FINANCIAL SECTOR DEVELOPMENT AND INCOME INEQUALITY NEXUS IN SOUTH AFRICA

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ABSTRACT

This study investigates the relationship between financial sector development and income inequality in South Africa. The study explores financial depth and efficiency as facets of financial sector development. Despite having the most developed financial sector in Africa, South Africa has the highest income inequality in the world, with a Gini score of 0.63 since 2022 despite government interventions such as social grants and minimum wage policies intended to reduce income inequality. The country's ongoing income inequality raises critical questions about the impact that the development of the financial sector may be exerting on this persistent inequality. The study utilizes annual time-series data from 1980 to 2020. The study applies the Autoregressive Distributed Lag (ARDL) model to examine both the short and long-run dynamics between financial development and income inequality, particularly focusing on the long-run dynamics. The ARDL model is best for this time-series analysis as it accepts variables of different integration of order. The analysis employs the Gini coefficient and the Palma ratio as complementary measures of inequality, and includes relevant macroeconomic control variables such as government expenditure, foreign direct investment (FDI), GDP per capita, inflation, and trade openness. Based on the key findings of the study, income inequality (proxied by the Gini coefficient) in South Africa can be reduced through the development of the financial sector (proxied by Public Debt Securities to GDP). In support of the Inequality-narrowing hypothesis, which posits that financial development reduces inequality by providing the marginalized population with better access to financial services, the study mainly found that in the long run, financial sector development reduces inequality through the facet of depth. Based on the findings of this study, relevant South African policymakers could promote financial inclusion initiatives, including expanding access to credit for low-income earners and small businesses. In addition, low-cost banking services or mobile banking platforms can also be implemented to increase credit penetration in underserved areas. This study contributes to the limited body of literature on the financial sector development and income inequality nexus in South Africa by incorporating both underexplored facets of financial development (financial efficiency) and complementary inequality metrics (Gini coefficient and Palma ratio).

Keywords – ARDL model; Financial depth; Financial efficiency; Financial sector development; Income inequality; South Africa.

PLAGIARISM DECLARATION

I, the undersigned, Agnes Tlhalefang Malatsi, student number G18M3041, hereby declare that this research is my own original work and that all the reference sources have been accurately reported and acknowledged and that this document has not been previously submitted at any University, Technikons or Colleges for a similar or any other academic qualification.

Name: Agnes Tlhalefang Malatsi

Signed: A.Malatsi

Date: 15 July 2025

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To my creator, the omnipresent being who walks before me, behind me, besides me, all around me, and dwells within me at all times… you are the best! It's a dream come true to live a life bringing me closer to you with each day I breathe. Continue to keep your gorgeous girl graceful, powerful, glorious and rich; it suits me so much.

Let this game called life begin. It's time. It's all true: E tsogile the beautiful **Kwena.**

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ACRONYMS

ADF test	Augmented Dickey-Fuller test
AIC	Akaike Information Criterion
AMG estimator	Augmented Mean Group
ARDL	Autoregressive Distributed Lag
ATM	Automated Teller Machine
BRICS	Brazil, Russia, India, China, and South Africa
CUSUM	Cumulative sum of residual
CUSUMSQ	Cumulative sum of squares of recursive residuals
ECM	Error Correction Model
FDI	Foreign Direct Investment
FD-IV	First-Difference Instrumental Variables
GDP	Gross Domestic Product
GEXP	Government expenditure
GJ hypothesis	Greenwood-Jovanovic hypothesis
HQ	Hannan-Quinn Criterion
IMF	International Monetary Fund
INF	Inflation
JB statistic	Jarque and Bera statistic
JSE	Johannesburg Stock Exchange

KPSS test	Kwiatkowski-Phillips-Schmidt-Shin test
LM	Lagrange Multiplier
LNGDPPC	GDP per Capita
Obs.	Observations
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PDSG	Public Debt Securities to GDP
PP test	Phillips-Perron test
P-Value	Probability Value
SARB	South African Reserve Bank
SC	Schwarz Bayesian Criterion
SMCG	Stock market capitalization to GDP
SMT	Turnover ratio for stock market
St. Error	Standard Error
Std. Dev.	standard deviation
STG	Stocks traded to GDP
Sum Sq.	sum of squares
S-VAR	Structural Vector Autoregression
System GMM	System Generalized Method of Moments
TRADEGDP	Trade

VAR	Vector Autoregressive
WIID	World Income Inequality Database

CHAPTER 1: INTRODUCTION

1.1 Research background

The role of financial development in reducing income inequality and promoting economic growth is widely studied in scholarly literature and policy discussions. Schumpeter (1911) defines financial development as the provision of financial services that facilitate economic growth and technological innovation. Financial development includes the development of financial systems, including financial markets and institutions, financial instruments, and the legal and regulatory framework (McKinnon, 1973; King and Levine, 1993; World Bank, 2001; Levine, 2005; Beck and Demirgüç-Kunt, 2009; IMF, 2022). Financial sector development is a component of financial development that focuses on reducing costs associated with financial systems that enable credit transactions (World Bank, 2012). Financial sector development has four facets: financial access, depth, efficiency, and stability (World Bank, 2012). A substantial amount of research indicates that financial sector development significantly contributes to economic growth (Bencivenga and Smith, 1991; Levine, 2005; World Bank, 2012; OECD, 2013). According to Altunbas and Thornton (2019), Bittencourt et al. (2019), and Jung and Vijverberg (2019), well-developed financial markets and institutions offer crucial funding alternatives for individuals across the economy. These funding alternatives reflect financial development, promote broad economic participation and development, and are essential for facilitating productive economic activities. Moreover, financial development provides the marginalized population with access to credit platforms that offer opportunities such as establishing businesses, investing in education, or achieving personal goals (Altunbas and Thornton, 2019; Bittencourt et al., 2019; Jung and Vijverberg, 2019).

Despite the opportunities created by financial development, its impact on income inequality, which is widely recognized as a global crisis, remains complex. While financial development is often regarded as a tool for promoting financial inclusion and reducing inequality, empirical findings remain inconclusive, with mixed findings on the financial sector development and income inequality nexus.

Income inequality refers to the unequal distribution of income among individuals or groups within a society (Stiglitz, 2012; Piketty, 2014; Atkinson, 2015; World Bank, 2022). OECD (2023) further defines income inequality as the degree to which income is unevenly distributed among individuals in a population. According to Atkinson (2015), income inequality reflects disparities in earnings, the accumulation of wealth, and access to opportunities within the economy. It is influenced by factors such as education, labour market structures, and government policies. In addition, income inequality arises when returns on capital exceed economic growth, leading to wealth concentration among the affluent (Piketty, 2014). Theoretical and empirical studies on the financial development and income inequality nexus provide mixed results. It is crucial to note that there are two channels through which these two variables, financial sector development and income inequality, relate based on existing literature (Kapingura, 2017). The two channels are the direct and indirect channels. Based on the direct channel, financial sector development is believed to lower credit constraints, enabling the marginalized populations to access financial services. On the other hand, financial sector development is believed to promote economic growth, which ultimately benefits both high- and low-income households, based on the indirect channel (Beck, Demirgüç-Kunt, and Levine, 2007). However, Piketty (2014) argues that income inequality arises when returns on capital exceed economic growth, leading to wealth concentration among the affluent.

There are three dominant theories found within the context of financial development and income inequality: the inequality-narrowing hypothesis, the inequality-widening hypothesis, and the nonlinear hypothesis. The three theories offer varied views on the ways in which financial development influences income inequality. The Inequality-narrowing hypothesis argues that financial development reduces inequality by providing the marginalized population with better access to financial services (Becker and Tomes, 1979; Banerjee and Newman, 1993; Galor and Zeira, 2004; Braun et al., 2019). By providing access to credit, savings, and insurance, financial systems assist the marginalized population in investing in business ventures, education, and health.

In contrast, the Inequality-widening hypothesis argues that financial development primarily benefits the affluent and large corporations that already have better access to financial services and resources (Lamoreaux, 1995; Haber, 2004).

Based on the inequality-widening hypothesis, the marginalized population is often excluded from the benefits of financial development due to a lack of collateral, financial knowledge, or a formal credit history. Therefore, financial development leads to a concentration of wealth among the affluent and further excludes the marginalized population. In addition, financial development increases the income inequality gap by favouring those already well-positioned in the economy (Bumann and Lensink, 2016; Zhang and Ben Naceur, 2019).

The third theory, namely the Nonlinear hypothesis, offers a more dynamic perspective. The Nonlinear hypothesis suggests that the effect of financial development on inequality changes over time. Based on this theory, in the early stages of financial growth, income inequality may rise as the affluent are better positioned to take advantage of the resulting financial benefits (Greenwood and Jovanovic, 1990; Baiardi and Morana, 2018; Jung and Vijverberg, 2019). However, as financial systems mature and become more inclusive, the resulting benefits are spread more evenly among the population, and inequality begins to decline. The pattern of the Nonlinear hypothesis follows an inverted U-shape similar to the Kuznets Curve. According to the Kuznets Curve, as economies develop, income inequality first rises and then declines (Kuznets, 1955). In the early phases of financial development, skilled workers and urban elites benefit most. Later, wider access to education, infrastructure, and financial services allows more people to participate in the economy and helps reduce inequality.

Despite these three main theories explaining the financial sector development and income inequality nexus, income inequality remains persistent, especially in South Africa. South Africa is the most unequal country in the world (Statista, 2025), yet the country has the most developed and advanced financial sector in the whole of Africa (Gwatidzo and Simbanegavi, 2024). This study aims to contribute to the limited literature, particularly in the South African context, using the most recently available data. The study aims to empirically investigate the linear relationship between financial sector development and income inequality in South Africa, using the Gini coefficient, and investigate the impact of financial sector development on income inequality on the top 10% earners and the bottom 40%, using the Palma ratio, contribute to respective policies aimed at reducing income inequality through financial development in South Africa.

1.2 Problem statement

The persistent income inequality in South Africa, despite the country's well-developed financial sector, raises concerns about the effectiveness of financial development in promoting equality. Although financial sector reforms have been implemented to promote financial inclusion, income inequality levels remain high. According to Kumo (2012) and Coetzee (2018), historical factors such as an oligopolistic banking system, the exclusion of marginalized populations from financial services, and economic policies that have failed to address wealth redistribution continue to reinforce income inequalities. Moreover, financial distress is widespread, with more than half of the population holding more liabilities than assets (Sguazzin, 2021). Empirical research on the relationship between financial sector development and income inequality in South Africa remains limited and outdated, posing a research gap. A South African study by Kapingura (2017), using annual data from 1990 to 2012, revealed that increasing financial access reduces inequality compared to increasing financial depth, supporting the Inequality-narrowing hypothesis. On the other hand, also using annual data from South Africa from 1970 to 2018, Hassan and Meyer (2021) found that financial sector development has a nonlinear impact on income inequality. Specifically, the study by Hassan and Meyer (2021) confirmed an inverted U-shaped relationship, positing that early stages of financial development reduce inequality and later exacerbate the inequality gap past a certain threshold. This study measured financial development through the Depth component. Therefore, there are mixed findings in the financial sector development and income inequality nexus in South Africa, with both studies solely relying on the Gini coefficient to measure income inequality.

Furthermore, based on the study's empirical literature section, majority of the existing literature on the financial sector development and income inequality nexus (including global studies) relies on the Gini coefficient as the primary measure of inequality, with limited consideration of the Palma ratio; further highlighting the identified research gap, like Kapinguara (2017) and Hassan and Meyer (2021). The Palma ratio offers a more nuanced perspective by capturing inequalities between the top 10% of earners and those of the bottom 40%. The use of the Palma ratio, together with the Gini coefficient, provides a broader perspective of income inequality by also assessing the existing inequality gap between earners.

1.3 Research objectives

Based on the scope of the study (half-thesis), the subgoals of the study, which focus on the long-run relationship between Income Inequality and Income inequality, include:

- Empirically investigating the linear relationship between financial sector development and income inequality in South Africa, using the Gini coefficient.

- Investigating the impact of financial sector development on income inequality among the top 10% earners and the bottom 40%, using the Palma ratio.

- Contributing to the respective policy aimed at reducing income inequality through financial development in South Africa.

The study focuses on the long-run relationship between Income inequality and financial sector development due to the persistence of South Africa's income inequality over a substantial number of years. The study seeks to propose long-term policy recommendations to curb the long-term, persistent income inequality in the country.

1.4 Rationale of study

This study aims to address the research gap highlighted in subsection 1.2 through a thorough analysis of the financial sector development and income inequality nexus in South Africa, using the most recently available data. The study's significance includes its incorporation of both the Gini coefficient and the Palma ratio to measure income inequality, elaborating both overall income distribution (Gini coefficient) and the disparity between the affluent and marginalized (Palma ratio). By identifying how different facets of financial sector development affect inequality (Depth and Efficiency), the findings can guide policymakers in designing interventions that promote genuine financial inclusion while reducing income inequality across different classes of income earners in South Africa.

1.5 Methods, Procedures, and Ethical Consideration

1.5.1 Methods

This study adopts a quantitative approach within a positivist research paradigm to examine the financial sector development and income inequality nexus in South Africa. The study utilizes annual time-series data from 1980 to 2020. The data was sourced from the World Income Inequality Database (WIID), the World Bank, and the International Monetary Fund (IMF). The chosen timeframe facilitates an examination of long-term trends, structural transformations, and the effects of banking sector reforms on income inequality.

1.5.2 Procedures

The Autoregressive Distributed Lag (ARDL) model is used to analyze both short and long-run relationships between financial sector development and income inequality. The ARDL model is best for this time-series analysis as it accepts variables of different integration of order (Pesaran et al., 2001).

1.5.3 Ethical consideration

This research is based solely on secondary data, which is publicly accessible from credible sources, including the WIID, World Bank, and IMF. Due to the nature of the secondary data used, the study did not require formal ethical application for the data. However, ethical research principles were strictly adhered to, ensuring data integrity, proper citation of sources, and transparency in methodology and reporting.

1.6 Outline of thesis

The thesis is structured in the following manner: Chapter 2 provides an overview of the study. The chapter offers definitions of key conceptual terms in the context of financial sector development and the income inequality nexus. The Overview chapter also provides a relevant background of the South African economy. Following Chapter 2 is the literature review presented in Chapter 3. The literature review chapter consists of both the theoretical framework and empirical literature relevant to this study. The research methodology is discussed in Chapter 4. The methodology chapter details the estimation techniques, modeling, appropriate protocols, and diagnostic tests employed in the study. The results and analysis of all tests discussed in Chapter 4 are presented in Chapter 5. In addition, other analyses and tests, including descriptive statistics, correlation analysis, and causality tests, are presented in Chapter 5. Finally, Chapter 6 presents the conclusions of the thesis, offering summaries of the key insights of the study. In addition, Chapter 6 provides policy recommendations based on the empirical findings of the study.

CHAPTER 2: OVERVIEW OF STUDY

2.1 Introduction

Chapter 2 presents an overview of financial development and income inequality, including the context of South Africa. The chapter begins with Section 2.2, which defines financial development, discusses the role of financial development, classifications of financial development, financial development in the South African context, and analyzes the trend of financial development variables used in the study. In Section 2.3, the following discussions are presented: definitions of income inequality, measurements of income inequality, income inequality in the South African context, and the trend analysis of income inequality. Finally, Section 2.4 concludes the Overview chapter.

2.2 Financial development

Schumpeter (1911) defines financial development as the provision of financial services that facilitate economic growth and technological innovation. According to McKinnon (1973), King and Levine (1993), World Bank (2001), Levine (2005), Beck and Demirgüç-Kunt (2009), and IMF (2022), this development includes the development of financial systems, including financial markets and institutions, financial instruments, and the legal and regulatory framework. The role of financial development in the economy includes facilitating trade, minimizing transaction costs, optimizing the allocation of resources, and stimulating innovation. In addition, financial development facilitates overall economic development, ultimately reducing poverty. Financial development enhances decision-making, mobilizes capital, and improves access to credit and financial products. This development should enhance the efficiency, inclusivity, and stability of financial systems (Schumpeter, 1911; OECD, 2013). In accordance with the study by Chisadza and Biyase (2023), this study defines financial development as the enhancement of financial markets and institutions to improve access to financial resources, stimulate investment, promote equitable economic growth, and mitigate income inequality.

Financial sector development is a component of financial development that focuses on reducing costs associated with financial systems that enable credit transactions (World Bank, 2012). A substantial amount of research indicates that financial sector development significantly contributes to economic development. Financial sector development promotes economic growth through the accumulation of capital and technological innovation. Moreover, financial sector development increases the savings rate, acquires and mobilizes savings, generates investment insights, attracts foreign capital inflows, and improves capital allocation efficiency (Bencivenga and Smith, 1991; Levine, 2005; World Bank, 2012; OECD, 2013). As presented in Table 2.1, Financial Access, Depth, Efficiency, and Stability are four categories used by the World Bank to classify financial sector development (World Bank, 2012). The classification accounts for both financial markets and financial institutions, the two major components in the financial sector.

Table 2.1 Summary of Financial Development Classification and metrics

	Financial Institutions	Financial Markets
Depth	Private Sector Credit to GDP	Stock market capitalization and outstanding domestic private debt securities to GDP
	Financial Institutions asset to GDP	Private Debt securities to GDP
	M2 to GDP	Public Debt Securities to GDP
	Deposits to GDP	International Debt Securities to GDP
	Gross value added of the financial sector to GDP	Stock Market Capitalization to GDP
		Stocks traded to GDP
Access	Accounts per thousand adults (commercial banks)	Percent of value traded outside of top 10 traded companies
	Branches per 100,000 adults (commercial banks)	Government bond yields (3 month and 10 years)
	% of people with a bank account (from user survey)	Ratio of domestic to total debt securities
	% of firms with line of credit (all firms)	Ratio of private to total debt securities (domestic)
	% of firms with line of credit (small firms)	Ratio of new corporate bond issues to GDP
		Turnover ratio for stock market
Efficiency	Net interest margin	Price synchronicity (co-movement)
	Lending-deposits spread	Private information trading
	Non-interest income to total income	Price impact
	Overhead costs (% of total assets)	Liquidity/transaction costs
	Profitability (return on assets, return on equity)	Quoted bid-ask spread for government bonds
	Boone indicator (or Herfindahl or H-statistics)	Turnover of bonds (private, public) on securities exchange
		Settlement efficiency
		Volatility (standard deviation / average) of stock price index, sovereign bond index
Stability	Z-score	Skewness of the index (stock price, sovereign bond)
	Capital adequacy ratios	Vulnerability to earnings manipulation
	Asset quality ratios	Price/earnings ratio
	Liquidity ratios	Duration
	Others (net foreign exchange position to capital etc.)	Ratio of short-term to total bonds (domestic, int’l)
		Correlation with major bond returns (German, US)

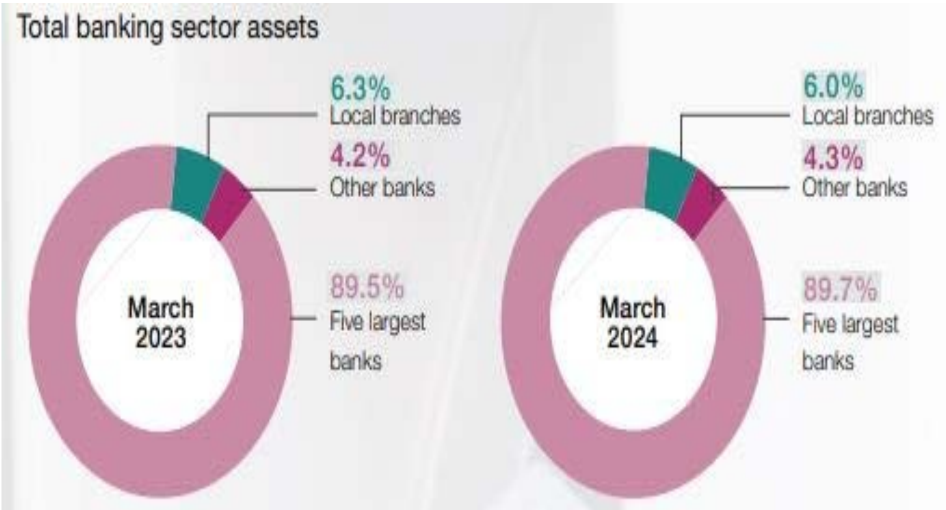
Source: World Bank (2012)

2.2.1 The South African financial sector

The South African financial sector is deemed the most developed and advanced in the whole of Africa (Gwatidzo and Simbanegavi, 2024). Furthermore, using the share of the population with a bank account, South Africa has the highest level of financial inclusion in Africa (World Bank 2022b). According to SARB (2024), the banking sector, a component of the financial sector, accounts for 35% of total financial assets, as shown in Figure 5.2. As seen in Figure 2.1, the five dominant banks (Absa, Investec, Nedbank, FirstRand, and Standard Bank) jointly hold 89.7% of the sector's total assets, marking a 0.2% increase from 2023 (South African Reserve Bank Prudential Authority, 2024). Locally registered banks hold 6% of the banking sector's total assets, and other smaller financial institutions hold 4.3%. According to SARB (2024), the country's banking system includes 17 registered banks, four mutual banks, and six cooperative banks, alongside 11 local branches of international banks and 30 foreign banks with representative offices.

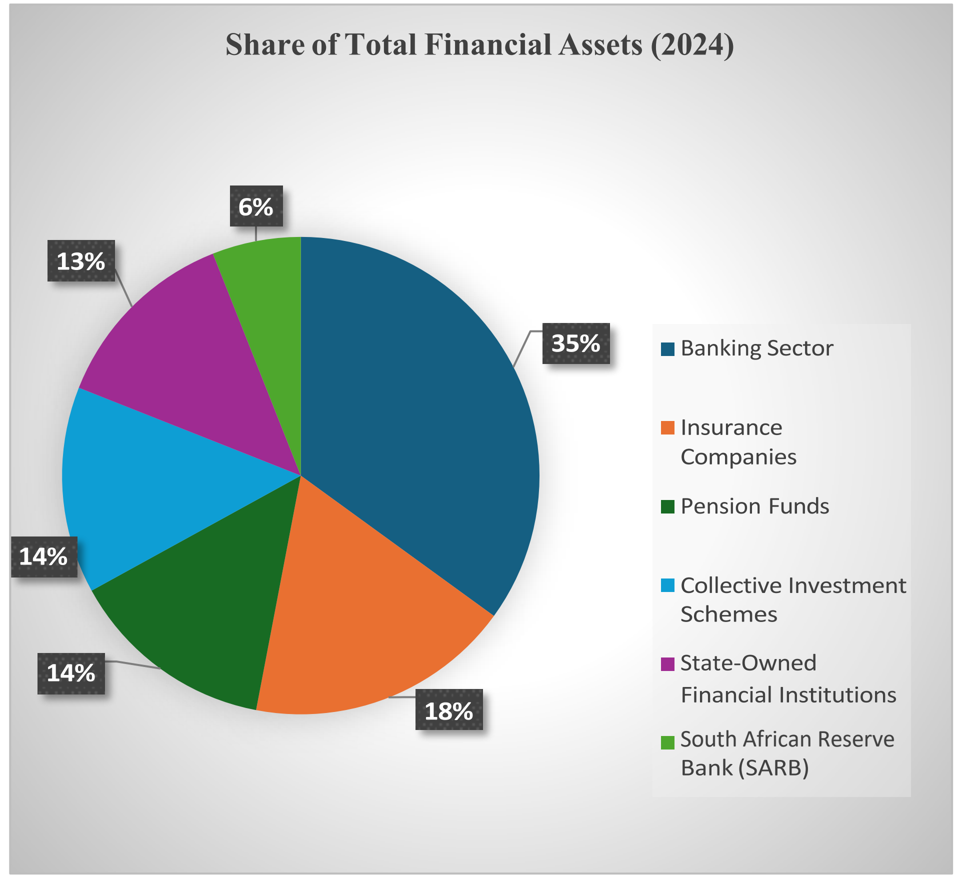
The banking sector remains profitable, with the return on equity increasing from 14.59% to 15.22% in June 2024 (SARB, 2024). Similarly, the return on assets also increased from 1.09% in 2023 to 1.14% in 2024. Cowling (2024) asserts that South Africa's banking sector has experienced significant growth in financial inclusion over the past decade. The adult population owning a bank account increased from 64% in 2014 to over 86% in 2023 (SARB, 2024). According to Cowling (2024), technological advancements, including Fintech and Techfin, have contributed significantly to the growth of the sector. Furthermore, the adoption of Internet banking is expected to expand further in the coming years. The banking sector continues to show resilience, maintaining stable and accessible financial services, with this trend expected to continue into 2025 (SARB, 2024).

Figure 2.1 Total banking sector assets



Source: South African Reserve Bank Prudential Authority (2024)

Figure 2.2 Share of total financial assets



Source: SARB (2024)

Following the banking industry, the insurance industry, which includes both life and non-life insurers, holds 18% of financial assets (SARB, 2024). Pension funds, managed by both public and private entities, contribute 14%, similar to Collective investment schemes comprising unit trusts and mutual funds. State-owned financial institutions hold 13% of financial assets, while the South African Bank holds only 6% (SARB, 2024).

Financial inclusion has improved significantly within the banking sector of South Africa over the past decade (Cowling, 2024). Supporting Cowling (2024), SARB (2024) further reports that over 86% of adults held a bank account in 2023, a significant increase from 64% in 2014. Cowling (2024) attributes this increase in financial inclusion to technological advancements, with Internet banking expected to expand further in the coming years.

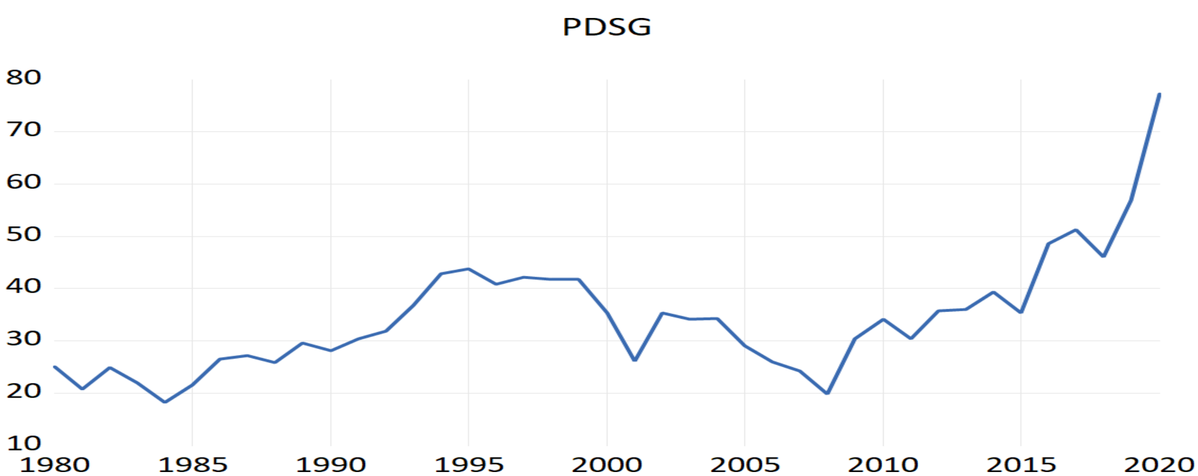
2.2.2 Trend analysis of financial sector development in South Africa (financial markets)

Subject to data availability, this study focuses on financial markets as a component of the financial sector. South Africa’s financial sector has evolved significantly over the past few decades, reflecting capital market efficiency, increasing market depth, and liquidity (SARB, 2024). Due to limited data, the study uses four proxies, namely Public Debt Securities to GDP (depth), Stock market capitalization to GDP (depth), Turnover ratio for stock market (efficiency), and Stocks traded to GDP (depth), to measure the development of South Africa’s financial sector from 1980 to 2020.

2.2.2.1 Public Debt Securities to GDP

Interpreting Figure 2.3, in 1980, the ratio of Public Debt Securities to GDP was around 25%, which is relatively low. By 1994, the ratio had escalated markedly to around 43%, indicative of heightened government borrowing during the concluding years of apartheid and the initial phase of democratic transition (National Treasury, 2020). The ratio then declined drastically around 2001, further declining up to 2008, with values of 27% and 20%, respectively. According to the IMF (2022), this downward movement reflects improved fiscal behaviour, substantial economic growth, and a commodity-driven revenue boom during the early 2000s. In addition, these improvements enabled debt consolidation, which reduced government borrowings. From 2008, Public Debt Securities to GDP rose to over 32% in 2010 and has since steadily increased, with notable increases recorded in 2015 and 2019 onwards, with values of 38% and 48%, respectively. The increased borrowings, which reflect structural constraints in revenue collection and increased spending pressures, are attributed to significant economic events, including the global financial crisis in 2008, the FIFA World Cup in 2010, the critical political instability in 2015, and the COVID-19 pandemic (World Bank, 2021; IMF, 2020). Overall, Public Debt Securities to GDP show a rising trend, which may favor financial sector development if the allocation of these funds is constructive.

Figure 2.3 Trend analysis of Public Debt Securities to GDP (PDSG)

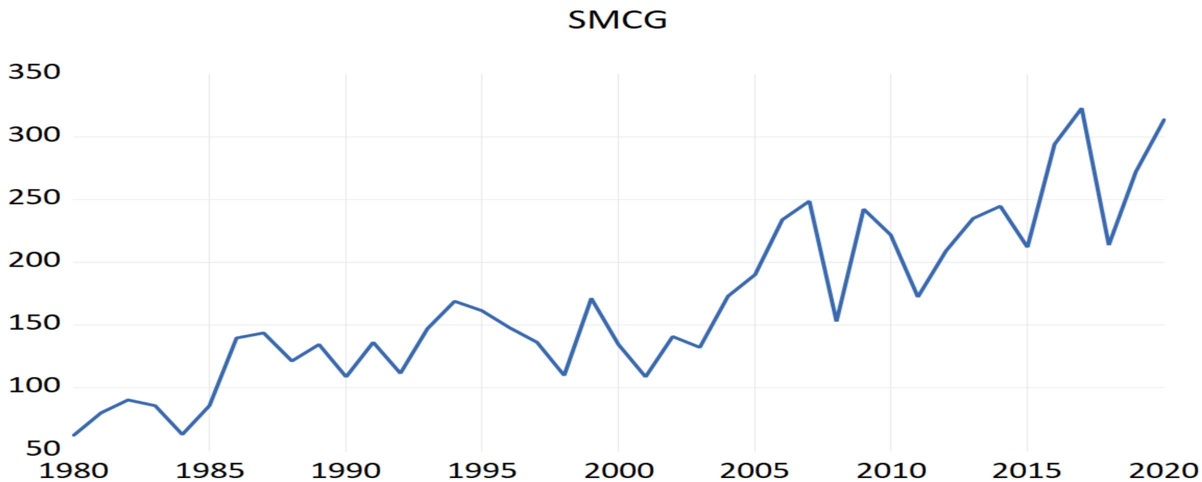


Source: EViews (14) output, compiled by author

2.2.2.2 Stock Market Capitalization to GDP

In 1980, the Stock market capitalization to GDP ratio, presented in Figure 2.4, stood at approximately 55%, indicating relatively low levels of depth. Very high levels of the Stock market capitalization to GDP ratio were recorded in 1986, 1993, 2007, and 2017. These periods have values of approximately 148%, 160%, 248%, and 320%, respectively. The high levels of the Stock market capitalization to GDP ratio reflect growth in investment participation, ultimately boosting the development of the financial market. Overall, Stock market capitalization to GDP shows a rising trend, which favours financial sector development.

Figure 2.4 Trend analysis of Stock Market Capitalization to GDP (SMCG)



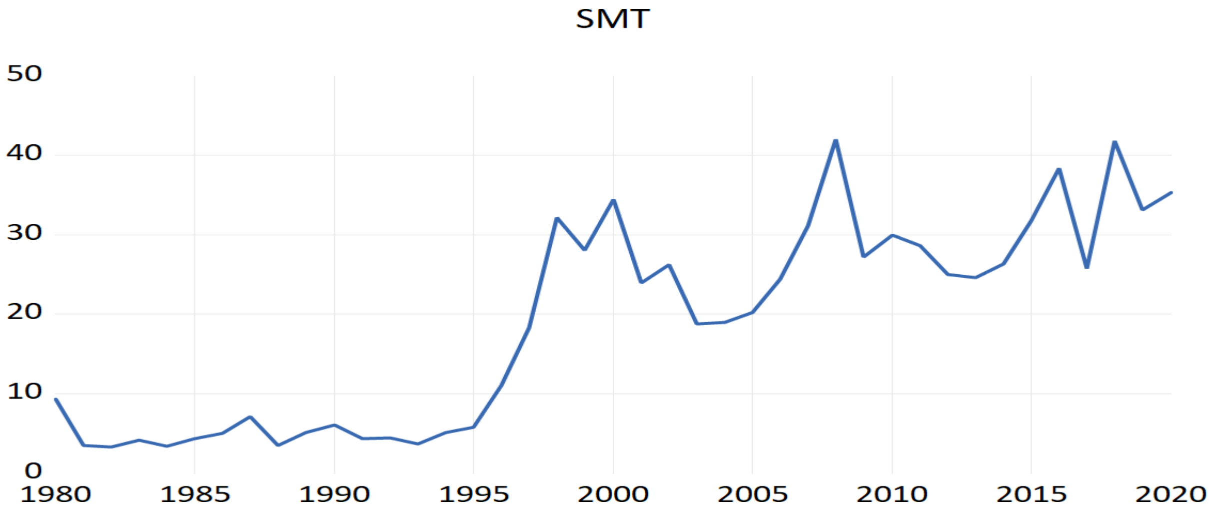
Source: EViews (14) output, compiled by author

2.2.2.3 Turnover ratio for stock market

Interpreting Figure 2.5, 1980, the Turnover ratio for stock market was approximately 9.5% in 1980, indicating relatively low levels of trading activity during that period. The ratio remained relatively low from 1980 to 1995. From thereon, the Turnover ratio for stock market recorded a sharp rise to approximately 32% in 1998 and 35% in 2000. Thereafter, significant increases were recorded in 2008 and 2018, with values of 43% and 42%, respectively. These significantly high levels of the Turnover ratio for stock market reflect increased investment activities in those periods. Overall, the Turnover ratio for stock market exhibits an upward trend, which favours financial sector development.

Overall, the upward trend reflects increased market liquidity, increased investor engagement, and growing dynamism in the operations of the Johannesburg Stock Exchange (JSE), the country's primary stock exchange.

Figure 2.5 Trend analysis of Turnover ratio for stock market (SMT)

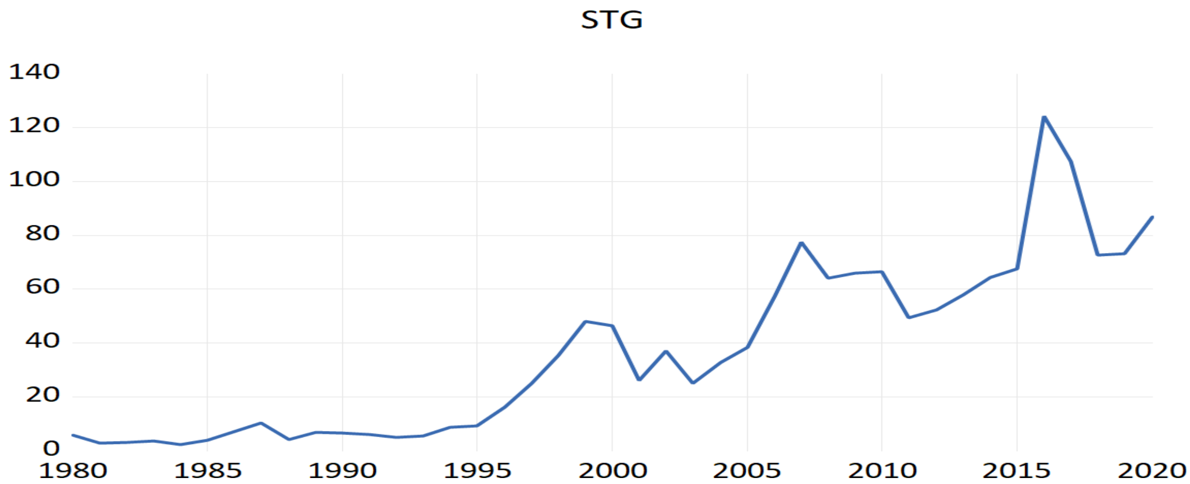


Source: EViews (14) output, compiled by author

2.2.2.4 Stocks traded to GDP

Interpreting Figure 2.6, in 1980, the Stocks traded to GDP ratio stood at approximately 5%, indicating low trading volumes relative to the size of the economy. The ratio remained low from 1980 to 1995, similar to stock turnover. From thereon, the Stocks traded to GDP ratio recorded a sharp rise to approximately 50% in 1998 and 79% in 2007. The ratio recorded its highest peak in 2016, with a value of over 125%, reflecting an exceptional increase in trading activity. The upward movement in the Stocks traded to GDP ratio highlights the development of South Africa's equity markets, as well as increasing liquidity. According to the World Bank (2020), technological advancements, increased investment participation, and structural reforms in the financial sector contributed significantly to this development.

Figure 2.6 Trend analysis of Stocks traded to GDP (STG)



Source: EViews (14) output, compiled by author

2.3 Income Inequality

Income inequality refers to the unequal distribution of income among individuals or groups within a society (Stiglitz, 2012; Piketty, 2014; Atkinson, 2015; World Bank, 2022). In accordance with the definition of income inequality by OECD (2023), this study defines income inequality as the degree to which income is unevenly distributed among individuals in a population. According to Atkinson (2015), income inequality reflects disparities in earnings, the accumulation of wealth, and access to opportunities within the economy. These disparities are often influenced by factors such as education, labour market structures, and government policies. Furthermore, income inequality arises when returns on capital exceed economic growth, leading to wealth concentration among the affluent (Piketty, 2014). The Gini coefficient (statistical metric) is commonly adopted to measure income inequality. The Gini coefficient measures the income distribution within a population (De Maio et al., 2007). This metric ranges from 0 to 1. Values close to 0 indicate perfect equality, whereas those close to 1 indicate extreme inequality (De Maio et al., 2007). A higher value suggests that a specific segment of the population receives a disproportionately outstanding share of total income. The extreme inequality highlights the income gap in the population. The Lorenz curve serves as the basis of the Gini coefficient.

The curve plots the cumulative share of income received against the cumulative share of the population, ranked from the marginalized to the wealthiest (Cowell, 2011). The value of the Gini coefficient rises with the increase in the distance between the Lorenz curve and the line of perfect equality. According to Cowell (2011), the Gini coefficient is mainly preferred for being simple and easy to interpret. However, this metric provides only a summary measure of income inequality. The Gini coefficient does not reveal the structure of income inequality within specific subgroups of the population. The metric relies on aggregated income distribution. It does not offer detailed insights into the fundamental dynamics of inequality (De Maio et al., 2007). Hence, this study adopts both the Gini coefficient and the Palma ratio to measure income inequality substantially.

The Palma Ratio measures the income inequality between the top 10% earners and the bottom 40%, highlighting inequality at both extremes of the economic spectrum (Palma, 2011). The ratio emphasizes the disparities in wealth between the affluent and the marginalized populations. The ratio is suitable for discovering substantial inequality in a population. However, a limitation of the Palma Ratio is that it overlooks the income distribution of the middle 50% of the population, which can mask inequality trends in this group (Palma, 2011). A Palma ratio of 0 to 1 indicates relatively equal income distribution. Values of 1 to 2 indicate moderate inequality (common in many developed countries). Values above 2 indicate high inequality (common in developing economies). Moreover, values equal to and greater than 10 indicate extreme inequality. In cases of extreme inequality, the top 10% earners control a vastly disproportionate share of income.

2.3.1 Income inequality in South Africa

South Africa has the highest income inequality in the world, with a Gini score of 0.63 (Statista, 2025). This extremely high Gini coefficient has remained at 0.63 since 2022 (Cowling, 2024) despite government interventions such as social grants and minimum wage policies intended to reduce income inequality. A 2022 report by World Inequality, South Africa remains among the most unequal countries in the world (Chancel et al., 2022). Based on this report, the top 10% income earners earn more than 60 times the income earned by the bottom 50% of earners.

The bottom 50% earn about R12,300 a year, while the top 10% earn about R780,300. Moreover, the top 1% earn about R2 584 000 a year. According to the World Bank (2024), approximately 63% of the South African population lived below the upper-middle-income threshold of R119.87 per day. This result indicates an increase of 2.2 million individuals living in poverty compared to previous years. With the aim of reducing poverty, the National Minimum Wage Commission has recommended a 1.5% plus CPI increase to the national minimum wage for 2025 (SAFTU, 2025). According to the National Minimum Wage Commission, the adjusted national minimum wage will raise the hourly minimum wage from R27.58 to R28.79, translating to a monthly income of R5,182.20 for a full-time worker. Despite the increase in the monthly minimum wage, over 17 million people are in extreme poverty, earning less than R3 500 per month (Mbulaheni, 2025). Moreover, approximately two-thirds of South Africans still live in households earning less than R8 000 per month (Mbulaheni, 2025).

According to Cowling (2024), the share of South Africans earning below the extreme poverty threshold of R37.63 per day is projected to reach 17.82% in 2025.

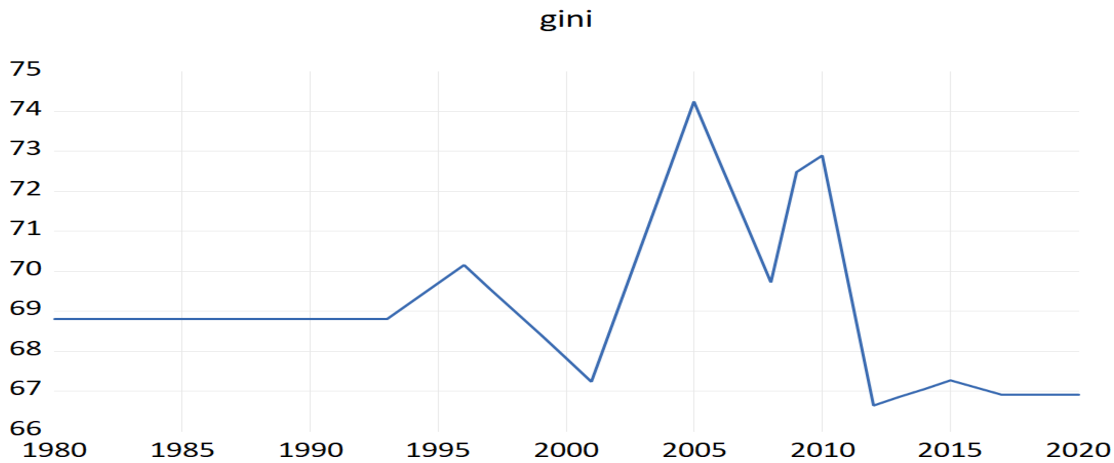
2.3.2 Trend analysis of income inequality in South Africa

Subject to data availability, this study uses two proxies, the Gini coefficient and the Palma ratio, to measure income inequality in South Africa for the period 1980 to 2020.

2.3.2.1 Gini coefficient trend analysis

Interpreting Figure 2.7 1980, the Gini coefficient was approximately 69% in 1980. It remained steady at 69% till mid-1993, then it rose and reached a peak of 70% in 1997. The Gini coefficient experienced a sharp decline to approximately 67.2% in 2001. From there, there is a sharp rise, reaching approximately 74.1% in 2005. The next trough was reached in 2008 with a value of roughly 69%. The Gini coefficient reached its next peak in 2010 with approximately 73%. From then on, the Gini coefficient dropped to 69% and remained steadily low. Overall, the Gini coefficient of South Africa is relatively high, reflecting extreme income inequality.

Figure 2.7 Trend analysis of the Gini coefficient (gini)

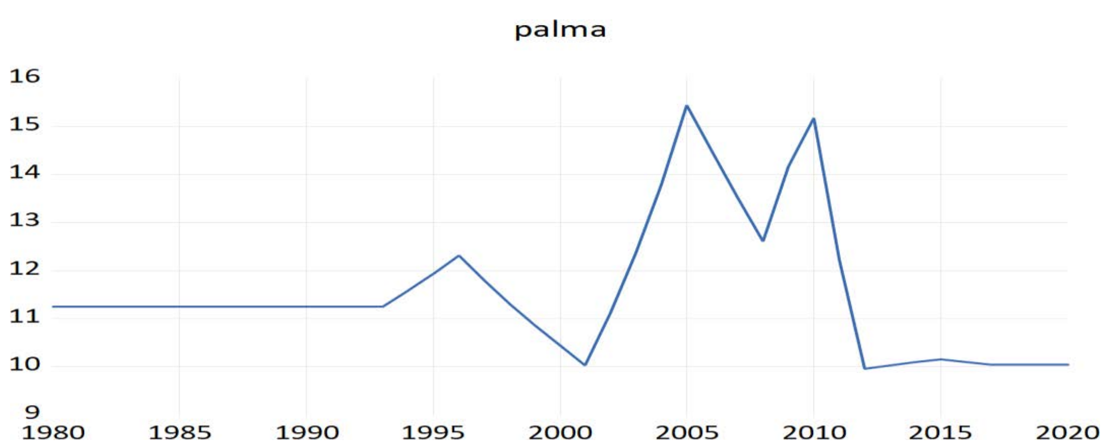


Source: EViews (14) output, compiled by author

2.3.2.2. Palma ratio trend analysis

The trend of the Palma ratio, presented in Figure 2.8, mimics that of the Gini coefficient, discussed in subsection 2.3.2.1 above. Similar to the Gini coefficient, the exceptionally high values of the Palma ratio emphasize the extreme income inequality present in South Africa, further highlighting the inequality gap between the top 10% earners and the bottom 40%.

Figure 2.8 Trend analysis of Palma ratio (palma)



Source: EViews (14) output, compiled by author

2.4 Conclusion

Chapter 2 presented a detailed overview of financial sector development, a component of financial development, and income inequality. The chapter focused on the South African context. Financial development and Income inequality were both explored through definitions, classifications, or measurements. The chapter explored the trend analysis of both financial sector development and income inequality. For financial sector development, Public Debt Securities to GDP, Stock Market Capitalization, Turnover ratio for stock market, and the Total Value of Stocks Traded were used as the variables of measure. The trend analysis showed a significant evolution of South Africa's financial sector, which was also found to be sustained. The trend analysis reflected increasing depth, efficiency, and liquidity.

In contrast, the chapter also highlighted the persistent and severe income inequality in South Africa through contextual discussion and the trend analysis of Income Inequality. Despite improvements in financial inclusion and sectoral reforms, the Gini coefficient and Palma ratio continue to reflect the highest levels of income inequality globally. Both variables revealed persistent trends of income inequality over the decades, with evidence of failure to change the broader income distribution challenges. Chapter 2 sets the stage for the literature review chapter. The chapter highlights the importance of understanding how financial sector development can be used for inclusive and equitable growth in the economy.

CHAPTER 3: LITERATURE REVIEW

3.1 Introduction

Chapter 3 discusses the literature behind the financial sector and income inequality nexus. The chapter combines theoretical and empirical literature to examine the relationship between financial development and income inequality. Section 3.2 presents theoretical literature, which identifies the three main themes in the financial sector development and income inequality nexus: the inequality-narrowing hypothesis, inequality-widening hypothesis, and the nonlinear hypothesis. Section 3.3 presents the empirical literature where different scholarly articles are reviewed to understand the financial sector development and income inequality nexus. Section 3.3 is further grouped into global studies, studies on developing countries, and country-specific studies. Finally, Section 3.4 concludes the Literature review chapter.

3.2 Theoretical Literature

The role of financial development in supporting economic growth and reducing income inequality has been widely recognized by scholarly literature and policy discussions. According to Altunbas and Thornton (2019), Bittencourt et al. (2019), and Jung and Vijverberg (2019), well-developed financial markets and institutions offer crucial funding alternatives for individuals across society. These funding alternatives reflect financial development, promote broad economic participation and development, and are essential for facilitating productive economic activities. Theoretically, financial development provides the marginalized population with access to credit platforms that offer opportunities such as establishing businesses, investing in education, or achieving personal goals (Altunbas and Thornton, 2019; Bittencourt et al., 2019; Jung and Vijverberg, 2019). According to Ahmed and Masih (2017), these opportunities substantially enhance economic growth and promote upward mobility. In addition, financial services aimed at marginalized populations reduce the inequality gap between the affluent and marginalized populations, fostering more lucrative economic participation.

Despite these opportunities offered by financial development, the relationship between financial development and income inequality remains complex and debated. Theoretical and empirical studies on the financial development and income inequality nexus provide mixed results. Three main theories explain the relationship between economic development and income inequality: the inequality-narrowing hypothesis, the inequality-widening hypothesis, and the nonlinear hypothesis. The three theories offer varied views on the ways in which financial development influences income inequality.

Inequality-narrowing hypothesis

The Inequality-narrowing hypothesis argues that financial development reduces inequality by providing the marginalized population with better access to financial services (Becker and Tomes, 1979; Banerjee and Newman, 1993; Galor and Zeira, 2004; Braun et al., 2019). By providing access to credit, savings, and insurance, the inequality-narrowing hypothesis assumes that financial systems assist the marginalized population in investing in business ventures, education, and health. These investments aid the marginalized population in increasing their earning potential over time (Galor and Zeira, 2004; Levine, 1997). Therefore, in accordance with the inequality-narrowing hypothesis, financial development improves human capital and promotes upward economic mobility, especially for low-income groups (Levine, 1997).

Inequality-widening hypothesis

In contrast, the Inequality-widening hypothesis argues that financial development primarily benefits the affluent and large corporations that already have better access to financial services and resources (Lamoreaux, 1995; Haber, 2004). The Inequality-widening hypothesis assumes that the marginalized population is often excluded from financial development benefits due to a lack of collateral, financial knowledge, or formal credit history. Therefore, financial development leads to a concentration of wealth among the affluent and further excludes the marginalized population. In addition, financial development increases the income inequality gap by favouring those already well-positioned in the economy (Bumann and Lensink, 2016; Zhang and Ben Naceur, 2019).

The inequality-widening hypothesis is held primarily in developing countries, where weak financial systems and inefficiencies limit the marginalized population and micro businesses from accessing financial services.

Nonlinear hypothesis

Finally, the Nonlinear hypothesis offers a more dynamic perspective. The Nonlinear hypothesis suggests that the effect of financial development on inequality changes over time. Based on this theory, in the early stages of financial development, income inequality may rise as the affluent are better positioned to take advantage of the resulting financial benefits (Greenwood and Jovanovic, 1990; Baiardi and Morana, 2018; Jung and Vijverberg, 2019). However, as financial systems mature and become more inclusive, the resulting benefits are spread more evenly among the population, and inequality begins to decline. The pattern of the Nonlinear hypothesis follows an inverted U-shape similar to the Kuznets Curve. According to the Kuznets Curve, as economies develop, income inequality first rises and then declines (Kuznets, 1955). In the early phases of financial development, skilled workers and urban elites benefit most. Later, wider access to education, infrastructure, and financial services allows more people to participate in the economy and helps reduce inequality. In summary, the Nonlinear hypothesis assumes that financial development initially benefits the affluent, but as systems mature and access broadens, benefits diffuse across society, reducing inequality over time.

3.3 Empirical Literature

The empirical literature encompasses all three main theoretical perspectives outlined in the theoretical literature: the Inequality-narrowing hypothesis, the Inequality-widening hypothesis, and the Nonlinear effects of financial development on income inequality. The empirical literature section critically assessed how financial sector development interacts with income inequality, with all studies using the Gini coefficient to measure income inequality. The empirical literature is grouped into three main themes: global studies, studies on emerging markets or developing countries, and studies focusing on specific countries.

Global studies

Using panel data covering 30 countries from 1980 to 2005, a study by Prete (2013) revealed that financial sector development, measured by Private sector credit to GDP, reduces income inequality. The study examined the link between Economic literacy, income inequality, and financial development. Based on this study, as financial markets become more developed, the resulting new investment opportunities may help reduce income inequality. Furthermore, the study found that financial development and reduced income inequality appear to be driven by economic literacy, highlighting that economic literacy affects access to and benefit from investment opportunities. The study found that countries with higher economic literacy have better-controlled income inequality, stating that income inequality is reduced by financial development only to the extent that financial development covaries with financial literacy. The study adopted the OLS methodology. Similarly, using panel data from 126 Countries from 1963 to 2002, a study by Hamori and Hashiguchi (2012) revealed that financial sector development, measured by M2 to GDP and Private sector credit to GDP, reduces income inequality. The authors' study analyzed the effects of financial deepening on income inequality. The study adopted the System GMM methodology. Verma and Giri (2024) also found evidence that an increase in financial access reduces income inequality in the long run. According to their study, the authors found that increased financial access to the larger population segments favors equal distribution of resources in the long term as commercial banks facilitate access to financial services for the marginalized, eventually reducing income inequality. The study used panel data from 2005 to 2019 and adopted the ARDL methodology. Financial development was measured using the number of commercial bank branches. The study aimed to examine the significance of financial inclusion in reducing income inequality in the Asian context.

Using cross-country panel data, Kappel (2010) revealed that developed stock markets, measured by Private sector credit to GDP, Stock market capitalization to GDP, Total value traded to GDP, and Turnover ratio for stock market, reduce inequality. The author examined the effects of financial development on income inequality and poverty in 78 Countries from 1960 to 2006. The findings highlight that income inequality is reduced through the advanced development of both the loan and stock markets. The study methodology included OLS, Random Effects, Two-Stage Least Squares, and Instrumental Variables. Also, in support of the Inequality-narrowing hypothesis, Mookerjee and Kalipioni (2010) found that increased access to bank branches drastically reduces income inequality, using a sample of 70 developing and developed countries. In addition, the study highlights that barriers to bank access significantly exacerbate income inequality. The study examined the effect that the availability of financial services has on income inequality. Financial development was measured in Branches per 100,000 population. The study methodology included OLS and Instrumental Variables covering the period 2000 to 2005.

On the other hand, in support of the Inequality-widening hypothesis, Gimet and Lagoarde-Segot (2011) found that financial sector development, particularly the banking sector, strongly exacerbates income inequality. Financial sector development was measured through the Stock market capitalization to GDP, the Turnover ratio for stock market, and the Private sector credit to GDP. The study used the structural vector autoregressive (SVAR) model on panel data from 49 countries for the period 1994 to 2002. Also, in support of the Inequality-widening hypothesis, a study by Cournède and Denk (2015) found that extreme credit intermediation and stock markets exacerbate income inequality. The study examined the link between finance and income inequality in OECD countries. Cournède and Denk (2015) used Private sector credit to GDP to measure financial development. The methodology of the study included OLS and Fixed Effects estimator, covering the period from 1974 to 2011.

De Haan and Sturm (2017) found that financial development increases income inequality in a sample of 121 countries. The study examined how the banking crisis, financial development, and financial liberalization relate to income inequality using panel data spanning from 1975 to 2005. The study used a Fixed Effects model. The study also found that the level of financial development influences the impact of financial liberalization on income inequality. The study used Private sector credit to GDP to measure financial development. Jauch and Watzka (2016) also revealed that financial development, measured by Private sector credit, increases income inequality. The study used panel data on 138 countries from 1960 to 2008. The study also examined the link between financial development and income inequality, employing System GMM and FE estimator methodology. Also, in support of the Inequality-widening hypothesis, a study by Chiu and Lee (2019) confirmed evidence of the inequality-widening hypothesis in its full sample.

The study confirmed the inequality-widening hypothesis for countries with political and financial stability, as well as those with economic instability. Specifically, the study confirmed the existence of a positive relationship between financial development and income inequality, particularly in low-income countries. Furthermore, for its sub-samples, the study found that in high-income countries, financial development can improve income inequality under financial and economic stability. The study examined the nonlinear effects of both country risks and financial development on income inequality. The period of the study spans from 1985 to 2015, based on a panel sample of 59 countries. The study adopted a Panel Smooth Transition Regression model with fixed effects. On the other hand, Nikoloski (2013) revealed that financial sector development, measured by Private sector credit to GDP, Bank Assets to GDP, initially increases income inequality but reduces it at higher levels of development, supporting the Nonlinear hypothesis. The study examined the presence of the financial Kuznets curve between financial sector development and inequality. Nikoloski (2013) confirmed the theoretical stipulations of Greenwood and Jovanovic (1990) for an inverted U-curve relationship between the financial sector and income inequality. The author used Panel data from 66 Countries from 1962 to 2006. Their study methodology included System GMM. Also supporting the Nonlinear hypothesis, Kim and Lin (2011) confirmed an inverted U-shaped curve relationship between financial sector development (measured by Private credit to GDP, Bank Assets to GDP, and M3 to GDP) and income inequality. Based on their study, financial sector development only reduces income inequality in a country if that country has reached the stipulated threshold level of financial development. Beyond the specified threshold of financial development, income inequality worsens. The authors examined nonlinearity in the financial development–income inequality nexus, using panel data from 72 Countries from 1960 to 2005. Their study methodology included Threshold estimation and Instrumental Variables.

Developing countries

In emerging countries, a study by Kebede et al. (2023) revealed that only a higher degree of financial inclusion, measured by ATMs per 100,000 adults and Branches per 100,000 adults, has a favourable distributional effect on income inequality. The study examined the nexus of financial inclusion and income inequality, particularly in Africa.

Using Quantile Regression and threshold methodology, the study revealed that pronounced, favourable distributional impacts of financial inclusion are observed in the higher inequality quantiles. Furthermore, the study shows that the favourable distributional implications of financial inclusion are more pronounced in the presence of higher institutional quality. The study emphasized that to achieve a reduction in income inequality, the promotion of an inclusive financial system is crucial, ultimately promoting inclusive economic growth. The results also imply that promoting institutional quality is essential for people to enjoy the pronounced distributional impacts of financial inclusion. Kebede et al. (2023) used panel data spanning from 2004 to 2018, covering 23 African countries. Similarly, Omar and Inaba (2020), using panel data from 116 developing countries from 2004 to 2006, revealed that financial inclusion, measured by Private credit to GDP, significantly reduces poverty rates and income inequality in developing countries. Based on this study, financial inclusion provides development opportunities that accommodate the marginalized population as well. Furthermore, the study found that inflation, income per capita, age dependency ratio, and the ratio of internet users affect levels of financial inclusion in developing countries. The study examined the effect of financial inclusion on income inequality and poverty alleviation. The methodology of the study included a one-way error component fixed effect model.

Batuo and Mlambo (2010), using panel data for 22 African countries from 1990 to 2004, revealed that financial development, measured by M2 to GDP and Private sector credit to GDP, reduces inequality in Africa by fostering economic opportunities and improving income distribution. In addition, the study found that investments in human capital and modern sectors further strengthen the impact of financial deepening. The study methodology included System GMM, investigating the link between financial development and income inequality. Conversely, a study by Adams and Klobodu (2016) examined the impact of corruption control and financial development on income inequality. The authors found that financial sector development exacerbates income inequality. The study used Private sector credit to GDP to measure financial sector development. The author used panel data spanning from 1985 to 2011 for 21 Sub-Saharan Africans, examining the impact of corruption control and financial development on income inequality. The methodology of the study included a Pooled Mean Group (PMG) estimator. Also in support of the Inequality-widening hypothesis, Seven and Coskun (2016) examined whether the development of the bank and stock market contributed to the reduction of poverty and income inequality in emerging countries, using Bank Assets to GDP, Private credit to GDP, M3 to GDP, Stock market capitalization to GDP, and Turnover ratio for stock market ratio to measure financial sector development. Instead, the authors found that the development of the bank and stock market worsens income inequality. The study used panel data from 45 developing countries spanning from 1987 to 2011. The study methodology included System GMM.

On the other hand, focusing on African countries, Tita and Aziakpono (2016) found evidence suggesting that the finance-inequality relationship in the sample of African countries studied is nonlinear. The study used Private sector credit to GDP and Bank deposits to GDP to measure financial development using the Augmented Mean Group estimator methodology. The study used panel data from 15 African countries to examine the finance-income inequality nexus. Also, in support of the Nonlinear hypothesis, Younsi and Bechtini (2020) confirmed Kuznets' inverted U-shaped relationship between financial development and income inequality in BRICS countries. The study uses panel data spanning from 1990 to 2015 to examine the causal relationships between financial development, economic growth, and income inequality in BRICS nations. The methodology of the study included Fixed Effects estimator, Pooled Ordinary Least Squares, and Systems GMM. Younsi and Bechtini (2020) support the existence of Kuznets' inverted U-shaped relationship between financial development and income inequality.

Country-specific

For studies focusing on specific countries, Kapingura (2017), using quarterly time series data on South Africa from 1990 to 2012, revealed that increasing inclusivity through financial access, measured by ATMs per 100,000 adults, reduces inequality both in the short- and long-run compared to increasing financial depth (measured by Private sector credit to GDP). The study examined the link between financial sector development and income inequality in South Africa. The study methodology included ARDL. In addition, the study found that economic growth, government activities, and external trade activities play a crucial role in reducing inequality in South Africa, whereas increasing inflation worsens inequality. On the other hand, using annual data on the economy of South Africa from 1970 to 2018, Hassan and Meyer (2021) found a nonlinear impact on income inequality from financial development. Specifically, the study found an inverted U-shaped relationship, positing that early stages of financial development reduce inequality and later exacerbate the inequality gap past a certain threshold of financial development. The study examined the nonlinear effect of financial development on income inequality in South

Africa, using the autoregressive distributed lag (ARDL) methodology. Financial development was measured through Private credit and M2 to GDP. Similarly to Kapingura (2017), who found the Inequality-narrowing hypothesis using Time-series data on a single country (South Africa), Shahbaz and Islam (2011) revealed that financial sector development, measured by Private sector credit to GDP, reduces income inequality in Pakistan. Their study used time series data from 1971 to 2005 to examine the financial development and income inequality nexus in Pakistan using the ARDL methodology. Bittencourt (2010) also revealed that financial development, measured by M2 to GDP and Private sector credit to GDP, has a significant and robust effect in reducing inequality. The author examined how financial development influences income inequality in Brazil. Their study revealed that a deeper and more active financial sector alleviates inequality. The study used Time series data spanning from 1985 to 1994. The methodology of the study included First-Difference Instrumental Variables and Two-Stage Least Squares. Conversely, Wahid et al. (2012) revealed that financial development, measured by Private credit to GDP, worsens income inequality, supporting the inequality-widening hypothesis. The study examined whether financial Sector development increased income inequality in Bangladesh using time series data from 1985 to 2006. The study further found that inflation and trade openness also worsen income inequality. The study employed ARDL methodology.

On the other hand, Shahbaz et al. (2015) found the GJ hypothesis as well as a U-shaped relationship between financial development (measured by Private credit to GDP) and income inequality in the case of Iran. The study examined whether there is a Financial Kuznets Curve in Iran. The study used Time series data from 1965 to 2011. The study methodology included ARDL.

3.4 Conclusion

This chapter reviewed both theoretical and empirical literature on the relationship between financial development and income inequality. Three main hypotheses emerged: the inequality-narrowing hypothesis, the inequality-widening hypothesis, and the nonlinear hypothesis. Each hypothesis received empirical support in different contexts. Global studies show mixed outcomes depending on the level of financial and institutional development, while evidence from developing countries often reflects challenges of access and exclusion.

For South Africa, previous studies present both narrowing and nonlinear effects, indicating the complexity of this relationship. Overall, the literature highlights that the impact of financial development on inequality is context-dependent, justifying further investigation in the South African setting.

CHAPTER 4: METHODOLOGY

4.1 Introduction

Chapter 4 presents the methodological approach employed in the study to examine the linear relationship between financial sector development and income inequality in South Africa. The chapter begins with section 4.2, highlighting the research paradigm adopted in the study. Section 4.3 presents the research design. The research design consists of the model selection and protocols, as well as the model specification. Section 4.4 presents the definitions of variables, followed by the data description and sources in Section 4.5. The chapter presents the diagnostic tests employed in this study, in Section 4.6, and finally, Section 4.7 concludes the Methodology chapter.

4.2 Research Paradigm

A research paradigm is the set of beliefs and ideas that guide how a study is conceptualized, executed, and interpreted (Kuhn, 1970). The paradigm includes the perspective of the researcher on the nature of reality (ontology), the nature of knowledge (epistemology), and the methods used to gain that knowledge (methodology) (Guba and Lincoln, 1994; Okesina, 2020). These three components help ensure consistency and logic in the research. The components match the worldview of the researcher with their chosen methods and strategies (Saunders et al., 2009). This study follows the positivist paradigm, which is based on the idea that knowledge comes from facts that can be observed and measured. A positivist paradigm promotes objective research using scientific methods (Comte, 1853; Chilisa and Kawulich, 2015). According to Guba and Lincoln (1994), positivism holds that reality exists independently of the researcher (realist ontology) and that knowledge should be gained through objective, independent observation (objectivist epistemology). The positivist paradigm is appropriate for this study, which examines the impact of financial sector development on income inequality in South Africa from 1980 to 2020 using quantitative time series data.

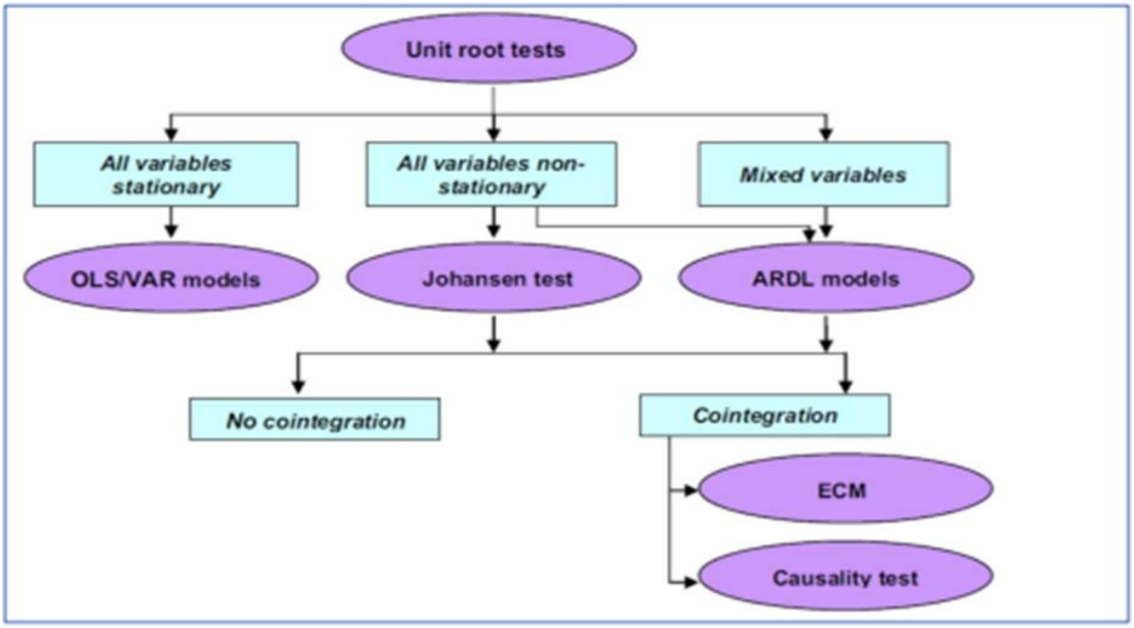
The study employs the Autoregressive Distributed Lag (ARDL) model to assess long-run and short-run dynamics between variables. Alternative research paradigms include Interpretivism and Pragmatism. According to Lincoln and Guba (1989) and Krauss (2005), Interpretivism focuses on understanding people's experiences and viewpoints. Pragmatism encourages the use of both qualitative and quantitative methods in accordance with the nature of the research question (Creswell, 2017; Kivunja and Kuyini, 2017). Although these alternative paradigms offer valuable research perspectives, they are best suited for qualitative studies that rely on interviews or case studies, which is not the focus of this study. As a result, the use of the positivist paradigm better aligns with the aim of this study, with its data-driven and objective analysis nature. As a result, positivism forms a solid foundation for the methodological approach of this study.

4.3 Research design

4.3.1 Model Selection and Protocols

This study uses time series data from 1980 to 2020 to analyze the financial sector development and income inequality nexus in South Africa. To select the appropriate model and estimation techniques, this study employs the method selection framework (Figure 4.1) proposed by Shrestha and Bhatta (2018)

Figure 4.1 Method selection framework for Time series data analysis



Source: Shrestha and Bhatta (2018)

Interpreting Figure 4.1 as a method selection framework for Time Series data analysis, the starting point is to conduct a unit root test to determine the stationarity of the time series data. If all variables in the time series are stationary at level (I (0)), Ordinary Least Squares (OLS) models or Vector Autoregressive (VAR) models may be used for modeling. However, suppose all variables are non-stationary at level, but all become stationary at the first difference (I (1)), in that case, the Johansen cointegration test may be conducted to assess long-run relationships (Johansen, 1988). Conversely, suppose variables in the time series data being used are a combination of stationarity at level (I (0)) and stationarity at the first difference (I (1)). In that case, the Autoregressive Distributed Lag (ARDL) models are appropriate for use (Pesaran et al., 2001). In addition, for both the Johansen test and ARDL models, if cointegration is established, an Error Correction Model (ECM) should be performed to explore short-run dynamics. Therefore, following the model section process as proposed by Shrestha and Bhatta (2018), the following procedures were taken to substantiate the selection of the ARDL model used in this study:

4.3.1.1 Unit Root Test

According to Gujarati and Porter (2009), the unit root test is used to establish whether time series data is stationary or has a unit root (non-stationary). Stationarity occurs when statistical properties of time series data, such as the mean, variance, and autocorrelation of a stochastic process, remain constant over time (Hamilton, 2020). A stochastic process refers to the collection of random variables ordered in time (Gujarati and Porter, 2009, p.740). According to Wooldridge (2016), testing for stationarity and the order of the integration of the data series is crucial for accurate modeling and reliable statistical results, especially when testing for the long and short-run relationships among variables in a dataset. If variables are stationary at level, the variables are said to be integrated of order I (0). Conversely, if the variables are not stationary at the level, they are differenced to make them stationary at the first difference. In such a case, the differenced variables, which are stationary at the first level, are said to be integrated of order I(1). According to Gujarati and Porter (2009), when conducting unit root tests, the variables should be integrated in the same order of either I (0) or I (1), but not beyond I (1), to ensure valid econometric modeling. Statistical properties of a stationary time series remain constant over time. Such a series is mean-reverting, and fluctuations around the mean tend to have a relatively constant amplitude. As a result, a stationary series is easier to model and forecast. Conversely, a time series with a unit root (non-stationary) may produce spurious results due to a time-varying mean or variance (or both), which prevents generalization across different periods (Gujarati and Porter, 2009). In addition, a non-stationary series may follow a random walk, indicating that a time series does not revert to a long-term mean and is permanently affected by random shocks (Dickey and Fuller, 1979). Consequently, the use of a non-stationary series in regression analysis can lead to misleading results. In addition, the unit root test is crucial for analyzing time-dependent patterns such as trends or seasonality in a series. There are three standard unit root tests, namely the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests.

The Augmented Dickey-Fuller (ADF) test is a commonly used unit root test in a time series. The ADF test extends the basic Dickey-Fuller test by including lagged values of the dependent variable to account for autocorrelation in the errors, thereby improving its reliability in the presence of serial correlation (Dickey and Fuller, 1979).

For this study, the ADF test is based on a regression framework, where the null hypothesis (H_0) states that the time series has a unit root or is non-stationary (H_0: ρ=1). In contrast, the alternative hypothesis (H_1) posits that the series has no unit root or is stationary (H_1: ρ=0). Rejection of the null hypothesis indicates that the time series is stationary, while failure to reject it implies non-stationarity (Dickey and Fuller, 1979). If the p-value is less than or equal to 5% and the t-statistic is greater than the t-critical, the null hypothesis (H_0) is rejected, concluding that the series has no unit root (stationary). Conversely, if the null hypothesis is not rejected (fails to reject the null hypothesis), the presence of a unit root in the time series is concluded (non-stationary). The specification of the ADF test is as follows:

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \varepsilon_t$$

The Phillips-Perron (PP) test is adopted to assess the validity of the ADF results in this study further. Similar to the ADF test, the null hypothesis of the PP test assumes the presence of a unit root in the data. However, unlike the ADF test, the PP test includes an automatic adjustment to correct for autocorrelation in the residuals (Phillips, and Perron, 1988). According to Cashin and McDermott (2003), the PP test offers superior comparative ability and produces more precise confidence intervals than the ADF test. In addition, serial correlation and heteroscedasticity are dealt with differently in the PP test compared to the ADF test. The specification of the PP test is as follows:

$$Y_t = \alpha + pY_{t-1} + \varepsilon_t$$

In cases where the ADF and PP tests yield inconsistent results, conducting the third unit root test, namely the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, is required (Kwiatkowski et al., 1992). Consequently, the results of the KPSS test would then be used to compare the inconsistent results of the ADF and PP tests. Compared to the ADF and PP tests, the null hypothesis (H_0) of the KPSS test states that the time series is stationary. In contrast, the alternative hypothesis (H_1) states that the time series is non-stationary (Kwiatkowski, Phillips, Schmidt, and Shin, 1992). The specification of the KPSS test is as follows:

$$Y_t = \mu_t + \varepsilon_t \ , \qquad \mu_t = \mu_{t-1} + \mu_t$$

For this study, all three-unit root tests were employed to assess the integration properties of the variables. Given that the ARDL framework accommodates variables with mixed orders of integration—whether stationary at level (I (0)) or first difference (I (1))—it was selected as the most suitable estimation technique. This approach is consistent with prior studies examining the relationship between financial development and income inequality, such as Bittencourt (2010), Shahbaz and Islam (2011), Wahid et al. (2012), Shahbaz et al. (2015), and Kapingura (2017), all of which utilized the ARDL model.

4.3.1.2 Optimal lag length selection

Before the estimation of an ARDL model, it is very necessary to determine the appropriate lag length for the model. Selecting the proper lag length for an ARDL model ensures that the model's error terms are normally distributed, free from autocorrelation and homoscedasticity. According to Brooks (2014), the optimal lag length can be identified using the lag selection criteria provided by the vector autoregression (VAR) framework. These criteria include the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SC), or Hannan-Quinn Criterion (HQ). According to Nkoro and Uko (2016), the model with the minimal AIC, SC, or HQ estimates, along with minimal standard errors and a high R2, is deemed to perform better. As a result**,** the long-run coefficients are thus derived from the model that performs best. The process of optimal Lag Length Selection is especially crucial when a long-run relationship exists among variables. This process helps to prevent a spurious regression.

4.3.1.3 Autoregressive Distributed Lag (ARDL) model

This study adopts the Autoregressive Distributed Lag (ARDL) model to investigate the relationship between financial sector development and income inequality in South Africa. The ARDL model is a flexible regression framework established to estimate both short-run dynamics and long-run relationships in time series data (Pesaran et al., 2001). The model is particularly appropriate when the variables are a combination of integrated orders I (0) and I (1) without the need for prior differencing. A key advantage of the ARDL model over OLS or VAR models, as well as the Johansen Cointegration test, is its ability to estimate cointegration relationships after identifying the optimal lag structure (Pesaran et al., 2001).

According to Nkoro and Uko (2016), the ARDL approach does not strictly require pre-testing for unit roots or stationarity, compared to traditional multivariate cointegration techniques. As a result, the ARDL approach simplifies the modeling process. The Bounds test of the ARDL is instrumental in assessing relationships among variables with a combination of integration orders.

In addition, the ARDL model is more appropriate for small sample sizes (Fosu and Magnus, 2006). Given that this study uses a small sample size of annual data, the adoption of the ARDL model is appropriate. Its ability to yield robust and consistent estimates in such contexts further justifies its application to this study.

4.3.1.4 Cointegration test

According to Pesaran et al. (2001), when there exists a long-term relationship between two variables, the variables are said to be cointegrated. The cointegration test allows the identification of meaningful long-term relationships between variables in time series data that may individually exhibit non-stationary, random trends, thereby avoiding spurious regression results. According to Nkoro and Uko (2016), cointegration implies the existence of a long-run relationship. This concept provides both statistical and economic justification for the application of an error correction model (ECM), which integrates short-run dynamics with long-run equilibrium relationships in the modeling process. Establishing cointegration is a critical step in determining whether a model accurately reflects long-run relationships among variables. Establishing the long-run relationship is crucial in establishing whether variables move together over time. The long-run relationship establishes whether variables share a stable equilibrium, further assessing if there is any deviation between the variables in the short run. Cointegration ensures that the model captures economic relationships that are not just temporary fluctuations, but meaningful and lasting, which is essential for policy implications.

If cointegration is not present, it becomes necessary to differentiate the variables to achieve stationarity. Nevertheless, by differencing the variables, long-term information embedded in the data would be lost (Pesaran et al., 2001). For this study, the ARDL Bounds test is employed to assess cointegration within the model. In the ARDL Bounds test, the null hypothesis (H_0) posits that no long-run relationship exists among the variables (no cointegration). The alternative hypothesis (H_1) posits the presence of a long-term equilibrium relationship among the variables (cointegration).

In this test, the calculated F-statistic is compared to the critical values provided by Pesaran et al. (2001) and Narayan (2005). If the F-statistic exceeds the essential value of the upper bound critical value, the null hypothesis is rejected, confirming cointegration. If the F-statistic falls below the critical value of the lower bound, the null hypothesis cannot be rejected, indicating no cointegration in the model. If the F-statistic lies between the bounds, no conclusion can be drawn from the results. For this study, the test was conducted at all levels of significance: 1%, 5%, and 10%. Exceeding the upper bound of a specific level of significance confirms cointegration at that level, while falling below the lower bound of a particular level of significance confirms no cointegration at that level.

4.3.1.5 Error Correction Model (ECM)

According to Engle and Granger (1987), the Error correction model is employed to determine the speed at which variables adjust back to equilibrium after a short-term deviation once cointegration has been established among them. This modeling allows the short-run coefficients, intercepts, and error terms to vary across the time series while simultaneously estimating the long-run parameters and the adjustment speed toward equilibrium. The error correction term, which ranges between negative one and zero, is expected to be negative and statistically significant.

It indicates that any short-run disequilibrium is corrected over time, guiding the system back to its long-run path (equilibrium).

4.3.2 Model specification

Based on the method selection framework for Time series data analysis proposed by Shrestha and Bhatta (2018), this study adopted the ARDL model to examine the relationship between South Africa's financial sector development and income inequality. Similarly, Kapingura (2017) also used the ARDL model to analyze financial sector development and income inequality in South Africa, although the study used only the Gini coefficient to measure income inequality. Consequently, the model estimation of Kapingura (2017) was adopted for this study. The primary model of this study, which incorporates both the Gini coefficient and the Palma ratio, is specified as follows:

$$Y = f(FSD, FDI, GEXP, LNGDPPC, INF, TRADE) \quad (1)$$

Where Y is income inequality, FSD is financial sector development proxied by. FDI is Foreign Direct Investment, GEXP is government expenditure, LNGDPPC is the log of GDP per capita, INF is inflation, and TRADE is trade. The linear function formulation of the model is stated as follows:

$$Y_t = \beta_0 + \beta_1 FSD_t + \beta_2 FDI_t + \beta_3 GEXP_t + \beta_4 INF_t + \beta_5 LNGDPPC_t + \beta_6 TRADE_t \quad (2)$$

The ARDL model employed to examine the long-run relationship between the financial sector development and income inequality for the Overall models is specified as follows:

$$\Delta Y_t = \alpha + \sum_{i=1}^{q} \beta_{1i}\, \Delta Y_{t-i} + \sum_{j=0}^{p} \beta_{2j}\, \Delta \mathrm{PDSG}_{t-j} + \sum_{j=0}^{p} \beta_{3j}\, \Delta \mathrm{SMCG}_{t-j} + \sum_{j=0}^{p} \beta_{4j}\, \Delta \mathrm{SMT}_{t-j}$$

$$+ \sum_{j=0}^{p} \beta_{5j}\, \Delta \mathrm{STG}_{t-j} + \sum_{j=0}^{p} \beta_{6j}\, \Delta FDI_{t-j} + \sum_{j=0}^{p} \beta_{7j}\, \Delta GEXP_{t-j} + \sum_{j=0}^{p} \beta_{8j}\, \Delta INF_{t-j}$$

$$+ \sum_{j=0}^{p} \beta_{9j}\, \Delta LNGDPPC_{t-j} + \sum_{j=0}^{p} \beta_{10j}\, \Delta TRADE_{t-j} + \varphi_1 Y_{t-1} + \varphi_2 \mathrm{PDSG}_{t-1}$$

$$+ \varphi_3 \mathrm{SMCG}_{t-1} + \varphi_4 \mathrm{SMT}_{t-1} + \varphi_5 \mathrm{STG}_{t-1} + \varphi_6 FDI_{t-1} + \varphi_7 GEXP_{t-1}$$

$$+ \varphi_9 LNGDPPC_{t-1} + \varphi_{10} TRADE_{t-1} + \varphi_7 GEXP_{t-1} + \varepsilon_t \quad (3)$$

Parameters β_1, β_2, β_3, β_4, β_5, β_6, β_7, β_8, β_9, and β_{10}, indicate the short run, whereas φ_1, φ_2, φ_3, φ_4, φ_5, φ_6, and φ_7, represent and the long run. α represents the mean or average effect of all the variables on Y. The null hypothesis of the ARDL model, which posits that there is no cointegration, is stated as follows: $\varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = \varphi_5 = \varphi_6 = \varphi_7 = 0$. The alternative hypothesis posits the presence of cointegration in the series. The alternative hypothesis is stated as follows: $\varphi_1 \neq \varphi_2 \neq \varphi_3 \neq \varphi_4 \neq \varphi_5 \neq \varphi_6 \neq \varphi_7 = 0$. ε_t represents the error term of the ARDL model. The ECM model for the Overall models is specified as follows:

$$\Delta Y_t = \alpha + \sum_{j=0}^{p} \beta_j \, \Delta\mathrm{PDSG}_{t-j} + \sum_{j=0}^{p} \beta_j \, \Delta\mathrm{SMCG}_{t-j} + \sum_{j=0}^{p} \beta_j \, \Delta\mathrm{SMT}_{t-j} + \sum_{j=0}^{p} \beta_j \, \Delta\mathrm{STG}_{t-j}$$

$$+ \sum_{j=0}^{p} \beta_j \, \Delta FDI_{t-j} + \sum_{j=0}^{p} \beta_j \, \Delta GEXP_{t-j} + \sum_{j=0}^{p} \beta_j \, \Delta INF_{t-j} + \sum_{j=0}^{p} \beta_j \, \Delta LNGDPPC_{t-j}$$

$$+ \sum_{j=0}^{p} \beta_j \, \Delta TRADE_{t-j} + \eta ECM_{t-1} + \mu_t \quad (4)$$

Similarly, the ECM model of the sub-models uses the same ECM model for the Overall models but focusing on one specific variable of Financial Sector Development.

4.4 Definitions of variables

4.4.1 Dependent Variable

The dependent variable, income inequality, is measured using two proxies: the Gini coefficient and the Palma Ratio.

Gini coefficient is a statistical measure commonly used to measure income or wealth inequality within a population (Atkinson, 2015). It is calculated as the ratio of the area between the Lorenz curve, which depicts the actual distribution of income, and the line of perfect equality, to the total area under the line of perfect equality. The Gini coefficient ranges from zero to one. Zero indicates ideal equality, where all individuals have equal income, whereas one indicates perfect inequality, where a single individual possesses all the income (Atkinson, 2015). For this study, the Gini coefficient is expressed as a percentage out of 100.

Palma Ratio measures the income share of the top 10% earners relative to the bottom 40% (Palma, 2011). The ratio emphasizes the inequalities between the wealthiest and the marginalized segments of society.

The Palma ratio is beneficial for understanding income inequality in contexts where wealth is concentrated at the top of the population. This study uses the Palma ratio together with the Gini coefficient to provide a better analysis of income inequality in South Africa. If the Palma ratio is equal to one, the top 10% earners earn the same share of income as the bottom 40%, indicating a relatively equal distribution. If the ratio is greater than one, the top 10% earners earn more than the bottom 40%, confirming income inequality. The higher the ratio, the greater the inequality.

4.4.2 Independent variable

The independent variable, Financial Sector Development (FSD), is measured using four proxies:

Public Debt Securities to GDP is defined as "the total amount of domestic private debt securities (amount outstanding) issued in domestic markets as a share of GDP" (World Bank, 2015). The ratio, representing the depth component of the financial development classification, covers data on short-term notes, including commercial paper and long-term bonds and notes. According to Reinhart and Rogoff (2010), this variable quantifies the fiscal health of a country and its reliance on debt financing for economic activities. A higher percentage indicates a larger government debt load. Alesina and Rodrik (1994) argue that as the government relies on public debt to finance spending, taxpayers, mostly the low-income earners, carry the tax burden the most, with the resulting taxation eroding the power or value of their income, reflecting worsened income inequality. On the other hand, Barro (1979) argues that if effectively used, public debt may reduce income inequality in the short to medium term by financing countercyclical spending and protecting vulnerable households through initiatives such as social grants.

Stock market capitalization to GDP is defined as "the total value of all listed shares in a stock market as a percentage of GDP" (World Bank, 2015). According to Beck et al. (2000), this ratio serves as a reflection of the size and development of the financial market. A higher ratio suggests a well-developed stock market with greater opportunities for investment and capital allocation. Roine et al. (2009) and Rajan and Zingales (2003) argue that Stock market development worsens income inequality by benefiting the affluent via capital gains, asset ownership, and wealth concentration within this group. In contrast, Beck, Demirgüç-Kunt and Levine (2008) argue that stock markets reduce income inequality by promoting inclusive growth.

Turnover ratio for stock market is defined as “the value of domestic shares traded divided by their market capitalization” (World Bank, 2015). According to Levine and Zervos (1998), the ratio indicates market liquidity and investor activity. A higher turnover indicates an active stock market, where securities can be easily bought and sold. According to Rajan and Zingales (2003), stock market development often results in accumulated capital gains for the affluent, especially when there are no inclusive financial policies, thereby worsening income inequality. On the other hand, Beck, Demirgüç-Kunt, and Levine (2008) find that well-functioning financial systems can reduce income inequality by providing enhanced access to financial services, enabling investment-driven job creation in the economy.

Stocks traded to GDP is defined as “the value of shares traded is the total number of shares traded, both domestic and foreign, multiplied by their respective matching prices” (World Bank, 2015). According to Demirgüç-Kunt and Levine (2001), the ratio is an indicator of stock market activity. A higher percentage indicates a more dynamic financial sector, facilitating better capital allocation and risk diversification. Levine and Zervos (1998) argue that Stock market liquidity indicators, including Stocks traded to GDP, are associated with higher long-run economic growth, which may indirectly reduce income inequality if growth is inclusive. However, Stocks traded to GDP may worsen income inequality should this growth not be inclusive.

4.4.3 Control variables

The control variables in the study include:

Foreign Direct Investment is defined as "the net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor" (World Bank, 2015). The ratio is the summation of equity capital, reinvestment of earnings, other long-term capital, and short-term capital, as shown in the balance of payments. Noorbakhsh et al. (2001) assert that FDI may reduce inequality by stimulating economic development and employment.

On the other hand, Lipsey (2004) posits that FDI can exacerbate inequality if it disproportionately benefits specific sectors or regions. As a result, controlling for FDI becomes necessary to assess its role in income distribution in South Africa.

GDP per capita is a measure of a country's economic output per person, calculated by dividing the country's gross domestic product by its population (Kuznets, 1955). The ratio reflects the level of economic growth. According to Kuznets' hypothesis, economic development may initially increase inequality before decreasing it as the economy matures (Mushinski, 2001).

Beck, Demirgüç-Kunt, and Levine (2007) argue that financial sector development promotes economic growth, which ultimately benefits both high- and low-income households, based on the indirect channel. However, Piketty (2014) argues that income inequality arises when returns on capital exceed economic growth, leading to wealth concentration among the affluent. GDP per capita is used to control the level of economic development, as growth is believed to influence income distribution.

Government expenditure refers to the total amount of government spending as a percentage of a country's GDP (Atkinson and Brandolini, 2006). The ratio includes spending on public goods, including education, healthcare, and infrastructure. Atkinson and Brandolini (2006) posit the wide recognition of government expenditure for its potential to reduce income inequality by improving wealth distribution through redistributive policies. Conversely, Li et al. (2000) argue that enormous government spending may reflect political rent-seeking behaviour. Consequently, political rent-seeking may increase inequality. Government expenditure is controlled to evaluate its potential role in reducing inequality through redistributive policies.

Inflation is the rate at which the general level of prices for goods and services rises, eroding purchasing power (Mishkin, 2007). According to the study by Berg and Ostry (2011), Inflation erodes purchasing power and disproportionately impacts marginalized groups. According to their research, the marginalized groups spend a higher portion of their income on essentials. In addition, a study by Mishkin (2007) suggests a positive correlation between Inflation and income inequality.

These findings are attributed to the ability of the wealthier populations to hedge against Inflation, compared to the marginalized groups. Inflation is controlled for due to its potential to worsen income inequality for marginalized groups.

Trade is measured as the total value of imports and exports as a percentage of GDP, which reflects a country's openness to international Trade (Rodrik, 1997). Global Trade is an essential control variable, as trade liberalization can influence income inequality through increased competition and growth. Studies by Rodrik (1997) and Birdsall (1998) suggest that Trade may reduce inequality by lowering consumer goods prices and improving demand for low-skilled labour.
On the other hand, a study by Feenstra and Hanson (1996) argues that Trade may increase inequality by fostering technological specialization that benefits skilled labour. Moreover, Trade can worsen inequality when it displaces local industries (e.g., textile industries) that provide jobs for low-income earners. Cheaper imports from countries with lower production costs can shut down local factories due to their inability to compete. Closure of these factories would result in job losses for workers, especially those with limited education. Trade is controlled to assess how it impacts inequality.

4.4.4 Priori expectations

Following the literature review, the impact of financial sector development on income inequality has been found to be negative in some cases and positive in other cases. Therefore, the a priori expectation for this study is that financial sector development has either a negative or positive impact on income inequality.

Table 4.1 Financial sector development expected sign

Financial sector development variables	Expected sign	
	Inequality-narrowing hypothesis	**Inequality-widening hypothesis**
Public Debt Securities to GDP	Negative (-)	Positive (+)
Stock market capitalization to GDP	Negative (-)	Positive (+)
Turnover ratio for stock market	Negative (-)	Positive (+)
Stocks traded to GDP	Negative (-)	Positive (+)

Source: Compiled by author

Table 4.2 Control variables expected signs

Control variables	Expected sign
Foreign Direct Investment	Positive (+) / Negative (-)
GDP per Capita	Positive (+) / Negative (-)
Government expenditure	Positive (+) / Negative (-)
Inflation	Negative (-)
Trade	Positive (+) / Negative (-)

Source: Compiled by author

4.5 Data description and sources

This study adopts credible secondary sources to investigate the development of South Africa's banking sector and its impact on persistent income inequality. Secondary data refers to information collected and organized by entities other than the researcher (Bryman and Bell, 2015). The study employed quantitative time-series data covering 40 years from 1980 to 2020. This period was chosen to record the effects of different economic cycles, including periods of economic expansions and economic recessions. The 40-year period offers a better understanding of both short-term and long-term trends and patterns in this research analysis. The study used a thorough review of empirical literature, along with data availability, to guide the process of selecting variables. The selection of the variables ensures the relevance of the selected variables to the research question and feasibility for analysis.

The Dependent variable, namely the Gini coefficient and the Palma ratio, were both sourced from the World Income Inequality Database (WIID). WIID is widely regarded for its extensive dataset. All proxies for the independent variable, namely Public Debt Securities to GDP, Stock market capitalization to GDP, Turnover ratio for stock market, and Stocks traded, total value, were sourced from the World Bank database. Researchers widely prefer the World Bank database due to its high reliability for examining macroeconomic factors. Similarly, to the independent variable, three control variables were also sourced from the World Bank database. These three control variables refer to Inflation, Foreign Direct Investment, and Trade. GDP per capita and government expenditure, the remaining two control variables, were sourced from the International Monetary Fund (IMF). The IMF is a widely trusted source for national accounting data. The summary of all variables used in the study, their source, and their Eviews name, has been outlined in Table 4.3.

Table 4.3 Summary of Data Sources

Dependent variable	**EViews variable name**	**Source**
Gini coefficient	GINI	WIID
Palma ratio	PALMA	WIID
Independent variable		
Public Debt Securities to GDP	PDSG	World Bank
Stock market capitalization to GDP	SMCG	World Bank
Turnover ratio for stock market	SMT	World Bank
Stocks traded to GDP	STG	World Bank
Control variables		
Foreign direct investment	FDI	World Bank
GDP per capita	LNGDPPC	IMF
Government expenditure	GEXP	IMF
Inflation, consumer prices	INF	World Bank
Trade	TRADEGDP	World Bank

Source: Compiled by author

4.6 Diagnostic tests

In addition to the ADRL model employed, diagnostic tests, namely the normality test, autocorrelation test, heteroscedasticity test, and stability test, are used. The diagnostic tests are employed to ensure the suitability of the model chosen, including the reliability of inferences pertaining to the short-run and long-run relationships identified, along with the coefficients (Gujarati and Porter, 2009).

4.6.1 Normality test

In time-series analysis, the normality test is employed to examine whether the residuals of the model follow a normal distribution (Gujarati and Porter, 2009). According to Jarque and Bera (1987), normally distributed residuals ensure efficient parameter estimates and reliable statistical inferences. The Jarque-Bera test, commonly used to test for normality, tests for normality by examining skewness and kurtosis (Jarque and Bera, 1987; Shapiro and Wilk, 1965). Hence, this study employs the Jarque-Bera test to test for normality. The null hypothesis of the Jarque-Bera test states that the residuals are normally distributed. Conversely, the alternative hypothesis states that the residuals are not normally distributed. If the p-value of the Jarque-Bera test statistic is less than 5%, we reject the null hypothesis, concluding the residuals are not normally distributed. Conversely, if the p-value is more than 5%, we fail to reject the null hypothesis; residuals are not normally distributed (Gujarati and Porter, 2009).

4.6.2 Autocorrelation test

According to Durbin (1970) and Godfrey (1978), the correlation of a variable with its past values over time indicates autocorrelation or serial correlation in the model. Autocorrelation violates the assumption of independent errors in time series analysis, possibly distorting the standard errors of regression coefficients. According to Brooks (2014), autocorrelation leads to biased and inefficient inferences in a model. This study employed the Breusch-Godfrey Lagrange Multiplier (LM) to test for autocorrelation in the model used. The null hypothesis of the Breusch-Godfrey LM test states that there is no serial correlation in the data.

In contrast, the alternative hypothesis states that there is no serial correlation in the model. If the p-value of the Breusch-Godfrey LM test statistic is less than 5%, we reject the null hypothesis, concluding there is a serial correlation in the model. Conversely, if the p-value is more than 5%, we fail to reject the null hypothesis, concluding there is no serial correlation in the model (Gujarati and Porter, 2009).

4.6.3 Heteroskedasticity test

The presence of heteroscedasticity, where the variance of errors varies across observations, can lead to inefficient parameter estimates and biased standard errors, distorting hypothesis testing and confidence intervals. This issue is particularly problematic when making inferences about the significance of regression coefficients, as it can result in underestimating or overestimating the true variability in the data (White, 1980).

Heteroscedasticity occurs when the residuals in a regression model have a non-constant variance across all levels of the independent variable (Brooks, 2014). According to Greene (2012), a model can produce biased standard errors, and inefficient parameter estimates due to the presence of heteroscedasticity. In addition, heteroscedasticity can result in the overestimation or underestimation of the true variability in the data. In this study, the Breusch-Pagan test was employed to test for heteroscedasticity. The null hypothesis of the Breusch-Pagan test states that the variance of the residuals is constant, indicating homoscedasticity. Conversely, the alternative hypothesis states that the variance of the residuals is not constant, indicating heteroscedasticity. If the p-value of the Breusch-Pagan test is less than 5%, we reject the null hypothesis, concluding the absence of heteroscedasticity in the model. Conversely, if the p-value is more than 5%, we fail to reject the null hypothesis, concluding the presence of heteroscedasticity in the model (Gujarati and Porter, 2009).

4.6.4 Stability test

The Stability test is used to assess whether the parameters of a model remain constant over time (Brown et al.,1975; Quandt, 1960). The CUSUM (Cumulative Sum) and the CUSUM of Squares tests are commonly used to evaluate the stability of a model. Both tests were designed to detect structural breaks in the parameters of the model (Turner, 2010).

The CUSUM test assesses model stability by plotting the cumulative sum of the residuals against the upper and lower boundaries of the 95% confidence interval at each point. To indicate parameter stability, the cumulative sum must remain within these boundaries (Brooks, 2014). In addition, the CUSUM of Squares test is used to validate the results of the CUSUM test. The CUSUM of Squares test examines the stability of the variance around the (Brooks, 2014). Similarly, the cumulative sum of squares must also remain within the boundaries of the 95% confidence interval at each point for the model to be considered stable.

4.7 Conclusion

Chapter 4 discussed the research goals, which are to empirically examine the linear relationship between financial sector development and income inequality in South Africa using the Gini coefficient and empirically investigate the impact of financial sector development on income inequality for the top 10% earners relative to the bottom 40%, using the Palma ratio. The ARDL methodology was selected to satisfy the above research goals. The section discussed the methodological framework employed to choose the ARDL method, including its advantages over other models. The chapter discussed the diagnostic tests used in the study to assess the relevance and robustness of all tests conducted in the study. The chapter sets the stage for Chapter 5, which discusses the results of all modelling and diagnostic tests performed in the study.

CHAPTER 5.

PRESENTATION AND DISCUSSION OF RESULTS

5.1. Introduction

Chapter 5 presents the presentation and discussion of results. The chapter presents all results for the analysis, models, and tests outlined in the Methodology chapter. The chapter begins with Descriptive Statistics in Section 5.2, which presents the measures of the normal distribution, central tendency, spread, and the range of the observations in the data used. Section 5.3 presents the Correlation analysis, which reveals the present linear relationship between income and financial sector development. Section 5.4 presents the Unit Root test results, followed by the Optimal lag selection in Section 5.5. Section 5.6 discusses the results of the ARDL model(s). Section 5.7 presents the results of the Cointegration test. Finally, Section 5.8 concludes the chapter.

5.2 Descriptive Statistics

Table 5.1 presents the descriptive statistics of the data used in this study. Descriptive statistics provide a general overview of the dataset (Trochim, 2006). Descriptive Statistics offer essential insights into the data, including measures of the normal distribution, central tendency, spread, and the range of the observations in the data used. The normal distribution is indicated by the Jarque-Bera test (commonly used), kurtosis and skewness, the central tendency by the mean and median, the spread by the standard deviation, and the range by the minimum and maximum values in the dataset.

The Gini coefficient possesses a mean and median with values of 68.801 and 74.243, respectively. The value of the mean indicates a high level of overall income inequality in South Africa, compared to the maximum Gini coefficient value of 74.243. The summary statistics also reveal greater variability in overall income inequality throughout the study, as shown by the Gini coefficient, which has a higher standard deviation of 1.838 compared to the standard deviation of 1.425 for the Palma ratio.

Based on the results discussed above, the Gini coefficient has revealed persistently high, variable, and widespread income inequality in South Africa throughout the study period, compared to the Palma ratio. The results indicate that income inequality in South Africa was not only confined to the extremes of the income distribution, including the gap between the top 10% of earners and that of the bottom 40% as measured by the Palma ratio, but extended across the middle class and broader population as well.

Stock market capitalization to GDP, Turnover ratio for stock market, and Stocks traded to GDP are normally distributed at 5% level of significance. Stock market capitalization to GDP has the highest standard deviation value of 67.371, motivating its need for control in the model. The standard deviations indicate that the size of the stock market, along with trading activity, experienced significant fluctuations over the study period. Conversely, Public Debt Securities to GDP has the lowest standard deviation value of 11.298, indicating much more stable government borrowing levels during the period. The Descriptive statistics of financial sector development show that although the stock market has contributed dynamically to the development of South Africa's financial sector, government debt remained a more stable component of the economic system during the study period.

GDP per Capita, Government expenditure, Inflation, and Trade are normally distributed. Trade has the highest mean and median values of 48.205 and 47.428, respectively. The results of the central tendency reveal that, on average, South Africa held relatively low levels of trade openness throughout the study, with a mean of 48.205, which is closer to the minimum value of 34.321, compared to the maximum value of 65.975. Trade also has the highest standard deviation of 7.457, indicating that among all control variables, Trade is the most volatile variable, which may result in significant influence over income inequality. The high volatility of Trade further substantiates the need for controlling for Trade in the model of the study. On the other hand, GDP per Capita has the least variability with a standard deviation value of 0.403, indicating that average levels of income per person remained relatively stable throughout the study. The low volatility of GDP per capita might not have a significant influence on income inequality.

Table 5.1 Descriptive statistics

Dependent Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB statistic	P-Value	Obs.
GINI	69.079	68.801	74.243	66.644	1.838	0.984	3.602	7.231**	0.027	41
PALMA	11.545	11.254	15.449	9.956	1.425	1.202	3.863	11.148**	0.004	41
Independent variables										
PDSG	34.344	34.166	77.302	18.185	11.298	1.466	6.412	34.574***	0.000	41
SMCG	167.752	147.988	322.711	62.441	67.371	0.557	2.556	2.455	0.293	41
SMT	18.924	20.264	41.98	3.332	12.789	0.098	1.597	3.426	0.1800	41
STG	36.777	32.747	124.369	2.159	32.227	0.723	2.756	3.673	0.1590	41
Control Variables										
FDI	0.845	0.5	5.368	-0.702	1.101	1.995	8.298	75.156***	0.000	41
LNGDPPC	8.376	8.261	9.081	7.578	0.403	0.069	1.816	2.428	0.297	41
GEXP	27.073	27.803	34.573	21.84	2.993	-0.02	2.466	0.491	0.782	41
INF	8.635	7.215	18.655	-0.692	4.675	0.363	2.138	2.173	0.337	41
TRADEGDP	48.205	47.428	65.975	34.321	7.457	0.041	2.425	0.576	0.75	41

Note: * denotes the rejection of the null hypothesis at a 10% level of significance, ** denotes the rejection of the null hypothesis at a 5% level of significance, and * denotes the rejection of the null hypothesis at a 1% level of significance. The 1% level indicates the strongest statistical evidence against the null hypothesis, followed by the 5% and then the 10% levels.**

Source: EViews (14) output, compiled by author

5.3 Correlation analysis

Table 5.2 presents the Correlation analysis of the dataset. The Correlation analysis reveals the present linear relationship between income inequality (dependent variable) and financial sector development (independent variable), including control variables. The coefficients of the Correlation analysis span from -1 (indicating a strong negative relationship between the two variables) to +1 (indicating a strong positive relationship between the two variables). The full results of the correlation analysis may be found in Appendix A.

Based on the correlation analysis of income inequality and financial sector development, as shown in Table 5.2, Public Debt Securities to GDP and Government expenditure are the only variables correlated with the Gini coefficient at 5% level of significance. Both variables have a strong negative correlation with the Gini coefficient. The Public Debt Securities to GDP have a correlation coefficient of -0.360, and Government expenditure has a correlation coefficient of -0.362. The results indicate that higher levels of public debt and government spending, commonly spent on social essentials such as education, health, and social grants, are associated with lower income inequality. The results align with Alesina and Rodrik (1994), who argue that as the government relies on public debt to finance spending, taxpayers, mostly the low-income earners, carry the tax burden the most, with the resulting taxation eroding the power or value of their income. The results also support Atkinson and Brandolini (2006), who argue that government expenditure has the potential to reduce income inequality.

Stock market capitalization to GDP, Turnover ratio for stock market, Stocks traded to GDP, Inflation, and Trade are all negatively correlated with the Gini coefficient, with correlation coefficients of -0.085, -0.096, -0.142, -0.183, and -0.146, respectively, but the correlation is not statistically significant. Similarly, Foreign Direct Investment and GDP per Capita are both positively correlated with the Gini coefficient, with correlation coefficients of 0.017 and 0.114, respectively, but the correlation is not statistically significant.

Table 5.2 Correlation analysis with the Gini coefficient (Overall model)

Financial sector development	Income inequality (Gini coefficient)	Income inequality (Palma ratio)
PDSG	-0.360**	-0.343**
SMCG	-0.085	-0.007
SMT	-0.096	-0.025
STG	-0.142	-0.058
FDI	0.017	0.062
LNGDPPC	0.114	0.210
GEXP	-0.362**	-0.299**
INF	-0.183	-0.213
TRADEGDP	-0.146	-0.061
SMT	-0.096	-0.343**

Note: * denotes statistical significance at 10% level, ** denotes statistical significance at 5% level, and * denotes statistical significance at 1% level. The 1% level indicates the strongest statistical evidence, followed by the 5% and then the 10% level.**

Source: EViews (14) output, compiled by author

5.4 UNIT ROOT TEST RESULTS

Following the Method Selection Framework for Time Series Data Analysis by Shrestha and Bhatta (2018), as discussed in Chapter 4, prior to estimating the model for use in a study, a unit root test is carried out. The examination of stationarity and the order of the integration of the data series is necessary when estimating the relationships among variables (long and short run). Tables 5.3, 5.4, and 5.5 report the results of the Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, respectively. The ADF and PP test results show consistency with all variables except for the Gini coefficient and the Total value of stocks traded as a percentage of GDP. Hence, the KPSS was adopted to test the stationarity and order of integration of the two inconsistent variables.

Interpreting Table 5.3, presenting the ADF test, the Gini coefficient is significant at a 5% level. At the same time, Stock market capitalization to GDP, Turnover ratio for stock market, Total value of stocks traded as a percentage of GDP, and Foreign Direct Investment are all significant at a 1% level. These five variables are all integrated of order I (0), meaning they are stationary at level. The remaining five variables, namely the Palma ratio, Public Debt Securities to GDP to GDP, Government expenditure, GDP per Capita, and Trade, were not stationary at level, hence first differenced, making them all integrated of order I (1). These remaining variables are all significant at the 1% level except for Trade, which is significant at the 10% level.

As mentioned earlier, the results of the PP test, shown in Table 5.4, were consistent with the findings of the ADF test except for two variables, the Gini coefficient and the Total value of stocks traded as a percentage of GDP. Therefore, interpreting the results of the KPSS found in Table 5.5, both the Gini coefficient and the Stocks traded to GDP are stationary at a level with a 1% level of significance. The two variables are integrated in order I (0).

Table 5.3 Summary of Augmented Dickey-Fuller (ADF) test

ADF test	Level (I0)			First level (I1)			Order of integration
	Intercept	Intercept, Trend	No Intercept, No Trend	Intercept	Intercept, Trend	No Intercept, No Trend	
Dependent variable							
GINI	-2.931** (0.051)	-2.929 (0.165)	-0.335 (0.558)	-5.593*** (0.000)	-5.598*** (0.000)	-5.657*** (0.000)	I (0)
PALMA	-1.685 (0.431)	-1.629 (0.762)	-0.419 (0.526)	-5.666*** (0.000)	-5.665*** (0.000)	-5.736*** (0.000)	I (1)
Independent variable							
PDSG	0.702 (0.991)	-0.322 (0.987)	1.557 (0.969)	-4.998*** (0.000)	-5.205*** (0.000)	-4.751*** (0.000)	I (1)
SMCG	-0.458 (0.888)	-4.968*** (0.001)	1.627 (0.973)	-8.544*** (0.000)	-8.423*** (0.000)	-8.045*** 0.000	I (0)
SMT	-0.968 (0.756)	-3.609** (0.042)	0.377 (0.789)	-9.140*** (0.000)	-9.015*** (0.000)	-9.052*** (0.000)	I (0)
STG	-1.061 (0.722)	-3.593** (0.045)	(0.004) (0.678)	-5.422*** (0.000)	-5.692*** (0.000)	-6.193*** (0.000)	I (0)
Control variables							
FDI	-4.690*** (0.000)	-5.488*** (0.000)	-0.702 (0.406)	-7.945*** (0.000)	-7.860*** (0.000)	-8.035*** (0.000)	I (0)
INF	-0.699 (0.835)	-2.884 (0.178)	-1.610 (0.100)	-5.469*** (0.000)	-5.372*** (0.000)	-2.739*** (0.008)	I (1)
GEXP	-1.610 (0.468)	-1.895 (0.639)	0.936 (0.904)	-8.258*** (0.000)	-8.169*** (0.000)	-8.086*** (0.000)	I (1)
LNGDPPC	-1.478 (0.534)	-2.851 (0.189)	0.381 (0.789)	-4.398775*** (0.001)	-4.333*** (0.007)	-4.427*** (0.000)	I (1)
TRADEGDP	-2.053 (0.264)	-3.256* (0.089)	-0.510 (0.489)	-6.256*** (0.000)	-6.189*** (0.000)	-6.339*** (0.000)	I (1)

Note: * denotes the rejection of the null hypothesis at a 10% level of significance, ** denotes the rejection of the null hypothesis at a 5% level of significance, and *** denotes the rejection of the null hypothesis at a 1% level of significance. The 1% level indicates the strongest statistical evidence against the null hypothesis, followed by the 5% and then the 10% levels. () denotes P-values.

Source: EViews (14) output, compiled by author

Table 5.4 Summary of Phillips-Perron (PP) test

Phillips-Perron test	Level I (0)			First level I (1)			Order of integration
	Intercept	Intercept, Trend	No Intercept, No Trend	Intercept	Intercept, Trend	No Intercept, No Trend	
Dependent variable							
GINI	-1.936 (0.313)	-1.895 (0.639)	-0.420 (0.525)	-4.670*** (0.000)	-5.122*** (0.000)	-4.723*** (0.000)	I (1)
PALMA	-1.986 (0.291)	-1.951 (0.609)	-0.431 (0.521)	-4.852*** (0.000)	-5.392*** (0.000)	-4.893*** (0.000)	I (1)
Independent variable							
PDSG	0.702 (0.991)	-0.379 (0.985)	1.557 (0.969)	-4.998*** (0.000)	-5.205*** (0.000)	-4.784*** (0.000)	I (1)
SMCG	-1.244 (0.646)	-4.983*** (0.001)	1.270 (0.946)	-13.370*** (0.000)	-13.405*** (0.000)	-8.839*** (0.000)	I (0)
SMT	-1.388 (0.578)	-3.684** (0.035)	0.007 (0.679)	-9.069*** (0.000)	-8.946*** (0.000)	-8.962*** (0.000)	I (0)
STG	-0.559 (0.869)	-3.251* (0.089)	0.931 (0.903)	-8.334*** (0.000)	-8.892*** (0.000)	-6.785*** (0.000)	I (1)
Control variables							
FDI	-4.659*** (0.000)	-5.507*** (0.000)	-3.219*** (0.002)	-18.383*** (0.000)	-19.131*** (0.000)	-17.865*** (0.000)	I (0)
INF	-1.256 (0.641)	-2.935 (0.1630)	-1.623* (0.098)	-10.424*** (0.000)	-10.770*** (0.000)	-6.049*** (0.000)	I (1)
GEXP	-1.475 (0.536)	-1.841 (0.666)	1.201 (0.939)	-8.257*** (0.000)	-8.173*** (0.000)	-7.100*** (0.000)	I (1)
LNGDPPC	-1.22 (0.656)	-1.931 (0.620)	0.596 (0.841)	-4.182*** (0.002)	-4.098** (0.013)	-4.301*** (0.000)	I (1)
TRADEGDP	-2.074 (0.256)	-3.212* (0.097)	-0.509 (0.490)	-6.521*** (0.000)	-6.537*** (0.000)	-6.685*** (0.000)	I (1)

Note: * denotes the rejection of the null hypothesis at a 10% level of significance, ** denotes the rejection of the null hypothesis at a 5% level of significance, and *** denotes the rejection of the null hypothesis at a 1% level of significance. The 1% level indicates the strongest statistical evidence against the null hypothesis, followed by the 5% and then the 10% levels. () denotes P-values.

Source: EViews (14) output, compiled by author

Table 5.5 Summary of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test

Kwiatkowski-Phillips-Schmidt-Shin test	Levels (I (0))		First difference (I (1))		Integration of order
	Intercept	Intercept, Trend	Intercept	Intercept, Trend	
Dependent variable					
GINI	0.134*** (0.739)	0.131*** (0.216)	0.225*** (0.739)	0.212*** (0.216)	I (0)
Independent variable					
STG	0.741 (0.739)	0.128*** (0.216)	0.197*** (0.739)	0.161*** (0.216)	I (0)

Note: * denotes failure to reject the null hypothesis at a 10% level of significance, ** denotes the rejection of the null hypothesis at a 5% level of significance, and * denotes the rejection of the null hypothesis at a 1% level of significance. The 1% level indicates the strongest statistical evidence in support of the null hypothesis, followed by the 5% and then the 10% levels. () denotes Asymptotic values.**

Source: EViews (14) output, compiled by author

5.5 OPTIMAL LAG SELECTION RESULTS

Following the Unit root test is the Optimal lag selection before the estimation of an ARDL model. Selecting the appropriate lag length for the model is crucial. Table 5.6 presents the results of the Optimal lag selection for individual variables in the ARDL model. The selection process is based on the Akaike Information Criterion (AIC). The Akaike Information Criterion had minimal values as compared to the Schwarz Criterion and the Hannan-Quinn Criterion. Amongst the provided optimal lags per variable presented in Table 5.6, the ARDL model selection process of Eviews selected the best combination of lags per variable to produce the optimal lag lengths for the ARDL models in the study.

Table 5.6 Summary of Optimal lag for ARDL model(s)

Variables	Optimal Lag Structure
GINI	3
PALMA	3
PDSG	1
SMCG	3
SMT	2
STG	1
FDI	4
LNGDPPC	3
GEXP	2
INF	3
TRADEGDP	1

Source: EViews (14) output, compiled by author

5.6 ARDL MODEL(S) RESULTS

Five separate models were used for both the Gini coefficient and the Palma ratio. The overall models examined the combined effects of the financial sector development proxies. Then, individual financial sector development proxies were analyzed against Income inequality. All models included the identified control variables in the study. The output results of the ARDL models, conducted through EViews (14), combine the long and short-run relationships, including the ECM.

Section 5.6 briefly states and explains coefficients that are statistically significant up to one lag in the long and short run for every model, focusing mainly on the long-run relationship of financial sector development as the variable of interest. Following the ARDL results, the Cointegration test, in Section 5.7, will be conducted to assess the validity of the long-run relationships identified in the ARDL output.

5.6.1 GINI models

The GINI models consist of the GINI and PDSG model, GINI and SMCG model, GINI and SMT model, GINI and STG model, and GINI Overall model, respectively.

5.6.1.1 GINI and PDSG

Based on Table 5.7, in the long run, the first lags of PDSG, INF, and TRADEGDP are negative and statistically significant at 1% level, with coefficient values of -0.138, -0.359, and -0.112, respectively. Holding all else constant, a one percentage point increase in PDSG (-1), INF (-1), and TRADEGDP (-1) leads to a -0.138, 0.359, and 0.112 percentage points decrease in income inequality, respectively, on average. These results are consistent with Bittencourt (2010), Kappel (2010), Mookerjee and Kalipioni (2010), Shahbaz and Islam (2011), Hamori and Hashiguchi (2012), Prete (2013), Adams and Klobodu (2016), Kapingura (2017), and Omar and Inaba (2020), who found the Inequality-narrowing hypothesis.

In the short run, the differenced first lag of PDSG is positive and statistically significant at 1% level with a coefficient of 0.135. Holding all else constant, a one percentage point increase in D(PDSG (-1)) leads to a 0.135 percentage point increase in income inequality, respectively, on average. The short-run results are consistent with the Income-widening hypothesis, which is supported by Gimet and Lagoarde-Segot (2011), Wahid et al. (2012), Cournède and Denk (2015), Jauch and Watzka (2016), Seven and Coskun (2016), de Haan and Sturm (2017), and Chiu and Lee (2019). Similarly, in support of the Income-widening hypothesis, D(FDI(-1)), D(INF(-2)), D(LNGDPPC(-1)), D(TRADEGDP(-1)), and D(TRADEGDP(-2)) are all positive and statistically significant at 1% level, whereas D(TRADEGDP) is negative and statistically significant at 1% level.

The Error Correction Term (COINTEQ), representing the model's speed of adjustment back to equilibrium after a shock in the short run, is negative and significant at the 1% level. Based on the -0.573 coefficient of the ECM, in the current year, about 42.7% of the previous year's disequilibrium is corrected. This speed of adjustment is moderately fast. In addition, the R-squared of the model has a coefficient of 0.873, meaning 87.3% of the variation in income inequality is explained by the model.

Table 5.7 Summary of ARDL (2,2,3,0,3,2,3) results: GINI and PDSG

Variable	Coefficient	St. Error	P-value
Long-run Regressors			
Linear: Independent			
PDSG(-1)	-0.138***	0.034	0.001
FDI(-1)	-0.215	0.314	0.503
GEXP	0.013	0.119	0.913
INF(-1)	-0.359***	0.114	0.006
LNGDPPC(-1)	-0.552	1.056	0.608
TRADEGDP(-1)	-0.112***	0.037	0.009
Short-run Regressors			
Linear: Independent			
D(PDSG)	-0.002	0.020	0.918
D(PDSG(-1)	0.135***	0.031	0.000
D(FDI)	-0.001	0.091	0.995
D(FDI(-1))	0.438****	0.106	0.000
D(FDI(-2))	0.152	0.096	0.127
D(INF)	-0.015	0.060	0.812
D(INF(-1))	0.033	0.064	0.614
D(INF(-2))	0.170***	0.050	0.003
D(LNGDPPC)	-0.852	1.174	0.476
D(LNGDPPC(-1))	3.707***	1.312	0.010
D(TRADEGDP)	-0.188***	0.033	0.000
D(TRADEGDP(-1))	0.105***	0.032	0.003
D(TRADEGDP(-2))	0.075***	0.027	0.010
C	57.000***	8.395	0.000
COINTEQ	-0.573***	0.084	0.000
R-squared	0.873		

Note: * denotes statistical significance at 10% level, ** denotes statistical significance at 5% level, and * denotes statistical significance at 1% level. The 1% level indicates the strongest statistical evidence, followed by the 5% and then the 10% level.**

Source: EViews (14) output, compiled by author

5.6.1.2 GINI and SMCG

Based on Table 5.8, in the long run, SMCG is positive and statistically significant at 10% level, with a coefficient value of -0.009. Holding all else constant, a one percentage point increase in SMCG leads to a 0.009 percentage point increase in income inequality, respectively, on average. Similarly, the first lags of GEXP and GEXP are statistically significant at 10%, but both have negative coefficients. These results are consistent with the Inequality-widening hypothesis supported by Gimet and Lagoarde-Segot (2011), Wahid et al. (2012), Cournède and Denk (2015), Jauch and Watzka (2016), Seven and Coskun (2016), de Haan and Sturm (2017), and Chiu and Lee (2019).

In the short run, the differenced first lag of GEXP and LNGDPPC are positive and statistically significant at 5% and 1% levels, respectively. In contrast, the difference of TRADE is negative and statistically significant at 1% level. The Error Correction Term (COINTEQ), representing the model's speed of adjustment back to equilibrium after a shock in the short run, is negative and significant at the 1% level. Based on the -0.262 coefficient of the ECM, in the current year, about 73.8% of the previous year's disequilibrium is corrected. This speed of adjustment is moderately fast. In addition, the R-squared of the model has a coefficient of 0.765, meaning that the model explains 76.5% of the variation in income inequality.

Table 5.8 Summary of ARDL (3,0,1,2,0,2,2) results: GINI and SMCG

Variable	Coefficient	St. Error	P-value
Long-run Regressors			
Linear: Dependent			
GINI(-1)	-0.262*	0.132235	0.0607
Linear: Independent			
SMCG	0.009*	0.004	0.052
FDI(-1)	0.225	0.236	0.353
GEXP(-1)	-0.240*	0.119	0.056
INF	-0.002	0.066	0.977
LNGDPPC(-1)	-0.568	1.136	0.622
TRADEGDP(-1)	-0.077*	0.039	0.063
Short-run Regressors			
Linear: Independent			
D(FDI)	0.019	0.087	0.826
D(GEXP)	0.026	0.067	0.696
D(GEXP(-1))	0.177**	0.079	0.033
D(LNGDPPC)	-0.755	1.087	0.493
D(LNGDPPC(-1))	3.179***	1.116	0.008
D(TRADEGDP)	-0.118***	0.031	0.001
D(TRADEGDP(-1))	0.054*	0.032	0.100
C	31.189***	5.905	0.000
COINTEQ	-0.262***	0.050	0.000
R-squared	0.765		

Note: * denotes statistical significance at 10% level, ** denotes statistical significance at 5% level, and * denotes statistical significance at 1% level. The 1% level indicates the strongest statistical evidence, followed by the 5% and then the 10% level.**

Source: EViews (14) output, compiled by author

5.6.1.3 GINI and SMT

Based on Table 5.9, in the long run, the first lag of SMT is negative and statistically significant at 10% level with a coefficient of -0.062. Holding all else constant, a one percentage point increase in SMT leads to a 0.062 percentage point decrease in income inequality, respectively, on average. The first lags of INF and LNGDPPC are also negative and statistically significant at 5% and 10% respectively.

These results are consistent with Bittencourt (2010), Kappel (2010), Mookerjee and Kalipioni (2010), Shahbaz and Islam (2011), Hamori and Hashiguchi (2012), Prete (2013), Adams and Klobodu (2016), Kapingura (2017), and Omar and Inaba (2020) found the inequality-narrowing hypothesis. In the short run, the differenced first lag of LNGDPPC is positive and statistically significant at 5% level, and the difference of TRADEGDP is negative and statistically significant at 1% level. The Error Correction Term (COINTEQ), representing the model's speed of adjustment back to equilibrium after a shock in the short run, is negative and significant at the 1% level. Based on the -0.120 coefficient of the ECM, in the current year, about 88% of the previous year's disequilibrium is corrected. This speed of adjustment is moderately fast. In addition, the R-squared of the model has a coefficient of 0.765, meaning that the model explains 76.5% of the variation in income inequality.

Table 5.9 Summary of ARDL (3,1,1,0,1,2,1) results: GINI and SMT

Variable	Coefficient	St. Error	P-value
Long-run Regressors			
Linear: Independent			
SMT(-1)	-0.062**	0.026	0.028
FDI(-1)	0.404	0.262	0.137
GEXP	0.058	0.093	0.538
INF(-1)	-0.228**	0.083	0.012
LNGDPPC(-1)	-2.089*	1.099	0.071
TRADEGDP(-1)	0.0327	0.038	0.394
C	25.298***	7.342	0.002
Short-run Regressors			
Linear: Independent			
D(SMT)	-0.024	0.020	0.241
D(FDI)	0.063	0.089	0.486
D(INF)	-0.041	0.065	0.535
D(LNGDPPC)	0.332	1.063	0.757
D(LNGDPPC(-1))	3.074**	1.170	0.014
D(TRADEGDP)	-0.141***	0.035	0.000
COINTEQ	-0.120***	0.022	0.000
R-squared	0.765		

Note: * denotes statistical significance at 10% level, ** denotes statistical significance at 5% level, and * denotes statistical significance at 1% level. The 1% level indicates the strongest statistical evidence, followed by the 5% and then the 10% level.**

Source: EViews (14) output, compiled by author

5.6.1.4 GINI and STG

Based on Table 5.10, in the long run, the impact of financial sector development on Income inequality is not statistically significant. The first lags of GEXP and TRADEGDP are both negative and significant at the 1% level, whereas the first lag of SMT and TRADEGDP are both positive and statistically significant at 10%. In the short run, the differenced first lag of LNGDPPC is positive and statistically significant at 5% level, and the difference of TRADEGDP is negative and statistically significant at 1% level. D(GEXP(-1)), D(GEXP(-2)), D(TRADEGDP(-1)), and D(TRADEGDP(-2)) are all positive and statistically significant at 1% level, with the exception of D(GEXP(-2)), which is statistically significant at 5% level. D(INF(-1)) and D(TRADEGDP) are both negative and are statistically significant at 1%. The Error Correction Term (COINTEQ), representing the model's speed of adjustment back to equilibrium after a shock in the short run, is negative and significant at the 1% level. Based on the -0.524 coefficient of the ECM, in the current year, about 47.6% of the previous year's disequilibrium is corrected. This speed of adjustment is moderately fast. In addition, the R-squared of the model has a coefficient of 0.803, meaning 80.3% of the variation in income inequality is explained by the model.

Table 5.10 Summary of ARDL (2,0,1,3,2,0,3) results: GINI and STG

Variable	Coefficient	St. Error	P-value
Long-run Regressors			
Linear: Independent			
STG	0.013	0.011	0.263
FDI(-1)	0.431*	0.211	0.055
GEXP(-1)	-0.358**	0.103	0.002
INF(-1)	0.129	0.084	0.141
LNGDPPC	1.541*	0.879	0.095
TRADEGDP(-1)	-0.119**	0.046	0.018
Short-run Regressors			
Linear: Independent			
D(FDI)	0.147	0.089	0.111
D(GEXP)	0.039	0.066	0.557
D(GEXP(-1))	0.370***	0.101	0.001
D(GEXP(-2))	0.197**	0.080	0.021
D(INF)	0.014	0.059	0.813
D(INF(-1))	-0.237***	0.061	0.001
D(TRADEGDP)	-0.091***	0.033	0.010
D(TRADEGDP(-1))	0.151***	0.038	0.001
D(TRADEGDP(-2))	0.104***	0.027	0.001
C	36.455***	5.956	0.000
COINTEQ	-0.524***	0.085	0.000
R-squared	0.803		

Note: * denotes statistical significance at 10% level, ** denotes statistical significance at 5% level, and * denotes statistical significance at 1% level. The 1% level indicates the strongest statistical evidence, followed by the 5% and then the 10% level.**

Source: EViews (14) output, compiled by author

5.6.1.5 GINI overall model

Based on Table 5.11, in the long run, the first lag of PDSG is negative and statistically significant at 1% level with a coefficient of -0.145. Holding all else constant, a one percentage point increase in PDSG leads to a 0.145 percentage point decrease in income inequality, respectively, on average. These results are consistent with Bittencourt (2010), Kappel (2010), Mookerjee and Kalipioni (2010), Shahbaz and Islam (2011), Hamori and Hashiguchi (2012), Prete (2013), Adams and Klobodu (2016), Kapingura (2017), and Omar and Inaba (2020), who found the inequality-narrowing hypothesis.

In the short run, the differenced first lag of PDSG and STG are positive and negative, respectively, and statistically significant at 1% level with coefficients of 0.183 and -0.034, respectively. Holding all else constant, a one percentage point increase in PDSG and STG leads to a 0.183 and 0.034 percentage point increase and decrease, respectively, in income inequality, on average. Based on the results, PDSG aligns with the Inequality-narrowing hypothesis, whereas STG supports the Inequality-widening hypothesis. D (SMT (-1)) is positive and significant at 5% level, whereas D(SMT) and D(STG) are both positive and statistically significant at 10%.

The Error Correction Term (COINTEQ), representing the model's speed of adjustment back to equilibrium after a shock in the short run, is negative and significant at the 1% level. Based on the -0.392 coefficient of the ECM, in the current year, about 39.2% of the previous year's disequilibrium is corrected. This speed of adjustment is moderately fast. In addition, the R-squared of the model has a coefficient of 0.873, meaning 88.3% of the variation in income inequality is explained by the model.

Table 5.11 Summary of ARDL (3,2,0,2,2,1,0,1,2,2) results: GINI Overall

Variable	Coefficient	St. Error	P-value
Long-run Regressors			
PDSG (-1)	-0.145***	0.049	0.010
SMCG	0.009	0.010	0.356
SMT (-1)	-0.095	0.059	0.133
STG (-1)	0.038	0.034	0.288
FDI (-1)	0.704**	0.277	0.024
GEXP	-0.038	0.138	0.788
INF (-1)	-0.356***	0.115	0.009
LNGDPPC (-1)	-3.103**	1.241	0.027
TRADEGDP (-1)	-0.118*	0.055	0.053
Short-run Regressors			
D(PDSG)	-0.005	0.025	0.847
D (PDSG (-1))	0.183***	0.046	0.001
D(SMT)	0.037*	0.020	0.073
D (SMT (-1)	0.069**	0.026	0.014
D(STG)	0.017*	0.009	0.084
D (STG (-1))	-0.034***	0.011	0.006
D(FDI)	0.237***	0.082	0.008
D(INF)	-0.113*	0.059	0.069
D(LNGDPPC)	-1.656*	0.961	0.099
D (LNGDPPC (-1))	5.376***	1.176	0.000
D(TRADEGDP)	-0.200***	0.031	0.000
D (TRADEGDP (-1))	0.076**	0.028	0.014
C	65.540***	8.756	0.000
COINTEQ	-0.392***	0.052	0.000
R-squared	0.883		

Note: * denotes statistical significance at 10% level, ** denotes statistical significance at 5% level, and * denotes statistical significance at 1% level. The 1% level indicates the strongest statistical evidence, followed by the 5% and then the 10% level.**

Source: EViews (14) output, compiled by author

5.6.2 PALMA models

The PALMA models consist of the PALMA Overall model, PALMA and PDSG model, PALMA and SMCG model, PALMA and SMT model, and PALMA and STG model, in the above order

5.6.2.1 PALMA and PDSG

Based on Table 5.12, in the long run, the first lags of PDSG and INF are both negative and statistically significant at 5% level. The first lag of PDSG has a coefficient of -0.056. Holding all else constant, a one percentage point increase in PDSG leads to a 0.056 percentage point decrease in the income distribution gap between the top 10% earners and the bottom 40%, on average. These results are consistent with the Inequality-narrowing hypothesis, empirically supported by Bittencourt (2010), Kappel (2010), Mookerjee and Kalipioni (2010), Shahbaz and Islam (2011), Hamori and Hashiguchi (2012), Prete (2013), Adams and Klobodu (2016), Kapingura (2017), and Omar and Inaba (2020), who found the Inequality-narrowing hypothesis. In the short run, the differenced first lag of LNGDPPC and TRADEGDP are both statistically significant at 5% level. The differenced first lag of LNGDPPC is positive, whereas the differenced first lag of TRADEGDP is negative. The Error Correction Term (COINTEQ), representing the model's speed of adjustment back to equilibrium after a shock in the short run, is negative and significant at the 1% level. Based on the -0.211 coefficient of the ECM, in the current year, about 78.9% of the previous year's disequilibrium is corrected. This speed of adjustment is moderately fast. In addition, the R-squared of the model has a coefficient of 0.695, meaning 69.5% of the variation in income inequality is explained by the model.

Table 5.12 Summary of ARDL (3,1,0,0,1,2,1) results: PALMA and PDSG

Variable	Coefficient	St. Error	P-value
Long-run Regressors			
Linear: Independent			
PDSG(-1)	-0.056**	0.028	0.056
FDI	0.008	0.134	0.954
GEXP	0.081	0.100	0.423
INF(-1)	-0.210**	0.083	0.018
LNGDPPC(-1)	-1.573	0.969	0.118
TRADEGDP(-1)	-0.022	0.027	0.424
Short-run Regressors			
Linear: Independent			
D(PDSG)	0.023	0.018	0.208
D(INF)	-0.072	0.055	0.203
D(LNGDPPC)	1.046	0.924	0.267
D(LNGDPPC(-1))	2.084**	0.978	0.042
D(TRADEGDP)	-0.077**	0.029	0.013
C	17.98***	3.814	0.000
COINTEQ	-0.211***	0.045	0.000
R-squared	0.695		

Note: * denotes statistical significance at 10% level, ** denotes statistical significance at 5% level, and * denotes statistical significance at 1% level. The 1% level indicates the strongest statistical evidence, followed by the 5% and then the 10% level.**

Source: EViews (14) output, compiled by author

5.6.2.2 PALMA and SMCG

Based on Table 5.13, in the long run, SMCG is positive and statistically significant at 5% level, with a coefficient of 0.008. Holding all else constant, a one percentage point increase in SMCG leads to a 0.008 percentage point increase in the income distribution gap between the top 10% earners and the bottom 40%, on average. These results are consistent with the Inequality-widening hypothesis, empirically supported by Gimet and Lagoarde-Segot (2011), Wahid et al. (2012), Cournède and Denk (2015), Jauch and Watzka (2016), Seven and Coskun (2016), de Haan and Sturm (2017), and Chiu and Lee (2019). GEXP(-1) and TRADEGDP are both negative and statistically significant at 1% level. No variables are statistically significant in the short run.

The Error Correction Term (COINTEQ), representing the model's speed of adjustment back to equilibrium after a shock in the short run, is negative and significant at the 1% level. Based on the -0.229 coefficient of the ECM, in the current year, about 77.1% of the previous year's disequilibrium is corrected. This speed of adjustment is moderately fast. In addition, the R-squared of the model has a coefficient of 0.686, meaning 68.6% of the variation in income inequality is explained by the model.

Table 5.13 Summary of ARDL (3,0,0,2,0,0,0) results: PALMA and SMCG

Variable	Coefficient	St. Error	P-value
Long-run Regressors			
Linear: Independent			
SMCG	0.008**	0.003	0.022
FDI	0.019	0.116	0.875
GEXP(-1)	-0.242***	0.065	0.001
INF	-0.003	0.044	0.946
LNGDPPC	0.112	0.647	0.864
TRADEGDP	-0.070***	0.021	0.003
Short-run Regressors			
Linear: Independent			
D(GEXP)	0.014	0.051	0.784
D(GEXP(-1))	0.131	0.055	0.023
C	10.271***	1.740	0.000
COINTEQ	-0.229***	0.039	0.000
R-squared	0.686		

Note: * denotes statistical significance at 10% level, ** denotes statistical significance at 5% level, and * denotes statistical significance at 1% level. The 1% level indicates the strongest statistical evidence, followed by the 5% and then the 10% level.**

Source: EViews (14) output, compiled by author

5.6.2.3 PALMA and SMT

Based on Table 5.14, in the long run, the first lags of SMT and INF are both negative and statistically significant at 5% level. The first lag of PDSG has a coefficient of -0.046. Holding all else constant, a one percentage point increase in SMT leads to a 0.046 percentage point decrease in the income distribution gap between the top 10% earners and the bottom 40%, on average.

These results are consistent with the Inequality-narrowing hypothesis, empirically supported by Bittencourt (2010), Kappel (2010), Mookerjee and Kalipioni (2010), Shahbaz and Islam (2011), Hamori and Hashiguchi (2012), Prete (2013), Adams and Klobodu (2016), Kapingura (2017), and Omar and Inaba (2020) found the Inequality-narrowing hypothesis. In the short run, D(LNGDPPC(-1)) is positive and statistically significant at 5%, and D(TRADEGDP) is negative and statistically significant at 1%. The Error Correction Term (COINTEQ), representing the model's speed of adjustment back to equilibrium after a shock in the short run, is negative and significant at the 1% level. Based on the -0.088 coefficient of the ECM, in the current year, about 12% of the previous year's disequilibrium is corrected. This speed of adjustment is moderately fast. In addition, the R-squared of the model has a coefficient of 0.689, meaning 68.9% of the variation in income inequality is explained by the model.

Table 5.14 Summary of ARDL (3,1,1,0,1,2,1) results: PALMA and SMT

Variable	Coefficient	St. Error	P-value
Long-run Regressors			
Linear: Independent			
SMT(-1)	-0.046**	0.022	0.050
FDI(-1)	0.276	0.219	0.221
GEXP	0.048	0.078	0.548
INF(-1)	-0.177**	0.071	0.021
LNGDPPC(-1)	-1.552	0.965	0.122
TRADEGDP(-1)	0.024	0.032	0.465
Short-run Regressors			
Linear: Independent			
D(STOCK_TURNOVOVER)	-0.011	0.017	0.534
D(FDI)	0.052	0.076	0.503
D(INF)	-0.038	0.056	0.503
D(LNGDPPC)	0.624	0.919	0.503
D(LNGDPPC(-1))	2.100**	1.014	0.048
D(TRADEGDP)	-0.096***	0.030	0.004
C	13.633***	2.981	0.000
COINTEQ	-0.088***	0.019	0.000
R-squared	0.689		

Note: * denotes statistical significance at 10% level, ** denotes statistical significance at 5% level, and * denotes statistical significance at 1% level. The 1% level indicates the strongest statistical evidence, followed by the 5% and then the 10% level.**

Source: EViews (14) output, compiled by author

5.6.2.4 PALMA and STG

Based on Table 5.15, the impact of financial sector development on income inequality is not statistically significant in the long run or the short run. However, in the long run, FDI(-1) is positive and statistically significant at 10%, GEXP(-1), and TRADEGDP(-1) are both negative and statistically significant at 1% and 5% respectively. In the short-run, D(FDI), D(GEXP(-1)), D(GEXP(-2)), D(TRADEGDP(-1), D(TRADEGDP(-2)) are all positive and statistically significant, whereas D(INF(-1)) is statistically significant but negative.

The Error Correction Term (COINTEQ), representing the model's speed of adjustment back to equilibrium after a shock in the short run, is negative and significant at the 1% level. Based on the -0.499 coefficient of the ECM, in the current year, about 50.1% of the previous year's disequilibrium is corrected. This speed of adjustment is moderately fast. In addition, the R-squared of the model has a coefficient of 0.813, meaning 81.3% of the variation in income inequality is explained by the model.

Table 5.15 Summary of ARDL (2,0,1,3,2,0,3) results: PALMA and STG

Variable	Coefficient	St. Error	P-value
Long-run Regressors			
Linear: Independent			
STG	0.009	0.008	0.270
FDI(-1)	0.299*	0.158	0.074
GEXP(-1)	-0.258***	0.072	0.002
INF(-1)	0.094	0.063	0.149
LNGDPPC	1.261	0.661	0.071
TRADEGDP(-1)	-0.088**	0.033	0.016
Short-run Regressors			
Linear: Independent			
D(FDI)	0.134**	0.065	0.050
D(GEXP)	0.051	0.050	0.316
D(GEXP(-1))	0.276***	0.076	0.001
D(GEXP(-2))	0.162**	0.060	0.012
D(INF)	0.035	0.044	0.443
D(INF(-1))	-0.174***	0.045	0.001
D(TRADEGDP)	-0.063	0.024	0.017
D(TRADEGDP(-1))	0.085***	0.028	0.006
D(TRADEGDP(-2))	0.108***	0.021	0.000
C	4.78***	0.783	0.000
COINTEQ	-0.499***	0.081	0.000
R-squared	0.812		

Note: * denotes statistical significance at 10% level, ** denotes statistical significance at 5% level, and * denotes statistical significance at 1% level. The 1% level indicates the strongest statistical evidence, followed by the 5% and then the 10% level.**

Source: EViews (14) output, compiled by author

5.6.2.5 PALMA Overall model

Based on Table 5.16, in the long run, the first lag of PDSG is negative and statistically significant at 1% level, with a coefficient of -0.118. Holding all else constant, a one percentage point increase in PDSG leads to a 0.118 percentage point decrease in the income distribution gap between the top 10% earners and the bottom 40%, on average. The results are consistent with the inequality-narrowing hypothesis, empirically supported by Bittencourt (2010), Kappel (2010), Mookerjee and Kalipioni (2010), Shahbaz and Islam (2011), Hamori and Hashiguchi (2012), Prete (2013), Adams and Klobodu (2016), Kapingura (2017), and Omar and Inaba (2020). INF(-1), LNGDPPC (-1), and TRADEGDP(-1) are also negative and statistically significant. FDI(-1) is also statistically significant but negative. In the short run, D(PDSG(-1)), D(SMT), and D(SMT(-1) are all positive and statistically significant. D(STG(-1)) is also statistically significant but negative. The Error Correction Term (COINTEQ), representing the model's speed of adjustment back to equilibrium after a shock in the short run, is negative and significant at the 1% level. Based on the -0.314 coefficient of the ECM, in the current year, about 68.6% of the previous year's disequilibrium is corrected. This speed of adjustment is moderately fast. In addition, the R-squared of the model has a coefficient of 0.870, meaning 87% of the variation in income inequality is explained by the model.

Table 5.16 Summary of ARDL (3,2,0,2,2,1,0,2,2,1) results: PALMA Overall

Variable	Coefficient	St. Error	P-value
Long-run Regressors			
Linear: Independent			
PDSG(-1)	-0.118***	0.039	0.010
SMCG	0.010	0.007	0.233
SMT(-1)	-0.083	0.049	0.117
STG(-1)	0.026	0.024	0.301
FDI(-1)	0.490	0.235	0.057
GEXP	-0.004	0.112	0.971
INF(-1)	-0.345***	0.104	0.006
LNGDPPC(-1)	-2.766**	1.070	0.023
TRADEGDP(-1)	-0.083*	0.040	0.056
Short-run Regressors			
Linear: Independent			
D(PDSG)	0.016	0.020	0.429
D(PDSG(-1))	0.119***	0.037	0.004
D(SMT)	0.039**	0.016	0.028
D(SMT(-1)	0.057***	0.021	0.011
D(STG)	0.002	0.008	0.782
D(STG(-1))	-0.022**	0.009	0.023
D(FDI)	0.211***	0.069	0.006
D(INF)	-0.113**	0.047	0.025
D(INF(-1))	0.065	0.043	0.143
D(LNGDPPC)	-1.187	0.877	0.190
D(LNGDPPC(-1))	3.889***	1.028	0.001
D(TRADEGDP)	-0.149***	0.026	0.000
C	36.155***	4.973	0.000
COINTEQ	-0.314***	0.043	0.000
R-squared	0.870		

Note: * denotes statistical significance at 10% level, ** denotes statistical significance at 5% level, and * denotes statistical significance at 1% level. The 1% level indicates the strongest statistical evidence, followed by the 5% and then the 10% level.**

Source: EViews (14) output, compiled by author

5.6.2.6 Summary of model(s) results

Table 5.17 provides a summary of theoretical hypotheses found per model of the study in the long run. Based on these results, the majority of the models support the Inequality-narrowing hypothesis, meaning that in the case of South Africa, financial sector development has empirical evidence of reducing income inequality when measured through both the Gini coefficient and the Palma ratio. For both the Gini and Palma models, SMCG is the only model supporting the Inequality-widening hypothesis, whereas STG is the only inconclusive model. PSG, SMT, and overall models all support the Inequality-narrowing hypothesis in the long run.

Table 5.17 Summary of model(s) long-run theoretical conclusion

GINI models ***Model Specification***	**Long-run theoretical Conclusion: Narrowing/ Widening hypothesis**
GINI and PDSG ***ARDL (2,2,3,0,3,2,3)***	Inequality-narrowing hypothesis
GINI and SMCG ***ARDL (3,0,1,2,0,2,2)***	Inequality-widening hypothesis
GINI and SMT ***ARDL (3,1,1,0,1,2,1)***	Inequality-narrowing hypothesis
GINI and STG ***ARDL (2,0,1,3,2,0,3)***	None
GINI Overall ***ARDL (3,2,0,2,2,1,0,1,2,2)***	Inequality-narrowing hypothesis
PALMA models ***Model Specification***	
PALMA and PDSG ***ARDL (3,1,0,0,1,2,1)***	Inequality-narrow hypothesis
PALMA and SMCG ***ARDL (3,0,0,2,0,0,0)***	Inequality-widening hypothesis
PALMA and SMT ***ARDL (3,1,1,0,1,2,1)***	Inequality-narrow hypothesis
PALMA and STG ***ARDL (2,0,1,3,2,0,3)***	None
PALMA Overall ***ARDL (3,2,0,2,2,1,0,2,2,1)***	Inequality-narrowing hypothesis

Source: EViews (14) output, compiled by author

5.7 COINTEGRATION TEST RESULTS

Following the presentation of the ARDL models' results in Section 5.6, Table 5.20 presents the results of the Bounds test done on all the models, to evaluate the long-run relationships found in the ARDL models' results. All models had 38 observations. The null hypothesis (H_0) of the Bounds test states that no long-run relationship exists among the variables (no cointegration). In contrast, the alternative hypothesis (H_1) states that a long-term equilibrium relationship exists among the variables (Cointegration). The F-statistic is compared to the critical values of the upper and lower bounds of specific levels of significance. Exceeding the critical values of the upper bound at a specific level of significance confirms cointegration at that level, rejecting the null hypothesis of the test, whereas falling below the critical values of the lower bound of a specific level of significance confirms no cointegration at that level, failing to reject the null hypothesis of the test.

Based on the Bounds test results presented in Table 5.21, the GINI and PDSG model is the only model that rejected the null hypothesis at 5% level, concluding the presence of cointegration in the model. The results confirmed a long-run relationship found in ARDL (2,2,3,0,3,2,3). Based on ARDL (2,2,3,0,3,2,3) results, financial sector development (proxied by Public Debt Securities to GDP) reduces income inequality (proxied by the Gini coefficient). The model controlled for Foreign Direct Investments, Government expenditure, Inflation, GDP per capita, and Trade. The model results support the Inequality-narrowing hypothesis.

Similarly, the GINI Overall, GINI and STG, PALMA Overall, PALMA and SMCG, and PALMA and STG models also rejected the null hypothesis at 10% level, suggesting weak evidence of cointegration in these models. Since 5% is the commonly accepted threshold for statistical significance in econometric studies, this study based its conclusions primarily on the stronger results observed at the 5% level. Consequently, this study concludes that financial sector development, measured by Public Debt Securities to GDP, reduces income inequality, measured by the Gini coefficient, in South Africa. These results align with the findings of Kapingura (2017), who found that financial sector development, measured through financial depth, reduces income inequality. The established cointegration implies the existence of stationary linear combinations among variables that are individually non-stationary but integrated of order one (I (1)).

On the other hand, the following models confirmed no cointegration: GINI and SMCG, GINI and SMT, PALMA and PDSG, and PALMA and SMT; meaning no valid long-run relationships exist among the variables in the given models, based on the Bounds test results.

Table 5.18 Summary of Bounds Test Results

GINI models *Model Specification*	**Obs.**	**F-statistic**	**Bounds Critical Values**						**Conclusion**
			Significance level						
			1%		**5%**		**10%**		
			I (0)	**I (1)**	**I (0)**	**I (1)**	**I (0)**	**I (1)**	
GINI Overall ***ARDL (3,2,0,2,2,1,0,1,2,2)***	38	3.311*	2.650	3.970	2.140	3.300	1.880	2.990	Cointegration
GINI and PDSG ***ARDL (2,2,3,0,3,2,3)***	38	4.797**	3.800	5.643	2.797	4.211	2.353	3.599	Cointegration
GINI and SMCG ***ARDL (3,0,1,2,0,2,2)***	38	3.114	3.800	5.643	2.797	4.211	2.353	3.599	No Cointegration
GINI and SMT ***ARDL (3,1,1,0,1,2,1)***	38	3.072	3.800	5.643	2.797	4.211	2.353	3.599	No Cointegration
GINI and STG ***ARDL (2,0,1,3,2,0,3)***	38	4.126*	3.800	5.643	2.797	4.211	2.353	3.599	Cointegration
PALMA models *Model Specification*									
PALMA Overall ***ARDL (3,2,0,2,2,1,0,2,2,1)***	38	3.128*	2.650	3.970	2.140	3.300	1.880	2.990	Cointegration
PALMA and PDSG ***ARDL (3,1,0,0,1,2,1)***	38	2.541	3.800	5.643	2.797	4.211	2.353	3.599	No Cointegration
PALMA and SMCG ***ARDL (3,0,0,2,0,0,0)***	38	4.102*	3.800	5.643	2.797	4.211	2.353	3.599	Cointegration
PALMA and SMT ***ARDL (3,1,1,0,1,2,1)***	38	2.365	3.800	5.643	2.797	4.211	2.353	3.599	No Cointegration
PALMA and STG ***ARDL (2,0,1,3,2,0,3)***	38	4.180*	3.800	5.643	2.797	4.211	2.353	3.599	Cointegration

Note: * denotes the rejection of the null hypothesis at a 10% level of significance, ** denotes the rejection of the null hypothesis at a 5% level of significance, and * denotes the rejection of the null hypothesis at a 1% level of significance. The 1% level indicates the strongest statistical evidence against the null hypothesis, followed by the 5% and then the 10% levels.**

Source: EViews (14) output, compiled by author

5.8 DIAGNOSTIC TESTS RESULTS

Table 5.22 presents a summary of results for all diagnostic tests conducted for all the models in the study, distinguishing between the GINI and PALMA models. All models in the study (all models of GINI and PALMA) failed to reject the null hypothesis of all diagnostic tests at a 5% level of significance. For the normality test, all models in the study failed to reject the null hypothesis, stating that the residuals are normally distributed, and it was concluded that the residuals are normally distributed. For the serial correlation test, all models in the study failed to reject the null hypothesis, stating that there is no serial correlation at up to 1 lag, and it was concluded that there is no serial correlation at up to 1 lag. Finally, for the Heteroskedasticity test, all models in the study failed to reject the null hypothesis positing homoskedasticity and concluded homoskedasticity.

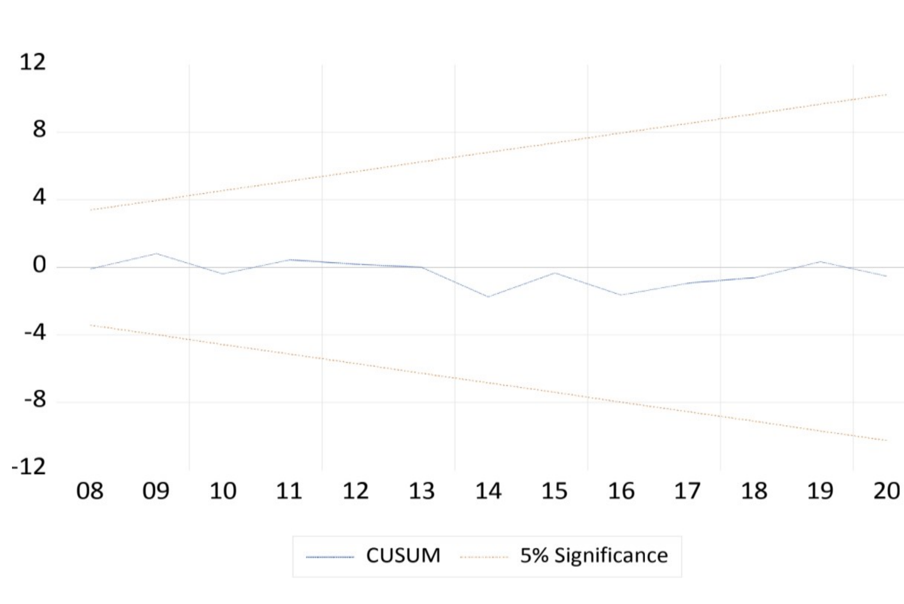
Furthermore, all models in the study confirmed model stability through the CUSUM and CUSUM of squares test. However, under the GINI models, the model ARDL (3,1,1,0,1,2,1) touched the lower boundary of the CUSUM of squares test minimally. Similarly, under PALMA models, models ARDL (3,1,0,0,1,2,1) and ARDL (3,1,1,0,1,2,1) also barely touched the lower boundary of the 95% confidence interval for the CUSUM of squares test. Overall, the joint results of the diagnostic tests confirm the robustness, reliability, and stability of all models used in this study.

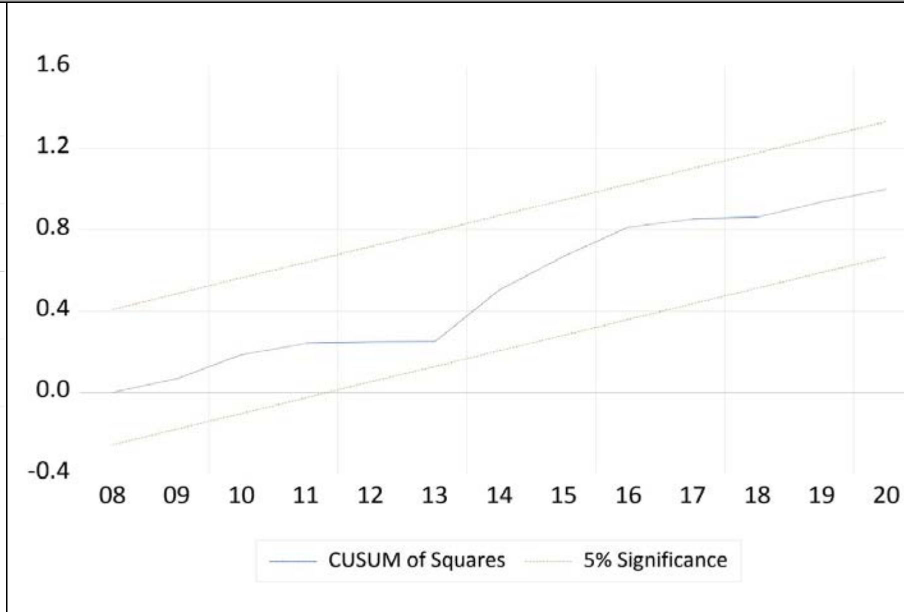
Table 5.22 Summary of Diagnostic Test Results

Normality Test H_0: Residuals are normally distributed, H_1: Residuals are not normally distributed				
GINI Models	**Model Specification**	**JB statistic**	**P-value**	**Conclusion**
GINI Overall	ARDL (3,2,0,2,2,1,0,1,2,2)	0.948	0.623	Residuals are normally distributed
GINI and PDSG	ARDL (2,2,3,0,3,2,3)	1.608	0.448	Residuals are normally distributed
GINI and SMCG	ARDL (3,0,1,2,0,2,2)	0.936	0.626	Residuals are normally distributed
GINI and SMT	ARDL (3,1,1,0,1,2,1)	1.556	0.459	Residuals are normally distributed
GINI and STG	ARDL (2,0,1,3,2,0,3)	1.598	0.450	Residuals are normally distributed
PALMA Models	**Model Specification**	**JB statistic**	**P-value**	**Conclusion**
PALMA Overall	ARDL (3,2,0,2,2,1,0,2,2,1)	0.191	0.909	Residuals are normally distributed
PALMA and PDSG	ARDL (3,1,0,0,1,2,1)	3.954	0.138	Residuals are normally distributed
PALMA and SMCG	ARDL (3,0,0,2,0,0,0)	0.668	0.716	Residuals are normally distributed
PALMA and SMT	ARDL (3,1,1,0,1,2,1)	3.197	0.202	Residuals are normally distributed
PALMA and STG	ARDL (2,0,1,3,2,0,3)	0.215	3.078	Residuals are normally distributed.
Serial correlation test H_0: No serial correlation at up to 1 lag, H_1: Serial correlation at up to 1 lag				
GINI Models	**Model Specification**	**Obs* R-Squared**	**P-value**	**Conclusion**
GINI Overall	ARDL (3,2,0,2,2,1,0,1,2,2)	5.862	0.053	No serial correlation

GINI and PDSG	ARDL (2,2,3,0,3,2,3)	5.237	0.073	No serial correlation
GINI and SMCG	ARDL (3,0,1,2,0,2,2)	3.578	0.167	No serial correlation
GINI and SMT	ARDL (3,1,1,0,1,2,1)	0.545	0.761	No serial correlation
GINI and STG	ARDL (2,0,1,3,2,0,3)	2.702	0.100	No serial correlation
PALMA Models	**Model Specification**	**Obs* R-Squared**	**P-value**	**Conclusion**
PALMA Overall	ARDL (3,2,0,2,2,1,0,2,2,1)	3.802	0.051	No serial correlation
PALMA and PDSG	ARDL (3,1,0,0,1,2,1)	0.969	0.616	No serial correlation
PALMA and SMCG	ARDL (3,0,0,2,0,0,0)	0.596	0.440	No serial correlation
PALMA and SMT	ARDL (3,1,1,0,1,2,1)	0.488	0.784	No serial correlation
PALMA and STG	ARDL (2,0,1,3,2,0,3)	1.730	0.188	No serial correlation
Heteroskedasticity Test H_0: Homoskedasticity, H_1: Heteroscedasticity				
GINI Models	**Model Specification**	**Obs* R-Squared**	**P-value**	**Conclusion**
GINI Overall	ARDL (3,2,0,2,2,1,0,1,2,2)	21.181	0.628	Homoskedasticity
GINI and PDSG	ARDL (2,2,3,0,3,2,3)	19.822	0.533	Homoskedasticity
GINI and SMCG	ARDL (3,0,1,2,0,2,2)	19.059	0.266	Homoskedasticity
GINI and SMT	ARDL (3,1,1,0,1,2,1)	22.121	0.105	Homoskedasticity
GINI and STG	ARDL (2,0,1,3,2,0,3)	15.617	0.551	Homoskedasticity
PALMA Models	**Model Specification**	**Obs* R-Squared**	**P-value**	**Conclusion**
PALMA Overall	ARDL (3,2,0,2,2,1,0,2,2,1)	28.242	0.250	Homoskedasticity
PALMA and PDSG	ARDL (3,1,0,0,1,2,1)	14.660	0.402	Homoskedasticity
PALMA and SMCG	ARDL (3,0,0,2,0,0,0)	16.836	0.113	Homoskedasticity
PALMA and SMT	ARDL (3,1,1,0,1,2,1)	18.600	0.232	Homoskedasticity
PALMA and STG	ARDL (2,0,1,3,2,0,3)	14.569	0.627	Homoskedasticity
Stability Test				
CUSUM test		**CUSUM of Squares test**		
GINI Models Specification				

ARDL (3,2,0,2,2,1,0,1,2,2)





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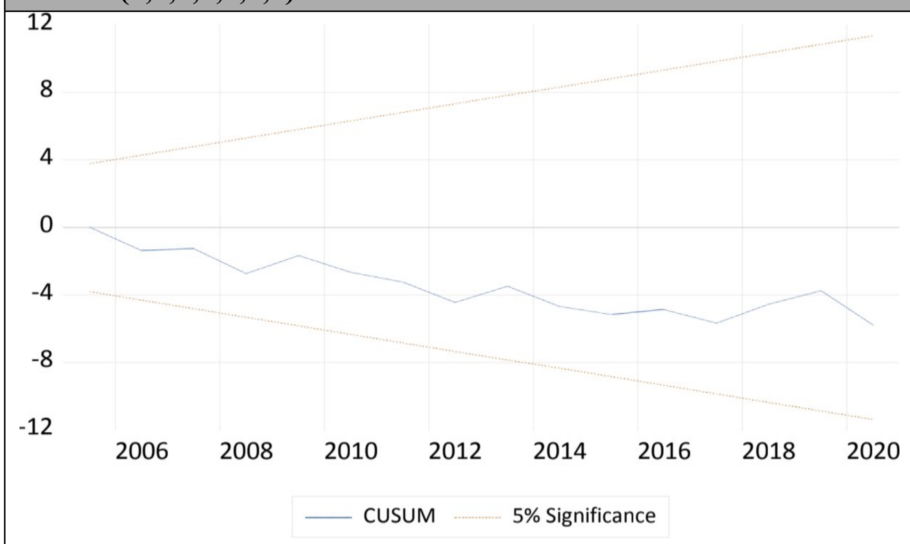

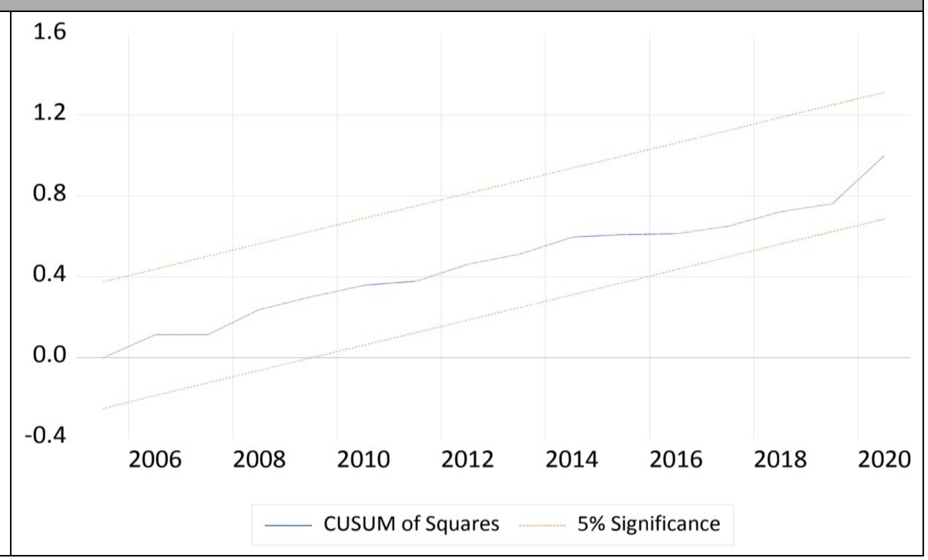

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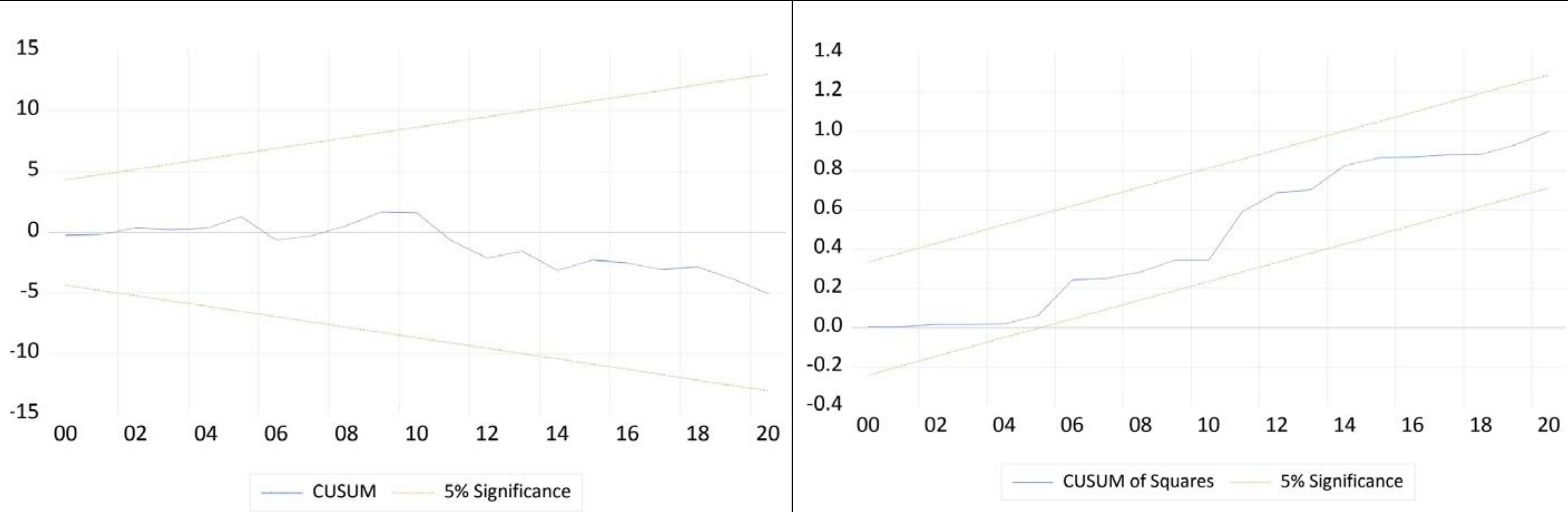

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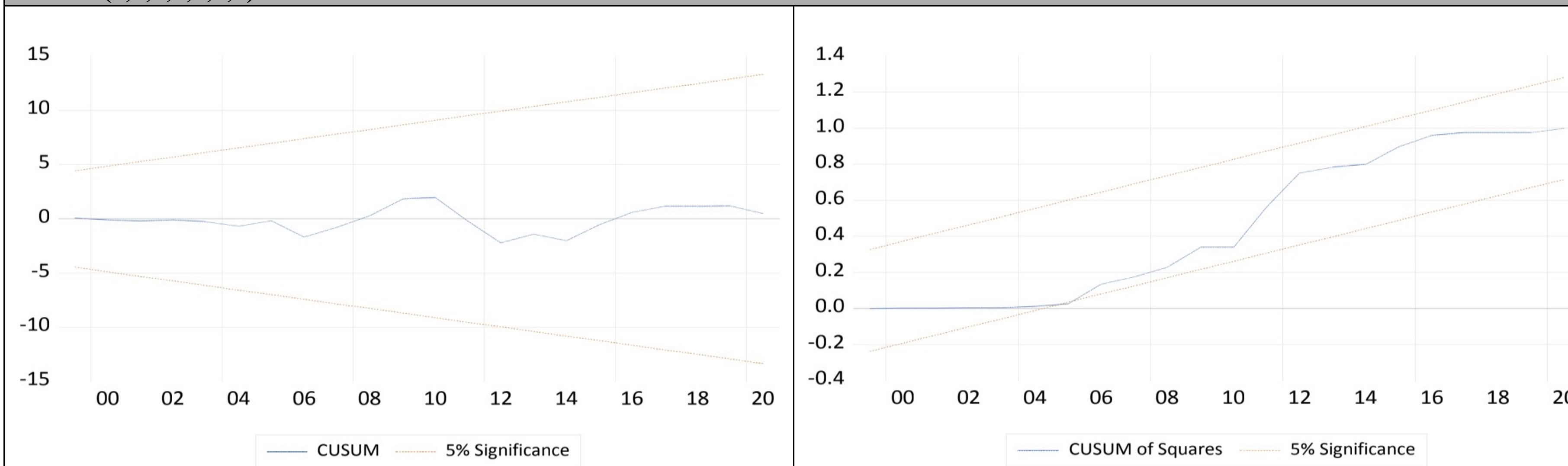

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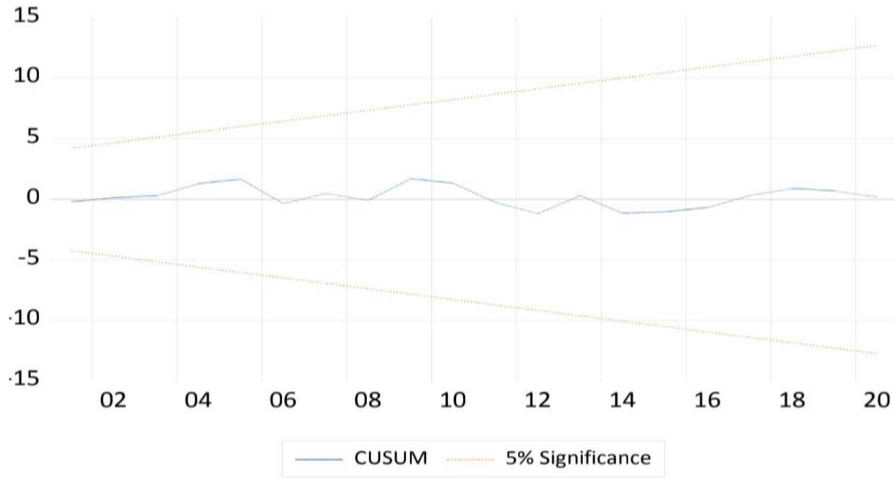
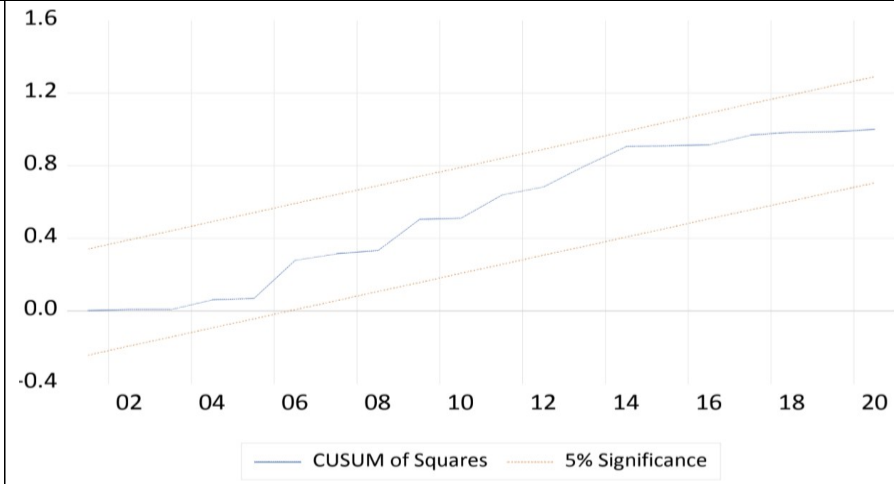
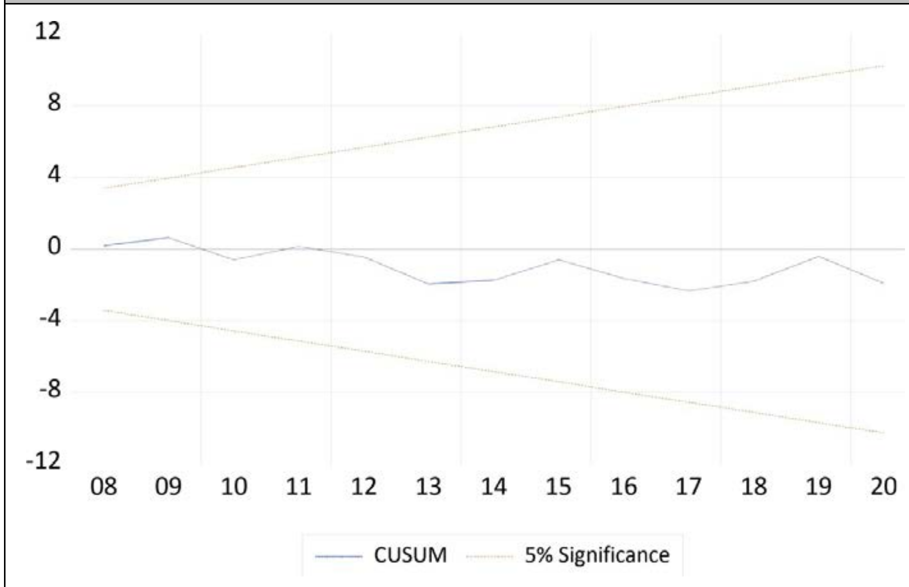
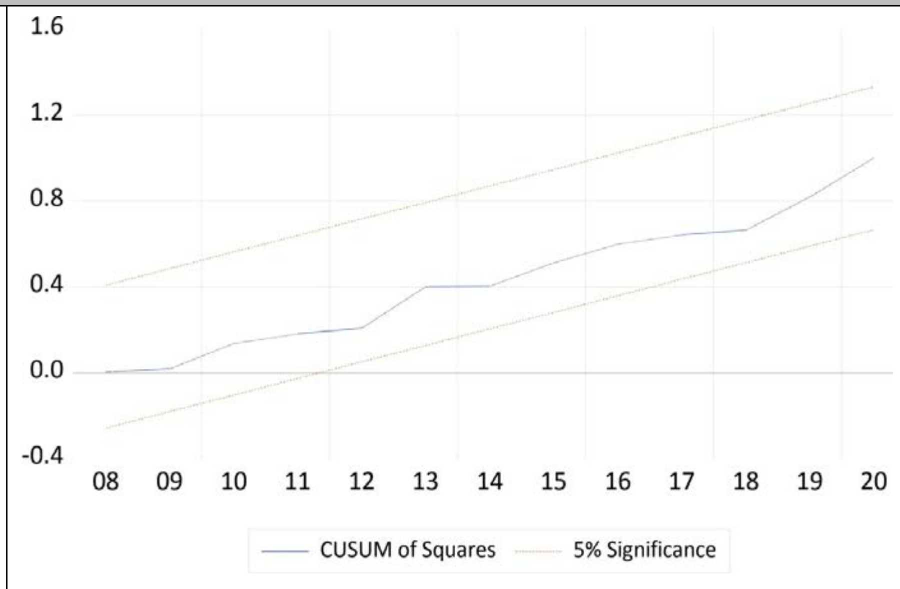




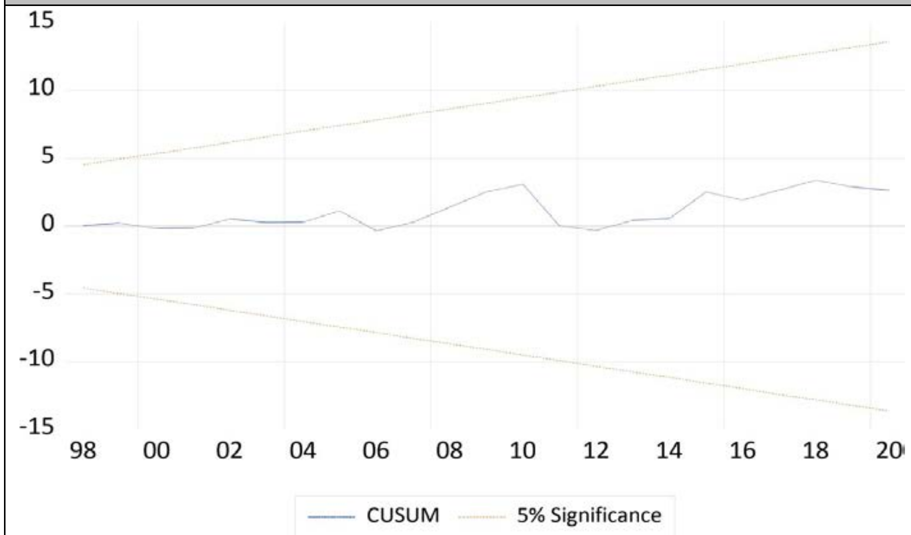
PALMA Models Specification

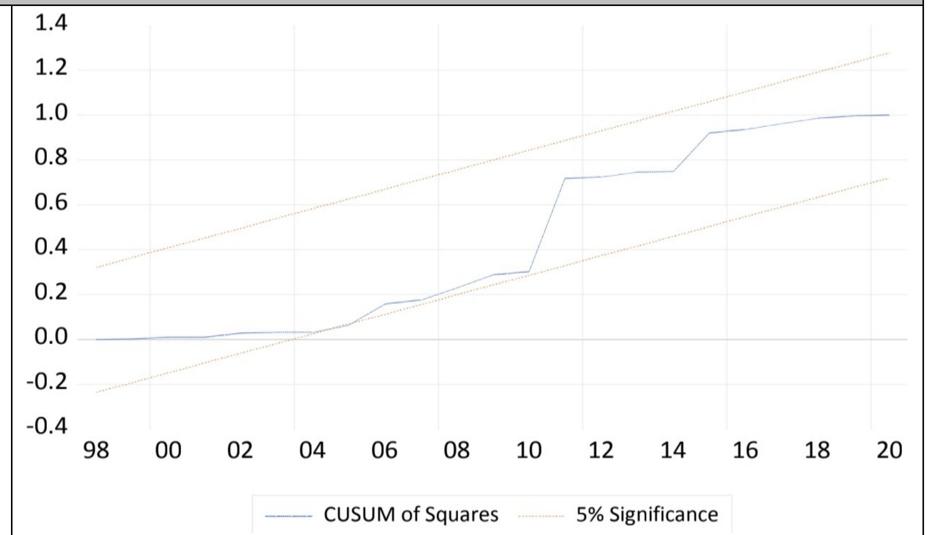
ARDL (3,2,0,2,2,1,0,2,2,1)



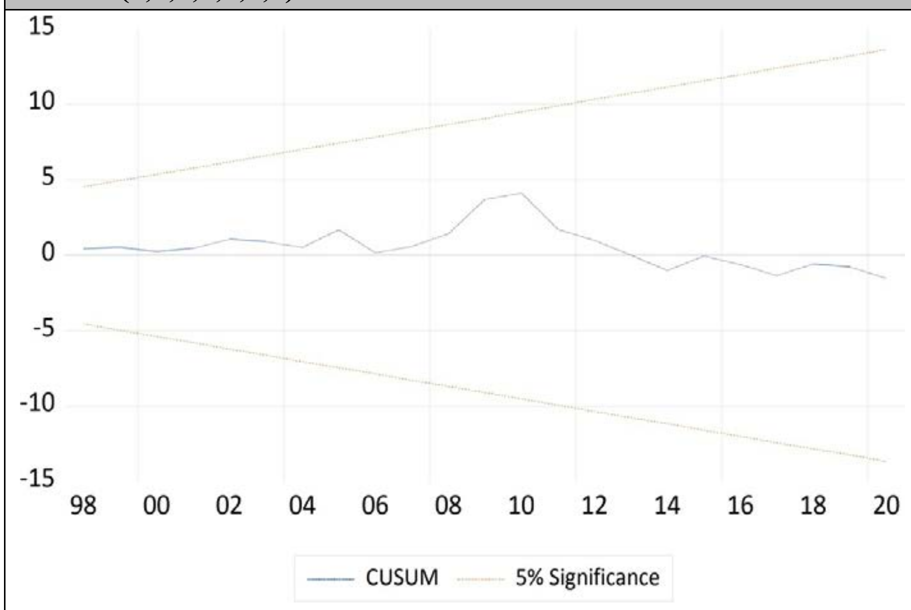


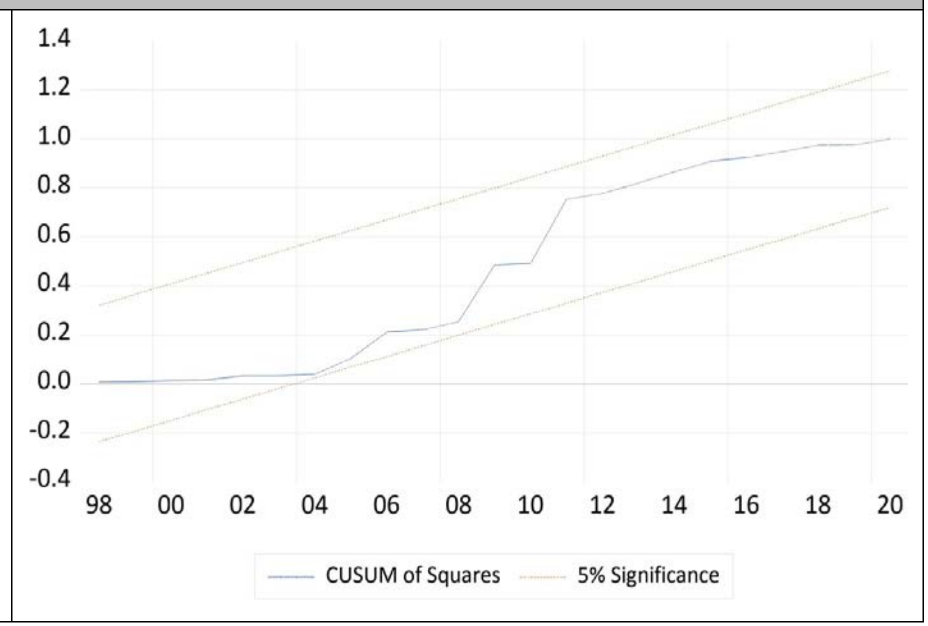
ARDL (3,1,0,0,1,2,1)



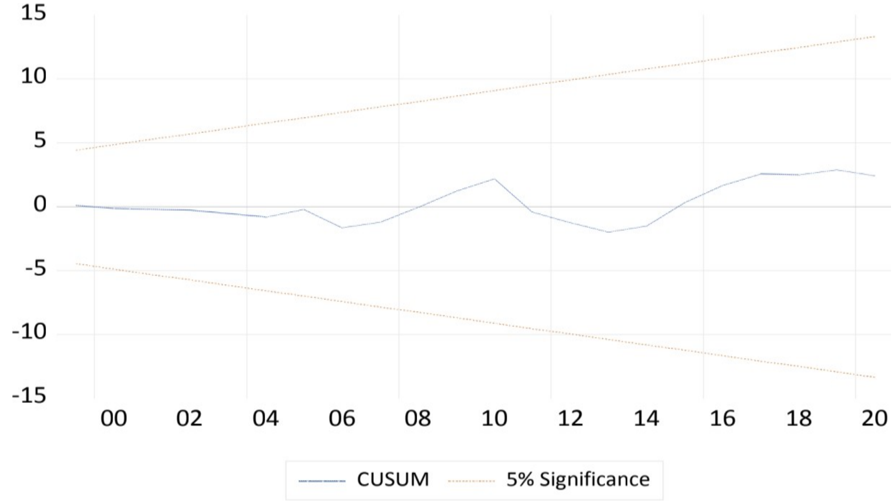


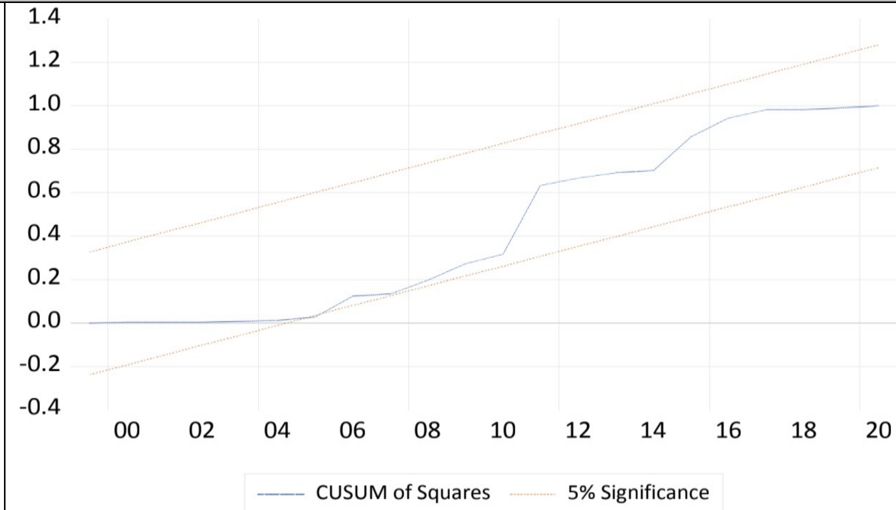
ARDL (3,0,0,2,0,0,0)



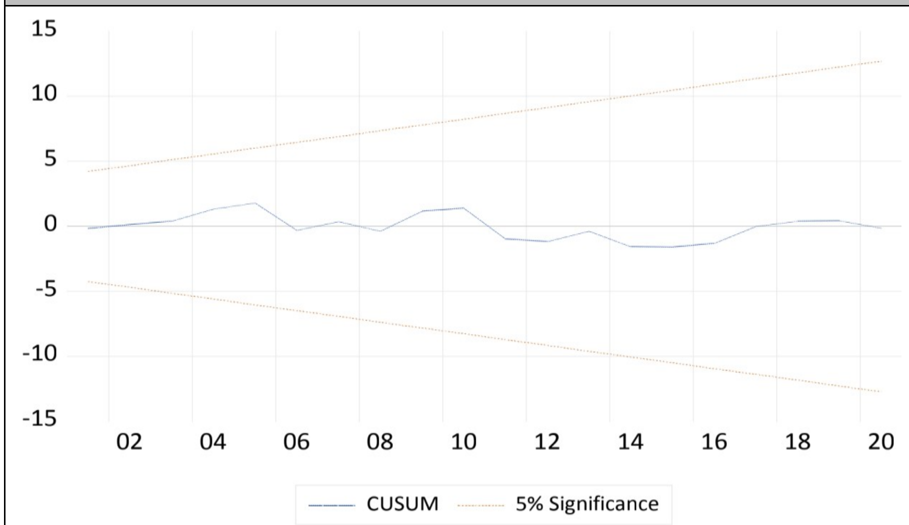


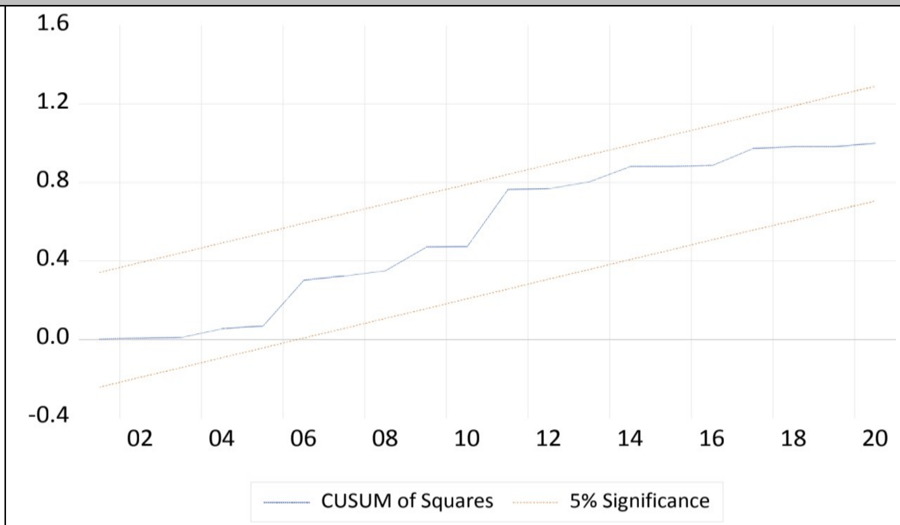
ARDL (3,1,1,0,1,2,1)





ARDL (2,0,1,3,2,0,3)





Source: EViews (14) output, compiled by author

5.12 Conclusion

Chapter 5 presented and discussed the results of all tests, modelling, and data analysis conducted in this study. The chapter began with descriptive statistics, highlighting the properties of data used in the study. The correlation analysis between the dependent variable and the independent variable was also discussed following the descriptive statistics. Based on the correlation analysis, Public Debt Securities to GDP has a strong correlation with the Gini coefficient at 5% level of significance. The chapter also discussed the Unit root test results, confirming that the variables in the data set consist of both I (0) and I (1) integration of order, justifying the use of the ARDL model in the study. The study employed two base models of the Gini coefficient and the Palma ratio, and their sub-models (four each). Based on the main findings of the study, in the long run, most of the ARDL models support the Income narrowing hypothesis. However, the bounds test only validated the long-run relationship of ARDL (2,2,3,0,3,2,3) at 5% level. Nonetheless, all models met the diagnostic tests requirements for linear ARDL modelling, making the inferences reliable and robust. Overall, the findings of the study satisfied the study goals and subgoals of empirically investigating the linear relationship between financial sector development and income inequality in South Africa, using both the Gini coefficient and the Palma ratio. The study, through model ARDL (2,2,3,0,3,2,3), found that financial sector development (proxied by Public Debt Securities to GDP) reduces income inequality (proxied by the Gini coefficient) in South Africa. The findings are also supported by the strong negative correlation between Public Debt Securities to GDP and Income inequality found earlier in Section 5.3.

Furthermore, within the same model, Inflation and Trade, at first lags, were both statistically significant at 1%, indicating that the two control variables do impact Income inequality. Both coefficients have a negative sign, meaning that the increase in Inflation and Trade lowers income inequality. These findings on inflation contradict the a priori expectations, which stated that increasing inflation is expected to worsen Income inequality. The findings on Trade are consistent with Rodrik (1997) and Birdsall (1998), who argue that Trade reduces Income inequality by lowering consumer goods prices and improving demand for low-skilled labour. The study found no long-run significant impact of financial sector development on income inequality using the Palma ratio.

CHAPTER 6: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

Chapter 6 presents the key findings drawn from the study. The chapter reflects on the findings in relation to the research objectives. In addition, the chapter synthesizes insights from the empirical analysis and theoretical discussions, highlighting the implications of the financial sector development and income inequality nexus in South Africa. In this chapter, Section 6.2 summarizes the key findings of the study. Section 6.3 outlines the limitations of the study. Areas for future research are discussed in Section 6.4. Finally, recommendations based on the findings of the study are provided in Section 6.5.

6.2 Key findings

Based on the key findings of the study, Income inequality can be reduced through the development of the financial sector (proxied by Public Debt Securities to GDP). In support of the inequality-narrowing hypothesis, the study mainly found that in the long run, financial sector development reduces inequality (proxied by the Gini coefficient) through the facet of depth. Using the ARDL methodology, financial sector development has been empirically proven to reduce income inequality while controlling for Government expenditure, FDI, GDP per capita, Inflation, and Trade. Although the study employed both the Gini coefficient and the Palma ratio to measure income inequality, there were no significant long-run relationships found within the Palma models, meaning that this study did not find any significant impact of financial sector development on income inequality for the top 10% earners and the bottom 40%. The findings emphasize that the high-income disparities in South Africa are experienced across all income groups as opposed to a certain proportion measured by the Palma ratio (top 10% and bottom 40% earners).

6.3 Limitations of the Study

The study only relied on a linear ARDL model due to a limited sample and scope (half-thesis). The annual data used in the study resulted in a small sample of 38 observations, which limited the use of the Nonlinear ARDL model. The study only assessed the depth and efficiency facets of financial sector development due to the data type (annual) and availability. The study failed to build on the existing empirical literature by Kapingura (2017), who revealed that increasing financial access reduces inequality compared to increasing financial depth. The study also failed to examine the inverted U-shaped relationship confirmed by Hassan and Meyer (2021), who found that financial sector development has a nonlinear impact on income inequality.

6.4 Areas for Further Research

Further research encompassing all four facets of financial sector developments should be conducted to assess its impact on income inequality. There are limited studies in the South African context, which necessitate more research within this context. As mentioned earlier, the other previous South African studies by Kapinguara (2017) and Hassan and Meyer (2021) measured financial sector development through either access, efficiency, or depth. So far, no study has explored the stability facet. Although this study examined both financial depth and efficiency, it could not demonstrate solid evidence of the effect of both financial depth and efficiency on income inequality due to the limited observation of the study. Research employing Stability to measure financial sector development could also contribute to the existing limited literature. Given that the study period of this study ends in 2020, more studies using recent data (up to 2024) could improve the existing empirical literature on the financial sector development and income inequality nexus in South Africa.

6.5 Recommendations

The study supports the Inequality-narrowing hypothesis, which is greatly supported by the literature. Based on the findings of this study, relevant policymakers of South Africa could focus on reducing income inequality through financial depth.

The policymakers could promote financial inclusion initiatives, including expanding access to credit for low-income earners and small businesses. These financial inclusion initiatives could deepen the South African economic system, which has been proven to narrow income inequality. In addition, low-cost banking services or mobile banking platforms can also be implemented to increase credit penetration in underserved areas.

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APPENDICES

APPENDIX A: CORRELATION ANALYSIS

Appendix A1: Correlation analysis with the Gini coefficient (Overall model)

Correlation Probability	GINI	PDSG	SMCG	SMT	STG	FDI	GEXP	INF	LNGDPPC	TRADEGDP
GINI	1.000000									

PDSG	-0.360187	1.000000								
	0.0207	-----								
SMCG	-0.084738	0.668460	1.000000							
	0.5984	0.0000	-----							
SMT	-0.096463	0.451865	0.661055	1.000000						
	0.5485	0.0030	0.0000	-----						
STG	-0.142294	0.547483	0.888725	0.878045	1.000000					
	0.3748	0.0002	0.0000	0.0000	-----					
FDI	0.017018	0.041059	0.240140	0.519304	0.365738	1.000000				
	0.9159	0.7988	0.1305	0.0005	0.0187	-----				
GEXP	-0.362336	0.650750	0.569598	0.182227	0.368007	-0.100859	1.000000			
	0.0199	0.0000	0.0001	0.2542	0.0179	0.5304	-----			
INF	-0.182521	-0.504443	-0.643863	-0.732509	-0.682394	-0.434233	-0.102986	1.000000		
	0.2534	0.0008	0.0000	0.0000	0.0000	0.0046	0.5217	-----		
LNGDPPC	0.113677	0.375976	0.777039	0.692985	0.763974	0.360206	0.377646	-0.741013	1.000000	
	0.4791	0.0154	0.0000	0.0000	0.0000	0.0207	0.0149	0.0000	-----	
TRADEGDP	-0.146164	0.028632	0.465830	0.675288	0.661818	0.403958	-0.055762	-0.357345	0.553970	1.000000
	0.3618	0.8590	0.0021	0.0000	0.0000	0.0088	0.7291	0.0218	0.0002	-----

Appendix A2: Correlation analysis with the Palma ratio (Overall model)

Correlation Probability	PALMA	PDSG	SMCG	SMT	STG	FDI	GEXP	INF	LNGDPPC	TRADEGDP
PALMA	1.000000									

PDSG	-0.343463	1.000000								
	0.0279	-----								
SMCG	-0.007113	0.668460	1.000000							
	0.9648	0.0000	-----							
SMT	-0.024530	0.451865	0.661055	1.000000						
	0.8790	0.0030	0.0000	-----						
STG	-0.058289	0.547483	0.888725	0.878045	1.000000					
	0.7174	0.0002	0.0000	0.0000	-----					
FDI	0.061847	0.041059	0.240140	0.519304	0.365738	1.000000				
	0.7009	0.7988	0.1305	0.0005	0.0187	-----				
GEXP	-0.299486	0.650750	0.569598	0.182227	0.368007	-0.100859	1.000000			
	0.0571	0.0000	0.0001	0.2542	0.0179	0.5304	-----			
INF	-0.213229	-0.504443	-0.643863	-0.732509	-0.682394	-0.434233	-0.102986	1.000000		
	0.1807	0.0008	0.0000	0.0000	0.0000	0.0046	0.5217	-----		
LNGDPPC	0.210412	0.375976	0.777039	0.692985	0.763974	0.360206	0.377646	-0.741013	1.000000	
	0.1867	0.0154	0.0000	0.0000	0.0000	0.0207	0.0149	0.0000	-----	
TRADEGDP	-0.061401	0.028632	0.465830	0.675288	0.661818	0.403958	-0.055762	-0.357345	0.553970	1.000000
	0.7029	0.8590	0.0021	0.0000	0.0000	0.0088	0.7291	0.0218	0.0002	-----

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RESEARCH ETHICS DECLARATION

To be included in the Appendices of research papers / dissertations / theses submitted for postgraduate examination where research did not involve interaction with human participants, or the use of animal subjects, and therefore did not require research ethics approval.

Candidates whose research did require ethics clearance must include their ethics approval letter in the Appendix of their examination submission.

Name of Candidate: Agnes Malatsi

Name of Supervisor: Prof. Sibanisezwe Khumalo

Degree: Master of Commerce in Financial Markets

Title of research: Financial sector development and income inequality nexus in South Africa

DECLARATION

I declare that my research did not require ethical clearance because (tick all that apply):

I did not collect data from human participants or animal subjects	√
I used previously collected data that had already received ethics clearance.	√
I analysed documents / open-access digital texts that are freely available in the public domain.	√
I did a literature review/analysis of theoretical or secondary material only.	
I used human datasets of non-sensitive information that are either anonymous (identifiers were never collected) or have been deidentified (identifiers have been completely removed).	
I used commercially produced human biological material (e.g. established human cell lines).	
I observed people in public spaces and natural environments where they had no reasonable expectation of privacy and I did not interact with them or intervene in any way.	
I used non-living animal materials (eg bones of already deceased organisms or fossils) while complying with any custody and/or jurisdiction requirements.	
I did a content analysis of public media (newspapers, advertisements, and social media posts).	
I did a simulation study with no real-world consequences and does not involve disturbing or distressing content.	
I observed flora, fauna, and ecosystems without interfering with or disturbing their natural state while complying with any jurisdiction requirements.	
Other (Please provide details):	

Signature of Candidate: A.Malatsi

Date: 04 July 2025

Signature of Supervisor:

Date: 14/07/2025