit supply channel which is illustrated in the figure below:

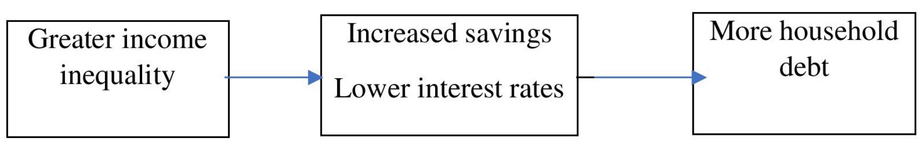


Figure 4.1: The Credit Supply Channel (Kumhof et al., 2015, p. 1234)

According to their model, permanent positive shocks to the income share of top earners increase the concentration of income and wealth, resulting in higher savings among high income households. These households allocate a substantial share of their additional income to interest-bearing financial assets, which expands the supply of credit in the economy. At the same time, low income households experience a loss of bargaining power and a decline in real income, which leads them to borrow in order to maintain a minimum standard of living that is embedded in their utility function. The increased availability of credit, facilitated by the savings of high income households, enables this borrowing behavior and is associated with lower interest rates. Consequently, the model demonstrates that rising inequality generates a self-reinforcing dynamic in which higher savings by top income earners fund increased debt accumulation by lower income households. The outcome is a sustained rise in household leverage driven by distributional shifts rather than short lived cyclical fluctuations.

Kumhof et al. (2015) highlight the structural nature of this mechanism by showing that increases in household debt emerge as a direct consequence of permanent shifts in income shares rather than temporary shocks. In their economy, households at the top of the income distribution act as net lenders and accumulate wealth, whereas households reliant on labor income become increasingly indebted. Rising inequality therefore produces a long run financial imbalance, which can amplify vulnerability in the financial system and magnify macroeconomic instability.

The broader literature also acknowledges an alternative pathway through which inequality may influence household indebtedness, commonly referred to as the credit demand channel (Hollander, 2001; Maki and Palumbo, 2001; Frank et al., 2014). This perspective draws on the relative income hypothesis, which posits that household consumption is influenced by comparison with a reference group, typically higher income peers. When income disparities widen, lower income households may increase borrowing to sustain consumption norms relative to their social comparators, often described as the "keeping up with the Joneses" effect. Although this mechanism plays an important role in explaining demand driven debt accumulation, the principal focus of this chapter remains on the structural credit supply mechanism formalized by Kumhof et al. (2015), given its clear theoretical predictions regarding the link between persistent income inequality and systemic growth in household debt.

In summary, the theoretical underpinning provided by Kumhof et al. (2015) establishes a compelling foundation for empirically exploring whether the long term rise in income inequality observed in advanced OECD economies has contributed to the expansion of household debt. This chapter tests the validity of that hypothesis using appropriate econometric techniques and improved measures of both inequality and household indebtedness.

## 4.4 Econometric methodology

This section sets out the econometric framework employed to investigate both the short run dynamics and the long run equilibrium relationship between household debt and income inequality across 20 advanced OECD countries over the period 1980–2019. To examine the existence and direction of causality within a potentially cointegrated system, this study adopts a panel VECM approach. Since the validity of a panel VECM requires that the variables exhibit non-stationarity in levels and share at least one cointegrating relationship, the empirical strategy begins by assessing the order of integration using panel unit root tests, followed by panel cointegration tests to verify the presence of a long run relationship. Given that these diagnostic procedures were previously introduced in Chapter 1, the discussion here provides a concise summary before presenting the VECM specification, its advantages for the present context, and the operational steps for its implementation.

### 4.4.1 Panel unit root

Establishing the order of integration is essential for the correct application of a panel VECM, since the framework requires that the variables be non-stationary in levels but stationary in first differences. To assess the stationarity properties of the data, the analysis employs a suite of widely accepted panel unit root tests, including Breitung (2000), Levin, Lin, and Chu (2002), and Im, Pesaran, and Shin (2003). Given the likelihood of cross-sectional dependence among OECD economies, the cross-sectionally augmented IPS (CIPS) test of Pesaran (2007) is also applied, which explicitly accounts for common shocks and interdependencies across panel units. These tests provide complementary strengths with regard to heterogeneity, cross-sectional correlation, and robustness of inference. Their theoretical bases and comparative advantages were outlined in Chapter 1, therefore the discussion here focuses on their empirical role in confirming the suitability of the panel VECM specification used in this chapter. The inclusion of both first- and second-generation unit root tests ensures that the underlying time series properties are correctly identified and that the subsequent cointegration analysis and error-correction modelling are methodologically sound.

### 4.4.2 Panel cointegration tests

Before estimating the panel VECM, it is essential to establish whether a long run equilibrium relationship exists among the variables. To this end, this study applies both first- and second-generation panel cointegration tests in order to obtain reliable and robust inference. The first-generation tests provide baseline evidence under the assumption of cross-sectional independence, while the second-generation Westerlund (2007) test offers a more rigorous approach by explicitly accommodating cross-sectional dependence and directly testing for error-correcting behavior. As outlined in Chapter 1, these complementary frameworks strengthen the validity of the empirical conclusions by confirming that household debt and income inequality are cointegrated across the OECD sample. Demonstrating cointegration is a necessary condition for the application of a panel VECM, since the model is specifically designed to capture both the long run equilibrium relationship and the short run adjustments toward that equilibrium.

### 4.4.3 Panel Vector Error Correction Model

The vector error correction model (VECM) represents a fundamental econometric framework for the analysis of both long term equilibrium relationships and short term adjustment dynamics among jointly endogenous variables. It is widely applied when the variables of interest are integrated of order one and exhibit cointegration. The concept of cointegration was initially formalized by Engle and Granger (1987), who demonstrated that a linear combination of nonstationary series may produce a stationary process, indicating the presence of a stable long term equilibrium that governs the evolution of the underlying variables. When such cointegrating relationships exist, conventional VAR models may be misspecified because they fail to incorporate the long term information contained in the cointegrating vectors. The VECM therefore emerges as an appropriate representation that integrates both the equilibrium correction mechanism and short run dynamic adjustments. To illustrate the VECM structure in a standard time series context, consider a $K$-dimensional VAR model of order $p$ composed of potentially nonstationary variables. The model can be expressed as

$$Z_t = A_1 Z_{t-1} + ... + A_p Z_{t-p} + u_t, \tag{4.1}$$

where $Z_t$ denotes a vector of endogenous variables and $u_t$ represents an error term with mean zero and finite variance.When these variables are I(1), subtracting $Z_{t-1}$ on both sides of the equation and rearranging terms yields the VECM:

$$\Delta Z_t = \Pi Z_{t-1} + \Gamma_1 \Delta Z_{t-1} + ... + \Gamma_{p-1} \Delta Z_{t-p+1} + u_t, \tag{4.2}$$

$$\Pi = A_1 + A_2 + ... + A_p - I_k,\ \Gamma_i = -(A_{i+1} + ... + A_p),\ i = 1, ..., p-1 \tag{4.3}$$

The matrix $\Pi$ plays a central role because its rank determines the number of cointegrating relationships among the variables. When $0 < rank(\Pi) = r < K$ the variables share r cointegrating vectors, meaning their long term comovement is characterized by $r$ stationary equilibrium constraints. The Johansen (1988, 1991) maximum likelihood approach formalizes the estimation of $\Pi$ through its decomposition $\Pi = \alpha\beta'$, where $\beta$ consists of the cointegrating vectors and

$\alpha$ contains the adjustment coefficients that capture how each variable reacts to deviations from equilibrium. The term $\alpha\beta' Z_{t-1}$ is therefore identified as the error correction component, quantifying the extent and speed of reversion toward long term equilibrium following short term shocks. The presence of a statistically significant error correction term indicates that the system corrects past disequilibrium and supports the inference of long term causality.

Although the VECM originated in the time-series literature, it has become increasingly employed in panel data analysis to capture dynamic causal interactions among cointegrated variables. The panel VECM framework is particularly advantageous as it accounts for country-specific heterogeneity, endogeneity, and cross-sectional dependence (Lütkepohl, 2009). This makes it a powerful tool for examining both the long-run equilibrium relationships and short-run adjustment dynamics among macroeconomic variables. As noted by Li (2001), the panel VECM effectively captures feedback effects among variables within a temporal causal structure, providing insights into how short-run deviations are corrected towards long-run equilibrium. Furthermore, panel extensions of the VECM accommodate unobserved heterogeneity across countries while preserving the model's ability to identify both equilibrium relationships and adjustment mechanisms over time, thereby offering a comprehensive framework for dynamic panel analysis.

The principal objective of applying panel cointegration tests in this chapter is to confirm the existence of a valid long term equilibrium relationship among the variables before estimating the panel VECM. Establishing cointegration ensures that the empirical specification is not affected by spurious correlations arising from the nonstationary nature of the variables under study. Once cointegration has been verified, the panel VECM can be employed to investigate the direction of causality and the combined short term and long term dynamics between household debt and income inequality. To examine the existence and direction of a long-run equilibrium relationship, the panel VECM is applied here using the two step procedure of Engle and Granger (1987). The first step of the Engle and Granger (1987) procedure is implemented to estimate the long run equilibrium model from which the residuals are extracted as the error correction term. These residuals capture deviations from the long term relationship and provide the basis for modeling the adjustment mechanism. The long run model is specified as follows:

$$\begin{aligned} HHD_{it} = \alpha_{it} + \delta_{it}t + \gamma_{1i}GINI_{it} + \gamma_{2i}IR_{it} + \gamma_{3i}RGDPpc_{it} + \gamma_{4i}FL_{it} + \\ + \gamma_{5i}INF_{it} + \gamma_{6i}HP_{it} + u_{it} \end{aligned} \tag{4.4}$$

where $HHD_{it}$, $GINI_{it}$, $IR_{it}$, $RGDPpc_{it}$, $FL_{it}$, $INF_{it}$ and $HP_{it}$ represent household debt, Gini index, long term interest rate, real GDP per capita, financial liberalization, inflation rate and real house price index respectively. Country specific fixed effects $\alpha_{it}$ and deterministic trends $\delta_{it}t$ are included to capture any disturbances that are common across different members of the panel. Once the residuals (ECT) are obtained by computing the equation (4.4), the next step is to estimate the panel Granger causality model with dynamic error correction:

$$\begin{aligned} \Delta HHD_{it} = \theta_{1j} + \lambda_{1i}ECT_{it-1} + \sum_k \theta_{11ik}\Delta HHD_{it-k} + \sum_k \theta_{12ik}\Delta GINI_{it-k} + \\ + \sum_k \theta_{13ik}\Delta IR_{it-k} + \sum_k \theta_{14ik}\Delta RGDPpc_{it-k} + \sum_k \theta_{15ik}\Delta FL_{it-k} + \\ + \sum_k \theta_{16ik}\Delta INF_{it-k} + \sum_k \theta_{17ik}\Delta HP_{it-k} + \epsilon_{1it} \end{aligned} \tag{4.5}$$

$$\begin{aligned} \Delta GINI_{it} = \theta_{2j} + \lambda_{2i}ECT_{it-1} + \sum_k \theta_{21ik}\Delta GINI_{it-k} + \sum_k \theta_{22ik}\Delta HHD_{it-k} + \\ + \sum_k \theta_{23ik}\Delta IR_{it-k} + \sum_k \theta_{24ik}\Delta RGDPpc_{it-k} + \sum_k \theta_{25ik}\Delta FL_{it-k} + \\ + \sum_k \theta_{26ik}\Delta INF_{it-k} + \sum_k \theta_{27ik}\Delta HP_{it-k} + \epsilon_{2it} \end{aligned} \tag{4.6}$$

$$\begin{aligned} \Delta IR_{it} = \theta_{3j} + \lambda_{3i}ECT_{it-1} + \sum_k \theta_{31ik}\Delta IR_{it-k} + \sum_k \theta_{32ik}\Delta HHD_{it-k} + \\ + \sum_k \theta_{33ik}\Delta GINI_{it-k} + \sum_k \theta_{34ik}\Delta RGDPpc_{it-k} + \sum_k \theta_{35ik}\Delta FL_{it-k} + \\ + \sum_k \theta_{36ik}\Delta INF_{it-k} + \sum_k \theta_{37ik}\Delta HP_{it-k} + \epsilon_{3it} \end{aligned} \tag{4.7}$$

$$\begin{aligned} \Delta RGDPpc_{it} = \theta_{4j} + \lambda_{4i}ECT_{it-1} + \sum_k \theta_{41ik}\Delta RGDPpc_{it-k} + \sum_k \theta_{42ik}\Delta HHD_{it-k} + \\ + \sum_k \theta_{43ik}\Delta GINI_{it-k} + \sum_k \theta_{44ik}\Delta IR_{it-k} + \sum_k \theta_{45ik}\Delta FL_{it-k} + \\ + \sum_k \theta_{46ik}\Delta INF_{it-k} + \sum_k \theta_{47ik}\Delta HP_{it-k} + \epsilon_{4it} \end{aligned} \tag{4.8}$$

$$\Delta FL_{it} = \theta_{5j} + \lambda_{5i}ECT_{it-1} + \sum_k \theta_{51ik}\Delta FL_{it-k} + \sum_k \theta_{52ik}\Delta HHD_{it-k} + \\ + \sum_k \theta_{53ik}\Delta GINI_{it-k} + \sum_k \theta_{54ik}\Delta IR_{it-k} + \sum_k \theta_{55ik}\Delta RGDPpc_{it-k} + \\ + \sum_k \theta_{56ik}\Delta INF_{it-k} + \sum_k \theta_{57ik}\Delta HP_{it-k} + \epsilon_{5it} \tag{4.9}$$

$$\Delta INF_{it} = \theta_{6j} + \lambda_{6i}ECT_{it-1} + \sum_k \theta_{61ik}\Delta INF_{it-k} + \sum_k \theta_{62ik}\Delta HHD_{it-k} + \\ + \sum_k \theta_{63ik}\Delta GINI_{it-k} + \sum_k \theta_{64ik}\Delta IR_{it-k} + \sum_k \theta_{65ik}\Delta RGDPpc_{it-k} + \\ + \sum_k \theta_{66ik}\Delta FL_{it-k} + \sum_k \theta_{67ik}\Delta HP_{it-k} + \epsilon_{6it} \tag{4.10}$$

$$\Delta HP_{it} = \theta_{7j} + \lambda_{7i}ECT_{it-1} + \sum_k \theta_{71ik}\Delta HP_{it-k} + \sum_k \theta_{72ik}\Delta HHD_{it-k} + \\ + \sum_k \theta_{73ik}\Delta GINI_{it-k} + \sum_k \theta_{74ik}\Delta IR_{it-k} + \sum_k \theta_{75ik}\Delta RGDPpc_{it-k} + \\ + \sum_k \theta_{76ik}\Delta FL_{it-k} + \sum_k \theta_{77ik}\Delta INF_{it-k} + \epsilon_{7it} \tag{4.11}$$

where $\Delta$ denotes first differences of the variables, $k$ is the optimal lag length derived from the Schwarz Information Criterion, and $ECT_{it-1}$ represents the lagged error correction term retrieved from the estimated cointegration vector. The error term $\epsilon_{it}$ is assumed to be serially uncorrelated, which is satisfied under the selected lag structure of $k = 2$. This specification allows the identification of both short run and long run causal dynamics between household debt and income inequality in line with the Engle and Granger (1987) two step approach. In this framework, Granger causality is investigated by exploiting both the short-run and long-run dynamics inherent in the VECM specification. Short run (weak) Granger causality is examined through joint Wald tests on the lagged differenced regressors. Testing $H_0 : \theta_{12ik} = 0 \forall i$ in the household debt equation (4.5) assesses whether variations in income inequality exert short run effects on household debt, while $H_0 : \theta_{22ik} = 0 \forall i$ determines the reverse direction of causality (4.6).

Long run causality is inferred from the significance of the adjustment coefficients $\lambda_{1i}$ and $\lambda_{2i}$. A statistically significant and negative coefficient provides confirmation that deviations from long run equilibrium are corrected over time and that the corresponding dependent variable responds to disequilibrium shocks. Formally, the hypotheses $H_0 : \lambda_{1i} = 0 \forall i$ or $\lambda_{2i} = 0 \forall i$ indicate the absence of long run causality from the respective explanatory variables. The significance of these coefficients is tested using the t-statistic. Furthermore, a joint significance test via the F-statistic evaluates whether both short run adjustments and long run feedback collectively contribute to causality within the system. The primary focus of this study is to examine the existence and direction of causal interactions between household debt and income inequality measures. The long term interest rates, real GDP per capita, financial liberalization, inflation, and real house price dynamics are incorporated as control variables to ensure that the estimated causal relationship is not confounded by broader economic conditions. The underlying sources and pathways of causation are therefore identified by assessing the statistical significance of the error correction terms and the lagged differenced terms within the household debt and Gini equations.

## 4.5 Data description

This study draws upon a panel of 20 advanced OECD economies over the period 1980-2019, a timeframe that has been marked by a pronounced and simultaneous increase in household indebtedness and income inequality. Before turning to the empirical results, this section explains the data and its sources, and provides precise definitions of the variables employed. Household debt and income inequality are the core variables of analytical interest, complemented by a set of control variables. These controls are selected based on their theoretical relevance and empirical significance in explaining household leverage dynamics, as documented in the existing literature (Klein, 2015; Kumhof et al., 2015; Bartscher et al., 2020; Bazillier et al., 2021). Their inclusion is essential for isolating and understanding the independent contribution of rising income inequality to household debt accumulation since the early 1980s.

### 4.5.1 Household debt data

**Real household debt per capita (RHHDpc)** is the total credit to households (core debt) in current US dollars and it is deflated by the Consumer Price Index and divided by the corresponding population numbers to get the real household debt per capita. The household debt is defined as the outstanding amount of credit to private households and non-profit institutions serving households. The data can be obtained from the Bank for International Settlements database.

**Household debt (HHD)** measures household credit as a share of GDP and it is available from the Bank for International Settlements (BIS). The data was collected by BIS based on national data sources which measure loans extended by banks to households for the acquisition of housing and other assets as well as unsecured debt (e.g. credit card, student debt, etc.).

### 4.5.2 Income inequality variables

**GINI index (GINI)** is the main measure of income inequality in this study and it represents the measure of the distribution of income across population. It is widely used in the empirical research in relation to inequality. The GINI index is based on gross income which is the sum of market income and transfer payments and it is defined as pre-tax and post transfer income. The data is available from the Standardized World Income Inequality Database (SWIID) and it is developed by Solt (2020).

**Labour share of income (LSI)** is defined as the compensation per employee as a share of GDP at factor costs per person employed. The labour share of income includes both employed and self-employed and it does not include taxes. The data is available from the AMECO database.

**Top 1%** represents the share of income that accounts for top 1 % of the population as a share of GDP and the data comes from the World Top Incomes Database.

**Top 10%** is the share of income that accounts for top 10% of the population as a share of GDP and the data is available from the World Inequality Database.

### 4.5.3 Macroeconomic variables

**Long term interest rates (IR)** are based on yields on 10-year local currency government securities. Rates are mainly determined by the price charged by the lender, the risk from the borrower and the reduction in the capital value. Long term interest rates are one of the main factors of business investment which is in turn a major source of economic growth. The data is available from the OECD database.

**Inflation (INF)** is measured by the consumer price index which is the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals. The laspeyres formula is generally used. The data can be obtained from the International Monetary Fund (IMF) database.

**Real GDP per capita (RGDPpc)** is defined as the total economic output of a country divided by it's population size and adjusted for inflation. It will be included in the equation in order to account for the standard of living between countries and over time. The data comes from the Our World in Data.

**Real GDP growth (RGDPG)** rate measures economic growth adjusted for the inflation rates and it will be included in the equation in order to account for economic development. The data is available from the Our World in Data.

**Financial liberalization (FL)** is based on several sub indices mostly pertaining to banking regulatory practices and it is developed by Abiad et al., (2010). The database recognizes the multi-faceted nature of financial reforms and records financial policy changes along seven different dimensions: credit controls and reserve requirements, interest rate controls, entry barriers, state ownership, policies on securities markets, banking regulations, and restrictions on the capital account. Liberalization scores for each category are then combined in a graded index that is normalized between zero and one.

**Real house price index (HP)** is given by the ratio of the nominal house price index to the consumers expenditure deflator in each country from the OECD national account database and it is seasonally adjusted. The data can be obtained from the OECD database.

The data required for household debt, income inequality, and the control variables are not uniformly available from a single source, which necessitated the compilation of information from several reputable international databases. Careful attention has been devoted to ensuring that all variables originate from institutional sources with established methodological standards and high data reliability. Given the use of multiple datasets, systematic efforts have been made to align definitions, ensure temporal and cross country consistency, and harmonize measurement units to maintain coherence across the panel. These procedures collectively mitigate potential data incompatibility concerns and reinforce the credibility of the empirical results that follow.

Figure 4.5 (please refer to the appendix) presents the time series of the household debt as a share of GDP for 20 advanced OECD countries. The individual graphs show that the household debt has increased significantly over the period 1980-2019 with the exception of Japan, Germany and Ireland. It is noticeable that despite its fall during the financial crisis in 2008, the household debt has continued to increase relative to the size of GDP in most of the developed OECD countries. Figure 4.6 (please refer to the appendix) shows how the income inequality measured by Gini index has evolved over time between 1980 and 2019 in OECD countries. It is remarkable to note that the Gini index has increased substantially over the period of 1980-2019 in most of the developed OECD countries. This clearly shows the issue of growing income inequality and why it has attracted the attention of academics, practitioners and policymakers lately. However, it is interesting to observe that countries like Italy, Greece and New Zealand have not experienced sharp increase in income inequality despite the fluctuations of Gini index during this period. Overall, the individual graphs indicate that the income inequality has exacerbated between 1980 and 2019 in most of developed countries. Figure 4.7 (please refer to the appendix) shows the time series of top 1% income share relative to the size of GDP in 1980-2019 in 20 advanced OECD countries. The individual graphs indicate that the income share of top 1% has increased considerably with some fluctuations triggered by financial crisis and other big events in most of the developed OECD countries. However, countries like Austria, Belgium, Ireland and Japan have experienced significant decline in the top 1% income share in some periods showing no clear trend over the course of 1980-2019. Figure 4.8 (please refer to the appendix) illustrates the time series of top 10% income share relative to the size of GDP over the period 1980-2019. The individual graphs demonstrate that the income share of top 10% similar to the income share of top 1% has increased significantly, albeit with business cycle fluctuations associated with financial crises and other economic downturns in many developed OECD countries. While countries such as Greece, Spain, Austria, and Belgium display no consistent trend in the top 10% income share, with notable fluctuations, peak levels were observed in 1989, 2000, and 2008, likely driven by financial crises and other major events. The trend of top 10% income share once again indicates a growing concentration of wealth among the highest earners, exacerbating income inequality during 1980-2019. Figure 4.9 (please refer to the appendix) presents how the long term interest rates have evolved in developed OECD countries between 1980 and 2019. A quick examination of the graphs tells that the long term interest rates have declined significantly during this period with the exception of Greece and Portugal where there are some missing data. It is interesting to observe that the continuous decrease of long term interest rates are coincided by the increasing household debt in 1980-2019. Figure 4.10 (please refer to the appendix) indicates the trend of the financial development index which is represented by the depth, access and efficiency of financial institutions and financial markets for the advanced OECD countries over the period 1980-2019. It is remarkable to note that the financial system has advanced considerably reaching the highest levels prior to the financial crisis 2008 for all of the OECD countries during this period. As can be seen from the graph, the highest levels of financial development index are recorded for the countries like the US, the UK, Canada, Japan, and Australia. It is important to point out that the rapid development of financial institutions and markets have coincided with the significant increase of household debt between 1980 and 2019.

Figure 4.2 illustrates a clear positive correlation between the evolution of income inequality, measured by the Gini index, and household leverage across 20 advanced OECD countries over the period 1980–2019. It is noteworthy that the sharp rise in household leverage during this period closely parallels the upward trend in income inequality, suggesting that both variables have moved together over time. This positive association between household indebtedness and inequality is consistent with the findings of previous studies, including Schularick and Taylor (2012), Klein (2015), and Bazillier et al. (2021), which similarly document that rising inequality tends to coincide with higher levels of household leverage in advanced economies.

Figure 4.3 also reveals a clear positive correlation between household debt and the income share of the top 1%, which serves as an alternative measure of income inequality in this study. A visual inspection of the graph shows that the regression line between household debt and the top 1% income share is considerably steeper than that between household leverage and the Gini index over the period 1980–2019.This stronger relationship can be interpreted through the credit supply channel, as described by Kumhof et al. (2015).

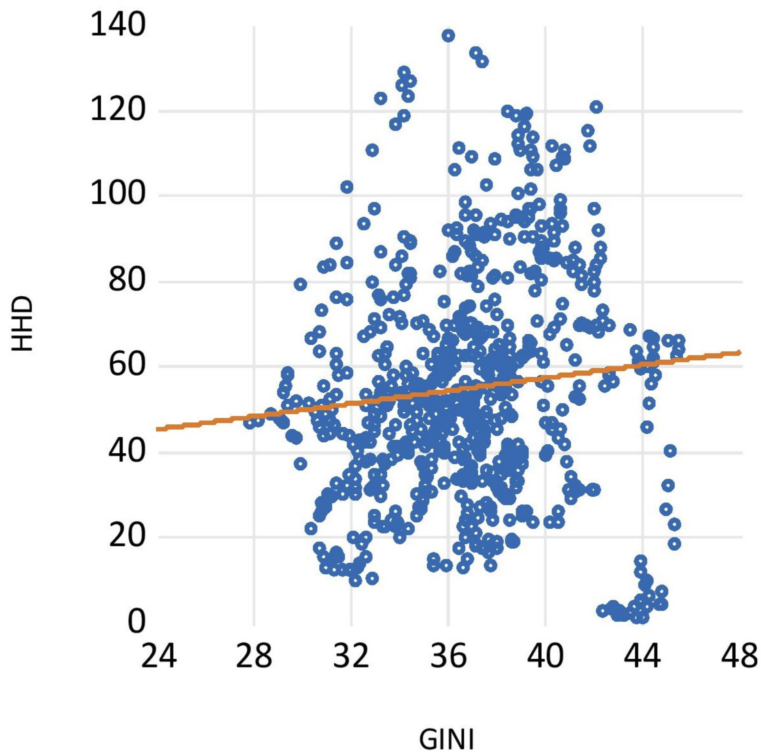


Figure 4.2: Household Debt and Gini index, 1980-2019

According to this mechanism, when the income share of the top 1% rises following persistent positive income shocks, high-income households—motivated by wealth accumulation—channel part of their additional income toward lower-income households through financial intermediaries. This process expands credit availability and enables lower-income households to increase borrowing in order to sustain consumption levels despite stagnant wages. Consequently, greater credit supply leads to a significant buildup of household debt in the economy. As shown in the figure, the top 1% income share has risen markedly across advanced OECD economies during 1980–2019, coinciding with the sharp increase in household indebtedness.

Figure 4.4 demonstrates a negative correlation between household debt and the labour share of income, another measure of income inequality employed in this analysis. This negative association is expected, as the labour share of income has declined significantly since 1980, reflecting prolonged wage stagnation in most advanced OECD countries.

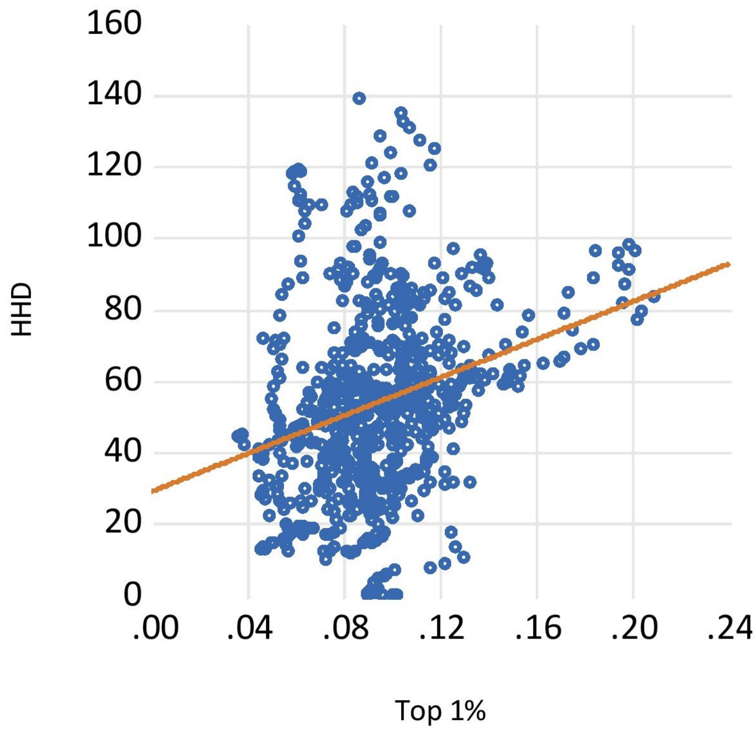


Figure 4.3: Household Debt and Top 1% income share, 1980-2019

The steep downward slope of the regression line underscores the simultaneous decline in labour income and rise in household leverage over the sample period. This suggests that as wages constitute a smaller proportion of national income, households increasingly rely on borrowing to maintain their living standards. Overall, the observed negative relationship between household leverage and the labour share of income is consistent with the findings of previous studies, including Klein (2015), Stockhammer (2015), and Bazillier et al. (2021), which highlight the crucial role of declining wage shares in driving household indebtedness in advanced economies.

Given the documented rise in both household debt and income inequality across advanced OECD countries over the period 1980–2019, and the limited empirical focus on how these two developments interact, this study will proceed to test the following hypotheses:

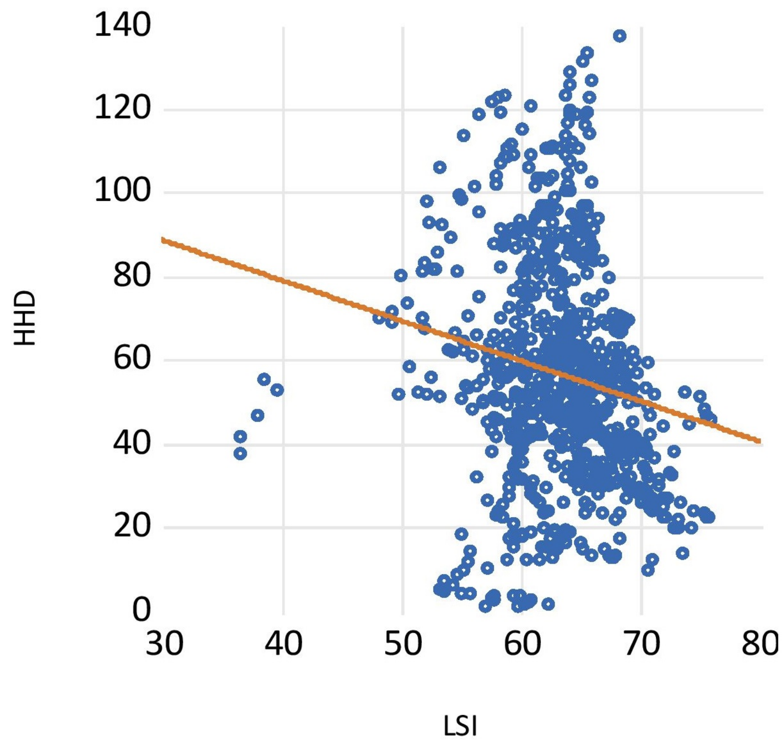


Figure 4.4: Household Debt and Labour Share of Income, 1980-2019

**H1. Rising income inequality is associated with higher household debt at both the per-capita and aggregate levels.**

A widening distribution of income is expected to place greater reliance on debt financing among households that experience stagnant or declining real income. Existing studies argue that lower and middle income groups increasingly resort to borrowing to sustain their standard of living in the face of rising income disparities (Barba and Pivetti, 2009; Maku and Palumbo, 2001; Wolf, 2010; Bibow, 2010). Empirical evidence from Mian et al. (2018) confirms that debt accumulation has become an important tool for households facing limited income growth, while Rajan (2011) similarly suggests that expanding credit has substituted for insufficient wage increases among lower income households.

**H2. An increase in the income share of high income households is associated with an expansion in household credit.**

Growth in top income shares is expected to contribute to higher aggregate household debt through greater credit supply. When high income households receive persistent positive income shocks, they channel part of their additional resources into financial markets, thereby increasing the availability of credit to the rest of the economy. This facilitates increased borrowing among lower income households seeking to maintain consumption, which in turn leads to a rise in overall household debt (Kumhof et al., 2015).

## 4.6 Empirical results and discussion

This section reports the empirical findings from the panel unit root, panel cointegration, and panel VECM tests concerning the relationship between household debt and income inequality in 20 advanced OECD countries over the period 1980–2019. The analysis begins by assessing the order of integration of the variables using panel unit root tests, followed by panel cointegration tests to determine whether a stable long-run equilibrium relationship exists between the variables under consideration. Upon establishing cointegration, the panel VECM framework is employed to explore both the long-run causality and short-run adjustment dynamics between household debt and income inequality. To ensure the robustness of the long-run estimates, the panel DOLS method is further applied as an additional validation technique.

Table 4.1: Descriptive statistics

| Variables | Obs. | Mean | Std. dev. | Min. | Max. |
|---|---|---|---|---|---|
| Household debt | 800 | 54.33 | 26.35 | 0.21 | 139.4 |
| Real household debt per capita (in log) | 800 | 9.64 | 0.91 | 4.81 | 11.37 |
| Gini | 800 | 36.86 | 3.58 | 27.77 | 45.51 |
| Top 1% income share | 800 | 0.10 | 0.026 | 0.03 | 0.19 |
| Top 10% income share | 800 | 0.33 | 0.04 | 0.22 | 0.45 |
| Labour share of income | 800 | 63.28 | 5.02 | 36.52 | 75.86 |
| Real GDP per capita (in log) | 800 | 10.26 | 0.36 | 9.16 | 11.34 |
| Interest rates | 800 | 6.55 | 3.71 | 0.35 | 22.50 |
| Financial liberalization | 700 | 0.77 | 0.22 | 0.09 | 1.00 |
| Inflation | 800 | 3.98 | 4.38 | -4.48 | 28.38 |
| Real house prices | 800 | 62.99 | 36.45 | 6.19 | 173.46 |

Table 4.1 reports descriptive statistics for 20 advanced OECD countries over the period 1980–2019. The main target variable, household debt, is measured as a continuous ratio expressed as a percentage of GDP, while real household debt per capita is included in logarithmic form to account for scale differences

and cross-country comparability. The income inequality indicators and the controls for financial liberalization and inflation follow the same definitions and continuous measurement structure as discussed in the previous chapters. Real GDP per capita is also expressed in logarithms. Interest rates are measured as long-term government bond yields in percentage terms. Real house prices are captured by a continuous index constructed as the ratio of nominal house prices to the consumer expenditure deflator. Overall, the dataset consists of continuous macroeconomic variables with differing degrees of scaling and boundedness, which are accommodated in the subsequent econometric analysis.

### 4.6.1 Panel unit root test

Tables 4.2 and 4.3 present the results of the Levin, Lin and Chu (2002), Breitung (2000), and Im, Pesaran and Shin (2003) panel unit root tests for the variables under investigation. In addition, Table 4.4 reports Pesaran's (2007) CIPS test to account for possible cross-sectional dependence across countries. The specifications reported in Table 4.1 include both individual intercepts and linear trends, with the test outcomes provided at levels and first differences for each variable. The test statistics indicate that household debt, the Gini index, labour share of income, top 1% income share, top 10% income share, real GDP per capita, interest rates, and financial liberalization are non-stationary in levels. However, when transformed into first differences, the null hypothesis of a unit root is rejected at 1% significance level for all variables. This confirms that each variable becomes stationary after first differencing. To support the robustness of these findings, Table 4.3 reports the corresponding panel unit root tests estimated without trend terms. Consistent with the earlier results, all three tests reaffirm that the variables contain unit roots in levels but become stationary after first differencing. Taken together, these results confirm that the series are integrated of order one. The study by Cavaliere and Xu (2014) indicates that panel stationary tests are more likely to overreject the null hypothesis of unit root when applied to bounded variables. However, the null hypothesis is not rejected here with respect to the variables of interest at levels which further confirm the unit root results of bounded inequality measures. Moreover, Granger (2010) argues that stationary test results are not reliable when the series hit the bounds frequently. Since the integration properties of the series are now clearly established based on the tests conducted the analysis can proceed to the panel cointegration stage in order to examine whether a long run equilibrium relationship exists among the variables.

Table 4.2: Panel unit root tests

| | **Levin, Lin and Chu** | | **Breitung t-test** | | **Im, Pesaran and Shin** | |
|---|---|---|---|---|---|---|
| | I(0) | I(1) | I(0) | I(1) | I(0) | I(1) |
| HHD | 0.99 | -3.02*** | 2.51 | -5.26*** | 0.88 | -4.84*** |
| RHHDpc | 1.52 | -10.88*** | 2.52 | -7.44*** | -0.10 | -11.58*** |
| GINI | -3.21 | -24.5*** | -2.31 | -16.3*** | -3.89 | -23.6*** |
| LSI | -2.53 | -20.2*** | -0.25 | -14.1*** | -2.69 | -19.4*** |
| Top 1% | -2.13 | -19.3** | -4.14 | -13.9*** | -1.63 | -20.6** |
| Top 10% | -1.16 | -18.55*** | -2.54 | -12.92*** | -1.33 | -20.37*** |
| RGDPpc | 2.29 | -8.02*** | -0.81 | -6.13*** | 0.77 | -12.21*** |
| IR | -1.54 | -14.44*** | 1.02 | -8.66*** | -1.60 | -17.39*** |
| FL | 0.70 | -9.10*** | 1.57 | -7.13*** | -0.42 | -13.14*** |
| HP | -1.76 | -4.66*** | -0.37 | -4.10*** | -0.25 | -5.73*** |
| INF | -7.47 | -19.89*** | -1.33 | -11.06*** | -5.94 | -19.14*** |

Panel unit root tests were performed with individual trends and intercepts for each series. *, **, *** represent statistical significance at 10%, 5% and 1% respectively.

Table 4.3: Panel unit root tests

| | **Levin, Lin and Chu** | | **Breitung t-test** | | **Im, Pesaran and Shin** | |
|---|---|---|---|---|---|---|
| | I(0) | I(1) | I(0) | I(1) | I(0) | I(1) |
| HHD | -3.23 | -4.45*** | | | 0.98 | -6.95*** |
| RHHDpc | -0.41 | -12.26*** | | | 3.48 | -13.97*** |
| GINI | -2.31 | -26.69*** | | | -0.34 | -25.51*** |
| LSI | -3.95 | -22.41*** | | | -2.19 | -20.32*** |
| Top 1% | -3.79 | -22.82*** | | | -2.64 | -23.33*** |
| Top 10% | -3.23 | -22.54*** | | | -1.25 | -22.99*** |
| RGDPpc | -1.49 | -9.81*** | | | 4.02 | -14.67*** |
| IR | -1.55 | -17.61*** | | | 2.01 | -18.21*** |
| FL | -5.74 | -11.37*** | | | -4.57 | -13.31*** |
| HP | 4.58 | -5.42*** | | | 8.15 | -5.89*** |
| INF | -10.71 | -21.26*** | | | -9.19 | -20.66*** |

Panel unit root tests were performed without trend for each series. *, **, *** represent statistical significance at 10%, 5% and 1% respectively.

The results of Pesaran's (2007) CIPS panel unit root test, reported in Table

4.4, show that all variables are non-stationary in their levels. These results again confirm that the variables under consideration follow an integrated process of order one, I(1), and therefore require first differencing to achieve stationarity. Establishing that the variables are integrated of order one is a crucial prerequisite for examining their long-run equilibrium relationship through panel cointegration analysis. Furthermore, the outcomes of the CIPS test are in line with those obtained from the first-generation panel unit root tests proposed by Breitung (2000), Levin et al. (2002), and Im et al. (2003), reinforcing the robustness and consistency of the stationarity properties across different testing approaches. Overall, the confirmation that all series are I(1) justifies the application of panel cointegration and panel VECM techniques in the subsequent empirical analysis.

Table 4.4: Pesaran's CIPS test results

| | CIPS Statistics | 10% CV | 5% CV | 1% CV | Order of Integration |
|---|---|---|---|---|---|
| HHD | -1.603 | –2.110 | –2.200 | –2.360 | I(1) |
| RHHDpc | -2.015 | -2.110 | -2.200 | -2.360 | I(1) |
| GINI | –1.440 | –2.110 | –2.200 | –2.360 | I(1) |
| LSI | -1.969 | -2.110 | -2.200 | -2.360 | I(1) |
| Top 1% | -1.863 | -2.110 | -2.200 | -2.360 | I(1) |
| Top 10% | -2.026 | -2.110 | -2.200 | -2.360 | I(1) |
| FL | -1.913 | -2.110 | -2.200 | -2.360 | I(1) |
| RGDPpc | -2.012 | -2.110 | -2.200 | -2.360 | I(1) |
| IR | -1.763 | -2.110 | -2.200 | -2.360 | I(1) |
| HP | -1.923 | -2.110 | -2.200 | -2.360 | I(1) |
| INF | -1.891 | -2.110 | -2.200 | -2.360 | I(1) |

### 4.6.2 Panel cointegration tests

The results of the panel cointegration tests between real household debt per capita and income inequality, measured by the Gini index, are presented in Table 4.5. The Pedroni (1999, 2004) test indicates that five out of seven test statistics reject the null hypothesis of no cointegration, thereby supporting the existence of a long-run equilibrium relationship between the two variables. Although the null hypothesis is rejected primarily for the panel v-statistic and the group rho-statistic, the overall evidence from the Pedroni test points to a stable long-term association between real household debt per capita and income inequality.

Table 4.5: Panel cointegration tests between RHHDpc and GINI

| | Test statistic | P-value |
|---|---|---|
| **Johansen Fischer test** | | |
| Fischer statistics from trace test | 99.74 | 0.000 |
| Fischer statistics from max-Eigen value test | 86.81 | 0.000 |
| **Kao test** | | |
| ADF t-statistic | -3.356 | 0.000 |
| **Pedroni test** | | |
| Panel v-statistic | 0.729 | 0.233 |
| Panel rho-statistic | -2.218 | 0.013 |
| Panel PP-statistic | -3.194 | 0.000 |
| Panel ADF-statistic | -2.39 | 0.000 |
| Group rho-statistic | -0.959 | 0.169 |
| Group PP-statistic | -3.884 | 0.000 |
| Group ADF-statistic | -3.383 | 0.000 |

The findings are further reinforced by the Fisher (1999) cointegration test, which strongly rejects the null hypothesis of no cointegration at the 1% significance level, providing additional support for the presence of a long-run relationship. Similarly, the Kao (1999) test based on the ADF statistic also rejects the null hypothesis of no cointegration, confirming that real household debt per capita and the Gini index share a common stochastic trend. Taken together, the results from the Pedroni (1999, 2004), Fisher (1999), and Kao (1999) panel cointegration tests consistently suggest that real household debt per capita and income inequality move together in the long run. This confirms the presence of a stable equilibrium relationship between the two variables, thereby justifying the application of the panel VECM framework in the subsequent empirical analysis to explore the direction and dynamics of causality between them.

While the Gini coefficient serves as the primary measure of income inequality in this study, additional indicators are examined to test the robustness of the long-run relationship between real household debt per capita and income inequality. Specifically, the labour share of income and the top 1% income share are employed as alternative measures to ensure that the cointegrating relationship is not dependent on a single proxy of inequality. Table 4.6 reports the panel cointegration test results for real household debt per capita and the labour share of income. The Fisher (1999) cointegration test rejects the null hypothesis of no cointegration at the 1% significance level, indicating a stable long-term relationship between the two variables.

Table 4.6: Panel cointegration tests between RHHDpc and LSI

| | **Test statistic** | **P-value** |
|---|---|---|
| **Johansen Fischer test** | | |
| Fischer statistics from trace test | 66.87 | 0.000 |
| Fischer statistics from max-Eigen value test | 58.97 | 0.027 |
| **Kao test** | | |
| ADF t-statistic | -3.184 | 0.000 |
| **Pedroni test** | | |
| Panel v-statistic | 5.147 | 0.000 |
| Panel rho-statistic | -0.142 | 0.000 |
| Panel PP-statistic | -0.569 | 0.285 |
| Panel ADF-statistic | -0.467 | 0.001 |
| Group rho-statistic | 1.752 | 0.004 |
| Group PP-statistic | 0.940 | 0.826 |
| Group ADF-statistic | 0.649 | 0.742 |

The Kao (1999) test, based on the ADF statistic, also rejects the null hypothesis of no cointegration at the 1% level, as reflected by the zero p-values. These results are further corroborated by the Pedroni (1999, 2004) test, where five out of the seven statistics reject the null hypothesis, confirming the presence of a long-run equilibrium association between household debt and the labour share of income. This evidence suggests that the evolution of household debt and the distribution of income between labour and capital are interlinked over time.

Similarly, the panel cointegration results for real household debt per capita and the top 1% income share are presented in Table 4.7. The Fisher and Kao tests both reject the null hypothesis of no cointegration at the 1% significance level, providing strong evidence of a cointegrating relationship between these variables. The Pedroni test further supports this finding, as five out of the seven statistics reject the null hypothesis at the 1% level, confirming that household debt and top income concentration share a common long-run trend. Taken together, the results of the Fisher (1999), Pedroni (1999, 2004), and Kao (1999) tests consistently indicate the existence of a long-run equilibrium relationship between real household debt per capita and all measures of income inequality considered—namely, the Gini index, labour share of income, and top 1% income share. These findings demonstrate that the observed association between household debt and income inequality is robust to alternative specifications of inequality and provide a strong empirical basis for employing the panel VECM approach in the subsequent analysis to explore their dynamic interrelations.

Table 4.7: Panel cointegration tests between RHHDpc and Top 1% income share

| | **Test statistic** | **P-value** |
|---|---|---|
| **Johansen Fischer test** | | |
| Fischer statistics from trace test | 81.13 | 0.000 |
| Fischer statistics from max-Eigen value test | 61.29 | 0.000 |
| **Kao test** | | |
| ADF t-statistic | -3.716 | 0.000 |
| **Pedroni test** | | |
| Panel v-statistic | -2.865 | 0.998 |
| Panel rho-statistic | -2.161 | 0.015 |
| Panel PP-statistic | -2.887 | 0.000 |
| Panel ADF-statistic | -2.877 | 0.000 |
| Group rho-statistic | 0.234 | 0.593 |
| Group PP-statistic | -3.127 | 0.000 |
| Group ADF-statistic | -2.994 | 0.000 |

To further validate the presence of a long-run equilibrium relationship between real household debt per capita and income inequality, the Westerlund (2007) panel cointegration test was employed, with results reported in Table 4.8. Unlike first-generation tests, the Westerlund (2007) approach explicitly accounts for cross-sectional dependence across countries, providing more reliable inference in panels where common shocks may be present. The p-values for all statistics were obtained through bootstrap procedures, enhancing the robustness of the results. The test produces two group-mean statistics ($G_\tau$ and $G_\alpha$) and two panel statistics ($P_\tau$ and $P_\alpha$). The group-mean tests assess the null hypothesis of no cointegration against the alternative that cointegration exists in at least one cross-sectional unit, while the panel tests evaluate the null of no cointegration for the entire panel.

Table 4.8: Westerlund test statistics

| Statistic | Value | Z-value | P-value |
|---|---|---|---|
| $G_t$ | -2.367 | -2.934 | 0.002 |
| $G_a$ | -6.442 | 0.575 | 0.217 |
| $P_t$ | -8.315 | -1.851 | 0.032 |
| $P_a$ | -5.743 | -1.524 | 0.000 |

The results show that both the group-mean $G_\tau$ and panel-mean $P_\tau$ statistics reject the null hypothesis of no cointegration at the 1% significance level, indicating that a stable long-run relationship exists between real household debt per capita and the Gini index both at the individual country level and for the panel as a whole. In contrast, the $G_\alpha$ statistic yields a p-value of 0.217, suggesting that not all countries exhibit cointegration, whereas the $P_\alpha$ statistic is highly significant at the 1% level. The mixed outcomes between the $\alpha$- and $\tau$-type statistics likely reflect heterogeneity in adjustment speeds and long-run dynamics across the sample of OECD countries. As the $G_\tau$ and $P_\tau$ statistics are generally considered as more robust in the presence of cross-sectional dependence, their significance provides strong and consistent evidence in favour of cointegration. Overall, the Westerlund (2007) test results reinforce the earlier findings from the Pedroni (1999, 2004), Fisher (1999), and Kao (1999) tests, confirming the existence of a stable long-run equilibrium relationship between real household debt per capita and income inequality. This provides a solid empirical foundation for applying the panel VECM framework in the subsequent analysis to investigate the direction and dynamics of causality between the variables.

### 4.6.3 Panel VECM results

The results of the panel VECM estimation are presented in Table 4.9. Based on the Schwarz Information Criterion, the optimal lag length was determined to be two. The estimated error correction term (ECT) in equation (4.5) is negative and statistically significant, with a coefficient of –0.089. This finding confirms the existence of a long-run adjustment mechanism, indicating that deviations from the long-run equilibrium between income inequality and household debt are corrected over time. Specifically, approximately 9% of the disequilibrium is corrected each year, suggesting a relatively moderate speed of adjustment toward long-run equilibrium. The negative and significant ECT further implies that in the long run, income inequality, as proxied by the Gini index, exerts a statistically significant influence on real household debt per capita.

In addition, the long-run coefficients of the control variables exhibit the expected theoretical signs. Interest rates and real GDP per capita are negatively associated with real household debt per capita, suggesting that higher interest rates and income growth tend to constrain household borrowing. In contrast, inflation, financial liberalization, and real house price index are positively related to household debt, indicating that macroeconomic and financial conditions promoting credit expansion and asset price appreciation contribute to rising household indebtedness. These relationships are consistent with theoretical expectations and previous empirical findings in the literature. The short-run dynamics, as examined through the Wald test, reveal no evidence of short-run causality running from income inequality to household debt. Similarly, short-run causality is not detected from interest rates or inflation to household debt. However, the results indicate statistically significant short-run causality from real GDP per capita and financial liberalization to household debt, suggesting that short-term fluctuations in economic growth and financial market conditions play an immediate role in influencing household borrowing behaviour.

The coefficient of the error correction term (ECT) in the Gini equation (4.6) is also negative and statistically significant (–0.059), confirming the existence of a long-run causal relationship running from real household debt per capita to income inequality. This implies that changes in household indebtedness have a persistent and significant influence on income inequality over time, indicating that household debt Granger causes the Gini index in the long run. However, the Wald test results for equation (4.6) show no evidence of short-run causality from real household debt per capita to the Gini index.

In contrast, the short-run dynamics reveal that real GDP per capita, interest rates, and financial liberalization exert statistically significant effects on income inequality, suggesting that short-term fluctuations in macroeconomic and financial conditions can temporarily influence the distribution of income. Meanwhile, the coefficients of inflation and the real house price index, although correctly signed, are statistically insignificant, indicating that their short-term impact on inequality is limited. Furthermore, the significance of the ECT, combined with the joint significance of the explanatory variables including the Gini index, interest rates, real GDP per capita, inflation, financial liberalization, and real house price index in the household debt equation (4.5), confirms that these variables collectively play a crucial role in determining household indebtedness. The direction and magnitude of these effects align closely with theoretical expectations and previous empirical evidence.

Table 4.10 reports the panel VECM estimation results where household debt as a share of GDP is specified as the target variable. The error correction term (ECT) is negative and statistically significant, confirming the presence of a long-run adjustment mechanism.

Table 4.9: Panel VECM results

| | $\Delta RHHDpc$ | $\Delta GINI$ | $\Delta RGDPpc$ | $\Delta IR$ | $\Delta FL$ | $\Delta HP$ | $\Delta INF$ |
|---|---|---|---|---|---|---|---|
| $ECT_{t-1}$ | -0.089*** | -0.059*** | 0.002 | 0.009 | -0.017 | -0.062*** | -0.502 |
| | (0.010) | (0.068) | (0.003) | (0.104) | (0.003) | (0.202) | (0.007) |
| $\Delta RHHDpc_{it-1}$ | 0.324*** | 0.713** | 0.091*** | 0.209 | -0.030 | 1.759*** | 0.060 |
| | (0.041) | (0.269) | (0.013) | (0.405) | (0.013) | (1.148) | (0.498) |
| $\Delta RHHDpc_{it-2}$ | -0.030 | 0.900 | -0.025* | 0.588 | 0.012 | -0.790 | 0.142 |
| | (0.043) | (0.283) | (0.013) | (0.426) | (0.013) | (1.199) | (0.509) |
| $\Delta GINI_{it-1}$ | 0.004 | -0.190*** | 0.002 | -0.129** | 0.003 | 0.120 | 0.085 |
| | (0.006) | (0.042) | (0.002) | (0.063) | (0.002) | (0.173) | (0.072) |
| $\Delta GINI_{it-2}$ | 0.003 | -0.092** | 0.001 | -0.049 | -0.001 | -0.392** | 0.130 |
| | (0.006) | (0.042) | (0.002) | (0.063) | (0.002) | (0.175) | (0.073) |
| $\Delta RGDPpc_{it-1}$ | 0.393*** | -2.821 | 0.201*** | -1.493 | 0.082 | -3.346 | 0.504 |
| | (0.138) | (0.910) | (0.044) | (1.367) | (0.043) | (3.883) | (1.675) |
| $\Delta RGDPpc_{it-2}$ | 0.275** | -0.836 | -0.003 | 1.242 | -0.015 | 9.357** | -1.234 |
| | (0.129) | (0.854) | (0.042) | (1.283) | (0.041) | (3.691) | (1.621) |
| $\Delta IR_{it-1}$ | -0.008** | 0.040 | -0.004** | 0.074*** | -0.006*** | -0.409*** | 0.217*** |
| | (0.004) | (0.028) | (0.001) | (0.042) | (0.001) | (0.118) | (0.052) |
| $\Delta IR_{it-2}$ | -0.004* | 0.043 | -0.005*** | -0.229* | -0.001 | -0.046 | -0.051 |
| | (0.004) | (0.028) | (0.001) | (0.042) | (0.001) | (0.116) | (0.051) |
| $\Delta FL_{it-1}$ | 0.415*** | 0.583* | 0.113** | 1.899 | -0.060 | -5.331 | 1.242 |
| | (0.138) | (0.912) | (0.044) | (1.370) | (0.044) | (3.742) | (1.535) |
| $\Delta FL_{it-2}$ | 0.138 | 0.289 | 0.031 | 2.084 | -0.079* | -9.024** | 0.375 |
| | (0.134) | (0.883) | (0.043) | (1.327) | (0.042) | (3.658) | (1.484) |
| $\Delta HP_{it-1}$ | -0.002 | -0.012 | 0.002*** | 0.0337** | -0.001 | 0.869*** | 0.108 |
| | (0.001) | (0.010) | (0.000) | (0.015) | (0.001) | (0.042) | (0.017) |
| $\Delta HP_{it-2}$ | -0.005 | -0.012 | 0.002*** | 0.033 | -0.001 | 0.869*** | -0.029 |
| | (0.002) | (0.010) | (0.001) | (0.016) | (0.001) | (0.042) | (0.018) |
| $\Delta INF_{it-1}$ | 0.010 | -0.014 | -0.002 | 0.067 | -0.002 | -0.096 | -0.057 |
| | (0.003) | (0.024) | (0.001) | (0.037) | (0.001) | (0.103) | (0.041) |
| $\Delta INF_{it-2}$ | -0.006 | -0.011 | 0.000 | -0.025 | -0.002 | 0.109 | -0.019 |
| | (0.003) | (0.022) | (0.001) | (0.034) | (0.001) | (0.096) | (0.039) |
| *Constant* | 0.009*** | 0.261*** | 0.011*** | -0.417*** | 0.008*** | 0.519*** | -0.431*** |
| | (0.007) | (0.045) | (0.002) | (0.068) | (0.002) | (0.190) | (0.076) |
| *Obs.* | 800 | 800 | 800 | 800 | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The optimal lag structure is p=2 and q=2 based on Schwarz Information Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Table 4.10: Panel VECM results

| | $\Delta HHD$ | $\Delta GINI$ | $\Delta RGDPpc$ | $\Delta IR$ | $\Delta FL$ | $\Delta HP$ | $\Delta INF$ |
|---|---|---|---|---|---|---|---|
| $ECT_{t-1}$ | -0.127*** | -0.021*** | 0.007 | 0.019 | -0.081 | -0.027*** | -0.489 |
| | (0.032) | (0.015) | (0.004) | (0.021) | (0.009) | (0.004) | (0.036) |
| $\Delta HHD_{it-1}$ | 0.662*** | 0.048*** | 0.017*** | -0.010 | -0.030 | 0.441*** | -0.012 |
| | (0.041) | (0.018) | (0.008) | (0.026) | (0.013) | (0.070) | (0.031) |
| $\Delta HHD_{it-2}$ | 0.151 | -0.010 | -0.006* | 0.125 | 0.012 | -0.341 | 0.069 |
| | (0.043) | (0.017) | (0.009) | (0.026) | (0.013) | (0.071) | (0.031) |
| $\Delta GINI_{it-1}$ | -0.391 | -0.246*** | 0.004 | -0.149** | 0.003 | 0.099 | 0.052 |
| | (0.113) | (0.042) | (0.002) | (0.063) | (0.002) | (0.168) | (0.073) |
| $\Delta GINI_{it-2}$ | -0.225 | -0.114** | 0.003 | -0.070 | -0.001 | -0.302** | 0.097 |
| | (0.115) | (0.043) | (0.002) | (0.064) | (0.002) | (0.171) | (0.074) |
| $\Delta RGDPpc_{it-1}$ | 0.481*** | -0.230*** | 0.152*** | -2.535 | 0.059 | -3.152 | 0.314 |
| | (0.266) | (0.969) | (0.048) | (1.432) | (0.068) | (3.883) | (1.705) |
| $\Delta RGDPpc_{it-2}$ | 0.232** | -0.312* | 0.039 | 2.949 | 0.011 | -0.101** | 0.111 |
| | (0.065) | (0.965) | (0.048) | (1.426) | (0.066) | (3.817) | (1.732) |
| $\Delta IR_{it-1}$ | -0.075** | 0.017 | -0.002** | 0.102*** | -0.005*** | -0.279*** | 0.205*** |
| | (0.008) | (0.028) | (0.001) | (0.043) | (0.002) | (0.114) | (0.051) |
| $\Delta IR_{it-2}$ | 0.159* | 0.013 | -0.004*** | -0.181* | -0.001 | -0.117 | -0.064 |
| | (0.078) | (0.026) | (0.001) | (0.042) | (0.001) | (0.112) | (0.050) |
| $\Delta FL_{it-1}$ | 0.567*** | 0.541* | 0.017** | -0.989 | -0.060 | -5.159 | 1.242 |
| | (0.197) | (0.887) | (0.042) | (1.285) | (0.044) | (2.604) | (1.535) |
| $\Delta FL_{it-2}$ | 0.282 | 0.173 | 0.067 | 0.714 | -0.079* | 0.199** | 0.375 |
| | (0.184) | (0.829) | (0.039) | (1.201) | (0.042) | (2.435) | (1.484) |
| $\Delta HP_{it-1}$ | -0.018 | -0.014 | 0.003*** | 0.013** | -0.001 | 0.869*** | 0.107 |
| | (0.028) | (0.011) | (0.000) | (0.015) | (0.001) | (0.042) | (0.017) |
| $\Delta HP_{it-2}$ | 0.137 | -0.013 | 0.002*** | -0.025 | -0.001 | 0.869*** | -0.041 |
| | (0.029) | (0.011) | (0.001) | (0.016) | (0.001) | (0.042) | (0.018) |
| $\Delta INF_{it-1}$ | -0.079 | -0.023 | 0.001 | 0.075 | -0.005 | 0.116 | -0.064 |
| | (0.006) | (0.027) | (0.001) | (0.039) | (0.001) | (0.079) | (0.042) |
| $\Delta INF_{it-2}$ | -0.036 | -0.006 | 0.000 | -0.018 | 0.001 | -0.024 | -0.004 |
| | (0.054) | (0.024) | (0.001) | (0.035) | (0.001) | (0.072) | (0.038) |
| *Constant* | 0.081*** | 0.229*** | 0.015*** | -0.694*** | 0.012*** | 0.482*** | -0.487*** |
| | (0.147) | (0.066) | (0.003) | (0.096) | (0.002) | (0.193) | (0.080) |
| *Obs.* | 800 | 800 | 800 | 800 | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The optimal lag structure is p=2 and q=2 based on Schwarz Information Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

This indicates that any short-term deviations from the long-run equilibrium between household debt and income inequality are gradually corrected over time. The negative and significant ECT further implies that the Gini index exerts a long-run causal effect on household debt, suggesting that rising income inequality contributes to higher levels of household indebtedness in the long run. To verify the bidirectional relationship, Table 4.10 also presents the results where the Gini index is treated as the target variable. The ECT in this specification is likewise negative and statistically significant, implying that household debt Granger causes income inequality in the long run. This confirms a two-way long-run causal relationship between household debt and the Gini index, consistent with the theoretical expectation that debt accumulation and inequality reinforce each other over time. However, the Wald test results reveal no evidence of short-run causality between the two variables, suggesting that contemporaneous changes in household debt and income inequality do not immediately influence each other within a short time horizon. The findings presented in Table 4.10 are in line with those reported in Table 4.9, where real household debt per capita is used as the target variable. Both sets of results consistently indicate that household debt and income inequality are cointegrated and mutually reinforcing in the long run. In particular, the evidence supports the conclusion that the Gini index Granger causes both household debt as a share of GDP and real household debt per capita in the long run, confirming the robustness of the long-run relationship between income inequality and household indebtedness across different debt specifications.

Overall, the panel VECM results suggest that there is a stable long run relationship between household debt and income inequality measures. The panel VECM estimation further substantiates this relationship, indicating a bidirectional long-run causality between household debt and income inequality. This suggests that not only does inequality drive higher household indebtedness, but increasing debt levels also reinforce inequality over time. However, the evidence is particularly strong in support of the hypothesis that rising income inequality acts as a key driver of household indebtedness in advanced economies. These findings are consistent with the broader empirical literature (Malinen, 2013; Kumhof et al., 2015; Bartscher et al., 2020 and Bazillier et al. 2021).

Although the Gini index remains the principal measure of income inequality used in most empirical studies, this analysis employs alternative indicators to assess the robustness of the causal relationship between real household debt per capita and income inequality. Accordingly, the labour share of income, along with the top 1% and top 10% income shares, are used to determine whether the long-run relationship between household debt and inequality measures remains stable across different specifications. Table 4.11 presents the panel VECM results for real household debt per capita and the labour share of income.

Table 4.11: Panel VECM results

| | $\Delta RHHDpc$ | $\Delta LSI$ | $\Delta RGDPpc$ | $\Delta IR$ | $\Delta FL$ | $\Delta HP$ | $\Delta INF$ |
|---|---|---|---|---|---|---|---|
| $ECT_{t-1}$ | -0.051*** | -0.032** | 0.005 | -0.039 | -0.014 | -0.084*** | 0.057 |
| | (0.009) | (0.103) | (0.003) | (0.089) | (0.002) | (0.108) | (0.003) |
| $\Delta RHHDpc_{it-1}$ | 0.346*** | 0.706 | 0.093*** | 0.039 | -0.027 | 1.354 | 0.174 |
| | (0.041) | (0.452) | (0.013) | (0.391) | (0.012) | (1.144) | (0.446) |
| $\Delta RHHDpc_{it-2}$ | -0.027 | 0.739 | -0.019 | 0.496 | 0.012* | -1.448 | -0.049 |
| | (0.046) | (0.504) | (0.014) | (0.435) | (0.014) | (1.234) | (0.478) |
| $\Delta LSI_{it-1}$ | -0.005 | 0.145*** | -0.003** | -0.070 | 0.001 | 0.049 | 0.029 |
| | (0.004) | (0.052) | (0.001) | (0.045) | (0.001) | (0.128) | (0.049) |
| $\Delta LSI_{it-2}$ | -0.002 | -0.051 | -0.000 | 0.112*** | -0.000 | 0.001 | 0.047 |
| | (0.004) | (0.046) | (0.001) | (0.040) | (0.001) | (0.114) | (0.043) |
| $\Delta RGDPpc_{it-1}$ | -0.380** | 6.691*** | 0.144* | -2.740* | 0.100 | -5.514 | 0.889 |
| | (0.167) | (1.805) | (0.052) | (1.559) | (0.051) | (4.582) | (1.778) |
| $\Delta RGDPpc_{it-2}$ | -0.326** | 4.003** | 0.013*** | 3.699** | -0.007 | 5.589 | -0.289 |
| | (0.155) | (1.679) | (0.048) | (1.449) | (0.047) | (4.338) | (1.689) |
| $\Delta IR_{it-1}$ | -0.010*** | 0.003*** | -0.005*** | 0.089** | -0.007*** | -0.319*** | 0.183*** |
| | (0.004) | (0.047) | (0.001) | (0.040) | (0.001) | (0.120) | (0.047) |
| $\Delta IR_{it-2}$ | -0.003 | 0.160 | -0.005*** | -0.234*** | -0.001 | 0.039 | -0.103** |
| | (0.004) | (0.047) | (0.001) | (0.041) | (0.001) | (0.120) | (0.047) |
| $\Delta FL_{it-1}$ | 0.355** | -1.730 | 0.109 | 2.052 | -0.067** | -5.406 | 0.721 |
| | (0.142) | (1.534) | (0.044) | (1.324) | (0.043) | (3.722) | (1.392) |
| $\Delta FL_{it-2}$ | 0.048 | 0.410 | 0.032 | 2.471* | -0.077 | -8.537** | 0.140 |
| | (0.137) | (1.483) | (0.043) | (1.281) | (0.042) | (3.608) | (1.341) |
| $\Delta HP_{it-1}$ | 0.001*** | -0.024 | 0.002 | 0.030** | -0.001** | 0.828*** | 0.140 |
| | (0.001) | (0.017) | (0.001) | (0.015) | (0.001) | (0.042) | (1.341) |
| $\Delta HP_{it-2}$ | 0.007 | 0.046 | -0.002 | -0.021 | 0.001 | -0.192*** | -0.036 |
| | (0.002) | (0.017) | (0.001) | (0.015) | (0.001) | (0.043) | (0.016) |
| $\Delta INF_{it-1}$ | 0.010* | 0.201 | -0.003 | 0.122 | -0.002* | -0.115 | -0.050 |
| | (0.004) | (0.042) | (0.001) | (0.037) | (0.001) | (0.109) | (0.039) |
| $\Delta INF_{it-2}$ | 0.002 | 0.060 | 0.000 | 0.003 | -0.002 | 0.163 | -0.029 |
| | (0.003) | (0.041) | (0.001) | (0.036) | (0.001) | (0.104) | (0.037) |
| Constant | 0.009*** | -0.387*** | 0.011*** | -0.442*** | 0.007*** | 0.419*** | -0.386*** |
| | (0.006) | (0.073) | (0.002) | (0.065) | (0.002) | (0.188) | (0.067) |
| *Obs.* | 800 | 800 | 800 | 800 | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The optimal lag structure is p=2 and q=2 based on Schwarz Information Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

The error correction term (ECT) is negative and statistically significant, indicating the presence of a long-run adjustment mechanism. This result confirms that changes in the labour share of income Granger cause real household debt per capita in the long run. The long-run coefficients of the control variables also exhibit the expected signs and are statistically significant, implying that interest rates, real GDP per capita, inflation, financial liberalization, and real house price index jointly influence household debt dynamics in a theoretically consistent manner. The Wald test results, however, reveal no short-run causality running from the labour share of income to household debt. Nonetheless, in the short run, interest rates, real GDP per capita, and financial liberalization exert statistically significant effects on the labour share of income.

Similarly, when the labour share of income is treated as the dependent variable, the ECT remains negative and significant, suggesting that real household debt per capita Granger causes the labour share of income in the long run. This finding indicates that rising household debt exerts a persistent influence on the distribution of income between labour and capital. In contrast, the Wald test results show no evidence of short-run causality from household debt to the labour share of income. Among the control variables, only real GDP per capita has a statistically significant short-run effect on the labour share of income, while interest rates, inflation, financial liberalization, and real house price index remain insignificant in the short term. Taken together, the VECM results provide robust evidence of a bidirectional long-run causal relationship between household debt and the labour share of income, suggesting a mutual dependence between financial conditions and income distribution dynamics. This reinforces the conclusion that the long-run association between household debt and inequality persists across different measures of income inequality.

Table 4.12 reports the panel VECM estimation results using the top 1% income share as an alternative measure of income inequality. The error correction term (ECT) is negative and statistically significant, confirming the existence of a long-run adjustment mechanism and indicating that the top 1% income share Granger causes real household debt per capita in the long run. The long-run coefficients for interest rates, real GDP per capita, inflation, financial liberalization, and real house price index are also statistically significant, implying that these variables, alongside income concentration, play a crucial role in shaping household indebtedness. These findings are consistent with theoretical expectations that link rising income inequality and credit expansion through changes in borrowing capacity and financial market conditions.

Table 4.12: Panel VECM results

| | $\Delta RHHDpc$ | $\Delta TOP1\%$ | $\Delta RGDPpc$ | $\Delta IR$ | $\Delta FL$ | $\Delta HP$ | $\Delta INF$ |
|---|---|---|---|---|---|---|---|
| $ECT_{t-1}$ | -0.076*** (0.010) | -0.045*** (0.001) | 0.003 (0.003) | 0.289 (0.103) | -0.014 (0.003) | -0.024*** (0.225) | 0.042 (0.003) |
| $\Delta RHHDpc_{it-1}$ | 0.329*** (0.041) | -0.004 (0.003) | 0.090*** (0.013) | 0.154 (0.405) | -0.030** (0.013) | 1.407 (1.134) | 0.204 (0.498) |
| $\Delta RHHDpc_{it-2}$ | -0.041 (0.043) | -0.006 (0.003) | -0.020 (0.013) | 0.662 (0.431) | 0.014 (0.013) | -0.404 (1.192) | 0.026 (0.512) |
| $\Delta TOP1\%_{it-1}$ | -0.644*** (0.529) | -0.053** (0.044) | 0.445** (0.168) | 0.175 (5.239) | 0.279* (0.166) | 36.359** (14.35) | -5.287 (6.053) |
| $\Delta TOP1\%_{it-2}$ | -0.499** (0.517) | -0.057 (0.043) | -0.042 (0.165) | 6.529 (5.127) | -0.064 (0.162) | -45.990*** (14.017) | -1.492 (5.903) |
| $\Delta RGDPpc_{it-1}$ | 0.472*** (0.144) | -0.006 (0.012) | 0.170*** (0.046) | -1.757 (1.435) | 0.067 (0.045) | -4.071 (3.995) | 0.909 (1.732) |
| $\Delta RGDPpc_{it-2}$ | 0.295** (0.132) | -0.013 (0.011) | 0.011 (0.042) | 1.163 (1.312) | 0.001 (0.041) | 13.476*** (3.733) | -1.453 (1.656) |
| $\Delta IR_{it-1}$ | 0.008** (0.004) | 0.002*** (0.001) | -0.004** (0.001) | 0.080* (0.041) | -0.006*** (0.002) | -0.372*** (0.115) | 0.192*** (0.052) |
| $\Delta IR_{it-2}$ | 0.007 (0.003) | 0.011* (0.001) | -0.004** (0.001) | 0.080*** (0.041) | -0.006 (0.002) | -0.020 (0.115) | -0.057 (0.052) |
| $\Delta FL_{it-1}$ | 0.390*** (0.138) | 0.005 (0.011) | 0.108** (0.044) | 1.815 (1.373) | -0.062 (0.043) | -5.793 (3.720) | 1.696 (1.538) |
| $\Delta FL_{it-2}$ | 0.116 (0.134) | -0.004 (0.011) | 0.029 (0.042) | 1.973 (1.331) | -0.078* (0.042) | -9.094*** (3.638) | 0.906 (1.490) |
| $\Delta HP_{it-1}$ | 0.003 (0.002) | -0.006** (0.001) | 0.002*** (0.001) | 0.034** (0.016) | -0.001* (0.001) | 0.872*** (0.042) | 0.110 (0.018) |
| $\Delta HP_{it-2}$ | 0.005*** (0.001) | -0.002** (0.001) | -0.002*** (0.002) | -0.017 (0.016) | 0.001 (0.003) | -0.232*** (0.042) | -0.036 (0.018) |
| $\Delta INF_{it-1}$ | 0.009** (0.004) | -0.001 (0.003) | -0.002 (0.001) | 0.075 (0.037) | -0.002 (0.001) | -0.116 (0.102) | -0.065 (0.041) |
| $\Delta INF_{it-2}$ | -0.006* (0.003) | -0.001 (0.000) | 0.000 (0.001) | -0.022 (0.034) | -0.002 (0.001) | 0.151 (0.094) | -0.034 (0.038) |
| Constant | 0.009*** (0.006) | 0.001*** (0.001) | 0.011*** (0.002) | -0.436*** (0.066) | 0.008*** (0.002) | 0.379*** (0.182) | -0.411*** (0.074) |
| *Obs.* | 800 | 800 | 800 | 800 | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The optimal lag structure is p=2 and q=2 based on Schwarz Information Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

The Wald test results reveal no short-run causality running from the top 1% income share to household debt. In the short run, however, real GDP per capita, financial liberalization, and real house price index exert statistically significant effects on household debt, while interest rates and inflation remain insignificant. When the top 1% income share is treated as the dependent variable, the ECT again appears negative and significant, suggesting that household debt per capita Granger causes the top 1% income share in the long run. This points to a bidirectional long-run causal relationship between household debt and income concentration. In contrast, the Wald test indicates no short-run causality from household debt to the top 1% income share. Among the control variables, interest rates and real house price index display statistically significant short-run effects on top income concentration, whereas real GDP per capita, inflation, and financial liberalization do not.

Table 4.13 presents the corresponding panel VECM results when the income inequality measure is the top 10% income share. The negative and statistically significant ECT confirms a long-run causal relationship running from the top 10% income share to household debt per capita. The long-run coefficients for interest rates, real GDP per capita, financial liberalization, house price index, and inflation are all significant, underscoring the relevance of macroeconomic and financial factors in determining household indebtedness. The joint significance of these variables, together with the ECT, further validates their long-run importance in the household debt equation. The Wald test, however, indicates no short-run causality from the top 10% income share to household debt. Similarly, when the top 10% income share is the dependent variable, the ECT remains negative and statistically significant, demonstrating that household debt per capita Granger causes top income shares in the long run. This confirms the existence of a bidirectional long-run causal relationship between household debt and income inequality. In the short run, the Wald test shows no evidence of causality from household debt to top 10% income share. The short-run coefficients suggest that interest rates and real house price index exert statistically significant effects on income concentration, while real GDP per capita, financial liberalization, and inflation remain insignificant. It is important to note that the panel VECM results in Tables 4.12 and 4.13 yield consistent findings when the income inequality measures are defined as the top 1% and top 10% income shares, respectively.

Overall, the panel VECM results provide strong evidence of a long-run bidirectional causality between household debt and income inequality, with particularly robust support for the hypothesis that rising income inequality contributes to higher levels of household indebtedness.

Table 4.13: Panel VECM results

| | $\Delta RHHDpc$ | $\Delta TOP10\%$ | $\Delta RGDPpc$ | $\Delta IR$ | $\Delta FL$ | $\Delta HP$ | $\Delta INF$ |
|---|---|---|---|---|---|---|---|
| $ECT_{t-1}$ | -0.071*** | -0.039*** | -0.002 | 0.276 | -0.016 | -0.024*** | 0.048 |
| | (0.010) | (0.002) | (0.002) | (0.0019) | (0.004) | (0.003) | (0.006) |
| $\Delta RHHDpc_{it-1}$ | 0.316*** | -0.001 | 0.092*** | 0.141 | -0.025** | 1.264 | 0.310 |
| | (0.041) | (0.003) | (0.013) | (0.414) | (0.014) | (1.254) | (0.507) |
| $\Delta RHHDpc_{it-2}$ | -0.046 | -0.006 | -0.023 | 0.698 | 0.004 | -0.848 | 0.051 |
| | (0.043) | (0.003) | (0.014) | (0.435) | (0.015) | (1.283) | (0.518) |
| $\Delta TOP10\%_{it-1}$ | -1.528*** | -0.060** | 0.740** | -1.761 | 0.398 | 18.821** | -13.587 |
| | (0.721) | (0.045) | (0.230) | (7.217) | (0.240) | (20.786) | (8.393) |
| $\Delta TOP10\%_{it-2}$ | -1.793** | -0.006 | -0.054 | 0.036 | 0.043 | -41.888*** | -6.621 |
| | (0.720) | (0.045) | (0.230) | (7.207) | (0.234) | (20.277) | (8.188) |
| $\Delta RGDPpc_{it-1}$ | 0.541*** | -0.004 | 0.163*** | -1.333 | 0.088 | -0.564 | 1.423 |
| | (0.148) | (0.009) | (0.047) | (1.481) | (0.050) | (4.372) | (1.765) |
| $\Delta RGDPpc_{it-2}$ | 0.322** | -0.019 | 0.016 | 1.534 | 0.014 | 12.171*** | -1.184 |
| | (0.137) | (0.008) | (0.044) | (1.371) | (0.049) | (4.218) | (1.703) |
| $\Delta IR_{it-1}$ | -0.008** | 0.003*** | -0.004*** | 0.080 | -0.005*** | -0.502*** | 0.171*** |
| | (0.004) | (0.000) | (0.001) | (0.042) | (0.001) | (0.132) | (0.053) |
| $\Delta IR_{it-2}$ | -0.004 | 0.001* | -0.004** | -0.240*** | 0.0004 | -0.203 | -0.071 |
| | (0.004) | (0.000) | (0.001) | (0.042) | (0.001) | (0.129) | (0.052) |
| $\Delta FL_{it-1}$ | 0.348*** | 0.008 | 0.105 | 1.792 | -0.022* | -1.093 | 1.554 |
| | (0.139) | (0.009) | (0.044) | (1.389) | (0.044) | (3.855) | (1.557) |
| $\Delta FL_{it-2}$ | 0.079 | -0.001 | 0.022 | 1.882 | -0.034* | -3.858*** | 0.849 |
| | (0.135) | (0.008) | (0.043) | (1.349) | (0.043) | (3.740) | (1.510) |
| $\Delta HP_{it-1}$ | 0.002 | 0.004** | 0.003*** | 0.030** | -0.0005 | 0.920*** | 0.112 |
| | (0.001) | (0.001) | (0.001) | (0.016) | (0.0005) | (0.045) | (0.018) |
| $\Delta HP_{it-2}$ | 0.003** | -0.003** | -0.002** | -0.013 | 0.0003 | -0.275*** | -0.040 |
| | (0.002) | (0.000) | (0.001) | (0.017) | (0.0005) | (0.046) | (0.019) |
| $\Delta INF_{it-1}$ | 0.010** | -0.004 | -0.002 | 0.074 | -0.002 | -0.123 | -0.052 |
| | (0.004) | (0.002) | (0.001) | (0.038) | (0.001) | (0.105) | (0.042) |
| $\Delta INF_{it-2}$ | -0.006* | -0.002 | 0.0005 | -0.025 | -0.0017 | 0.160 | -0.029 |
| | (0.004) | (0.000) | (0.001) | (0.035) | (0.001) | (0.097) | (0.039) |
| Constant | 0.013*** | 0.001*** | 0.011*** | -0.484*** | 0.010*** | 0.389*** | -0.432*** |
| | (0.007) | (0.0004) | (0.002) | (0.065) | (0.002) | (0.189) | (0.076) |
| *Obs.* | 800 | 800 | 800 | 800 | 800 | 800 | 800 |

*Notes:* standard errors are presented in parantheses. The optimal lag structure is p=2 and q=2 based on Schwarz Information Criterion (SBC). *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

This finding is consistent with the empirical evidence presented by Kumhof et al. (2015), Klein (2015), Bartscher et al., (2020) and Bazillier et al. (2021), who argue that widening income disparities have been a key driver of household debt accumulation over recent decades in advanced economies.

### 4.6.4 Robustness tests

Table 4.14 presents the results of the panel DOLS estimation examining the long-run relationship between household debt and income inequality measures. The DOLS approach is employed as a robustness check to verify the stability of the cointegrating relationship established in the previous analyses. In this specification, the logarithm of real household debt per capita is regressed on the Gini index, labour share of income, the top 1% and top 10% income shares, along with the relevant control variables. The results reveal that all income inequality measures are statistically significant and exhibit the expected signs. Specifically, the Gini coefficient is positive and significant, indicating that a 1% point increase in income inequality raises real household debt per capita by approximately 3.5% in the long run. Likewise, the top 1% income share has a positive and significant association with household debt, suggesting that rising income concentration at the top contributes to higher indebtedness. In contrast, the labour share of income exerts a negative and significant effect on household debt per capita, implying that a 1% point increase in labour's share of total income reduces household borrowing by around 3.2% in the long run.

Table 4.14: Panel DOLS estimates

| **Household debt (RHHDpc)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| GINI | 0.035***<br>(0.005) | Top 1% | 0.068***<br>(0.014) | Top 10% | 0.072***<br>(0.016) | LSI | -0.032**<br>(0.006) |
| RGDPpc | -0.062***<br>(0.012) | RGDPpc | -0.108***<br>(0.018) | RGDPpc | -0.124***<br>(0.022) | RGDPpc | -0.156***<br>(0.041) |
| IR | -0.021***<br>(0.013) | IR | -0.124**<br>(0.026) | IR | -0.134***<br>(0.021) | IR | -0.078***<br>(0.009) |
| FL | 0.82***<br>(0.034) | FL | 0.96***<br>(0. 039) | FL | 0.55***<br>(0.023) | FL | 0.76**<br>(0.027) |
| HP | 0.016***<br>(0.004) | HP | 0.024***<br>(0.006) | HP | 0.018***<br>(0.008) | HP | 0.036**<br>(0.012) |
| INF | -0.012*<br>(0.002) | INF | -0.013<br>(0.003) | INF | -0.016<br>(0.004) | INF | -0.014*<br>(0.006) |

*Notes:* standard errors are presented in parenthesis. Lag and lead lengths were determined by the Schwarz Information Criterion. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Regarding the control variables, real GDP per capita, interest rates, financial liberalization, and real house price index all carry the expected signs and are statistically significant across the specifications, reinforcing their relevance in explaining household debt dynamics. Although the inflation variable shows the anticipated sign, it does not reach statistical significance in any of the regressions. Overall, the DOLS estimation results confirm a stable long-run relationship between household debt and income inequality measures, providing robust support for the findings obtained from the panel VECM analysis. These results are consistent with the empirical evidence of Bordo and Meissner (2012) and Bartscher et al., (2020) who emphasize that rising income inequality has been a key driver of household debt accumulation over time.

To further support the robustness of the results, this section also reports the results of fixed effects (FE) and random effects (RE) regressions estimated with cluster-robust standard errors which account for any potential autocorrelation and heteroskedasticity. The FE and RE estimates should provide a useful benchmark by showing whether the observed association persists under standard static panel specifications. Table 4.15 presents the estimation results using real household debt per capita as the dependent variable, while Table 4.16 reports the findings using household debt as a share of GDP. The Hausman test results indicate that the FE model is the appropriate specification across all regressions. As shown in Table 4.15, the overall model is statistically significant at all conventional levels. The R-squared value of the baseline FE regression suggests that approximately 85% of the variation in household debt per capita is explained by the Gini coefficient and control variables, which include inflation rate, long-term interest rate, real GDP per capita, financial liberalization, and the house price index. All estimated coefficients display the expected signs and are statistically significant. The Gini coefficient, the main variable of interest, is positive and significant at the 1% level, implying that a 1% rise in the Gini index increases real household debt per capita by about 5.4% on average. Likewise, the top 10% income share is positively associated with household debt, indicating that a greater concentration of income at the top end of the distribution tends to increase household indebtedness. Conversely, the labour share of income exerts a negative effect: a 1% increase in the labour share corresponds to a 1.5% decline in real household debt per capita, consistent with the notion that higher wage income mitigates borrowing needs. Regarding the control variables, inflation and interest rates both exhibit statistically significant negative effects on real household debt per capita.

Table 4.15: Household Debt (RHHDpc) and Income Inequality: Static Models

| | FE 1 | RE 1 | | FE 2 | RE 2 |
|---|---|---|---|---|---|
| GINI | 0.054*** | 0.041*** | LSI | -0.015*** | -0.015*** |
| | (0.007) | (0.007) | | (0.004) | (0.004) |
| IR | -0.024*** | -0.019*** | IR | -0.013** | 0.011 |
| | ((0.006) | (0.006) | | (0.007) | (0.007) |
| RGDPpc | -0.011*** | -0.013*** | RGDPpc | -0.024*** | -0.024*** |
| | (0.004) | (0.004) | | (0.005) | (0.005) |
| INF | -0.032*** | -0.031*** | INF | -0.025*** | -0.023*** |
| | (0.005) | (0.005) | | (0.005) | (0.005) |
| FL | 0.667*** | 0.776*** | FL | 0.764*** | 0.833*** |
| | (0.136) | (0.135) | | (0.139) | (0.138) |
| HP | 0.013*** | 0.013*** | HP | 0.013*** | 0.012*** |
| | (0.001) | (0.001) | | (0.001) | (0.001) |
| Constant | 6.505*** | 6.923*** | Constant | 9.512*** | 9.453*** |
| | (0.289) | (0.286) | | (0.301) | (0.302) |
| *R-squared* | 0.895 | 0.798 | *R-squared* | 0.886 | 0.784 |
| *Hausman test* | 85.129*** | | *Hausman test* | 69.44*** | |
| *Obs.* | 800 | 800 | *Obs.* | 800 | 800 |
| | **FE 3** | **RE 3** | | **FE 4** | **RE 4** |
| TOP 1% | 0.027*** | 0.027*** | TOP 10% | 0.049*** | 0.039** |
| | (0.085) | (0.083) | | (0.059) | (0.057) |
| IR | -0.012** | -0.010 | IR | -0.017** | -0.011 |
| | (0.007) | (0.007) | | (0.007) | (0.007) |
| RGDPpc | -0.015*** | -0.015*** | RGDPpc | -0.019*** | -0.018*** |
| | (0.004) | (0.004) | | (0.004) | (0.004) |
| INF | -0.036 | -0.034*** | INF | -0.037*** | -0.034*** |
| | (0.005) | (0.005) | | (0.005) | (0.005) |
| FL | 0.952*** | 0.971*** | FL | 0.819*** | 0.950*** |
| | (0.148) | (0.146) | | (0.147) | (0.144) |
| HP | 0.013*** | 0.013*** | HP | 0.013*** | 0.012*** |
| | (0.001) | (0.001) | | (0.001) | (0.001) |
| Constant | 8.676 | 8.619 | Constant | 8.329*** | 8.557*** |
| | (0.138) | (0.154) | | (0.229) | (0.233) |
| *R-squared* | 0.889 | 0.789 | *R-squared* | 0.885 | 0.785 |
| *Hausman test* | 64.890*** | | *Hausman test* | 64.121*** | |
| *Obs.* | 800 | 800 | *Obs.* | 800 | 800 |

*Notes:* standard errors are presented in parenthesis. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

A 1% rise in inflation reduces household debt by about 3.2%, while higher interest rates increase borrowing costs and thus lower household debt levels.

Table 4.16: Household Debt (HHD) and Income Inequality: Static Models

| | **FE 1** | **RE 1** | | **FE 2** | **RE 2** |
|---|---|---|---|---|---|
| GINI | 2.695*** | 2.322*** | LSI | -0.563*** | -0.541*** |
| | (0.276) | (0.276) | | (0.167) | (0.165) |
| IR | -0.926*** | -0.808*** | IR | -0.464** | -0.422* |
| | (0.255) | (0.253) | | (0.272) | (0.270) |
| RGDPpc | -0.709*** | -0.763*** | RGDPpc | -1.277*** | -1.266*** |
| | (0.166) | (0.165) | | (0.182) | (0.182) |
| INF | -0.937*** | -0.925*** | INF | -0.835*** | -0.793*** |
| | (0.190) | (0.189) | | (0.218) | (0.218) |
| FL | 5.854*** | 9.295* | FL | 12.199*** | 14.740*** |
| | (5.287) | (5.242) | | (5.617) | (5.565) |
| HP | 0.530*** | 0.511*** | HP | 0.509*** | 0.493*** |
| | (0.021) | (0.021) | | (0.022) | (0.022) |
| Constant | -80.766*** | -69.355*** | Constant | 56.041*** | 51.883*** |
| | (11.196) | (11.326) | | (12.124) | (12.335) |
| *R-squared* | 0.871 | 0.782 | *R-squared* | 0.852 | 0.753 |
| *Hausman test* | 48.346*** | | *Hausman test* | 31.346*** | |
| *Obs.* | 800 | 800 | *Obs.* | 800 | 800 |
| | **FE 3** | **RE 3** | | **FE 4** | **RE 4** |
| TOP 1% | 0.124* | 0.164* | TOP 10% | 0.308* | 0.898* |
| | (0.346) | (0.339) | | (0.024) | (0.023) |
| IR | -0.483** | -0.435* | IR | -0.562** | -0.442* |
| | (0.279) | (0.278) | | (0.285) | (0.282) |
| RGDPpc | -1.042*** | -1.036*** | RGDPpc | -1.11*** | -1.081*** |
| | (0.179) | (0.179) | | (0.176) | (0.176) |
| INF | -1.202*** | -1.152*** | INF | -1.194*** | -1.123*** |
| | (0.207) | (0.207) | | (0.206) | (0.205) |
| FL | 14.239*** | 17.000*** | FL | 13.032** | 16.926*** |
| | (6.012) | (5.957) | | (5.841) | (5.775) |
| HP | 0.529*** | 0.511*** | HP | 0.525*** | 0.504*** |
| | (0.024) | (0.023) | | (0.023) | (0.023) |
| Constant | 19.477*** | 16.911*** | Constant | 8.62 | 12.876 |
| | (5.597) | (6.489) | | (9.126) | (9.504) |
| *R-squared* | 0.849 | 0.751 | *R-squared* | 0.851 | 0.755 |
| *Hausman test* | 26.961*** | | *Hausman test* | 29.452*** | |
| *Obs.* | 800 | 800 | *Obs.* | 800 | 800 |

*Notes:* standard errors are presented in parenthesis. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Real GDP per capita also has a negative and significant impact, suggesting that as income per person rises, households become less reliant on debt financing. By contrast, financial liberalization is positively related to household debt, indicating that more open and efficient financial systems tend to facilitate greater access to credit. This finding aligns with earlier studies emphasizing that rising household indebtedness over recent decades has been supported by the expansion and deepening of financial systems, as well as more accommodative lending practices (Debelle, 2004; Kim et al., 2012; Svirydzenka, 2016).

Table 4.16 reports analogous results using household debt as a share of GDP as the dependent variable. The estimated coefficients retain the expected signs and remain statistically significant across all models, with R-squared values ranging between 0.849 and 0.871, underscoring the strong explanatory power of the specifications. Consistent with Table 4.15, the Gini index, top 1%, and top 10% income shares are all positively associated with household debt, while the labour share of income exhibits a negative relationship. Control variables, including the interest rate, real GDP per capita, financial liberalization, house price index, and inflation, continue to exert statistically significant effects.

## 4.7 Concluding remarks

The objective of this chapter has been to empirically examine the long-run relationship between household debt and income inequality using panel data for 20 advanced OECD countries over the period 1980–2019. The analysis begins with panel unit root and cointegration tests to establish the integration properties of the variables and to verify the existence of a stable long-run equilibrium between household debt and income inequality measures. Building on this foundation, the study employs the panel VECM to investigate the existence and direction of causal relationships between household debt and income inequality. In addition, the panel DOLS method is applied as a robustness check to confirm the stability and consistency of the long-run effects of income inequality measures on household debt.

The results of the panel cointegration analysis confirm the existence of a long-run equilibrium relationship between household debt and income inequality measures. This finding is supported across multiple cointegration tests, including those of Fischer (1999), Kao (1999), Pedroni (1999, 2004), and Westerlund (2007), and aligns with theoretical frameworks proposed by Iacoviello (2008), Rajan (2010) and Kumhof et al. (2015) which collectively highlight how changes in income distribution can contribute to persistent increases in household indebtedness. Thus, the panel VECM results also suggest that there is a stable long run relationship between household debt and income inequality measures. The panel VECM estimation further substantiates this relationship, indicating a bidirectional long-run causality between household debt and income inequality. However, the evidence is particularly strong in support of the hypothesis that rising income inequality acts as a key driver of household indebtedness in advanced economies. These findings are consistent with the broader empirical literature (Malinen, 2013; Kumhof et al., 2015; Bartscher et al., 2020 and Bazillier et al. 2021).

This chapter contributes to the existing literature in two main ways. First, it extends the empirical analysis of the relationship between household debt and income inequality by employing the panel VECM, a method not previously applied in this context to examine both the existence and direction of causality between the two variables. This approach allows for a more comprehensive understanding of the short run and long run dynamics between household debt and income inequality. Second, the study incorporates more accurate and comprehensive measures of both household debt and income inequality, thereby addressing data and measurement limitations present in earlier research and enhancing the robustness and reliability of the empirical findings.

This research has important policy implications for governments in advanced OECD countries on how to prevent financial crisis. In fact, the findings of this study clearly show that income inequality dynamics have played a paramount role in the development of household leverage bubbles since 1980. It follows from our econometric estimation that rising income inequality has a significantly positive impact on household leverage and hence on banking crises. The examination of different income inequality measures provides evidence that income inequality fuels household debt through different channels. The empirical analysis of Gini measure demonstrates that rising income inequality leads to higher household borrowing at the aggregate level in the long run. How an increase in the income share of top income households contributes to higher household debt is presented in this study through the measures of top 1% and top 10% income shares. These findings are strongly supported by the studies of Kumhof et al. (2015), Klein (2015), Mian and Sufi (2018), Bartscher et al., (2020) and Bazillier et al. (2021). In particular, Kumhof et al. (2015) provide evidence that higher household debt arises as a result of permanent positive shocks to the income share of top income households who due to their preferences for wealth lend part of their additional income back to lower and middle income households. As a consequence of excessive credit supply, lower and middle income households borrow in order to maintain higher consumption levels. The result is that loans keep growing which in turn increases the probability of a crisis in the real economy. Therefore, the government should implement progressive taxation and social safety nets to reduce inequality and decrease the reliance on debt for consumption. Strengthening macroprudential regulations is critical for monitoring and managing household debt levels. Moreover, Bartscher et al. (2020) argue that housing bubbles lead to financial fragility through lending frenzies. Rajan (2010) attributes financial crisis to rising inequality through its induced higher household leverage under aggressive policy interventions. Our work shows that the Rajan hypothesis can be proved by theory and confirmed by evidence. It is then safe to draw from this hypothesis a policy lesson for practical use. Therefore, government programs and policies intended to tackle rising income inequality, especially those affecting the lower and middle class could help reduce the risk of financial crisis.

Acemoglu (2011) argues that income inequality can reduce overall demand, as lower-income households have a higher marginal propensity to consume compared to wealthier households. When consumption is debt-financed, it is unsustainable and can lead to economic downturns. Hence, the governments should promote wage growth for lower-income groups through minimum wage laws, collective bargaining, and support for job creation in sectors with decent wages (ILO, 2013). Designing policies to ensure that economic growth benefits all income groups which in turn should reduce the need for debt-driven consumption. Svirydzenka (2016) claims that easy access to credit without adequate regulation can lead to unsustainable debt levels, particularly among vulnerable households. Rising inequality may push these households to borrow excessively, leading to higher default rates and financial crises. Therefore, the governments should tighten lending standards, particularly for subprime borrowers, and ensure that credit is extended based on the ability to repay rather than reliance on collateral. In this process, promoting financial literacy is helpful for households to make informed borrowing decisions. Also, according to Stiglitz (2012), the financial sector may exacerbate income inequality by channeling credit towards asset purchases rather than productive investments, leading to asset bubbles and further wealth concentration. Therefore, Stiglitz (2012) suggests that the governments should implement policies that discourage speculative lending and promote lending to productive sectors of the economy by considering capital controls or taxes on financial transactions to curb speculative behavior. Furthermore, ILO (2013) report states that high levels of household debt linked to income inequality can have long-term negative effects on consumption, investment, and social stability, potentially leading to a more unequal and polarized society. Thus, the policymakers should focus on long-term structural reforms that reduce inequality, such as investing in education, healthcare, and social welfare programs (Barba and Pivetti, 2009). In this regard, ensuring that the financial system supports sustainable economic growth rather than exacerbating inequality is important. Finally, Kumhof et al. (2015) claim that economies reliant on debt-fueled growth, driven by rising inequality, may face slower recoveries after downturns, as households are burdened with debt and reduce consumption. For this reason, Bazillier et al. (2021) suggest that the government should consider shifting towards a growth model that relies less on household debt and more on equitable income distribution. Policies could include strengthening labor markets, promoting fair wages, and encouraging savings over debt-driven consumption. In summary, the interaction between rising income inequality and household debt has far-reaching implications for economic stability, growth, and social cohesion. Policymakers need to address the root causes of inequality, regulate credit markets, and promote inclusive growth to mitigate the risks associated with rising household debt. This holistic approach will help ensure that economic growth is sustainable and benefits all segments of society.

The empirical relationship identified in this chapter between household debt and income inequality represents an important contribution to a relatively limited body of empirical research on the topic. While the analysis has not explicitly integrated a theoretical model into the empirical framework, the empirical results nonetheless offer valuable insights into the mechanisms linking inequality and household borrowing. Overall, the findings add to the broader debate on the role of rising income inequality in driving household indebtedness across advanced economies and underscore the importance of considering distributional factors when analysing debt dynamics and financial stability.

# Appendix 4.A Theoretical model

Kumhof et al. (2015: pp. 1227-1230) develop an economic model with two types of households. One group of households represent highest earners with population share of $\chi$ whereas other group of households represent lowest earners with population share of $1-\chi$. Thus, the following equation referred to as the autoregressive stochastic process indicates total output (Kumhof et al., 2015, p. 1227):

$$y_t = (1-\rho_y)\bar{y} + \rho_y y_{t-1} + \epsilon_{y,t}, \tag{4.12}$$

where $\bar{y}$ is defined as the steady state value of total output. The highest earners share of output $(z_t)$ is represented by the equation below:

$$z_t = (1-\rho_z)\bar{z} + \rho_z z_{t-1} + \epsilon_{z,t}. \tag{4.13}$$

$\sigma_y$ and $\sigma_z$ are the standard deviations of $\epsilon_{y,t}$ and $\epsilon_{z,t}$ respectively. Highest earners maximize the following utility function:

$$U_t = E_t \sum_{k\geq 0}^{\infty} \beta_\tau^k \left\{ \frac{(c_{t+k}^{\tau})^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} + \phi \frac{(1+b_{t+k}\frac{1-\chi}{\chi})^{1-\frac{1}{\eta}}}{1-\frac{1}{\eta}} \right\}, \tag{4.14}$$

where $\beta_\tau$ is the discount factor, $c_t^\tau$ is each highest earner's consumption, $b_t\frac{1-\chi}{\chi}$ is the financial wealth of highest earners per capita and it is lent to lowest earners. $\sigma$ and $\eta$ represent the curvature of the utility function with reference to consumption and wealth. $\phi$ is the weight of wealth in the equation.

The utility function shows that highest earners take $(1-h)$ units of consumption tomorrow if lowest earners default during economic decline.$h$ takes the value between 0 and 1 and it is defined as the share of loans defaulted. However, the lowest earners do not have incentive to default as it will involve significant output and utility losses. The following equation represents the consumption of highest earners per capita:

$$c_t^\tau = y_t z_t \frac{1}{\chi} + (l_t - b_t p_t)\frac{1-\chi}{\chi}, \tag{4.15}$$

where $b_t$ is the loan that is issued for each lowest earner in period $t$ at price $p_t$ and they repay the loan in period $t+1$. $l_t$ is the loan each lowest earner repays in period $t$ and it is equal to $b_{t-1}(1-h\delta_t)$. $\delta_t$ is the default occurrence and it takes the value of 0 or 1. If it is equal to 0, it means no default otherwise default when it is equal to 1.

It should now be clear that highest earners maximize the utility function (4.14) subject to equation (4.15) and $l_t = b_{t-1}(1 - h\delta_t)$. By maximizing the utility function (4.14) subject to the above equations, one can get the following optimality condition for highest earners:

$$p_t = \beta_\tau E_t \left[ \left( \frac{c^\tau_{t+1}}{c^\tau_t} \right)^{-\frac{1}{\sigma}} (1 - h\delta_{t+1}) \right] + \phi \frac{\left(1 + b_t \frac{1-\chi}{\chi}\right)^{-\frac{1}{\eta}}}{(c^\tau_t)^{-\frac{1}{\sigma}}}. \tag{4.16}$$

The equation (4.16) shows that the costs of gaining an additional unit of financial wealth is equated to its benefits.

The functional form of the utility function for lowest earners is similar to highest earners' utility equation and it is as follows:

$$V_t = E_t \sum_{k\geq}^{\infty} \beta_b^k \left\{ \frac{(c^b_{t+k})^{1-\frac{1}{\sigma}}}{1 - \frac{1}{\sigma}} \right\}. \tag{4.17}$$

whereas the budget constraint for lowest earners is as follows:

$$c^b_t = y_t(1 - z_t)(1 - u_t)\frac{1}{1-\chi} + (b_t p_t - l_t), \tag{4.18}$$

where $u_t$ is the share of lowest earners' fund that foregoes due to defaults, referred to as a penalty. $y_t(1 - z_t)u_t$ is defined as the output penalty which is the output loss to the economy.

$$u_t = \rho_u u_{t-1} + \gamma_u \delta_t, \tag{4.19}$$

where $\gamma_u$ represents the impact of a default and $\rho_u$ is referred to as the decline rate with no future defaults.

Lowest earners maximise the utility function (4.17) subject to equations (4.18) and (4.19). By maximizing the utility function (4.17) subject to the above equations, one can get the following optimality condition for lowest earners:

$$p_t = \beta_b E_t \left[ \left( \frac{c^b_{t+1}}{c^b_t} \right)^{-\frac{1}{\sigma}} (1 - h\delta_{t+1}) \right] \tag{4.20}$$

Lowest earners make a decision whether to default in period $t$ on their previous debt $b_{t-1}$. As indicated above, $b_{t-1}$ along with $h$ determine $l_t$ which is the debt that lowest earner pays back in period $t$. Lowest earners' utility equation is a function of the state of the economy $s_t = (l_t, y_t, z_t, u_t)$, and it can be expressed as follows:

$$V(s_t) = \frac{(c_t^b)^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} + E_t[V(s_{t+1})]. \tag{4.21}$$

Given the pre-default state $\tilde{s}_t(b_{t-1}, y_t, z_t, u_{t-1})$ lowest earner decides whether to repay the debt $(\delta)$ at the start of the period based on the utility derived from no default $V_t^N = V(\tilde{s}_t, \delta = 0)$ vs the utility derived from default $V_t^D = V(\tilde{s}_t, \delta = 1)$. Thus, the decision to default can be mathematically expressed as follows:

$$\delta_t = argmax\{V_t^D - \xi_t, V_t^N\} \tag{4.22}$$

where $\delta_t$ takes the value of 0 or 1 and $V_t^D = V(b_{t-1}(1-h), t_t, z_t, \rho_t, u_{t-1} + \gamma_u)$ while $V_t^N = V(b_{t-1}, y_t, z_t, \rho_t, u_{t-1})$. The distribution of additive utility cost of default $(\xi)$ determines the distribution of $\delta_t$.

$$prob(\delta_t = 1/\tilde{s}_t) = \Xi(V_t^D - V_t^N), \tag{4.23}$$

where $\Xi$ is the cumulative distribution function of $\xi_t$ and it can be expressed as follows:

$$\Xi = \begin{cases} \frac{\psi}{1+e(-\theta x)} & \text{if } x < \infty \\ 1 & \text{if } x = \infty \end{cases}$$

where $\psi < 1$ and it assists to define the average level of recession likelihood over the sample while $\theta$ defines the curvature of recession likelihood with reference to $V_t^D - V_t^N$. $\gamma_u$ and $\rho_u$ are also the parameters which are made to match the empirical evidence for the likelihood of economic decline.

Highest earners and lowest earners maximize their consumption utility in equilibrium and it is represented by the following equation (Kumhof et al., 2015, p. 1230):

$$y_t(1 - (1 - z_t)u_t) = \chi c_t^\tau + (1 - \chi)c_t^b. \tag{4.24}$$

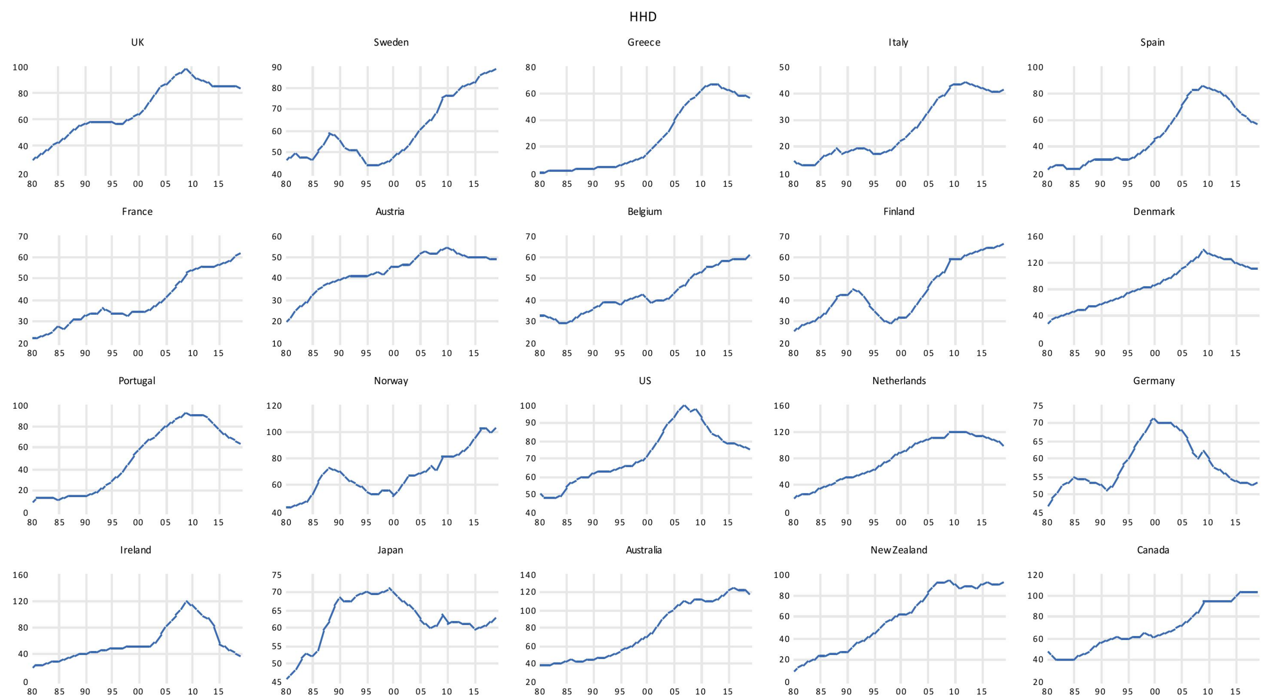


Figure 4.5: Household debt as a share of GDP, 1980-2019


Figure 4.6: GINI index, 1980-2019


Figure 4.7: Top 1% as a share of GDP, 1980-2019

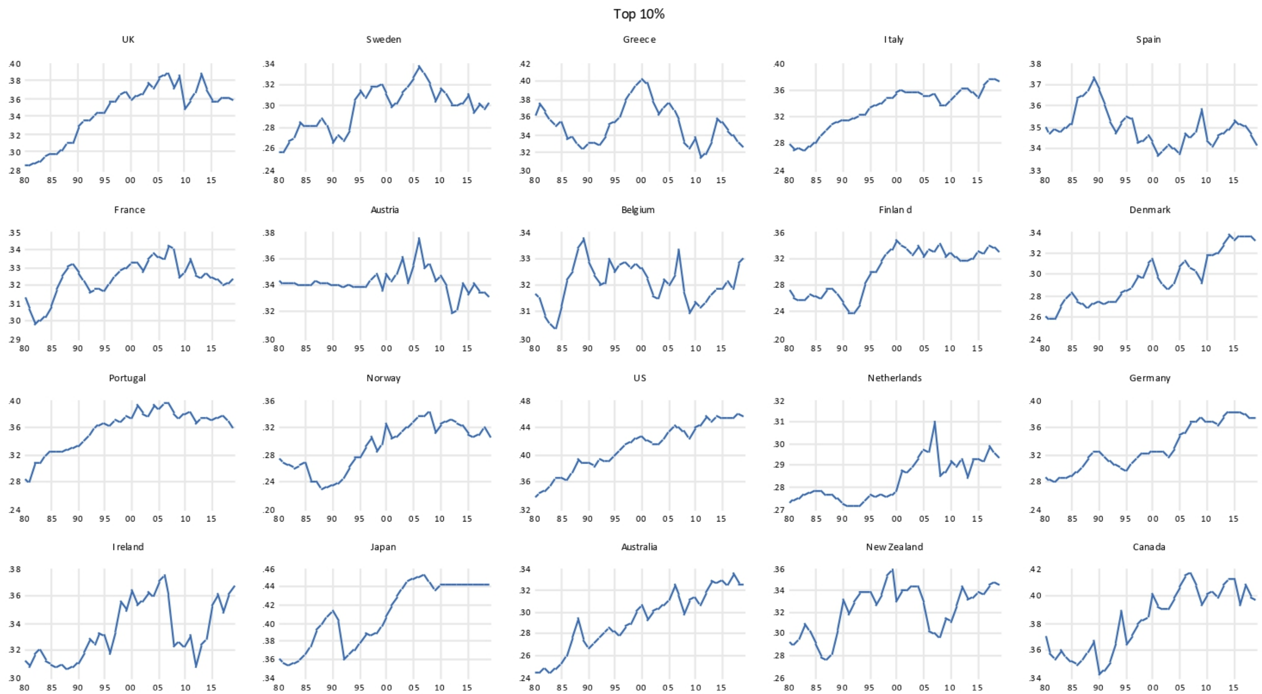


Figure 4.8: Top 10% as a share of GDP, 1980-2019

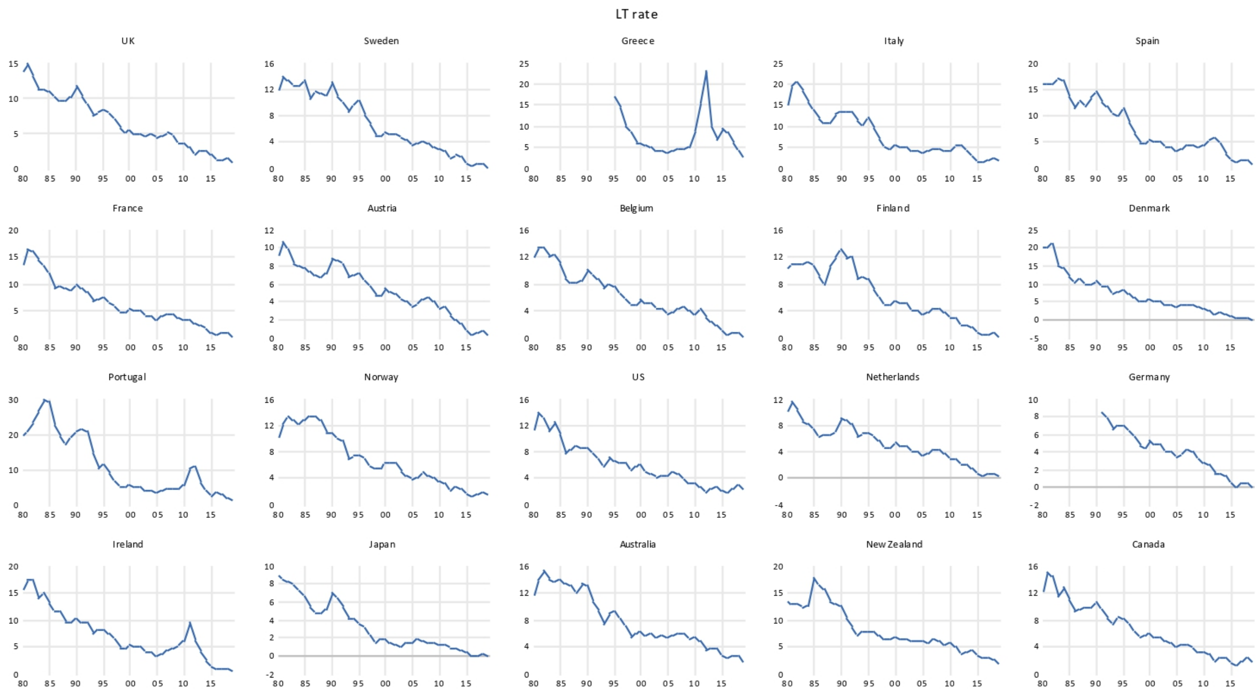


Figure 4.9: Long term interest rate, 1980-2019

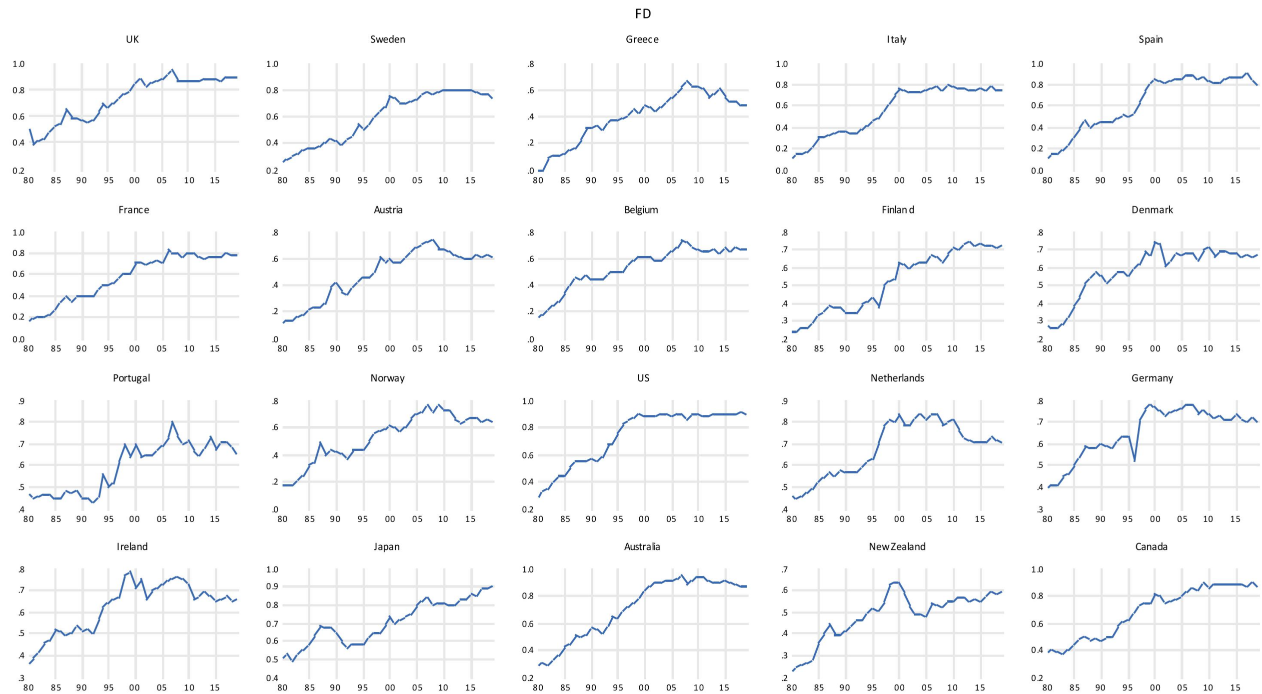


Figure 4.10: Financial Development Index, 1980-2019

# Chapter 5

## 5.1 Conclusions

This thesis contributes to the growing body of literature by examining the complex and evolving relationship between finance and income inequality based on the panel study of advanced OECD economies over the period 1980-2019. It does so through three interrelated empirical investigations, each presented as a standalone chapter. Chapter 2 focuses on the link between financialization and income inequality; Chapter 3 explores the role of financial structure in shaping income disparities; and Chapter 4 investigates the influence of rising inequality on household debt accumulation. Together, these chapters aim to answer the following pressing, yet understudied, research questions:

- Is financialization associated with rising income inequality and declining labour share of income in advanced OECD countries?
- Does a more market-dominated financial system exacerbate income inequality as opposed to a more bank-dominated system which tends to reduce it in advanced OECD countries?
- Does greater income inequality contribute to surging household debt in advanced OECD countries?

Chapter 2 provides an in-depth empirical examination of the long-run relationship between financialization and income inequality in 20 advanced OECD countries over the period 1980–2019. Using the panel ARDL approach, the results reveal that key indicators of financialization are positively and significantly associated with higher levels of income inequality, as measured by the Gini index and alternative inequality metrics. These findings remain consistent and statistically robust across different model specifications and measures of financialization. In addition, the use of the CS-ARDL estimator complements the panel ARDL results by accounting for cross sectional dependence and induced feedback effects between the variables, thereby reinforcing the evidence of a stable long run relationship between financialization and income inequality. The results suggest that financialization, alongside globalization, technological change, and weakening labor market institutions has emerged as a major driver of rising inequality. The robustness of these findings is further supported through alternative estimation using the DOLS method, which confirms the long-run inequality-widening effect of financialization.

Chapter 3 shifts the focus to the composition of financial systems—specifically, the distinction between bank-dominated and market-dominated financial structures—and their distributional implications. Employing the panel ARDL methodology, the study establishes a cointegrating relationship between income inequality and measures of financial structure, with a statistically significant and negative error correction term. The pooled mean group (PMG), mean group (MG), and dynamic fixed effects (DFE) estimators consistently indicate that a bank-dominated financial system tends to reduce income inequality, while a market-dominated system tends to exacerbate it over the long run. These findings are robust to alternative inequality measures and further validated using CS-ARDL estimations. The expected signs and significance of the financial institutions and financial markets indices reinforce the theoretical proposition that the composition of the financial system has important implications for income distribution. The DOLS results further corroborate the long-run relationship, providing strong evidence that financial structure matters for inequality outcomes.

Chapter 4 extends the analysis by examining the reverse channel—how income inequality, in turn, influences household indebtedness. Drawing on panel data from the same sample of OECD countries, this chapter applies the panel vector error correction model (VECM) to analyse both the existence of the long-run equilibrium relationship and the direction of causality between inequality and household debt. The empirical evidence indicates a stable, long-run relationship whereby rising income inequality leads to greater household debt. Moreover, the results reveal bidirectional long-run causality, suggesting a feedback mechanism through which inequality and household indebtedness reinforce each other over time. These findings remain consistent across different specifications and alternative measures of both inequality and debt, and are further supported by the DOLS estimation, which confirms the inequality-induced rise in household debt over the long term.

Collectively, the findings of this thesis highlight the multifaceted and complex nature of the relationship between finance and inequality. The evidence presented suggests that earlier studies may have underestimated the systemic role of finance reflected through financialization, and in its structure, reflected through the importance of bank dominated and market dominated financial systems, in shaping income disparities and broader macroeconomic outcomes. Furthermore, the results indicate that income inequality should be viewed not merely as a consequence but also as a contributing factor in the accumulation of household debt, thereby reinforcing cycles of financial vulnerability. Recognizing the reciprocal nature of these dynamics is essential for a more comprehensive understanding of inequality trends in advanced economies.

Although limitations exist such as the unavailability of comprehensive data for certain financialization indicators or the absence of a formal theoretical model explicitly integrated into the empirical framework, this thesis nonetheless makes a substantive contribution to the broader literature. By offering a comprehensive and empirically rigorous assessment of the links between financialization, financial structure, inequality, and household debt, the research sheds light on the structural mechanisms that underpin rising inequality in developed economies. The findings offer important policy implications: addressing inequality requires not only labor market and fiscal reforms but also a critical re-evaluation of the design, regulation and functioning of financial systems.

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