Household Finance and Wealth Inequality in South Africa: Evidence from the National Income Dynamics Study Survey

By

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DECLARATION

I declare that this thesis is my original work, except where acknowledged in the text. I further declare that it has never been presented for a degree at any other University.

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ABSTRACT

Wealth inequality remains a persistent challenge, especially in South Africa, where historical disparities continue to influence economic outcomes. Understanding household financial decision-making is crucial for addressing this issue, as these decisions significantly impact both short-term and long-term wealth accumulation. This thesis examines the roles of household balance sheet components and characteristics in wealth inequality, the relationship between asset allocation and wealth distribution, the connection between diversification and wealth outcomes, and the impact of adverse life events on households that are diversified versus those that are not.

Using data from the National Income Dynamics Survey (NIDS), covering approximately 11889 and 13719 households across survey waves four and five (2014 – 2017), this study employs econometric techniques, including the Recentred Influence Function (RIF) regression and the Fractional Multinomial Logit (FMLOGIT) model, to analyse wealth distribution dynamics. The findings reveal that business assets significantly contribute to wealth concentration, while real estate helps to equalise wealth distribution. Moreover, higher levels of wealth are associated with increased risk tolerance and investment in moderate- and high-risk assets. A curvilinear relationship exists between wealth and asset diversification, with upper-middle-class households exhibiting the most diversified portfolios. The study also highlights that households with diversified portfolios demonstrate greater resilience to financial shocks, maintaining or even increasing their net worth during adverse life events.

This research makes three important contributions. First, it broadens the literature on household finance by examining South Africa, a developing economy marked by distinct structural inequalities. Second, it introduces innovative indicators of diversification and life event impacts, providing valuable insights into financial resilience. Third, it offers a comprehensive analysis of the factors influencing wealth inequality, highlighting the role of demographic factors such as education, employment, and race.

The thesis findings carry important implications for policymakers, financial planners, and educators. For policymakers, the results emphasise the need to improve access to entrepreneurship opportunities and support small-business financing, especially for historically disadvantaged groups. Financial planners should create tailored savings and investment products that reflect different levels of risk tolerance and diversification needs, focusing on middle-income households that are increasingly exposed to riskier assets. For educators, customised financial literacy programmes should be introduced in schools and community centres, with curricula developed to cover both the basics of household budgeting and more advanced portfolio management skills. Collectively, these targeted measures can help reduce wealth disparities, enhance household financial resilience, and promote a more equitable and inclusive economy.

While the study provides valuable insights, future research should consider extending the timeframe of analysis, refining asset categorisation methodologies, and examining the long-term effects of financial shocks on household wealth.

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DEDICATION

To my wife, Mantoetsi Mohatonyane, my daughter Ntoetsi, my son Khosi, and in memory of my mother, Masebopeho (Nkhono Emely) Mohatonyane, who passed away during the early stages of my PhD journey.

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CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

Household finance and wealth inequality are pressing issues in South Africa, arising from the country's significant income disparity and the historical impact of apartheid. As one of the most unequal nations globally, South Africa had a Gini coefficient of 0.63 in 2021 (Tregenna & Tsela, 2012; World Bank, 2022). Since a Gini coefficient of 0 denotes perfect equality and 1 indicates total inequality, values below 0.30 are generally regarded as low inequality, those between 0.30 and 0.50 as moderate inequality, and those above 0.50 as high inequality. South Africa’s figure of 0.63, therefore, indicates a very high level of income disparity. Wealth, being more unevenly distributed than income, exacerbates wealth inequality in South Africa, where the top 10% of households own more than 85% of the nation’s wealth (Chatterjee et al., 2020).

Closely tied to wealth inequality is household finance, which plays a crucial role in building wealth. The way families manage their money can significantly impact their long-term financial well-being and ability to accumulate assets over time (Joubert & Van Der Merwe, 2021). Effective household financial management, including budgeting, saving, and investment strategies, is essential for individuals and families to grow their wealth and reduce their vulnerability to economic shocks and instability (Martin & Hill, 2015; Oppong et al., 2023). Despite the significance of wealth inequality in South Africa and its close tie with household finance, the relationship between household finance and this pronounced disparity remains poorly understood.

Von Fintel and Orthofer (2020) found a negative relationship between financial inclusion and wealth inequality, arguing that better oversight of the provision of financial services can significantly enhance the impact of financial inclusion on reducing wealth inequality in South Africa. That is evidence that effective household financial management can significantly impact the ability to accumulate wealth over time. By adopting sound financial practices, such as saving a portion of their income, investing in asset-building opportunities, and managing debt prudently, households can build their net worth and pass on wealth to future generations. This, in turn, could contribute to a more equitable distribution of wealth in the country. Given the entrenched wealth inequality in South Africa, a closer examination of the link between household financial practices and this pronounced disparity is warranted. This thesis examines the relationship between household finance and wealth inequality in South Africa, with a focus on understanding how financial behaviours and strategies contribute to the persistence or reduction of wealth disparities.

1.2 SOUTH AFRICA'S CONTEXT OF WEALTH INEQUALITY

Previous studies have firmly established that wealth inequality remains one of the most pressing and persistent issues in South Africa (Chatterjee, 2019; Chatterjee et al., 2020; Orthofer et al., 2019; Pellicer et al., 2011; Von Fintel & Orthofer, 2020). A country that is both developed and deeply divided along racial, economic, and social lines (Babarinde, 2009; Webster & Francis, 2019). The legacy of apartheid, combined with structural challenges in the post-apartheid era, has contributed to a stark disparity in wealth distribution that continues to shape the country's economic landscape. The context of wealth inequality in South Africa can be better understood by considering the historical context, key drivers, and potential policy solutions.

1.2.1 Historical Context of South Africa's Wealth Inequality

Wealth inequality in South Africa has deep roots in the apartheid era (Mohautse, 2014; Wilson, 2011). Under apartheid, the white minority controlled most of the nation's wealth, resources and opportunities, while the black majority had limited access to well-paying jobs, land, education, and economic opportunities (Mosomi & Wittenberg, 2020). This legacy of racial segregation and economic disenfranchisement has had a lasting impact on wealth distribution patterns.

After apartheid ended in 1994, the post-apartheid transition promised greater social and economic equality. However, some scholars argue that the economic reforms introduced by the new democratic government were insufficient to tackle the entrenched structures of inequality (Ngqulunga, 2019; Webster & Francis, 2019). Policies such as the Growth, Employment, and Redistribution (GEAR) strategy in the mid-1990s have also been criticised for perpetuating inequalities rather than addressing the systemic disadvantages inherited from the apartheid system (Gelb, 2003). As a result, wealth inequality has remained a persistent challenge. Recent estimates from various sources show varying figures, but all indicate a stark picture of wealth inequality (Korhonen, 2018; World Bank, 2022). For instance, the World Bank (2022) shows that the top 10% of households own approximately 71.3% of the country's wealth. Korhonen (2018) presents a more stark picture—the wealthiest 1% of the population is estimated to own more than 50% of South Africa's wealth, and 10% own at least 90-95% of the country's wealth.

1.2.2 Key drivers

One key contributor to wealth inequality is the racial wealth gap. Black South Africans continue to face severe disadvantages in wealth accumulation, primarily due to historical land dispossession and racial discrimination in employment and education (Ngqulunga, 2019; Seekings, 2008; Wilson, 2011). The wealth gap between black and white South Africans is still vast, with the average wealth of a white household being approximately 5-10 times higher than that of a black household (Michie & Padayachee, 2019; Webster & Francis, 2019). This racial wealth disparity is compounded by limited access to formal financial services and investment opportunities for the majority of black South Africans (Fortuin, Makoni, et al., 2022; Matsebula & Yu, 2020; Von Fintel & Orthofer, 2020).

Other key drivers contributing to the persistence of wealth inequality in South Africa include:

Land and Property Ownership: Despite post-apartheid land reform efforts, land distribution in South Africa remains one of the most significant drivers of wealth inequality. Lahiff (2016) highlights that the government's land redistribution policies have largely failed to address the deeply entrenched inequalities in land ownership. As a result, the bulk of land and property remains in the hands of the white minority, with the majority of black South Africans still excluded from meaningful land ownership.

Education and Skills Development: Educational attainment is a crucial determinant of wealth accumulation. Letseka et al. (2018) and Lee (2010) argue that the quality of education in South Africa remains deeply unequal. Historically disadvantaged communities have limited access to high-quality education and skills development opportunities. This limits the earning potential of a large population segment, contributing to wealth disparities across generations.

Access to Capital and Financial Services: Wealth creation is often tied to access to capital and financial markets. Scholars argue that black South Africans are significantly less likely to have access to formal banking services, credit, or investment opportunities (Chitimira & Ncube, 2020; Matsebula & Yu, 2020; Omran, 2018). This lack of financial inclusion prevents many citizens from accumulating wealth and participating fully in the economy.

Economic Structure and Employment Patterns: South Africa's economy is characterised by industries that require substantial capital and highly skilled workers. Such industries tend to benefit the wealthy and well-educated (Bell et al., 2018; Mosomi & Wittenberg, 2020). Research indicates that the country's job market is divided, with a significant skills gap and limited opportunities for low-skilled workers to secure well-paid jobs (Bhorat et al., 2020; Mosomi & Wittenberg, 2020). This further deepens the wealth gap.

1.2.3 Policy Responses and Solutions

Despite numerous progressive policy frameworks introduced since the early 1990s aimed at reducing inherited economic disparities, wealth inequality in South Africa has remained notably stable and exceptionally high (Chatterjee et al., 2022). This persistence is demonstrated by studies indicating that the wealthiest 10% of the population controls about 86% of the total wealth, with the top 0.1% holding nearly a third, thereby maintaining a deeply stratified economic landscape (Chatterjee et al., 2022). Such extreme concentration means that the top 0.01% alone possess more net worth than the bottom 90% combined, highlighting the widespread and profound nature of wealth disparities across various asset classes, including housing, pensions, and financial instruments (Chatterjee et al., 2020). These figures suggest that although some policy measures have tried to address historical imbalances, they have largely failed to effectively redistribute wealth or challenge the deeply entrenched structures of economic power established during apartheid (Chatterjee et al., 2020).

Furthermore, analyses reveal that, contrary to expectations, wealth inequality may have subtly worsened among the highest wealth brackets since the end of apartheid, indicating a continued lack of effective redistribution (Chatterjee et al., 2020). This is particularly concerning given that South Africa could now be the most consistently unequal economy in the world, with persistent inequality acting as a significant barrier to poverty reduction despite economic growth (Bhorat et al., 2009, 2020). The persistent and extreme nature of wealth inequality is further emphasised by findings that, even between 2010 and 2019, the decline in wealth inequality was minimal, reflecting the limited impact of macroeconomic policies on this long-standing issue (Fortuin, Grebe, et al., 2022). Consequently, the dominant economic policies since the end of apartheid, characterised by a neoliberal approach, have been criticised for worsening this wealth disparity by prioritising short-term profits and rent-seeking over productive sector investments (Mohamed, 2024). This approach has led to an unprecedented concentration of wealth, where the top 10% of income earners in South Africa held 65% of the total income in 2021, vastly surpassing proportions seen in countries such as France or the United States (Shifa et al., 2023). This sharp concentration of wealth is not merely a statistical anomaly but reflects systemic failure to dismantle the economic architecture of apartheid, where historical disadvantages continue to influence access to capital and opportunities (Chatterjee et al., 2020, 2022).

Researchers have proposed various policy solutions to address the persistent and entrenched wealth inequality in South Africa. These include progressive taxation measures, such as higher taxes on the wealthy and capital gains, aimed at redistributing wealth more equitably (Chatterjee et al., 2021; Czajka et al., 2021; Winchester, 2021). Winchester (2021) even advocates for a policy shift from taxing labour income to taxing wealth.

Expanding the social safety net through enhanced social grants, unemployment benefits, and universal access to quality public services, such as healthcare and education, could also play a key role in reducing wealth disparities (Babarinde, 2009; Chibba & Luiz, 2011; Mthethwa & Wale, 2023; World Bank, 2019). Additionally, improving the implementation and impact of land reform initiatives (Hall, 2004; Lahiff, 2016) and Black Economic Empowerment (BEE) policies (Shava, 2017) may help address the historical wealth disparities stemming from the legacy of apartheid. Collectively, these policy interventions aimed at redistributing assets, expanding opportunities, and providing a more robust social welfare system could help to narrow the wealth gap and foster a more inclusive and equitable society.

Additionally, Bhorat et al. (2020) recommend that South Africa focus on economic restructuring to address its wealth inequality. This could involve diversifying the economy, supporting the growth of labour-intensive industries, and creating more high-quality jobs, especially for marginalised groups. Currently, the services sector dominates the economy, while agriculture, mining, and manufacturing have become less important (Bhorat et al., 2020). Shifting towards higher-skilled and higher-value manufacturing, while promoting job-creating service industries, could help build a more inclusive and dynamic economy, expand economic participation, and enable more people to build wealth.

1.2.4 The Role of Household Finance

Household financial circumstances, shaped by factors such as access to capital, savings, investment opportunities, debt management, and financial literacy, are crucial determinants of wealth inequality in South Africa. Disparities in household finance, profoundly influenced by the country's history of apartheid, contribute significantly to the wealth gap, particularly along racial and socio-economic lines. The following factors illustrate how household finance can operate as both a cause and a consequence of wealth inequality in South Africa.

Access to Financial Services: Access to formal financial services is crucial for household finance and wealth inequality in South Africa (Mahalika et al., 2023; Von Fintel & Orthofer, 2020). While the country has a sophisticated banking system, access remains unequal, particularly for historically disadvantaged groups. Black South Africans and those from lower-income households are disproportionately excluded from the formal financial system, limiting their ability to save, invest, and build wealth (Chitimira & Ncube, 2020; Matsebula & Yu, 2020; World Bank Group, 2013). A lack of access to credit, savings accounts, and investment opportunities restricts wealth-building for most of the population. Many black South African households rely on informal financial systems, such as stokvels or informal lending, which often offer lower returns and higher risk than formal institutions (Ngcobo, 2021; Schoombee, 2009). In contrast, wealthier, mainly white households have greater access to various financial services, including mortgages, insurance, and retirement savings, boosting their capacity to accumulate wealth over time (Von Fintel & Orthofer, 2020).

Savings and Investments: Savings behaviour is another crucial aspect of household finance that contributes to wealth inequality. Research has shown that savings rates in South Africa are highly unequal, with wealthier households having a much greater capacity and incentive to save (Ardington et al., 2004; Makgetla, 1995; Ngcobo, 2021; Orthofer, 2017). These wealthier households can save and invest more effectively, benefiting from their higher financial literacy. This enables them to make informed decisions about long-term investments, such as stocks or property ownership—key strategies for building wealth. In contrast, many lower-income South African households struggle to save, as they must allocate a significant portion of their income to necessities such as food, housing, and transportation (Engelbrecht, 2014; Ngcobo, 2021). Additionally, poorer households' limited access to investment opportunities, such as stocks, bonds, or pension funds, constrains their ability to accumulate wealth (Mahalika et al., 2023; Von Fintel & Orthofer, 2020).

Property Ownership and Debt: Property ownership is also key in wealth accumulation (Arundel & Hochstenbach, 2020). Homeownership is often the principal asset for middle and upper-class households (Cho, 2014; Vestman, 2019). However, in South Africa, the legacy of apartheid land dispossession and segregation means that property ownership remains highly concentrated among white South Africans (Litheko et al., 2019; Marais et al., 2020; Todes, 2020; Todes & Robinson, 2020). The wealthiest households hold substantial real estate, which appreciates over time, further exacerbating the wealth gap.

For poorer households, owning property is often not feasible due to high upfront costs, limited access to credit, and unstable incomes (Schoombee, 2009). These households are also vulnerable to housing-related debt (Ntsalaze & Ikhide, 2016). While mortgage lending has become more widespread in South Africa, black South Africans are less likely to secure home loans, as banks often have stricter lending criteria and higher interest rates for them, a practice known as redlining (Marais & Cloete, 2015; Ntsalaze & Ikhide, 2016; Pillay & Naudé, 2006; Schreiner et al., 1996). These barriers limit the ability of poorer households to utilise homeownership as a means of wealth accumulation, thereby excluding many South Africans from the property market.

Furthermore, debt management is another factor affecting wealth inequality. Many low-income South Africans face high levels of unsecured debt, such as credit card debt or payday loans, which often carry high interest rates and fees (Chitimira & Ncube, 2020; Collins, 2008; Fatoki, 2015; Von Fintel & Orthofer, 2020). This results in financial instability, preventing them from saving or investing in wealth-building assets. Ntsalaze and Ikhide (2016) highlight how over-indebtedness disproportionately affects low-income households, exacerbating wealth inequality by trapping them in cycles of debt.

Financial Literacy and Education: Financial literacy is also crucial for household finance and wealth inequality in South Africa. Nanziri & Leibbrandt (2018) found that, among other factors, high incomes and being white are associated with higher literacy scores. Nyakurukwa and Seetharam (2024) found that household stock market participation is associated with higher financial literacy. This evidence shows that households with better financial knowledge are more likely to make informed choices about saving, investing, and managing debt. Wealthier households tend to have greater access to financial education and guidance, enabling them to optimise their financial strategies and build long-term wealth (Al-Bahrani et al., 2019; Lusardi, 2019; Shah & Thakkar, 2023).

In contrast, lower-income households often lack access to financial education and struggle to navigate complex financial products (Ngcobo, 2021). This gap in financial literacy, particularly among historically marginalised groups (Chitimira & Ncube, 2020), restricts their ability to maximise wealth-building opportunities. Studies indicate that financial literacy programs in South Africa remain largely inaccessible to disadvantaged communities (Ngcobo, 2021), reinforcing the cycle of poverty and inequality.

Overall, the role of household finance in South Africa’s context of wealth inequality is apparent. South Africa's history of apartheid and continuing socio-economic disparities have created an uneven system where access to financial services, savings, investments, property ownership, and financial literacy varies across the population. These differences in household finance contribute to the persistence of wealth inequality. Poorer households may be trapped in financial insecurity, unable to build assets or withstand economic shocks, while wealthier households can accumulate assets and pass them on to their descendants. Understanding the nuances in household financial behaviours, such as asset choice decisions, balance sheet compositions, and investment strategies across the wealth spectrum, is crucial for designing targeted policies to address wealth inequality.

Research highlights that households' financial decisions and practices vary significantly based on their wealth levels (Boulware & Kuttner, 2020; Bricker et al., 2019; Doorley & Sierminska, 2014; Feiveson & Sabelhaus, 2019). Poorer households tend to hold a larger share of their wealth in more liquid and less risky assets, such as cash and bank deposits, while wealthier households allocate a larger portion of their assets to riskier, higher-return investments, such as stocks, private equity, and real estate (Chatterjee et al., 2020; Thompson & Suarez, 2019; Wolff, 2016). Additionally, Kuhn et al. (2020) emphasise that less risky assets comprise most of the wealth poorer households hold, while housing becomes the dominant asset for higher-wealth households. However, private equity surpasses housing for the top 1% (Bricker et al., 2019; Saez & Zucman, 2016; Wolff, 2017). This wealth-dependent heterogeneity in asset holding can contribute to widening wealth gaps, as the higher-return investments enjoyed by the wealthy generate larger asset appreciation and wealth accumulation over time.

The literature also indicates differences in the types of debt, with consumer debts more common at the lower end and secured debts more prevalent towards the higher end of the wealth distribution (Haughwout et al., 2019). Lower-wealth households are more likely to rely on high-interest consumer debts, such as payday loans and credit card balances, which can hinder their ability to build assets. In contrast, higher-wealth households tend to access lower-cost, secured debts, such as mortgage loans, which can facilitate investment in wealth-generating assets like real estate (Von Fintel & Orthofer, 2020). Therefore, differences in the composition of the liability side of the household balance sheet can also perpetuate wealth inequality.

Variations in household portfolios and balance sheets across the wealth spectrum are noteworthy. Understanding these nuances of household finance and their connection to wealth inequality is crucial for policymakers seeking to address such disparities.

1.3 THEORETICAL FRAMEWORK

The theoretical premises for this thesis are the life-cycle hypothesis, the permanent income hypothesis, and the portfolio theory framework, which provide insight into the relationship between household finance and wealth inequality. The life-cycle hypothesis of Modigliani and Brumberg (1954) suggests that people aim to smooth their consumption over their lifetime. During their working years, they save and then withdraw their savings in retirement. This model illustrates how variations in household savings and investment patterns can result in divergent wealth outcomes over time. Rather than making financial decisions solely to maximise wealth at a single point, people often aim to smooth their consumption and maintain a stable standard of living throughout their lifetimes. This can result in varying levels of savings and investment, which in turn contribute to the unequal distribution of wealth across households.

The permanent income hypothesis, proposed by Friedman (1957), suggests that people base their spending on their expected long-term income rather than their current income. Households with higher permanent incomes tend to have greater savings and investment capacity, resulting in increased wealth accumulation over time. This framework illustrates how differences in permanent income across households can lead to varying patterns of saving, investment, and wealth accumulation. Precautionary savings also play a role, as individuals facing income uncertainties save for emergencies, balancing current consumption and future security (Antonin, 2020; Carroll & Samwick, 1998).

Behavioural economics examines how psychological and cognitive biases influence decision-making (Beshears et al., 2018), shedding light on household finance and wealth inequality. Factors such as risk aversion and time preferences may systematically influence the financial decisions of different households (Beshears et al., 2018; Buss et al., 2020; Frydman & Camerer, 2016; Lyons & Kass-Hanna, 2021), leading to unequal wealth outcomes.

The portfolio theory provides insights into how individuals' risk preferences and investment strategies influence their wealth outcomes. Wealthy individuals often exhibit higher risk tolerance and have access to a broader range of investment opportunities, enabling them to earn higher returns on their assets. In contrast, less affluent households may prioritise security and face investment constraints, limiting their ability to accumulate wealth at the same pace as their wealthier counterparts. This theory emphasises how people allocate wealth across asset classes based on risk preferences and expected returns. Wealthier households frequently diversify their portfolios, accessing higher-yielding assets, while less affluent individuals may be restricted to lower-risk, lower-return investments, constraining their wealth growth (Buss et al., 2018; Campbell et al., 2018). This theory highlights how differences in investment access and risk-taking capacity perpetuate wealth inequality.

Together, these frameworks elucidate how household financial decisions, particularly those related to saving and investing, are crucial to the persistence of wealth inequality. Concepts such as the life-cycle hypothesis, permanent income hypothesis, precautionary savings, and portfolio choice theory illuminate how differences in saving and investing contribute to the widening wealth gap (Benhabib et al., 2017). Racial disparities in wealth accumulation further exacerbate these inequalities, with substantial implications for broader socioeconomic outcomes (Boen et al., 2020; Thompson & Suarez, 2019).

1.4 RESEARCH QUESTIONS

This study aims to provide a comprehensive discussion on wealth inequality, its determinants, and related policy and theoretical perspectives. Previous research has mainly focused on developed economies (Acemoğlu & Restrepo, 2019; Berns et al., 2023; Motahar & Mamipour, 2025), with comparatively limited attention given to household finance and wealth inequality in developing countries, such as South Africa. Existing studies in South Africa often examine income inequality or consumption patterns (Chatterjee et al., 2020; Fintel & Orthofer, 2020; Jansen & Lensink, 2024; Joubert & Merwe, 2021; Oluwatayo & Babalola, 2019), but few offer a detailed analysis of household balance sheets, asset allocation, and diversification in relation to wealth inequality. Furthermore, the role of adverse life events in influencing wealth outcomes across different levels of diversification remains insufficiently explored. This gap in the literature hampers policymakers' ability to design targeted interventions that consider household financial behaviour and resilience.

This thesis examines the relationship between household finance and wealth inequality in South Africa, addressing three primary questions. Firstly, how does the composition of household balance sheets contribute to the observed wealth inequality in South Africa? Secondly, how do asset allocation decisions among South African households differ across the wealth spectrum, and how do these choices impact wealth accumulation? Finally, to what extent do South African households diversify their assets, and how does this vary across different levels of wealth? Are households with diversified portfolios more resilient to adverse shocks? Addressing these questions will fill an important gap in the literature by connecting household financial decisions to wealth inequality within a developing country context. This understanding can guide the development of more effective interventions to address this issue and foster a fairer distribution of wealth.

1.5 CONTRIBUTIONS

This thesis presents three key contributions. First, it examines the relationship between components of household balance sheets and wealth inequality in South Africa, taking into account various socioeconomic and demographic factors. It employs the Recentred Influence Function (RIF) regression to illustrate how different elements of balance sheets contribute to wealth disparities, informing policymakers and stakeholders about potential avenues for addressing wealth inequality.

Secondly, it examines how households of varying wealth levels allocate their assets, taking into account their socioeconomic and demographic characteristics. It employs Fractional Multinomial regression to elucidate the allocation decisions regarding multiple asset classes. Understanding these patterns offers insights into the financial decision-making of households across different wealth levels, which can inform financial education and investment strategies tailored to specific population groups.

Lastly, the thesis examines the extent of asset diversification across different wealth levels, taking into account relevant socioeconomic and demographic factors. It utilises the Fractional Regression Model (FRM) to investigate how household wealth affects the diversification index and the Ordered Logit Model to elucidate its impact on varying levels of diversification. This understanding can enhance household financial resilience and stability while informing policy interventions that promote more diversified asset portfolios. This thesis contributes to the academic literature regarding wealth distribution, asset allocation, and asset diversification. Furthermore, it offers practical implications for policymakers, financial institutions, and individuals seeking to address wealth disparities and understand financial decision-making processes in South Africa.

1.6 THESIS STRUCTURE

The thesis comprises five chapters. Chapter 1 serves as an introduction. The subsequent three chapters each present a research essay. The first essay examines how the composition of household balance sheets influences wealth inequality. The second essay investigates how households across the wealth spectrum make asset allocation decisions and the impact of these decisions on wealth accumulation. The third essay analyses patterns of household asset diversification and its relationship to wealth levels. Finally, Chapter 5 offers a comprehensive conclusion of the thesis.

CHAPTER 2: THE ROLE OF HOUSEHOLD BALANCE SHEET COMPONENTS ON WEALTH INEQUALITY

2.1 INTRODUCTION

South Africa's extreme wealth inequality raises critical questions about the mechanisms underlying this divide. The country is renowned for its rich cultural heritage, yet infamous for being one of the world's most unequal societies (Webster & Francis, 2019; World Bank, 2022). Recent research highlights significant differences in household asset ownership and debt levels (Engelbrecht, 2014; SA-TIED, 2020), suggesting that both assets and liabilities contribute to wealth disparities. Understanding the distribution of what South African households own and owe can provide valuable insights for tackling South Africa's wealth inequality.

Further evidence suggests that the wealthiest 1% of South African households possess over 55% of the country's wealth, while many face financial difficulties (Chatterjee et al., 2020; SA-TIED, 2020). These stark disparities reflect not only income gaps but also differences in household balance sheets—the assets families own and the debts they owe (Engelbrecht, 2014; Orthofer et al., 2019). Tackling household financial imbalances, such as enhancing access to appreciating assets and reducing high-interest debt, could be vital in addressing wealth inequalities (Chitimira & Ncube, 2020; Orthofer et al., 2019).

Despite efforts to tackle income inequality, wealth inequality remains consistently high (Chatterjee, 2019), potentially driven by differences in household balance sheets. This raises essential questions about the role of household assets and liabilities in perpetuating wealth inequality. Evidence suggests that unequal access to appreciating assets, such as property and financial investments, along with the disproportionate burden of high-interest debt among low-income households, could be significant factors sustaining wealth disparity (Engelbrecht, 2014). This study investigates the contribution of balance sheet composition to wealth inequality, utilising evidence from the National Income Dynamic Study dataset.

Numerous studies have examined wealth inequality in South Africa, providing a solid foundation for this research (Chatterjee, 2019; Chatterjee et al., 2022; Czajka et al., 2021; Fortuin et al., 2022; Fortuin et al., 2022; Orthofer, 2016; Von Fintel & Orthofer, 2020). By examining the relationship between household balance sheets and wealth inequality, this study builds upon previous research that has explored asset ownership and debt burdens as contributors to economic disparities. These earlier studies include a comprehensive analysis of wealth inequality in South Africa, relying on survey and tax data (Orthofer, 2016; Orthofer et al., 2019). This body of work has highlighted the concentration of wealth among the top decile and identified disparities in asset ownership as a significant contributor to inequality. Additional research has revealed that the wealthiest 1% hold over half of the country's wealth, emphasising the prominent role of financial and real estate assets in wealth concentration (Chatterjee, 2019; Chatterjee et al., 2020, 2022). While prior studies largely focused on aggregate wealth distributions, this research narrows the scope to examine household balance sheets[1], disaggregating the influence of specific assets and liabilities on wealth inequality. Building on earlier findings, this study examines the balance sheet composition across wealth distribution and racial groups, investigating how individual components of balance sheets contribute to wealth inequality.

Additionally, Seekings and Nattrass's (2008) work has been crucial in examining the historical and structural factors that contribute to inequality in South Africa. Their research provides crucial insights into

[1] The balance sheet components referred to are assets that include real-estates, business ownership, financial assets, retirement annuities, vehicles, livestock, and liabilities that include business debts, mortgage debt, vehicle debts and financial debts.

racial disparities in wealth accumulation. Their analysis of the long-term effects of apartheid policies offers a vital framework for understanding current wealth disparities. This study builds directly upon their work by analysing how the legacy of historical exclusions continues to influence the composition of household balance sheets.

Mbewe and Woolard's (2016) research indicates that household debt is highly concentrated in South Africa, with wealthier households bearing a larger share of the country's total debt. Similarly, Magwedere and Marozva (2023) found a positive link between household indebtedness and wealth inequality, suggesting that the unequal distribution of debt perpetuates economic disparities. These findings inform the examination of household liabilities in this study, particularly unsecured debt, as a key factor hindering wealth accumulation for disadvantaged groups and exacerbating existing wealth disparities.

Previous studies have also highlighted the exclusion of low-income households from formal financial services, which limits their ability to accumulate wealth (Schoombee, 2009; Von Fintel & Orthofer, 2020). This research aims to build on these findings by examining how the distribution of appreciating assets, such as stocks and retirement funds, could affect wealth inequality in South Africa. Specifically, it investigates whether these financial assets have equalising or exacerbating effects on wealth inequality. In this way, the study reaffirms whether policy solutions to promote wealth equality across South African society, such as improving financial inclusion, could provide more equitable access to wealth-generating instruments.

This study builds on prior work by analysing household balance sheets—how assets, liabilities, and wealth inequality interrelate. It aims to provide practical insights for addressing imbalances in balance sheets, thereby reducing inequality and contributing to both academic literature and policy. It advances research on wealth inequality by thoroughly examining household balance sheets and proposing actionable policy solutions. It complements and expands upon previous research by offering a framework to understand the extent of wealth disparities, the mechanisms that sustain them, and ways to address these issues.

The remainder of this chapter is organised as follows. Section 2.2 summarises a literature review on how the composition of household balance sheets impacts wealth inequality; section 2.3 outlines the theoretical foundations for this chapter. Section 2.4 details the data and methodology. Section 2.5 presents and discusses the empirical results. Finally, section 2.6 offers concluding remarks.

2.2 LITERATURE REVIEW

The makeup of household balance sheets—comprising the assets and liabilities households hold—has significant implications for wealth inequality. This section examines key findings from the literature and highlights methodological gaps, data limitations, and inconsistencies that inform the current study. The composition of the balance sheet can either lessen or increase wealth disparities through the following important mechanisms:

Differential access to wealth-building assets: Wealthier households typically hold a significant portion of their wealth in appreciating assets, such as stocks, bonds, and real estate, whereas less affluent households tend to rely more on cash or non-appreciating assets (Badarinza et al., 2019; Bricker et al., 2019b). Using the U.S. Survey of Consumer Finances (SCF), Bricker et al. (2019b) identify businesses, equity, and housing as three main "risky assets," defining risk as exposure to sudden, unexpected declines in asset prices.

The analysis consistently shows that ownership and portfolio shares of these assets vary significantly across different wealth and income groups, providing strong evidence that wealthier households hold a larger proportion of high-return, riskier assets, such as businesses and equities. This concentration, along with the significant role of capital gains in wealth accumulation, directly influences the patterns of wealth inequality over time.

Badarinza et al. (2019) employ a dual methodology, combining a quantitative analysis of household balance sheet microdata with a comprehensive literature review. The quantitative component relies on official household surveys from six emerging economies (China, India, Bangladesh, the Philippines, Thailand, and South Africa), which are harmonised and compared against data from four advanced economies. The analysis examines both participation rates and allocation decisions across various asset and liability classes. Based on this analysis, the study suggests that differential access to high-return, risky assets contributes to wealth inequality through inefficient participation. While barriers such as high transaction costs and lack of trust limit overall participation, the key issue is that when households in emerging markets do invest, their participation can be inefficient, reducing expected returns. This can directly increase wealth inequality if this "inefficient portfolio construction is more prevalent amongst the less wealthy”. This evidence not only highlights the need for country-specific empirical work but also underscores the importance of investigating the extent to which these assets contribute to wealth inequality in developing countries.

Impact of Debt Composition on Wealth Accumulation: The composition of household debt is also a key factor (Kochhar & Moslimani, 2023; Wolff, 2017). Mortgage debt, often associated with homeownership, usually adds positively to wealth over time, as real estate generally appreciates in value. In contrast, revolving consumer debt, such as credit card debt, does not increase wealth and carries high interest rates, which can diminish wealth. Wolff (2017), using SCF data, demonstrates how high levels of revolving consumer debt hinder wealth accumulation in U.S. households, whereas mortgage debt has a positive impact on long-term wealth. Kochhar and Moslimani (2023), using panel data from the Pew Research Centre, support these findings. However, most of such studies focus on developed economies, leaving a gap in understanding how different types of debt influence household wealth in developing contexts where credit markets tend to be less inclusive.

Financial Exclusion and Limited Access to Services: Disadvantaged households often lack access to formal financial services, including investment accounts and credit, which hampers wealth accumulation (Thompson & Suarez, 2019; Von Fintel & Orthofer, 2020). Von Fintel and Orthofer (2020), using South Africa's National Income Dynamics Survey (NIDS), provide one of the few examples from a developing country that demonstrates how exclusion from financial services sustains inequality. However, their analysis mainly focuses on overall wealth inequality and does not delve deeply into household balance sheet composition.

Effects of Financial Market Participation and Stock Ownership: Participation in financial markets is a crucial factor in wealth accumulation and the distribution of income. Wealthier households are more likely to invest in the stock market, gaining from capital increases. Conversely, lower-income households may have limited access to such investments due to liquidity constraints and a risk-averse attitude. These studies show that households with higher levels of financial assets tend to benefit more from stock market returns, especially during economic upswings, which worsens wealth inequality. Using Norwegian administrative tax data, Fagereng et al. (2017, 2020) demonstrate that wealthier households disproportionately benefit from stock market participation. Similarly, Favilukis (2013) employs calibrated general equilibrium models to highlight these patterns. The "participation divide" thus increases inequality. However, these studies are limited to advanced economies with highly developed financial markets, raising questions about how similar mechanisms operate in South Africa.

Inheritance and Intergenerational Wealth Transfers: Wealth inequality is further intensified by intergenerational transfers. Piketty (2014), using long-term historical data from France, and Keister et al. (2019), based on U.S. household survey data, demonstrate that inheritances significantly concentrate wealth among already wealthy households. While these studies provide strong historical and cross-sectional evidence, data limitations in South Africa mean that intergenerational transfers remain underexplored, creating uncertainty about their role in maintaining local inequality.

Policy Interventions in Balance Sheet Composition: Policy measures aimed at strengthening household balance sheets, such as promoting asset-building programmes for lower-income families, can help reduce wealth inequality. Research indicates that encouraging savings and providing assets through matched or children's savings accounts can enhance the asset portfolios of less affluent households (Boshara & Emmons, 2015). Such policies can narrow wealth gaps over time by helping these families accumulate appreciating assets. Additionally, expanding access to retirement accounts and offering tax credits for contributions have been suggested as effective strategies to enhance balance sheets among disadvantaged groups (Rhee & Boivie, 2015). These policy-focused studies highlight the potential of asset-building programmes to lessen wealth inequality. For example, Boshara and Emmons (2015), using programme evaluation methods in the U.S., find that matched savings accounts increase asset accumulation among low-income households. Similarly, Rhee and Boivie (2015) document how retirement account expansions could support disadvantaged groups. Such evidence emphasises the potential role of targeted interventions but remains largely derived from developed economies.

Synthesis and Research Gap: The reviewed literature consistently shows that the composition of household assets and liabilities influences wealth inequality. However, a notable gap is that most studies rely on datasets from developed economies (e.g., SCF, HFCS, Norwegian tax records), while evidence from developing countries, including South Africa, is limited and often based on aggregate measures of inequality rather than detailed household balance sheet composition analysis. By utilising the NIDS dataset, which includes household-level balance sheet information, and employing econometric methods such as RIF regression, this chapter directly addresses this gap. It contributes to the literature by analysing how household balance sheet composition shapes wealth outcomes. This approach provides a more comprehensive understanding of how household finance contributes to wealth inequality in a developing country context.

2.3 THEORETICAL FOUNDATIONS

2.3.1 Economic Theories or Concepts

The research on household balance sheet composition and wealth inequality can be framed within the theoretical lens of the permanent income hypothesis and life-cycle models of consumption and savings. The permanent income hypothesis posits that households strive to smooth their consumption over their lifetimes, based on their expected long-term income (Fisher et al., 2020; Friedman, 1957). In this framework, the composition of household assets and liabilities influences their ability to achieve this consumption smoothing. Households with greater wealth in the form of appreciating assets, such as real estate or financial investments, can draw on these assets to fund consumption during periods of lower income, thereby maintaining a relatively stable standard of living. These households possess greater financial flexibility and can better withstand economic downturns or fluctuations in income. In contrast, households with limited assets and high-interest debt may struggle to smooth their consumption, as their available resources are constrained. They have fewer options to utilise during times of financial stress and may struggle to sustain their standard of living when faced with reduced income or unexpected expenses.

According to life-cycle models, the accumulation of assets and debts by households over their lifetimes shapes their wealth and consumption (Fernández-Villaverde & Krueger, 2011). Households that can establish appreciating assets, such as homes or financial investments, tend to grow wealthier and exhibit more stable consumption patterns over time. These models indicate that households make savings and investment decisions to support their desired consumption patterns. Households capable of saving and investing in appreciating assets, such as stocks or real estate, can earn higher returns, leading to quicker wealth growth compared to those with primarily non-appreciating assets or high-interest debt.

These theoretical frameworks suggest that the composition of household balance sheets, including the types of assets and liabilities held, can have significant implications for the distribution and accumulation of wealth across households. The permanent income hypothesis and life-cycle models of consumption and savings indicate that the specific makeup of a household's balance sheet, such as the mix of appreciating versus non-appreciating assets or high-interest versus low-interest debt, can either facilitate or hinder a household's ability to smooth consumption, weather economic shocks, and grow its wealth over time. Consequently, the heterogeneity in household balance sheet composition is a crucial factor in understanding and addressing wealth inequality within a society.

2.3.2 Inequality Measures

This study employs the Gini index and percentile shares (P-shares) as primary measures of wealth inequality. These measures are selected for their complementary strengths in capturing both overall inequality and concentration at the top of the distribution.

The Gini index is commonly used in inequality research (Farris, 2010) and offers a single, scale-invariant measure of overall dispersion (Bowles & Carlin, 2020; Gastwirth, 2017). It also adheres to the transfer principle, making it theoretically robust. However, a significant limitation is that the Gini was originally developed for income and might not fully reflect household wealth in contexts where assets such as livestock, land, or informal savings are important (Cowell, 2011). While this study concentrates on the measurable components of wealth in the NIDS dataset, it recognises that the Gini index may underestimate inequality in environments with substantial non-monetary or informal wealth.

Percentile shares (P-shares) provide a complementary perspective by illustrating the proportion of wealth held by specific groups (e.g., the top 1%, the top 10%, the bottom 50%). They are especially effective in revealing extreme concentration at the top (Jann, 2016; Jasso, 2020) and are more intuitive for policy communication than a single Gini coefficient. P-shares are also valuable for decomposition across subgroups (Blanchet et al., 2018). However, they primarily highlight differences between groups and cannot capture disparities within groups. To address this limitation, results from P-shares are interpreted in conjunction with the Gini index, which reflects the overall distribution. Together, these measures help strike a balance between detail and comparability.

Alternative indices, such as the Theil or Atkinson measures, offer the advantage of explicitly capturing both within- and between-group variation, enabling richer decompositions (Shorrocks, 1980). However, they are less intuitive for broader audiences and less commonly used in South African wealth studies, making comparisons across the literature more difficult. The choice of the Gini and P-shares reflects a deliberate trade-off: prioritising interpretability, comparability, and policy relevance, while recognising and acknowledging the limitations inherent in these measures. In sum, while neither the Gini index nor P-shares alone provides a complete picture of wealth inequality, their combined use offers a comprehensive framework for this study. The Gini captures the overall extent of inequality, while P-shares illuminate concentration at the top, both of which are crucial for understanding South Africa's wealth disparities.

2.3.3 Basics of Inequality Measures

When examining inequality or any metric that captures the distributional properties of a specific outcome, having access to essential information is crucial. Typically, this involves the complete set of values related to each observation in the population or sample. If the population or sample $Y = [y_1, y_1, \ldots, y_n]$ consists of a finite number of observations, denoted as n, each value, y_i represents the outcome of interest (such as household wealth).

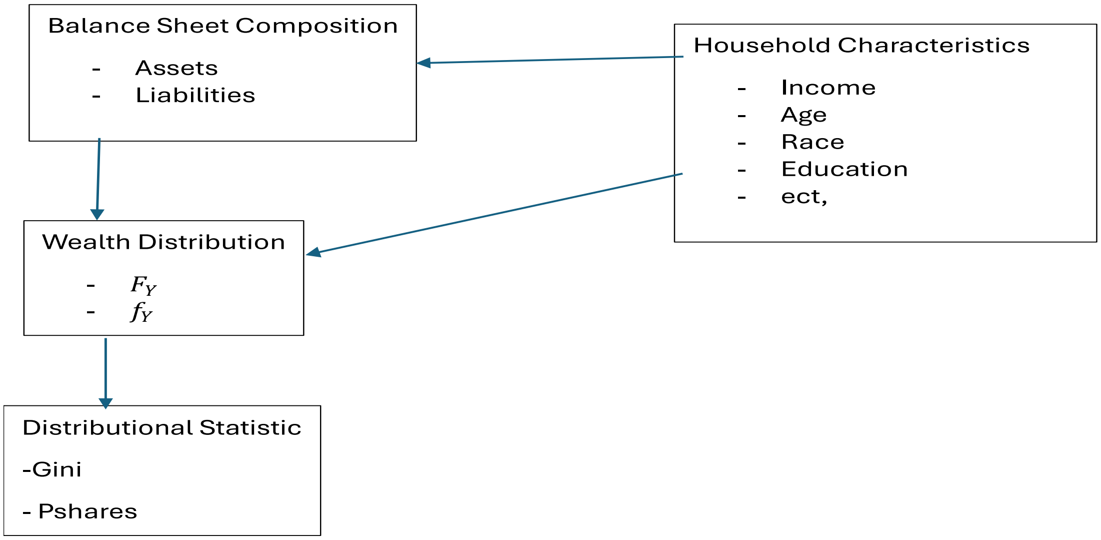
The second scenario occurs when we know the outcome distribution through either the cumulative distribution function (c.d.f, represented as $F_Y(.)$) or the probability distribution function (p.d.f., denoted as $f_Y(.)$). The essential vector of information for analysing distributions can be summarised as a set of ordered pairs, $F_Y = [\{y, F_Y(y)\} | y \in \mathbb{R}]$ or $f_Y = [\{y, f_Y(y)\} | y \in \mathbb{R}]$, where y represents any real number, specifically household wealth in this context. This means that if one has access to any of this information (Y, F_Y, f_Y), all distributional statistics can be derived.

Let $\upsilon(.)$ represents a function that uses all available information from $Y, F_Y, or\ f_Y$ to estimate a distributional statistic for Y. This functional can estimate statistics related to policy analysis, including the mean, q^th quantile, or any inequality index. To evaluate how changes in wealth distribution affect the distributional statistic, one can compare indices by replacing the cumulative distribution function (c.d.f.) from the observed distribution F_Y with the ex-post distribution G_Y. This is articulated as follows:

$$\Delta\upsilon = \upsilon(G_Y) - \upsilon(F_Y) \qquad \ldots (2.1)$$

Consequently, $\Delta\upsilon$ illustrates the change in the distribution statistic resulting from the transition from F_Y to G_Y. We can conduct an experiment involving two scenarios to elucidate this transition. Firstly, let us consider altering the distribution of the components of Y, which causes the function F_Y to shift to G_Y. Secondly, suppose we introduce a new household (with random wealth) to the sample and/or a fixed transfer occurs from one subpopulation to another, thereby impacting the rankings of every household in the distribution. The first scenario emphasises the aim of this study, which is to investigate how variations in household balance sheet components influence shifts in wealth distribution. The second scenario offers a valuable exercise for understanding the relationship between household characteristics and changes in wealth distribution. This leads to the conceptual framework of this study, as summarised in Figure 2.1.

Figure 2.1: Conceptual Framework



This study conceptualises the change in the distributional statistic as a function of wealth components and household characteristics. We continue with the thought experiment to further clarify the change in the distributional statistic.

Considering the addition of a new household to a sample can be seen as an instance of data contamination within the original distribution (Rios-Avila, 2020). This approach helps in estimating how this thought experiment affects the statistic υ. By standardising the change in the statistic $\Delta\upsilon$ relative to a measure that captures the shift in the distribution $[\Delta(G_Y - F_Y)]$, we can quantify the rate at which the statistic υ changes due to the modification of the distribution of Y from F_Y to G_Y.

$$\Delta^s\upsilon = \frac{\Delta\upsilon}{\Delta(G_Y - F_Y)} = \frac{\upsilon(G_Y) - \upsilon(F_Y)}{\Delta(G_Y - F_Y)}$$

Rios-Avila (2020) applied this process to assess $\Delta^s\upsilon$ for an infinitesimally small adjustment in the distribution function from F_Y to G_Y. This idea serves as the foundation for the so-called Gateaux derivative, which extends the directional derivative of a functional. This derivative is used to create influence functions (IFs), which measure the robustness of functionals against data outliers (Hampel, 1974). However, in this experiment, they help illustrate the structure of the distributional statistic based on the available data. Before defining the IF formally, it is helpful to clarify the thought experiment.

Let's assume that the wealth of the observation added to the sample equals y_i. Since this is the only element in that distribution, its cumulative distribution function, $H_{y_i}(y)$, can be defined as follows:

$$H_{y_i}(y) = 0 \ \ \forall \, y < y_i$$
$$H_{y_i}(y) = 1 \ \ \forall \, y \geq y_i$$

This shows that the distribution $H_{y_i}(y)$ assigns mass exclusively to the value y_i. With this understanding, the distribution G_Y can be redefined as a blend of the distributions F_Y and H_{y_i}:

$$G_Y = (1 - \varepsilon)F_Y + \varepsilon H_{y_i} \qquad \ldots (2.2)$$

Where $0 < \varepsilon < 1$. This means that G_Y represents the new distribution created when the original distribution F_Y is shifted toward H_{y_i}. This shift can be viewed as a contamination or perturbation of the distribution F_Y towards H_{y_i}. Additionally, equation … (2.2) quantifies how much the distribution changes when moving from F_Y to G_Y, represented by ε.

Now that we have established this concept, we can present the formal definition of the IF.

$$IF(y_i, \upsilon(F_Y) = \lim_{\varepsilon \to 0} \frac{\upsilon\{(1 - \varepsilon)F_Y - \varepsilon H_{y_i}\}}{\varepsilon} = \frac{\partial \upsilon(F_Y \to H_{y_i})}{\partial \varepsilon}$$

The IF represents a directional derivative that shows how the distributional statistic υ changes in response to an infinitesimally small modification in the distribution F_Y, specifically in the direction of H_{y_i}. Additionally, it can be seen as the impact of observation y_i on estimating the distributional statistic υ. For instance, let's say the distributional statistic is the mean. Here are the definitions for both the statistic and its IF:

$$\mu_{F_Y} = \int y dF_Y$$

$$IF\{y_i, \upsilon(F_Y) = y_i - \mu_y$$

The IF indicates that when the distribution F_Y is altered by giving more weight to observations with wealth y_i, the mean shifts by a rate of $y_i - \mu_y$. If the distribution experiences a change of ε, the mean changes are represented as $\Delta\mu_y = \varepsilon \times IF\{y_i, \upsilon(F_Y)\}$. It is important to note that the IF varies based on each reference point y_i (the contamination point) used in its calculation.

Instead of applying the IF directly, Firpo et al. (2009) recommend using the recentred version, the Recentred Influence Function (RIF):

$$RIF\{y_i, \upsilon(F_Y)\} = \upsilon(F_Y) + IF(y_i, \upsilon(F_Y)\} \qquad \ldots (2.3)$$

This expression can be broadly interpreted as the role that observation y_i plays in forming the statistic υ. It also serves as an approximation of the statistic υ, taking into account the impact of observation y_i. Referring to the earlier discussion on the mean, the $RIF(y_i, \mu_{F_Y})$ is represented by the observation y_i itself, highlighting that y_i indicates the specific contribution of observation i to the computation of the mean.

As noted in the works of Firpo et al. (2009) and Rios-Avila (2020), the IF and RIF possess the following characteristics:

$$\int IF\{y, \upsilon(F_Y)\} dF_Y = 0 \qquad \ldots (2.4)$$

$$\int RIF\{y, \upsilon(F_Y)\} = \upsilon(F_Y) \qquad \ldots (2.5)$$

$$\upsilon(F_y) \sim N\left\{\upsilon(F_Y), \frac{\sigma_{IF}^2}{N}\right\} \qquad \ldots (2.6)$$

$$\sigma_{IF}^2 = \int IF\{y, \upsilon(F_Y)\}^2 \, dF_Y \qquad \ldots (2.7)$$

Equation … (2.4) indicates that the expected value of IFs created from all values of y_i equals 0. This characteristic leads to … (2.5), asserting that the expected value of RIFs corresponds to the distributional statistic. Furthermore, equations … (2.6) and … (2.7) illustrate that the asymptotic variance of any statistic can be derived by estimating the variance of either the IF or RIF from sample data. These properties will make RIF regression quite useful when analysing the effect of balance sheet composition and household characteristics on the distributional statistics of wealth.

2.4 DATA AND METHODOLOGY

This study utilises statistical techniques, including descriptive statistics and regression analysis, to explore the relationships between household balance sheet composition and wealth inequality. It assesses how the assets, debts, and other characteristics of South African households influence measures of wealth distribution, such as the Gini coefficient and the P-shares. This provides insights into the key factors driving wealth inequality in the country. This section outlines the data, descriptive statistics, and Recentred Influence Function (RIF) regression employed to examine the connections between balance sheet composition and wealth inequality.

2.4.1 Data

The study employs the National Income Dynamic Study (NIDS) Survey dataset, a nationally representative longitudinal dataset in South Africa. It offers comprehensive information on components of household balance sheets, socio-demographic characteristics, and income, making it ideal for examining wealth inequality. This dataset is accessible through DataFirst at the University of Cape Town School of Economics. Information regarding household assets and liabilities is available only in waves 2, 4, and 5, collected in 2010/12, 2014/15, and 2017, respectively.

The dataset comprises two types of variables: one-shot and derived variables. One-shot variables are measured directly from questionnaire responses, and these can be subject to recall bias, leading respondents to either underestimate or overestimate the values. The NIDS team prepared derived variables by combining other variables or imputing from responses to follow-up questions related to one-shot responses (Brophy et al., 2018). The study relies more heavily on derived net worth, assets, and liabilities values to adjust for biases stemming from one-shot variables.

NIDS follows up with individuals who are members of the baseline (wave 1) sample of households, referred to as continuing sample members (CSM). Although the dataset is longitudinal in design, its panel structure is somewhat distorted because children born to CSM also become CSM, even though they are not part of the original sample. Additionally, temporary sample members (TSM) who did not participate in the original sample and were not born to a CSM, yet were present in the households during the interview, complicate matters. The overall sample comprises 66.5% CSM and 33.5% TSM. A CSM may disappear in one wave but return in subsequent waves, and some CSMs and TSMs could be lost if we were to enforce a balanced panel, resulting in a sample that would be less than 66.5% of the original. All these factors render the panel structure of NIDS very challenging.

Although NIDS is available in five waves, this study utilises only waves 4 and 5, as waves 1 and 3 did not include wealth questions. While wave 2 addressed wealth questions, its wealth module differs from those in waves 4 and 5, rendering it non-comparable. For instance, wave 2 entirely omitted household possessions, which waves 4 and 5 included. Additionally, wave 2 inquired about the value of life insurance, whereas waves 4 and 5 only asked whether household members possessed life insurance, without inquiring about the value, as respondents are likely to provide inaccurate figures (Brophy et al., 2018). Waves 4 and 5 are similar in all aspects except that wave 5 incorporates a top-up sample of affluent households. This top-up sample is vital for avoiding the underestimation of wealth.

An underestimation of wealth in consumer surveys can arise from an under-sampling of wealthy households, which tend to hold disproportionately higher shares of more valuable assets (Avery et al., 1988). Consequently, population estimates based on these assets may be biased downward. In the context of NIDS wave five, a specific top-up sample was introduced to enrich the data with more high-income and wealthier households. Daniels and Khan (2019) demonstrate that the top-up sample significantly enhances the external validity of the data compared to Wave 4, particularly in terms of household wealth distribution. It also raises the median values of wealth components after weighting and outlier removal, making estimates more consistent with the macroeconomic figures provided by the South African Reserve Bank (SARB).

Overall, the top-up sample in wave 5 corrects for sample attrition and reduces the impact of outliers, thereby enhancing the reliability of the NIDS data for comprehensive research on household wealth. This study only considers waves 4 and 5 because these are directly comparable, unlike wave 2.

2.4.2 Descriptive Statistics and Stylised Facts

Table 2.1 reports the mean and median of household wealth components for waves 4 and 5. The mean values are much higher than the median values, indicating a highly positively skewed distribution of wealth.

Table 2.1: Summary Statistics of Balance Sheet Components

	2014			2017		
Assets/Debts	N	Mean	Median	N	Mean	Median
Real estates	7616	231755.3	55280.89	8155	474349.73	65000
Business assets	337	488730.76	11162.59	411	210460.49	20015.67
Financial assets	4778	23997.48	690.27	5559	81145.07	843.40
Retirement annuities	757	1415584.7	114038.02	1046	694364.97	193031.38
Livestock assets	716	48823.08	13642.87	675	43452.07	15875.68
Possessions[2]	9042	67889.28	19821.41	9978	96226.02	24921.94
Vehicles	1247	123146.3	65859.27	1901	134691.03	78705.70
Total Assets	**9042**	**432124.22**	**75701.70**	**9979**	**624095.13**	**90018.03**
Real estate debts	391	328388.13	150732.81	508	505123.88	245765.97
Business debts	41	48984.945	7119.96	29	42909.36	9968.77
Vehicle debts	374	165821.22	78809.71	553	127466.59	85066.61
Financial debts	4529	26293.51	4026.39	4648	20679.06	3875.73
Total Debts	**4677**	**66604.35**	**4799.91**	**4877**	**87031.49**	**4934.78**

Note: N =number of households with positive holdings of these components. Therefore, calculations have not included households with zero holdings. The mean and median are Rand values adjusted to March 2017 prices.

The skewness is evident in all the balance sheet components, indicating inequality in households' assets and debts. The mean-to-median ratio of total assets is 5.7 in 2014 and 6.9 in 2017, respectively, demonstrating how the observations at the upper end of the asset distribution skew the mean upwards. This effect is even more pronounced for the total debt distribution, which has respective mean-to-median ratios of 13.9 and 17.6. Such skewness suggests that understanding the distribution of each component is crucial in dissecting how they contribute to overall wealth inequality.

Following Davies et al. (2017), this study adopts the widely used indicators of wealth inequality—the Gini index and the percentile shares (P-shares) of household net worth[3]. Table 2.2 and Figure 2.2 show that

[2] In NIDS, Possessions are households' belongings such as durable goods.
[3] Household net worth is the difference between household total assets and total liabilities. In this study it is a measure of household wealth.

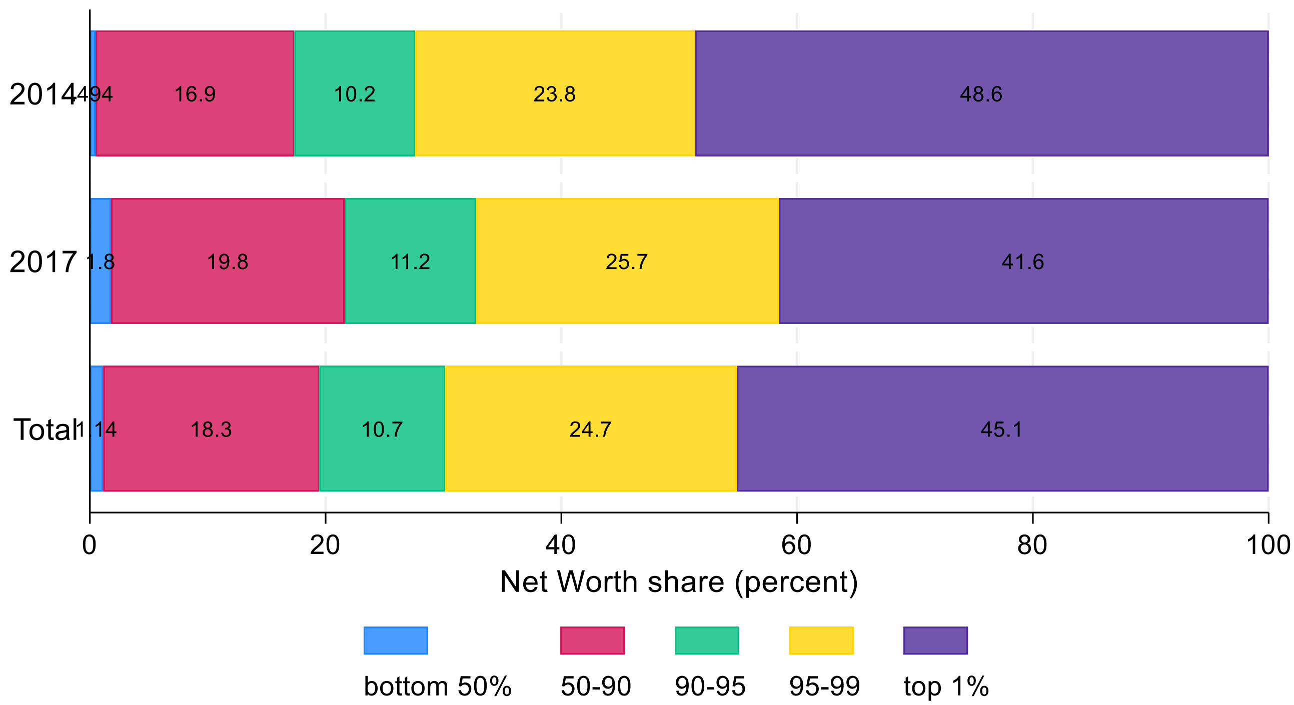
both indicators illustrate a highly skewed distribution of wealth. However, there was a slight decrease in wealth inequality in 2017. The Gini index declined from 87% in 2014 to 85% in 2017. P-shares also demonstrate a declining pattern in wealth inequality, as the wealth share of the poorest 50% of the population increased from less than 0.49% in 2014 to around 1.8% in 2017. Conversely, the wealth share of the wealthiest 1% of the population fell from 48.6% in 2014 to 41.6% in 2017, indicating a declining pattern of wealth inequality.

Table 2.2: Wealth Inequality Indicators

INDICATORS	2014	2017
Gini	0.87***	0.85***
	(0.030)	(0.018)
P-Shares (%)		
0-50	0.494	1.796***
	(0.780)	(0.227)
50-90	16.864***	19.819***
	(3.441)	(2.283)
90-95	10.243***	11.160***
	(2.052)	(1.242)
95-99	23.766***	25.674***
	(4.780)	(2.710)
99-100	48.633***	41.550***
	(9.260)	(5.876)
Observations	9,271	10,366

Note: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

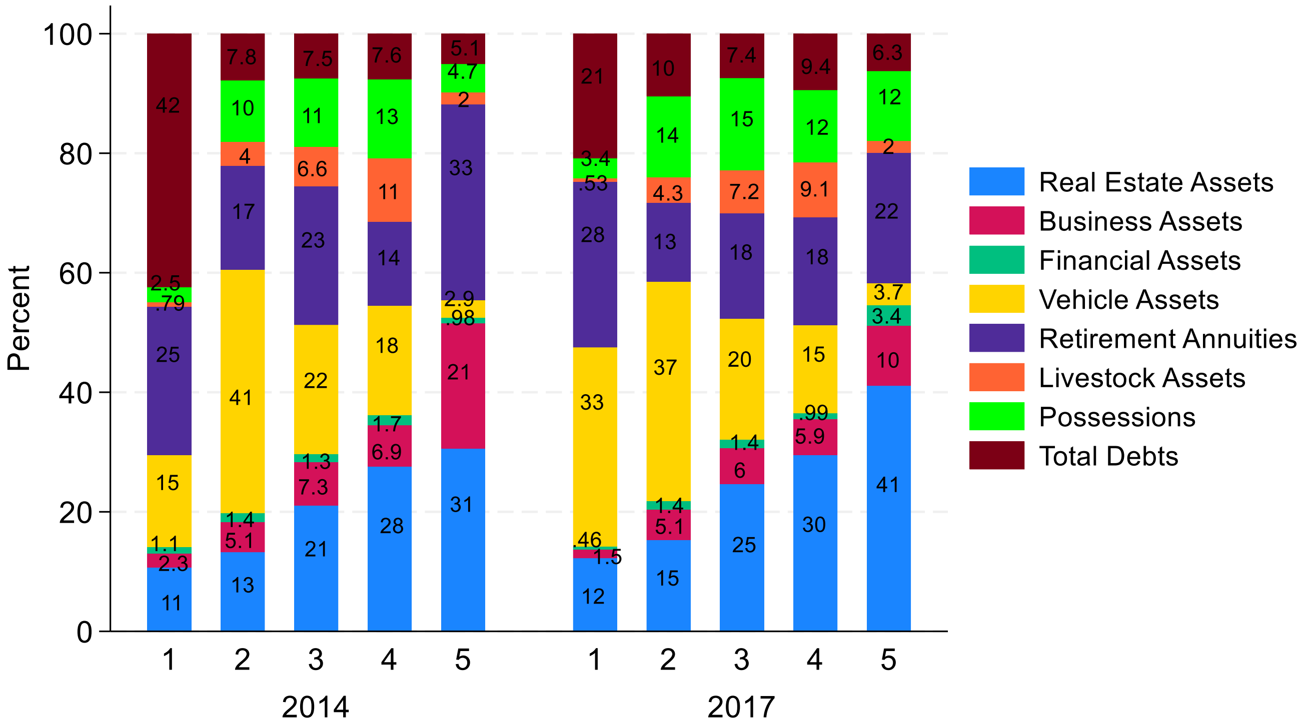
Figure 2.2: Percentile Shares of Household Wealth



Source: Own Computation from waves 4 and 5 using NIDS weights

Table 2.2 and Figure 2.2 reveal a stark picture of inequality. Although there is evidence of a slight decrease in wealth inequality between 2014 and 2017, the overall distribution remains highly skewed, with a disproportionate share of wealth concentrated in the hands of the top 1%. To understand how this inequality relates to the components of the household balance sheet, Figure 2.3 illustrates how the composition of household assets and liabilities varies across the net worth quintiles.

Figure 2.3: Balance Sheet Composition by Wealth Quintiles



Source: Own Mean Computations from waves 4 and 5 using NIDS Weights

In both 2014 and 2017, the wealth composition of South African households indicates that business and real estate assets increase with wealth, whereas vehicle assets decrease as wealth rises. Other assets, including household possessions, retirement annuities, and livestock, exhibit varying trends across different wealth levels. Financial assets also present varying trends but appear negligible overall, except in 2017, when they are significant among the wealthiest 20% following the top-up sample inclusion. At lower wealth levels, vehicles and retirement annuities dominate household portfolios, while real estate and retirement annuities become predominant at higher wealth levels, with business assets also holding a significant share within the wealthiest 20%.

These variations in asset composition by wealth quintile are crucial for understanding the drivers of wealth inequality. The prominence of vehicles and retirement annuities among lower-wealth households suggests a focus on immediate consumption and long-term savings. Conversely, the concentration of real estate and business assets in higher-wealth households indicates a strategic approach to wealth accumulation and diversification. The substantial share of real estate and business assets among the wealthiest quintiles may highlight their role in exacerbating wealth inequality. The relatively low proportion of financial assets held by lower-wealth households signifies limited access to investment opportunities and barriers to wealth accumulation.

Another notable observation is that total debt holdings diminish as net worth increases, suggesting a strong correlation between wealth accumulation and effective debt management. Households with higher net worth typically enjoy better access to credit under more favourable terms, enabling them to leverage their financial positions more effectively. In contrast, lower-net-worth households may depend more heavily on debt to finance consumption or investments, potentially hindering their capacity to accumulate wealth.

Overall, the diverse asset and debt compositions across wealth levels highlight the complexity of wealth inequality and the necessity for a nuanced understanding of the factors contributing to wealth disparities. Additionally, incorporating household characteristics such as age, gender, race, education, and occupation will facilitate the exploration of how these factors interact with asset and debt holdings to shape wealth distribution. As a preliminary example, this section only shows a glimpse of wealth distribution by racial groups. The remaining characteristics are reserved for in-depth analysis in the next section.

Figures 2.4 and 2.5 indicate that Coloureds are the most unequal group, with 64% of their wealth concentrated in the wealthiest 1%, leading to a Gini coefficient of 0.9. Africans come second to Coloureds, with 52% of their wealth in the top 1% and a Gini coefficient of 0.86. Asian/Indians emerge as the third most unequal group, with 16.5% of their wealth belonging to the top 1%, accompanied by a Gini coefficient of 0.77. Whites represent the least unequal group, with only 13.4% of their wealth in the wealthiest 1%, resulting in a Gini coefficient of 0.70.

Figure 2.4: Lorenz Curves of Race Groups

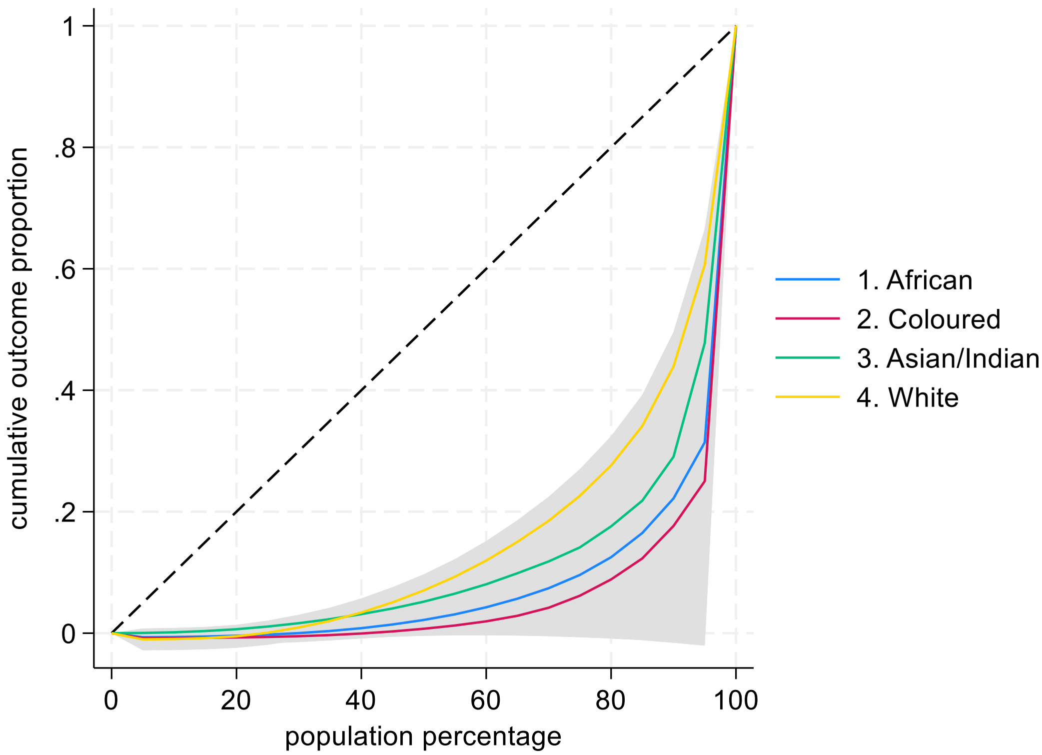
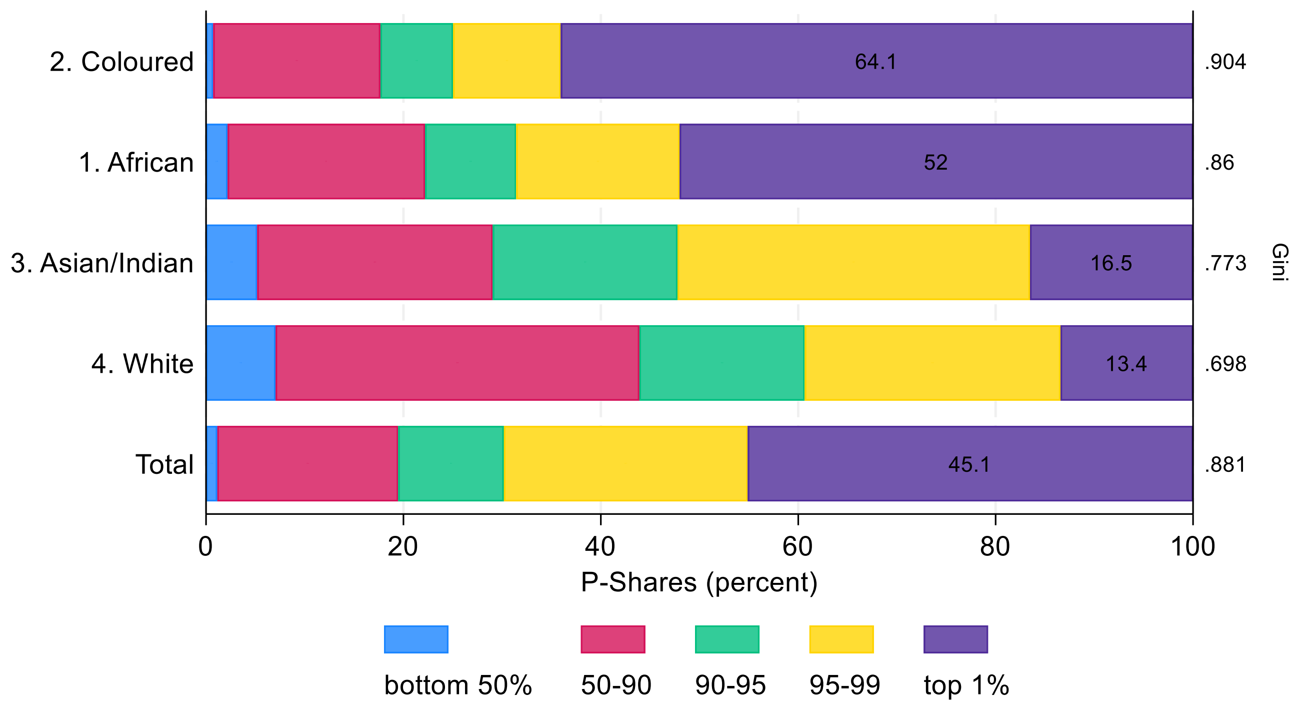


Figure 2.5: Percentile Shares of Wealth by Race



Source: Own computation from pooling Waves 4 & 5. NIDS weights applied

These figures reveal significant disparities. Particularly, wealth concentration among the top 1% remains pronounced, especially for Coloured and African households. These disparities highlight the enduring legacy of historical disadvantage and ongoing structural inequalities. Factors such as access to education, employment opportunities, and financial markets likely contribute to these racial wealth gaps. To fully understand racial wealth inequality, it is essential to explore the specific factors driving these disparities, including asset ownership, debt, and other socioeconomic characteristics.

2.4.3 RIF Regression Technique

As indicated above, IFs and RIFs are utilised in statistics to assess the robustness of data against outliers and to make statistical inferences from complex datasets (Hampel, 1974). Nonetheless, Firpo et al. (2009) advanced the use of RIF regression estimation. The authors leverage this approach to quantify unconditional partial effects (UPE) resulting from small shifts in the distribution of independent variables, X, on the distributional statistic υ. This technique is also applied to estimate unconditional quantile regressions (UQRs), employing linear models as the most straightforward method for approximating these partial effects. Rios-Avila (2020) outlines the estimation of RIF regressions as follows:

Consider a joint distribution function $dF_{Y,X}(y,x) = dF_{Y|X}(y|X = x)dF_X(x)$ that defines both linear and nonlinear relationships between the dependent variable Y and all independent or exogenous variables X. With this function, the probability density function (p.d.f.) and cumulative distribution function (c.d.f.) of the unconditional distribution of Y can be expressed as

$$dF_Y(y_i) = \int dF_{Y|X}(y_i|X = x)dF_X(x) \qquad \ldots (2.8)$$

$$F_Y(y_i) = \int F_{Y|X}(y_i|X = x)dF_X(x) \qquad \ldots (2.9)$$

These expressions indicate that the unconditional c.d.f. and p.d.f. of Y can be obtained by integrating the conditional distributions $F_{Y|X}(.)$, which averages across all realisations of X. It further implies that if we assume $F_{Y|X}(y|x)$ remains constant, then shifts in the distribution of X, such as transitioning from F_X to G_X, will lead to changes in the unconditional distribution of Y.

$$G_Y = \int F_{Y|X}(y_i|X = x)dG_X(x) \qquad \ldots (2.10)$$

Next, let us consider the analysis of the distributional statistic $\upsilon(F_Y)$. From equations … (2.8) and … (2.5), we can express the statistic υ in the following way:

$$\upsilon(F_Y) = \iint RIF\{y, \upsilon(F_Y)dF_{y|X}(y|X = x)dF_X(x) \qquad \ldots (2.11)$$

$$\upsilon(F_Y) = \int E[RIF\{y, \upsilon(F_Y)\}|X = x]dF_X(x) \qquad \text{… (2.12)}$$

A straightforward interpretation of the equation … (2.11) is that any distributional statistic υ can be expressed as the average of the RIFs weighted by the joint distribution $dF_{Y,X}(y, x) = dF_{y|X}(y|X = x)dF_X(x)$. Alternatively, equation … (2.12) shows that any distributional statistic can be obtained by averaging the conditional expectations of the RIFs with respect to X across the distribution $dF_X(x)$. Additionally, equations … (2.10) and … (2.11) indicate that if the distribution of exogenous characteristics X shifts from F_X to G_X, while the conditional distribution $F_{y|X}$ remains constant, the unconditional distribution of Y will change from F_Y to G_Y, resulting in a variation of the distributional statistic from $\upsilon(F_Y)$ to $\upsilon(G_Y)$. Equation … (2.12), utilised by Firpo et al. (2009) to support the application of RIFs in regression analysis, suggests that the change in the distributional statistic due to the transition from F_X to G_X can be approximated by

$$\upsilon(G_Y) - \upsilon(F_Y) = \int E[RIF\{y, \upsilon(F_Y)\}|X = x]\, d(G_X - F_X)(x) \qquad \text{… (2.13)}$$

Equations … (2.12) and … (2.13) also imply that if $E[RIF\{y, \upsilon(F_Y)\}|X = x]$ can be modelled as a function of the distribution of X, those results can be used to estimate how changes in the distribution of X may affect the distributional statistic υ.

Following Firpo et al. (2009), the most straightforward way to estimate RIF regressions is to assume a linear relationship between $RIF\{y, \upsilon(F_Y)\}$ and the explanatory variables X. With this premise, OLS can be used to capture how small shifts in the distribution of the independent variables X affect $\upsilon(F_Y)$. The key difference from the typical OLS model is that while OLS makes y_i a dependent variable, RIF–OLS utilises the $RIF\{y, \upsilon(F_Y)\}$ for each observation y_i as the dependent variable, regressing it on all relevant variables of interest:

$$RIF\{y, \upsilon(F_Y)\} = X'\beta + \varepsilon_i \qquad \text{… (2.14)}$$
$$E(\varepsilon_i) = 0$$

Using OLS directly links RIF regression to standard regression analysis. However, differences exist in the interpretation of results. In standard OLS, coefficients typically imply that a one-unit rise in X results in an average change of β units in y, with all else held constant. However, the interpretation of RIF–OLS varies slightly since it relates to unconditional partial effects (UPE). To derive the UPE for the statistic υ, it is essential first to determine the unconditional expectations on both sides of the equation … (2.14).

$$\upsilon(F_Y) = E[RIF\{y, \upsilon(F_Y)\}] = E(X'\beta) + E(\varepsilon_i) = \bar{X}'\beta \qquad \text{… (2.15)}$$

Where $\bar{X}$ is the unconditional mean of X. From here, the UPE is given by

$$\frac{\partial \upsilon(F_Y)}{\partial \bar{X}_k} = \beta_k \qquad \text{… (2.16)}$$

According to equation … (2.16), the correct interpretation of the UPE is that if the distribution of x_k shifts so that its unconditional average rises by one unit ($\Delta\bar{X}_k = 1$), then the corresponding distributional statistic is expected to change by β_k units. However, this clear and intuitive interpretation encounters limitations with categorical or binary variables because their unconditional mean represents a proportion. This situation requires a more advanced RIF regression approach, detailed in section 2.4.4.

Equation … (2.14) defines the empirical investigation for this study in its explicit form as follows:

$$RIF\{y, \upsilon(F_Y)\} = \delta_{0t} + \sum_{k=1}^{K} \beta_{kt} x_{ikt} + \delta_1 D17 + \varepsilon_{it} \qquad \text{… (2.17)}$$

where $i = household$. x_{ikt} denotes a k^{th} explanatory variable of the i^{th} household in time t, and this includes balance sheet components and household characteristics; β_k denotes the unconditional partial effects of a small change in the distribution of k^{th} explanatory variable on the distributional statistic, and δ_1 denotes time effects on the distributional statistic, and ε_{it} is an error term. $D14$, and $D17$ represent year dummies for 2014 and 2017, respectively, and leave out $D14$ to avoid the dummy variable trap.

Y is the household net worth, and $\upsilon(F_Y)$ is the distributional statistic of the net worth. However, in the case of quantiles, I transform Y because of skewness in the net worth distribution and negative net worth values for some households. I transform each net worth value (y_i) by employing an inverse hyperbolic sine (IHS) transformation, following Meriküll et al. (2021) to transform negative net worth values to positive through the following expression:

$$IHS(y_i) = \ln\left(y_i + (y_i^2 + 1)^{1/2}\right) \qquad \ldots (2.18)$$

The transformed values of net worth, $IHS(y_i)$, have the same interpretation as the log of net worth (Pence, 2006). Therefore, the dependent variable in the equation … (2.17) becomes the RIF of the transformed net worth values in the case of quantiles.

The explanatory variables will be the household net worth components and socioeconomic-demographic characteristics of the household head. The characteristics include race, gender, age, education, marital status, geographical location, and employment status. Beyond just been controls, these variables are crucial for understanding how household attributes correlate with wealth disparities.

Gender is a dummy variable, while race is a categorical variable of four population groups in South Africa. Gender and race are included because of the historical exclusions of women and Africans in South Africa (Chatterjee et al., 2020). Due to such exclusions, we expect differences in gender and race to contribute positively to wealth inequality.

Years of education is a continuous variable ranging from 0 to 17, 17 being the highest number of years one could take to obtain the highest education qualification in South Africa. Given the relationship between education and labour market inequalities in South Africa (Branson et al., 2012; Reddy & Mncwango, 2021), differences in education are expected to contribute positively to wealth inequality as well. Employment status is a binary variable expressed as either employed or unemployed. We expect households headed by employed individuals to have higher net worth, as employment income enhances wealth accumulation through its impact on earnings (Tregenna, 2011). Marital status is a binary variable and helps examine how differences between married-headed and unmarried-headed households relate to wealth inequality.

Another categorical variable is geographical location, with three categories defined according to the 2011 census. The categories are Traditional Authority Area (TAA), urban area, and Farm area. Urban dwellers are likely to have more net worth than other dwellers because assets have more value in urban areas and, therefore, are of higher value. Therefore, we can expect the location to have a significant effect on wealth inequality. We also include age following the lifecycle theory and expect it to have a positive coefficient sign for P-shares. In contrast, we expect the age square term to have a negative coefficient, indicating that individuals accumulate wealth as they age until a certain point, after which wealth begins to decrease.

2.4.4 Effects of Binary Variable in RIF

The regression … (2.17) includes binary variables such as gender and year dummy, and categorical variables such as race. As indicated, the standard RIF regression has limitations when interpreting results for categorical variables. Rios-Avila (2020) illustrates how to properly interpret the results for categorical variables that are involved in RIF regression. This study has a specific interest in the race variable.

I have made whites the reference group for a categorical race variable in the RIF regression. The signs and significance of the coefficients allow us to compare each race with Whites and determine quantiles above or below those of White families. Based on historical context and previous studies, we expect negative coefficients for all other races at all quantiles, mainly higher ones, as White families tend to be wealthier. RIF regressions for Pshares and the Gini coefficient help us assess within-race inequality for each race relative to White families. A positive and significant coefficient for a race indicates greater within-race disparities compared to the White group and vice versa.

RIF regression can intuitively provide the impact of a small distributional change in the explanatory variable, but this is less intuitive in the case of categorical variables (Rios-Avila, 2020). Better intuition can be achieved if we allow a complete transition from one category to another. For a complete change in a binary variable, such as from 0 to 1, Firpo and Pinto (2016) introduced what they call the inequality treatment effect. Using the equation, $Y = X'\beta + \varepsilon$, and following Rios-Avila (2020), we can illustrate inequality treatment effects as follows: suppose T denotes the categorical variable race such that the joint distribution function of *Y, X,* and T is given by $f_{Y,X,T}(y_i, x_i, T_i)$. In the case of two groups ($T = 0\ and\ T = 1$), the joint distribution function is given as:

$$f_{Y,X}^{t}(y, x) = f_{Y|X}^{t}(T|X) f_{X}^{t}(X) \qquad \dots (2.19)$$

where $T = t \in [0,1]$; and its CDF conditional on T as:

$$F_Y^t(y) = \int f_{Y|X}^t(Y|X)dF_X^t(X)$$

This study aims to compare Whites with each one of the other races (African, Coloured, and Indian), so T is defined as follows:

$$T = \begin{cases} 1, & if\ other\ race \\ 0, & if\qquad white \end{cases}$$

We use the CDF of Y conditional on T to compare the distributional statistic υ between the two groups as follows:

$$\Delta\upsilon = \upsilon_1 - \upsilon_0 = \upsilon\left(F_{Y_1}\right) - \upsilon(F_{Y_0}) \qquad \dots (2.20)$$

where F_{Y_1} and F_{Y_0} represent the unconditional cumulative distribution of two potential outcomes. Since the two outcomes are not simultaneously observable, one of them is observable, and dependent on whether an individual is part of the treated population,

$$Y = T \times Y_1 + (1 - T)Y_0 \qquad \dots (2.21)$$

If the assumptions of unconfoundedness and overlapping hold, Firpo and Pinto (2016) identify the treatment effects defined by the equation … (2.20) using the following procedure:

Since we write the unconditional c.d.f. by integrating the conditional distribution with respect to $\boldsymbol{X}$ and T:

$$F_{Y_t} = \int F_{Y_t|X,T}dF_{X,T} \qquad \dots (2.22)$$

The unconfoundedness assumption implies that $F_{Y_t|X,T=1} = F_{Y_t|X,T=0} = F_{Y_t|X}$, allowing equation … (2.22) to be written solely in terms of the distribution of X:

$$F_{Y_t} = \int F_{Y_t|X} dF_X \qquad \text{… (2.23)}$$

The total distribution of the potential outcomes is never observable; only the distribution of the realised outcome after the assigned treatment is observable. The unconfoundedness assumption further means that we can write the observed distribution of the outcome among individuals who are treated and untreated as:

$$F_{Y_t|T=t} = \int_{i\in t}^{\cdot} F_{Y_t|X} dF_{X|T=t} \quad for \quad t = 0,1 \qquad \text{… (2.24)}$$

which considers only observations in the treated or untreated group. Because the distribution implied by … (2.24) is fully observable, we can use it to identify F_{Y_t} using

$$\hat{F}_{Y_t} = \int_{i\in t}^{\cdot} F_{Y_t|X} \omega_t(X) dF_{X|T=t} \qquad \text{… (2.25)}$$

Where $\omega_t(X)$ is a weighting factor such that $\omega_t(X)dF_{X|T=t}$ resembles the unconditional distribution dF_X. The following is the calculation of the weighting factor:

$$\omega_t(X) = \frac{dF_X}{dF_{X|T=t}} = dF_X \times \frac{P(T=t)}{P(T=t|X=x)dF_X} = \frac{P(T=t)}{P(T=t|X=x)} \qquad \text{… (2.26)}$$

$$\omega_1(X) = \frac{P(T=1)}{P(T=1|X=x)} \quad and \quad \omega_0(X) = \frac{1-P(T=1)}{1-P(T=1|X=x)}$$

When $t = 1$, $P(T = 1)$ is the overall probability that an observation is assigned to the treatment group[4], and $P(T = 1|X = x)$ is the probability that an observation is assigned to the treatment group conditional on the observed characteristics. We can estimate this probability using parametric methods, such as logit or probit models (Firpo & Pinto, 2016).

After obtaining the weights $\omega_1(X)$ and $\omega_0(X)$, we can estimate the treatment effects defined in … (2.20):

$$\Delta\hat{\upsilon} = \upsilon\left(\hat{F}_{Y_1}\right) - \upsilon\left(\hat{F}_{Y_0}\right) \qquad \text{… (2.27)}$$

According to Firpo and Pinto (2016), this is like the estimation of average treatment effects, which $\upsilon\left(\hat{F}_{Y_1}\right)$ and $\upsilon\left(\hat{F}_{Y_0}\right)$ can be obtained by simply estimating the statistic of interest υ using the reweighting factors $\omega_1(X)$ and $\omega_0(X)$ over the sample of treated and untreated observations. However, they can similarly be estimated using RIF regression.

2.5 RESULTS AND DISCUSSION

2.5.1 Pooled RIF Regression

Table 2.3 presents the RIF regression results for wealth inequality measures, including the Gini coefficient, P-shares (bottom 50% and top 1%), and quantiles (median and 90th percentile). The RIF regression results offer insights into the relationship between net worth components, household characteristics, and wealth inequality. Components associated with higher wealth inequality should exhibit positive and significant coefficients in the Gini regression or disproportionate increases in magnitude across the P-shares and quantiles. These coefficients could even exhibit opposing signs, with positive values for higher P-shares and quantiles and negative values for lower P-shares and quantiles, indicating that they widen the

[4] White is the base group in this analysis serving as a control group, and is compared to each one of African, Coloured and Indian. Each of these other race groups will serve as treatment group and will be compared to white.

wealth gap. Conversely, components associated with lower wealth inequality should exhibit negative coefficients for the Gini. Additionally, these components should demonstrate significant positive coefficients in the P-shares and quantile regressions, with greater magnitudes at lower P-shares and quantiles than at higher ones or exhibit significant negative coefficients with larger magnitudes at higher P-shares and quantiles than lower ones.

Table 2.3: RIF Regression of Inequality Measures

	Inequality Measures			Unconditional quantiles	
VARIABLES	Gini	Bottom 50%	Top 1%	Median	P90
Net Worth Components					
Real estates	-0.008***	0.003***	-0.013*	0.132***	0.103***
	(0.002)	(0.000)	(0.007)	(0.003)	(0.005)
Business assets	0.010	-0.002	0.006	0.018***	0.068***
	(0.008)	(0.001)	(0.024)	(0.005)	(0.014)
Financial assets	0.002	-0.000	0.014	0.010***	0.020***
	(0.004)	(0.001)	(0.012)	(0.004)	(0.005)
Vehicle assets	-0.004*	0.001	-0.007	0.048***	0.107***
	(0.002)	(0.001)	(0.005)	(0.003)	(0.009)
Retirement annuities	0.013	-0.003	0.029	0.037***	0.168***
	(0.013)	(0.002)	(0.044)	(0.003)	(0.011)
Livestock	-0.004**	0.001***	-0.007	0.057***	-0.013*
	(0.002)	(0.000)	(0.007)	(0.004)	(0.007)
Possessions	-0.004	0.003***	0.019	0.126***	0.063***
	(0.006)	(0.001)	(0.020)	(0.007)	(0.012)
Consumer debts	-0.001	-0.001	-0.007	-0.020***	-0.056***
	(0.002)	(0.001)	(0.005)	(0.002)	(0.005)
Non-consumer debts	0.029***	-0.010***	0.051**	-0.041***	0.041***
	(0.007)	(0.002)	(0.021)	(0.004)	(0.014)
Household Characteristics					
Household income	0.001	-0.000	0.014	0.401***	0.399***
	(0.011)	(0.002)	(0.032)	(0.014)	(0.028)
Education years	-0.003	-0.000	-0.017	0.056***	0.091***
	(0.004)	(0.001)	(0.015)	(0.003)	(0.007)
Employed vs Unemployed	-0.058	0.010	-0.204	-0.185***	-0.213***
	(0.037)	(0.006)	(0.139)	(0.022)	(0.047)
Age	-0.001	0.001*	0.004	0.027***	0.014**
	(0.002)	(0.000)	(0.004)	(0.004)	(0.006)
Age square	-0.000	-0.000	-0.000	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Race: Ref (4. Whites)					
1. African	-0.208	0.089**	0.526	0.259***	-3.764***
	(0.141)	(0.037)	(0.423)	(0.044)	(0.224)
2. Coloured	-0.218*	0.089**	0.473	0.210***	-3.887***

	(0.131)	(0.035)	(0.382)	(0.049)	(0.226)
3. Indian/Asian	-0.303***	0.091***	0.098	0.639***	-2.303***
	(0.112)	(0.030)	(0.293)	(0.074)	(0.322)
Male vs Female	-0.031	0.002	-0.132	-0.015	0.093**
	(0.032)	(0.005)	(0.099)	(0.027)	(0.039)
Married vs Single	0.001	0.001	0.040	0.071**	-0.080**
	(0.029)	(0.006)	(0.091)	(0.028)	(0.033)
2. Urban	0.030	-0.009*	0.107	0.025	0.098***
	(0.022)	(0.005)	(0.076)	(0.026)	(0.037)
3. Farms	0.112***	-0.031***	0.231**	-0.235***	0.293***
	(0.033)	(0.007)	(0.092)	(0.046)	(0.076)
2017 vs 2014	-0.038	0.010*	-0.113	0.063***	0.126***
	(0.024)	(0.006)	(0.078)	(0.023)	(0.033)
Constant	1.235***	-0.126***	-0.069	4.237***	10.976***
	(0.227)	(0.048)	(0.642)	(0.178)	(0.350)
Average RIF	.853	.025	.435	11.921	14.247
Observations	19,503	19,503	19,503	19,503	19,503

Note: Bootstrapped Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Inequality measures are based on net worth, while quantiles are based on the IHS of net worth. All net worth components, including household income, are in logs. Household characteristics are those of the household head. The coefficients are interpreted in reference to the average distributional statistics provided in the second-to-last row.

The results indicate that business assets contribute to increased wealth inequality. Although the coefficients for business assets are not statistically significant in the Gini and percentile share regressions, the quantile regressions demonstrate that their effects are disproportionately concentrated at the top of the distribution. A 1% rise in the average of business assets leads to a 0.2% (0.018/11.921) increase in median net worth but a 0.5% (0.068/14.247) increase in the 90th percentile. This finding is consistent with Piketty's (2014) framework, which posits that returns on capital tend to exceed income growth, enabling wealthy households to accumulate wealth more rapidly than others. It also corroborates South African evidence that capital-intensive assets disproportionately benefit higher-wealth households (Chatterjee et al., 2020), underscoring the dis-equalising nature of business and financial assets.

Similarly, financial assets and retirement annuities also exhibit dis-equalising influences, with stronger effects at the 90th percentile than at the median. These results align with the existing literature on financial market participation (Fagereng et al., 2017, 2020), which indicates that access to sophisticated financial products and stock ownership primarily benefits wealthier households. They reinforce the theoretical argument that unequal access to financial markets exacerbates wealth inequality (Favilukis, 2013).

In contrast, real estate and livestock have an equalising effect on wealth distribution. A 1% increase in average real estate holdings reduces the Gini coefficient by 0.9% (-0.008/0.853) and decreases the wealth share of the top 1% while boosting the share of the bottom 50%. This supports studies emphasising the wealth-equalising role of homeownership (Di, 2005; Foster & Kleit, 2015) and the theoretical perspective that tangible, widely accessible assets provide households with more secure pathways to wealth accumulation. Livestock, similarly, enhances wealth shares at the bottom and middle of the distribution while reducing those at the top, echoing findings in the agricultural economics literature (Ngigi et al., 2021) and aligning with asset-based theories of poverty reduction (Blank et al., 2009). These results indicate that broad-based access to tangible assets can narrow wealth gaps.

Vehicle assets present a more complex picture. While they show an equalising effect in the Gini regression, their positive and significant impact at higher percentiles suggests that they may exacerbate inequality at the top. This nuance resonates with Duque et al. (2018), who argue that vehicles can be indicators of wealth accumulation but do not provide the long-term returns of appreciating assets such as real estate. This finding underscores the theoretical distinction between depreciating and appreciating assets in household balance sheets.

On the liability side, consumer and non-consumer debts affect inequality in different ways. A 1% rise in consumer debt holdings is associated with a 0.2% decline in median wealth (-0.02/11.921) but a more pronounced 0.4% decrease in the 90th percentile of wealth (-0.056/14.247). Consumer debt exhibits an equalising influence, disproportionately reducing wealth at the top relative to the middle, suggesting it provides liquidity for lower-income households. This finding is consistent with studies that highlight how access to consumer credit can support investments in education and healthcare (Gallagher & Sabat, 2018), even if it does not directly build long-term wealth. In contrast, non-consumer debt—often tied to business loans or mortgages—exacerbates inequality, benefiting households that are already well-positioned to leverage such debt for wealth accumulation. Specifically, a 1% increase in non-consumer debt holdings is linked to a rise in the 90th percentile, the Gini coefficient, and the wealth share of the top 1%, as well as a decline in the wealth share of the bottom 50% and the median. This finding confirms Szymborska's (2019) argument that debt dynamics can reinforce wealth disparities when access is unequal.

Household characteristics also matter. The finding that education widens inequality by disproportionately raising wealth at the top supports the theoretical framework of human capital accumulation (Barth et al., 2020; De Nardi & Fella, 2017; Deming, 2022), while also reflecting the structural inequalities in returns to education in South Africa (Branson et al., 2012). Similarly, age-related wealth accumulation follows a nonlinear pattern, in line with life-cycle models of savings and wealth (Modigliani & Brumberg, 1954). Gender and marital status effects also align with empirical evidence that male-led households and single-headed households tend to experience higher wealth, reflecting persistent gender and household structure disparities.

Geographic and racial disparities reinforce the legacies of apartheid-era spatial and racial segregation (Lehohla & Shabalala, 2014). The finding that Black African, Coloured, and Indian households experience lower wealth than White households reflects both historical disadvantages in wealth accumulation and differential access to capital-intensive assets, aligning with broader theories of structural inequality.

Altogether, these findings strengthen the theoretical link between household balance sheet composition and wealth inequality. Consistent with the literature, capital-intensive and financial assets disproportionately benefit wealthier households, while real estate and livestock help mitigate disparities. The divergent effects of consumer and non-consumer debt highlight the role of credit structures in either reinforcing or reducing inequality. By situating these empirical results within established theoretical frameworks—such as capital accumulation (Piketty, 2014), life-cycle savings (Modigliani & Brumberg, 1954), and financial market participation (Fagereng et al., 2017, 2020)—this study demonstrates how asset composition, liabilities, and household characteristics jointly shape South Africa's persistent wealth inequality.

2.5.2 Inequality Treatment Effects of Race Groups

RIF regression has limitations in interpreting categorical variables, as noted by Rios-Avila (2020). Firpo and Pinto (2016) addressed this issue by introducing the "inequality treatment effect" methodology, which I applied to analyse wealth inequality between and within racial groups relative to Whites[5]. This methodology presents wealth distribution gaps, both raw and controlled for covariates, although the raw gaps may be biased due to the exclusion of covariates.

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[5] This makes a pairwise comparison with White as a control group and each of the other races as a treatment group.

Table 2.4: Estimation of Race Treatment Effects

	Inequality Measures			Unconditional quantiles	
VARIABLES	Gini	Top 10%	Top 1%	Median	P90
Raw Wealth Gap (Ref: 4. White)					
1. African	0.154***	0.183***	0.318***	-2.994***	-2.768***
	(0.024)	(0.037)	(0.076)	(0.041)	(0.134)
2. Coloured	0.186***	0.201***	0.312**	-3.022***	-2.600***
	(0.039)	(0.063)	(0.131)	(0.052)	(0.130)
3. Indian/Asian	0.055	0.085*	0.059*	-1.041***	-1.103***
	(0.034)	(0.046)	(0.032)	(0.105)	(0.226)
With Covariates[6]					
1. African	0.419***	0.535***	0.811***	-1.114***	0.628***
	(0.074)	(0.113)	(0.210)	(0.057)	(0.146)
2. Coloured	0.382***	0.472***	0.693***	-1.151***	0.472***
	(0.058)	(0.087)	(0.173)	(0.063)	(0.150)
3. Indian/Asian	0.183***	0.250***	0.269**	-0.250***	0.552**
	(0.041)	(0.073)	(0.106)	(0.081)	(0.264)
Observations	19,503	19,503	19,503	19,503	19,503

Note: Bootstrapped Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Inequality measures are based on net worth, while quantiles are based on the IHS of net worth. All net worth components, including household income, are in logs. Household characteristics are those of the household head. Observations were pooled over the two waves, 2014 and 2017.

The analysis reveals that inequality measures (Gini, top 10% share, and top 1% share) for Africans, Coloureds, and Indians are significantly higher than for Whites, indicating greater within-group inequality among these groups than among Whites. Without covariates, the largest disparity between unconditional quantiles is observed between Coloureds and Whites, followed by Africans and Whites, with the smallest disparity found between Indians and Whites. This pattern aligns with Figure 2.4 indicating that Coloureds constitute the most unequal population, followed by Africans and then Indians, while Whites represent the least unequal group.

[6] The covariates here includes balance sheet components and household characteristics as in Table 2.4.

With covariates, these inequality measures become even more pronounced. However, Africans now top the list regarding inequality within the group. Africans exhibit the most significant disparities relative to Whites, followed by Coloureds, while Indians show the least inequality. Despite higher within-group inequality among Africans, Coloureds, and Indians, their median wealth remains significantly lower than that of Whites, as indicated by the median wealth gap. This gap is widest for Coloureds, followed by Africans, and narrowest for Indians. The raw 90^{th} percentile wealth gap is negative and significant, reflecting the dominance of Whites. However, after accounting for covariates, this dominance reverses: Africans possess the highest 90th percentile wealth, followed by Indians, with Coloureds displaying the smallest advantage over Whites. This shift underscores the influence of covariates, including net worth components and household characteristics, on reshaping wealth distribution (see Table A2 in the Appendix).

The findings consistently reveal significant wealth disparities between White households and other racial groups, particularly when considering both median and 90th-percentile wealth. While disparities between groups are evident, substantial inequality exists within groups, particularly among Africans and Coloureds. This suggests that factors beyond race, such as education, occupation, and asset ownership, contribute to the exacerbation of wealth gaps within these groups.

Including covariates significantly alters the observed wealth gaps, underscoring the importance of controlling for factors influencing wealth accumulation. For example, White dominance at the top of the wealth distribution diminishes when considering factors such as balance sheet components, household income, education, and occupation. The analysis also reveals varying wealth distribution patterns among racial groups, with a small segment of Africans and Coloureds attaining substantial wealth, likely through entrepreneurship or high-skilled occupations.

These findings underscore the complexity of racial wealth inequality and the necessity for targeted policy interventions. While tackling historical disadvantages and systemic racism is essential, it is equally important to concentrate on the factors that drive wealth accumulation among racial groups. Policies that encourage asset ownership, enhance access to education, and promote entrepreneurship within disadvantaged communities are crucial for alleviating racial wealth disparities.

2.6 CONCLUDING REMARKS

This chapter aimed to investigate the relationship between household balance sheet composition and wealth inequality in South Africa, a country characterised by deep and persistent disparities. The analysis reveals that different components of the balance sheet exert distinct and sometimes opposing effects on wealth distribution. Business assets, financial investments, and retirement annuities tend to widen wealth gaps, disproportionately benefiting households at the top of the distribution. These findings reinforce Piketty's (2014) thesis on capital accumulation and highlight the limited accessibility of capital-intensive assets to most households.

By contrast, real estate, livestock, and household possessions emerge as equalising assets, reducing inequality by enhancing wealth shares among lower- and middle-income households. This resonates with asset-based poverty reduction frameworks (Blank et al., 2009) and supports the view that broad-based ownership of tangible assets can play a stabilising role in wealth distribution. The findings on livestock are particularly relevant in the South African context, where rural and agricultural livelihoods remain important for many households.

Debt structures also carry important distributional consequences. Consumer debt, while often criticised for its risks, appears to have an equalising effect, largely because it reduces wealth at the top more than at the median. In contrast, non-consumer debt, such as mortgages and business loans, exacerbates inequality by primarily benefiting those who are already well-positioned to leverage such credit. This divergence highlights Szymborska's (2019) assertion that debt dynamics can either reinforce or mitigate inequality, depending on access and purpose.

The analysis of household characteristics provides further insights into the persistence of inequality. Education, while increasing overall wealth, tends to benefit higher-wealth households disproportionately, reflecting unequal returns to human capital investment in South Africa. Age-related effects confirm the life-cycle hypothesis (Modigliani & Brumberg, 1954), while gender, marital status, and geographic location reveal the continued salience of structural and demographic factors. Racial disparities remain stark, echoing the legacy of apartheid-era exclusion from wealth accumulation (Lehohla & Shabalala, 2014).

From a policy perspective, these findings underscore the need for interventions that extend beyond income redistribution to address the underlying structural composition of wealth. Expanding access to appreciating assets such as housing and productive agricultural resources, promoting inclusive and affordable credit systems, and creating opportunities for small business development are critical steps toward narrowing wealth gaps. At the same time, structural reforms aimed at improving the returns to education, reducing gendered disparities, and addressing spatial inequalities are necessary for sustained progress.

This study also makes a theoretical contribution by demonstrating how the interplay between asset ownership, liability structures, and demographic factors aligns with and extends established frameworks such as capital accumulation theory, human capital theory, and life-cycle models of wealth. By situating South Africa's experience within these broader perspectives, the findings highlight both the universality of certain dynamics and the distinctiveness of contexts shaped by historical inequality.

Nevertheless, limitations remain. The reliance on survey data means that informal and non-monetary wealth—such as community-based assets, informal savings mechanisms, and social capital—are not fully captured. Similarly, the measures of inequality employed, while robust, may not reflect within-group disparities or dynamic changes over longer periods.

Future research could address these gaps by incorporating longitudinal and administrative data to track wealth accumulation over time, as well as exploring the role of informal and non-financial assets in shaping wealth outcomes. Further investigation into the long-term effects of financial shocks, the intergenerational transmission of wealth, and the implications of emerging asset classes (such as digital assets) would also add valuable insights. Comparative studies with other developing economies could deepen understanding of how structural and institutional differences mediate the relationship between household finance and wealth inequality.

Generally, this study underscores the central role of household finance in driving wealth inequality in South Africa. It demonstrates that addressing inequality requires not only tackling income disparities but also reshaping access to and the distribution of wealth-building assets. By integrating empirical evidence with theoretical frameworks, the study provides a foundation for policy and academic debates on how to foster a more inclusive and resilient economic system.

Appendix A Chapter 2

Table A1 provides RIF regression to analyse the change in wealth distribution between the periods 2014 and 2017. The base period is 2014, and 2017 serves as a treatment variable.

Table A1: RIF Estimation of Year Treatment Effects

	Inequality Measures			Unconditional quantiles	
VARIABLES	Gini	Top 10%	Top 1%	Median	P90
Raw Gap					
2017	-0.013	-0.003	-0.081	0.193***	0.515***
	(0.028)	(0.047)	(0.085)	(0.032)	(0.0343)
With Covariates					
2017	-0.036	-0.035	-0.111	0.058***	0.120***
	(0.027)	(0.035)	(0.093)	(0.017)	(0.037)
Covariates					
Real estates	-0.009***	-0.010***	-0.014**	0.132***	0.096***
	(0.002)	(0.003)	(0.006)	(0.004)	(0.005)
Business assets	0.010	0.020	0.009	0.017***	0.083***
	(0.008)	(0.017)	(0.028)	(0.004)	(0.013)
Financial assets	0.002	0.007	0.016	0.009***	0.023***
	(0.004)	(0.005)	(0.010)	(0.003)	(0.006)
Vehicle assets	-0.004*	-0.008**	-0.008	0.049***	0.109***
	(0.003)	(0.003)	(0.006)	(0.003)	(0.009)
Retirement annuities	0.015	0.026	0.031	0.038***	0.158***
	(0.010)	(0.016)	(0.036)	(0.003)	(0.010)
Livestock	-0.004*	-0.006*	-0.005	0.058***	-0.012*
	(0.002)	(0.003)	(0.009)	(0.005)	(0.007)
Possessions	-0.003	-0.003	0.019	0.127***	0.062***
	(0.005)	(0.008)	(0.018)	(0.007)	(0.012)
Consumer debts	-0.000	-0.004	-0.007	-0.019***	-0.053***
	(0.002)	(0.003)	(0.007)	(0.003)	(0.005)
Non-consumer debts	0.032***	0.036***	0.056***	-0.041***	0.036***
	(0.006)	(0.010)	(0.020)	(0.003)	(0.011)
Household income	-0.001	-0.009	0.006	0.412***	0.368***
	(0.009)	(0.019)	(0.033)	(0.018)	(0.033)
Education years	-0.003	-0.010	-0.018	0.056***	0.091***
	(0.005)	(0.006)	(0.014)	(0.003)	(0.007)
Employed vs Unemployed	-0.064*	-0.097*	-0.220*	-0.173***	-0.197***
	(0.034)	(0.058)	(0.121)	(0.024)	(0.039)
Age	-0.001	-0.000	0.003	0.027***	0.013**
	(0.002)	(0.003)	(0.005)	(0.004)	(0.006)
Age square	-0.000	-0.000	-0.000	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male vs Female	-0.032	-0.058	-0.148	-0.013	0.092***
	(0.027)	(0.041)	(0.102)	(0.027)	(0.034)

Married vs Single	0.002	0.007	0.039	0.075***	-0.041
	(0.025)	(0.040)	(0.090)	(0.026)	(0.034)
Location: Ref (Traditional Authority Areas-TAA)					
2. Urban	0.032	0.040	0.114	0.007	0.057
	(0.020)	(0.033)	(0.074)	(0.030)	(0.044)
3. Farms	0.120***	0.175***	0.271***	-0.275***	0.268***
	(0.029)	(0.052)	(0.077)	(0.044)	(0.069)
Race: Ref (4. Whites)					
1. African	-0.176	-0.267	0.562	0.221***	-3.394***
	(0.136)	(0.234)	(0.446)	(0.059)	(0.186)
2. Coloured	-0.187	-0.301	0.498	0.165***	-3.492***
	(0.123)	(0.204)	(0.408)	(0.064)	(0.190)
3. Indian/Asian	-0.280**	-0.448**	0.143	0.656***	-2.201***
	(0.112)	(0.227)	(0.286)	(0.101)	(0.315)
Constant	1.213***	1.369***	-0.004	4.191***	10.976***
	(0.197)	(0.375)	(0.685)	(0.213)	(0.332)
Observations	19,503	19,503	19,503	19,503	19,503

Note: Bootstrapped Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Inequality measures are based on net worth, while quantiles are based on the IHS of net worth. All net worth components, including household income, are in logs. Household characteristics are that of the household head.

While the data in Table 2.2 and Figure 2.2 suggest that wealth inequality declined between 2014 and 2017, the results do not fully corroborate this change in inequality measures. The only exception is that the wealth share of the bottom 50% differed significantly between the two years, albeit at a 10% significance level. The median and 90th percentile wealth values also differ significantly across these years. This study examines the role of net worth components and household characteristics in determining wealth inequality. However, future research could explore the drivers of the observed changes in wealth distribution over time. However, Table A1 provides insights into the net worth components and household characteristics that contribute to the wealth gap between 2014 and 2017.

Table A2 provides a RIF regression that analyses the wealth distribution between races, Africans, Coloureds, and Indians, each compared to Whites. The Whites serve as a base group, and each of the other races serves as a treatment variable.

Table A2: RIF Estimation of Race Treatment Effects

	Inequality Measures			Unconditional quantiles	
VARIABLES	Gini	Top 10%	Top 1%	Median	P90
Raw Wealth Gap					
1. African	0.154***	0.183***	0.318***	-2.994***	-2.768***
	(0.024)	(0.037)	(0.076)	(0.041)	(0.134)
2. Coloured	0.186***	0.201***	0.312**	-3.022***	-2.600***
	(0.039)	(0.063)	(0.131)	(0.052)	(0.130)
3. Indian/Asian	0.055	0.085*	0.059*	-1.041***	-1.103***
	(0.034)	(0.046)	(0.032)	(0.105)	(0.226)
With Covariates					
1. African	0.419***	0.535***	0.811***	-1.114***	0.628***
	(0.074)	(0.113)	(0.210)	(0.057)	(0.146)
2. Coloured	0.382***	0.472***	0.693***	-1.151***	0.472***
	(0.058)	(0.087)	(0.173)	(0.063)	(0.150)
3. Indian/Asian	0.183***	0.250***	0.269**	-0.250***	0.552**
	(0.041)	(0.073)	(0.106)	(0.081)	(0.264)
Real estates	-0.011***	-0.010	-0.006	0.130***	0.085***
	(0.003)	(0.006)	(0.011)	(0.003)	(0.004)
Business assets	-0.005	-0.007	-0.027	0.024***	0.065***
	(0.005)	(0.010)	(0.016)	(0.004)	(0.015)
Financial assets	0.003	0.007	0.016	0.007**	0.016**
	(0.007)	(0.011)	(0.022)	(0.003)	(0.006)
Vehicle assets	0.005	0.007	0.007	0.041***	0.111***
	(0.004)	(0.005)	(0.009)	(0.003)	(0.009)
Retirement annuities	0.024	0.037	0.046	0.039***	0.158***
	(0.018)	(0.032)	(0.062)	(0.003)	(0.009)
Livestock	-0.008***	-0.012***	-0.015***	0.054***	0.001
	(0.002)	(0.003)	(0.005)	(0.004)	(0.008)
Possessions	-0.000	0.005	0.018	0.120***	0.089***
	(0.005)	(0.009)	(0.015)	(0.006)	(0.012)
Consumer debts	-0.003	-0.009***	-0.013**	-0.020***	-0.046***
	(0.003)	(0.003)	(0.005)	(0.002)	(0.005)
Non-consumer debts	0.043***	0.051***	0.076**	-0.042***	0.026***
	(0.010)	(0.015)	(0.033)	(0.004)	(0.010)
Household income	0.022	0.029	0.076*	0.409***	0.465***
	(0.014)	(0.022)	(0.042)	(0.021)	(0.027)
Education years	-0.004	-0.010	-0.025	0.054***	0.094***
	(0.008)	(0.013)	(0.022)	(0.004)	(0.006)
Employed vs Unemployed	-0.091	-0.129	-0.275	-0.191***	-0.223***
	(0.066)	(0.115)	(0.192)	(0.024)	(0.035)
Age	0.000	0.001	0.005	0.028***	0.029***
	(0.003)	(0.005)	(0.009)	(0.004)	(0.005)
Age square	-0.000	-0.000	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male vs Female	-0.047	-0.083	-0.176	-0.021	0.112***
	(0.055)	(0.083)	(0.143)	(0.020)	(0.039)
Married vs Single	-0.008	-0.006	0.011	0.061**	0.009

	(0.054)	(0.084)	(0.145)	(0.024)	(0.042)
Location: Ref (TAA)					
2. Urban	0.081***	0.108**	0.219***	0.005	0.079*
	(0.029)	(0.047)	(0.081)	(0.028)	(0.046)
3. Farms	0.132***	0.167***	0.231***	-0.241***	0.150**
	(0.027)	(0.032)	(0.066)	(0.039)	(0.071)
2017 vs 2014	-0.065**	-0.073	-0.132	0.091***	0.068**
	(0.033)	(0.057)	(0.114)	(0.020)	(0.034)
Constant	0.370*	0.106	-0.891	5.645***	5.595***
	(0.215)	(0.309)	(0.577)	(0.264)	(0.375)
Observations	19,503	19,503	19,503	19,503	19,503

Note: Bootstrapped Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Inequality measures are based on net worth, while quantiles are based on the IHS of net worth. All net worth components, including household income, are in logs. Household characteristics are that of the household head. White is the base group. Observations were pooled over the two waves, 2014 and 2017.

CHAPTER 3: HOUSEHOLD ASSET ALLOCATION ACROSS WEALTH DISTRIBUTION IN SOUTH AFRICA

3.1 INTRODUCTION

Wealth is a key element of financial security and economic resilience. However, households vary greatly not only in the amount of wealth they gather but also in how they distribute it across different asset types. While wealthier households typically diversify their portfolios between financial markets and physical assets, many lower- and middle-income households struggle to develop or maintain even modest asset holdings (Bricker et al., 2019b; Gabaix et al., 2023). These gaps are especially evident in emerging economies, where structural obstacles to market access, unequal availability of financial products, and deficiencies in financial literacy increase wealth inequality (Adel, 2024). South Africa illustrates this well: even after significant institutional reforms following the end of apartheid, it remains among the most unequal societies worldwide (Chatterjee et al., 2020; Von Fintel & Orthofer, 2020).

The primary question driving this study is therefore: How does household wealth, in a context of severe inequality such as South Africa, influence asset allocation across a portfolio that includes both financial and non-financial assets? This question is essential not only for academic discussions in household finance but also for shaping financial inclusion and redistribution policies in societies with deep disparities. Specifically, understanding the unique asset allocation patterns across South Africa's wealth spectrum is vital for identifying targeted interventions that can promote greater financial resilience and help close the persistent wealth gap (Fortuin, Grebe, et al., 2022; Fortuin, Makoni, et al., 2022; Von Fintel & Orthofer, 2020). This study, therefore, aims to explore the intricate relationship between household wealth levels and asset allocation strategies, offering insights into how households manage their portfolios across the wealth spectrum in South Africa (Joubert & Van Der Merwe, 2021; Tita & Aziakpono, 2017). The results will provide policymakers with valuable data for improving financial inclusion and asset-building efforts, particularly given the notable research gaps in these areas within South Africa.

Existing research provides a solid foundation for understanding how wealth influences portfolio choices. Theoretical and empirical studies from developed economies consistently show that as households accumulate more wealth, they diversify across a broader range of assets, often moving toward riskier financial products, such as stocks (Campbell, 2006; Gollier, 2002; Guiso & Sodini, 2013; Kochaniak, 2017, 2020). These studies confirm that wealth influences not only what assets households own but also how they structure their portfolios and their risk preferences. However, two main limitations still exist. First, much of this research focuses on developed economies, where financial market participation is common and household portfolios mainly consist of financial assets. Second, existing studies rarely include both financial and non-financial assets in a single framework, ignoring the importance of tangible assets like housing, vehicles, livestock, and durable goods, which are often more central to household wealth in developing economies (Bijgaart & Rodriguez, 2020; Hruschka et al., 2017; Lu et al., 2020).

South African research on household portfolios, while insightful, remains partial. Collins (2005) highlighted the financial diaries of low-income households, demonstrating how resource constraints influence daily allocation choices. Ngwenya and Paas (2012) examined patterns of asset ownership across the life cycle, while Nyakurukwa and Seetharam (2024) explored the connections between financial literacy and participation in the stock market. However, these studies fall short of analysing the broader household assets, leaving unanswered how wealth distribution affects both financial and non-financial components of the portfolio. This gap is notable given South Africa's historical context: apartheid-era policies systematically excluded most of the population from wealth-building opportunities, especially through land and housing ownership, leaving a legacy that continues to influence household portfolios today (Mosomi & Wittenberg, 2020).

South Africa's broader context highlights the importance of this gap. Portfolio allocation in South Africa does not happen in a neutral environment. It reflects persistent inequalities in access to land, housing finance, capital markets, and even basic financial literacy (Dhlembeu et al., 2022; Karambakuwa & Ncwadi, 2021). Non-financial assets, like housing and livestock, remain vital stores of value and sources of resilience for many households (Nguena et al., 2021; Oluwatayo & Babalola, 2020). However, systematic empirical research linking wealth inequality to the full range of household assets is missing, leaving policymakers without solid evidence on how to promote inclusive asset ownership.

This study aims to address these gaps. Using waves 4 and 5 of the National Income Dynamics Study (NIDS), it employs the fractional multinomial logit (FMLOGIT) model to analyse how households across the wealth distribution allocate their resources among financial and non-financial assets. Unlike previous research, this study adopts a comprehensive approach to household portfolios, encompassing both formal financial holdings and tangible non-financial assets within a single analytical framework. This approach facilitates a more nuanced understanding of wealth accumulation strategies, particularly in contexts where informal and tangible assets substantially contribute to household economic security. The methodology overcomes the limitations of earlier studies, which either focus on a narrow set of financial assets or rely on data that significantly underestimates wealth concentration among the wealthiest households (Chatterjee et al., 2020, 2022; Czajka et al., 2021). By combining financial and non-financial assets, this research aims to provide a more accurate representation of household wealth portfolios, particularly in light of the prominent role of housing, pension funds, and other financial assets in the high levels of inequality observed in South Africa.

The contributions of this study are threefold. First, it expands household finance research by including non-financial assets in portfolio allocation analysis within a developing economy. Second, it offers a contextualised view of how South Africa's structural inequalities and historical legacies continue to implicitly influence household financial behaviour. Third, it provides policy-relevant insights by identifying which asset categories can act as tools for more inclusive wealth accumulation and which need targeted interventions, such as financial education, market access reforms, and asset-building programs. Taken together, this study presents both theoretical and practical contributions to understanding wealth and portfolio dynamics in South Africa and beyond. The unique socio-economic landscape of South Africa, characterised by extreme wealth disparity, presents a compelling case for examining the relationship between wealth and asset allocation.

The remainder of this chapter is organised as follows: Section 3.2 summarises the literature review, Section 3.3 presents the data, descriptive statistics and methodology, Section 3.4 discusses the empirical results, and finally, Section 3.5 concludes.

3.2 LITERATURE REVIEW

3.2.1 Theoretical Framework

A theoretical framework for examining how household wealth influences household portfolio allocation decisions draws upon several key economic and financial theories. The first one is the Life-Cycle

Hypothesis (LCH) of Modigliani and Brumberg (1954), which posits that individuals plan their consumption and savings over their lifetime, aiming to smooth consumption across different life stages. Wealth accumulation is central to this, as households save during their working years to finance retirement. In portfolio allocation, LCH suggests that wealthier households, particularly those nearing retirement, may shift their portfolios toward less risky assets to preserve their accumulated wealth. Younger, wealthier households might take on more risk for higher returns (Gomes, 2020).

The second theory is the Permanent Income Hypothesis (PIH) of Friedman (1957), which suggests that consumption decisions are based on long-term expected income rather than current income. Wealth acts as a buffer, enabling households to maintain their consumption during temporary fluctuations in income. It implies that wealthier households with higher permanent income can afford to take on more risk in their portfolios, as they have a larger buffer against potential losses. This hypothesis suggests that wealthier households can better smooth their consumption over time and, therefore, allocate a greater proportion of their assets to higher-risk, higher-return investments. The ability to absorb temporary income shocks enables wealthier households to pursue more aggressive investment strategies that focus on long-term growth, rather than being constrained to hold safer assets to protect against short-term volatility (Gomes & Michaelides, 2005).

A core theory in this analysis is the Modern Portfolio Theory (MPT). MPT, pioneered by Harry Markowitz (1952), emphasises diversification to optimise risk-return trade-offs. It suggests that investors should construct portfolios that maximise expected return for a given level of risk. Wealthier households, with more resources, can create more diversified portfolios, potentially access a wider range of asset classes and achieve a more efficient risk-return trade-off. They can also afford professional financial advice that poorer households cannot.

In finance, a peculiar field exists known as behavioural finance. This field acknowledges that individuals do not always make rational financial decisions (Shefrin, 2009; Statman, 2008). Psychological biases, such as risk aversion, overconfidence, and herding behaviour, can influence portfolio allocation (Byegon, 2020). In this context, wealthier households may be more susceptible to certain biases, particularly over-confidence, which can lead them to assume excessive risk. Conversely, less wealthy households may demonstrate stronger risk aversion, resulting in overly conservative portfolios. A related theory is prospect theory, which elucidates how people make choices in conditions of risk and uncertainty. It illustrates that individuals place greater weight on potential losses than on potential gains (Buss et al., 2020; Kahneman & Tversky, 1979). This can explain why less affluent households, who are more vulnerable to financial losses, tend to invest in safer assets.

In addition to these theories, households face various financial constraints that can significantly influence their portfolio allocation decisions (Curcuru et al., 2010; Von Fintel & Orthofer, 2020). These constraints include limited access to credit, information, and investment opportunities. Less wealthy households often face greater financial constraints, limiting their ability to diversify their portfolios or access higher-yielding investments. In contrast, wealthier households typically have greater access to a broader range of financial markets and products, which allows them to create more diversified portfolios and potentially achieve a more efficient risk-return trade-off. Furthermore, wealthier households may be able to afford professional financial advice, which can further enhance their investment decision-making (Gaudecker, 2015). These financial constraints faced by less wealthy households can contribute to persistent wealth disparities, as their limited ability to accumulate and grow their assets restricts their opportunities for upward mobility.

Additionally, socioeconomic factors such as education, occupation, and social networks can influence financial literacy and investment behaviour (Lusardi & Mitchell, 2014; Van Rooij et al., 2012). Wealthier households often have higher levels of education and access to social networks that provide financial information and advice, leading to more informed portfolio allocation decisions.

More importantly, the relevance of theories on inequality and wealth distribution cannot be overlooked. These theories examine the distribution of wealth within a society. They can explain how historical and structural factors contribute to wealth disparities and how these disparities influence financial behaviour (Boulware & Kuttner, 2020). In highly unequal societies, such as South Africa, wealth concentration can lead to significant differences in portfolio allocation, with wealthier households having greater access to and control over financial resources.

These theories—the LCH, PIH, and MPT—along with behavioural and inequality-focused perspectives, offer valuable insights into how wealth influences portfolio choices. Together, they suggest that wealthier households tend to diversify more, take on higher risks, and utilise financial advice and markets more effectively, while less wealthy households often opt for safer and more limited portfolios. However, these frameworks are primarily developed in settings with mature financial markets, broad access to financial products, and moderate inequality. They provide limited guidance for environments where non-financial assets—such as housing, livestock, and durable goods—are central to household portfolios, and where deep-rooted and structural inequalities heavily influence financial behaviour. This highlights the need to expand household finance theories to include developing economies with extreme inequality, like South Africa, where traditional models may only partially explain asset allocation patterns.

3.2.2 Empirical Evidence

The empirical evidence on how household wealth influences financial decisions originates from the emerging field of household finance. Campbell (2006) pioneered this field, together with other comprehensive overviews by Bertaut and Starr-McCluer (2002) and Guiso and Sodini (2013). This section highlights vital empirical findings in household finance. These empirical analyses often control for demographic factors, such as age and education, as well as financial resources, including income and wealth, to explain portfolio composition. Some studies examine the impact of behavioural characteristics, including risk aversion and preferences, as well as other risks such as health.

According to Gollier (2002), a comprehensive review of theoretical household finance models reveals that household wealth is a crucial variable in asset allocation. Gollier concludes that higher wealth correlates with riskier investment behaviour due to declining relative risk aversion. While Paya and Wang (2016) oppose the view that increases in wealth increase the share invested in risky assets, Cocco (2005) and Cocco et al. (2005) emphasise that higher wealth mitigates the deterrent effect of fixed participation costs. Several more empirical studies on portfolio choice consistently support this positive relationship between wealth and the share of risky assets (Campbell, 2006; Carroll, 2000; Guiso et al., 2002; Guiso & Paiella, 2008; Guiso & Sodini, 2013; Kochaniak, 2017, 2020; Wachter, 2010).

Specifically, Kochaniak (2017, 2020) show that household wealth causes a shift between portfolios of different risk types. They find that increased household net worth encourages households to shift from safe assets to relatively safe and risky ones. A similar relationship holds for nonfinancial risky assets such as real estate and business ownership (Campbell, 2006; Hurst & Lusardi, 2004). Campbell (2006) uncovers that households at the bottom of the wealth distribution tend to hold safe assets, including deposits, US savings bonds, and vehicles.

Income has a similar positive effect to wealth. A study by Cardak and Wilkins (2009) finds that labour income uncertainty discourages investments in risky assets, implying that income stability has a positive effect on the share invested in such assets. One might argue that the mechanism of action in this case is that a higher monthly income provides a better cushion against losses realised on the risky part of one's portfolio. Moreover, numerous studies confirm the positive relationship between household income and the probability of stock market participation (Cho, 2014; Nyakurukwa & Seetharam, 2024).

Labour income risk is an integral part of the concept, which researchers have introduced as background risk. Background risk includes factors such as labour income risk, health risks, homeownership, private business ownership, and other real estate (Blanchett & Guillemette, 2019; Cardak & Wilkins, 2009; Cho, 2014; Gomes & Michaelides, 2004; Vestman, 2019; Yao & Zhang, 2005). The general finding suggests that background risk negatively affects the proportion of investments in stocks, as these risks serve as substitutes for equity risk. The findings suggest interdependence between asset allocations of different risk types. Background risks, such as health risks, shift the portfolio towards safer assets as they increase the overall risk exposure of a household (Heaton & Lucas, 2000). Rosen and Wu (2004) find that individuals with poor health are more likely to hold conservative portfolios.

Another essential factor in a household asset allocation decision is risk tolerance. Households with risk-tolerant members naturally hold riskier assets than those with risk-averse members. Thus, risk preference is crucial in any theoretical portfolio choice model (Gollier, 2002). Several studies (Campbell, 2006; Guiso & Sodini, 2013; Yilmazer & Lich, 2015) have examined and confirmed the effect of risk preferences. Guiso and Paiella (2008) provide a detailed analysis, concluding that more risk-averse individuals choose outcomes with lower risk exposure.

Studies on the life cycle hypothesis show that younger households tend to hold fewer risky assets, with that proportion increasing at a decreasing rate as they age (Ameriks & Zeldes, 2011). Existing views suggest that older investors typically avoid risky and illiquid investments due to shorter time horizons (Brunetti & Torricelli, 2010; Campbell, 2006; Cappelletti et al., 2014; Gollier, 2002; Guiso & Sodini, 2013). However, King and Leape (1998) argue that older investors may manage riskier, more complex portfolios due to greater investment experience, allowing better risk-return assessments. This view aligns with Ameriks and Zeldes (2011), who found no decline in the proportion of financial wealth invested in equities among older investors, making the effect of age on portfolio choices ambiguous. Campbell (2006) notes the difficulty of distinguishing age, time, and cohort effects, often excluding cohort effects as an identifying assumption. In South Africa, Ngwenya and Paas (2012) found that the life cycle hypothesis does not hold for ethnic groups, except for White households in the intermediate stages, who have more financial products than younger and older households.

Education or Financial literacy is generally linked to riskier portfolios (Campbell, 2006; King & Leape, 1998; Lusardi et al., 2017; Nyakurukwa & Seetharam, 2024; Van Rooij et al., 2011). King and Leape

(1998) suggest that highly educated individuals face lower costs in obtaining and understanding asset information. Similarly, Campbell (2006) argues that educated households process information more efficiently, reducing investment errors. Black et al. (2018) find that, for men, higher financial wealth and lower risk aversion are key channels through which additional years of education lead to increased investment in risky assets. In South Africa, Nyakurukwa and Seetharam (2024) demonstrate that educational levels have a significant influence on stock market participation.

Gender is also a significant factor influencing investment behaviour. Empirical studies consistently find that men pursue riskier investment strategies than women (Cupák et al., 2021; Dickason & Ferreira, 2018; Felton et al., 2003; Giannikos & Korkou, 2024). Felton et al. (2003) suggest this gender gap may stem from higher optimism among men about the economy. It can influence investment behaviour, so that when expecting positive economic development, one can rationalise investing in equities. Self-assessed positive expectations may indicate a generally higher level of optimism (Puri & Robinson, 2007). In addition, Cupak et al. (2021) attribute gender differences in risky asset behaviour to self-confidence and financial literacy. However, Hillesland (2019) finds no systematic gender differences in risk preferences in Ghana.

This empirical research consistently shows that wealth and income increase the likelihood of investing in risky assets and promote diversification; however, most of this evidence is primarily based on studies from developed economies. In South Africa, existing research has looked at financial diaries, market participation, and financial literacy; however, it has not systematically linked wealth distribution to comprehensive portfolio allocation. Specifically, little is known about how South African households, in the context of historical legacies and structural barriers (such as the impact of apartheid on asset ownership, ongoing financial exclusion, and unequal access to information), make allocation decisions across different levels of wealth. This study addresses these gaps by using NIDS data and a fractional multinomial logit model to analyse household portfolios across wealth levels. In doing so, it offers (i) a broader empirical framework that includes the entire household portfolio, (ii) a contextual understanding of household investment behaviour in one of the world's most unequal societies, and (iii) policy-relevant evidence to support inclusive asset-building strategies.

3.3 DATA AND ESTIMATION STRATEGIES

3.3.1 Data

This chapter uses the South African National Income Dynamic Survey (NIDS) data set. Before delving into the objective of this chapter, I provide a descriptive analysis of asset ownership rates across the wealth distribution. The aim is to examine how households' wealth allocation into low-risk, moderate-risk, and high-risk categories differs between households at different wealth levels. I aim to investigate how wealth levels influence household risk-taking behaviour, and I categorise all assets available in waves 4 and 5 of NIDS into these three risk classes.

NIDS data on household assets is only available in waves 2, 4, and 5. Other waves did not cover asset questions. However, the Wave 2 wealth module is not directly comparable to Waves 4 and 5 because household wealth in Wave 2 includes a value of life insurance, which the respondents incorrectly provided (Brophy et al., 2018). Waves 4 and 5 avoided this by only asking whether any household member has life insurance, not the value of life insurance. Additionally, Wave 2 did not cover household possessions[7],

[7] Possessions are household belongings that include durable goods.

which were covered in Waves 4 and 5. Therefore, this chapter only utilises waves 4 and 5, where wealth is directly comparable.

Firstly, I aim to understand how wealth levels influence household decisions regarding asset ownership. The asset ownership is a dummy variable. It assigns a 1 to households holding positive values (those greater than R0) and a 0 to non-holders (those with values less than or equal to R0). Due to computational difficulties[8], I analyse this asset ownership variable descriptively. Secondly, I categorise all households' assets available in NIDS into three risk classes—low-risk, moderate-risk, and high-risk —and calculate the share of total assets allocated to each risk class. Then, analyse how these differ across the wealth distribution by creating an indicator variable for each quintile of household net worth, with the first quintile (lowest net worth) as the reference category. Then, I compare each quintile (second, third, fourth, and fifth) to the first quintile across the two periods (waves 4 and 5), using regression techniques explained in section 3.3.5.

Analysing descriptive data using advanced regression techniques offers insight into households' individual asset choices and decisions between asset risk classes. The remainder of this chapter is structured as follows: Section 3.3.2 provides descriptive details of the distribution of assets and ownership rates across nine asset classes, followed by Section 3.3.3, which presents a discussion of these descriptive statistics. Section 3.3.4 details the construction and composition of portfolio shares of each risk class, followed by a descriptive analysis of these risk classes in Section 3.3.4. Section 3.3.5 presents an empirical estimation strategy, followed by empirical results in Section 3.4. Lastly, section 3.5 contains the concluding remarks.

[8] The multivariate probit analysis of the ownership of 9 assets becomes impossible due to a few observations for some assets, leading to very low degrees of freedom (see Table 3.1). e.g. stock holding only has 121 observations.

3.3.2 Descriptive Statistics of Household Assets

This section provides a description of household assets based on NIDS data, categorised by net worth distribution and selected household characteristics. Table 3.1 shows the overall distribution of 9[9] household assets pooled over NIDS waves 4 and 5.

Table 3.1: Descriptive Statistics of Household Assets

Assets	Observations	Mean	Median	Std. Dev.	Min	Max
Owner-occupied House	12244	378069.41	59719.41	2047034.8	0	98306384
Real Estate-excl Home	15771	82068.04	0	1612042.2	0	1.831e+08
Unincorporated Business	748	335830.91	13830.33	2759516	33	54995692
Stocks	121	1246891.8	60000	4510041.9	0	38496984
Bank balance	10337	43891.71	787.51	3388896.3	0	3.443e+08
Vehicles	3148	130117.88	70054.86	242608.15	1.12	8385535
Superannuation	1803	997173.24	157084.78	13696661	1.15	5.742e+08
Livestock assets	1391	46216.73	14314.85	133367	2.2	3079758.8
Possessions (durables)	19020	82754.90	22581.79	999968.66	1.15	1.250e+08
Total Assets	19021	532838.05	82493.54	5751972	51.87	5.767e+08

Notes: Source: Own computation from waves 4 and 5 using NIDS weights. Rand values were adjusted to March 2017 Prices.

Apparently, the standard deviation values are very large relative to the mean values, indicating significant variability or the presence of outliers in the asset values. Meanwhile, the mean and median values of all assets exhibit right skewness. The mean values are significantly higher than the median values for all assets, indicating a right-skewed distribution, where a small number of households own a large portion of the total assets. The median value for Real Estate (excluding Owner-occupied houses) is zero, suggesting that most households do not own real estate. Investment in Stocks has the highest mean value but the lowest participation rate, showing that the fewest households own stocks (121 observations). Investment in Possessions is the most common asset (almost all households have Possession assets), but with a skewed

[9] NIDS provides 7 classes of assets (Real assets, Unincorporated businesses, Financial assets, Livestock, Vehicles, Possessions, and Superannuation). For reasons explained in section 3.3.4, I disaggregated real assets into Owner-occupied house, and Real-estates (excluding owner-occupied house), and Financial assets into Bank Account Balance and Stocks. This disaggregation makes a total of 9 asset classes.

distribution (mean values far greater than median values), indicating that a few households may have valuable possessions.

Table 3.2 shows the distribution of observations and mean values across household net worth quartiles, illustrating ownership patterns at different wealth levels.

Table 3.2: Descriptive Statistics by Household Net Worth Quartiles

	1st quartile		2nd quartile		3rd quartile		4th quartile		All households	
Household Assets	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
Owner-occupied House	2128	38707	2823	31503	3212	92970	4081	1019152	12244	378069
Real estate-excl Home	2422	9220	4130	12396	4577	27326	4642	236040	15771	82068
Unincorporated Business	74	5155	109	10020	187	19424	378	651046	748	335831
Stocks	10	326672	2	673	8	1914884	101	1309770	121	1246892
Bank balance	1879	1739	2097	1977	2654	3405	3707	117955	10337	43892
Vehicles	101	74533	208	43801	600	65247	2239	158028	3148	130118
Superannuation	57	60155	117	27675	279	64771	1350	1313456	1803	997173
Livestock	100	3395	350	10411	580	34052	361	112338	1391	46217
Possessions (Durables)	4615	9489	4805	20136	4832	45140	4768	254894	19020	82755
Total Assets	4616	21744	4805	51844	4832	145786	4768	1904613	19021	532838

Notes: Source: Own computation from waves 4 and 5 using NIDS weights. Means are Rand values adjusted to March 2017 Prices.

Table 3.2 shows that the number of households owning assets and the wealth invested in them increase as net worth rises. The top end of the wealth distribution shows a radical concentration of asset ownership and investment compared to the lower quartiles. The exception is the investment in possession assets. Ownership of possessions remains relatively constant across wealth levels, although the amount invested might still be skewed. Table 3.3 shows a clear pattern of asset ownership in relation to wealth distribution, displaying the percentages of households owning each asset across four quartiles of household net worth.

Table 3.3: Ownership in Asset Classes by Net Worth Quartiles

	Net Worth Quartiles				
Household Assets	1st quartile	2nd quartile	3rd quartile	4th quartile	All Households
Owner-occupied House	43.6%	57.6%	65.5%	83.4%	62.6%

Real Estate-excl House	11.3%	29.9%	32.1%	23.8%	24.3%
Unincorporated Business	1.5%	2.2%	3.8%	7.7%	3.8%
Stocks	0.2%	0%	0.1%	2%	0.6%
Bank Balance	39%	42.9%	54.2%	75.6%	53%
Vehicles	2.1%	4.3%	12.3%	45.7%	16.2%
Superannuation	1.2%	2.4%	5.7%	27.6%	9.3%
Livestock	2.1%	7.2%	11.9%	7.4%	7.1%
Possessions (durables)	96%	98.4%	98.8%	97.4%	97.6

Notes: Source: Own computation from waves 4 and 5 using NIDS weights. The values represent the percentage of households with a positive amount (greater than R0) invested in each asset.

The ownership rate for most assets increases significantly as household net worth rises. However, the ownership of possession assets is roughly constant across the net worth distribution, and it is the highest among all the assets. Ownership of houses increases with wealth, from 43.6% to 83.4%. Bank account ownership rises with wealth, from 39% to 75.6%. Stock ownership is very low across all wealth levels, with only 2% in the top quartile. Except for possession assets, ownership rates at the top end of the distribution significantly dominate those at the lower end.

This descriptive analysis provides a clear picture of the unequal distribution of wealth. The skewed distribution, characterised by low median values compared to mean values for most assets, suggests a significant wealth gap in the population. The low participation in unincorporated businesses, real estate, and stock ownership indicates that many households might lack access to these wealth-building assets. Additionally, the increase in homeownership (i.e., owner-occupied houses) among wealthier individuals suggests that it may be a significant driver of wealth inequality. The increasing ownership of bank accounts by higher-net-worth individuals suggests a potential lack of access to essential financial services for lower-wealth households, implying financial exclusion. However, Possession assets might be relatively constant because they represent essential household items that everyone needs, regardless of their wealth level.

Further analysis of asset ownership by groups (e.g., income level, race, education) helps illuminate which socioeconomic and demographic factors are likely to affect asset allocation patterns. Income level is a crucial factor influencing asset accumulation (Oluwatayo & Babalola, 2020). Analysing ownership patterns across income quartiles or quintiles can reveal significant disparities. Table 3.4 shows asset ownership rates by household income quartiles.

Table 3.4: Ownership in Asset Classes by Income Quartiles

	Household Income Quartiles				
Household Assets	1st quartile	2nd quartile	3rd quartile	4th quartile	All Households
Owner-occupied House	55.3%	58.3%	63.6%	73.2%	62.6%
Real Estate-excl Home	25.4%	24.8%	23.1%	23.9%	24.3%
Unincorporated Business	2.2%	2.1%	3.7%	7.4%	3.8%
Stocks	0%	0%	0.2%	2.2%	0.6%
Bank Balance	26.3%	42.9%	60.6%	82.2%	53%
Vehicles	2.2%	4%	10.8%	47.6%	16.2%
Superannuation	0.5%	1.4%	5.8%	29.3%	9.3%
Livestock	6.6%	8.3%	8.1%	5.6%	7.1%
Possessions (durables)	98.7%	98%	97.4%	96.5%	97.6

Notes: Source: Own computation from waves 4 and 5 using NIDS weights

The results in Table 3.4 reinforce evidence of wealth inequality and reveal interesting asset ownership patterns across income levels. As expected, ownership rates for most assets (including owner-occupied housing, businesses, stocks, bank accounts, vehicles, and superannuation) increase with income quartiles, confirming that higher-income households tend to possess a greater number of wealth-building assets. Real estate ownership, excluding owner-occupied homes (which are likely rental properties), declines with higher income. It might seem counterintuitive, but higher-income households may prefer other investments with potentially higher returns, rely less on rental income, or find managing rental properties less appealing.

Livestock ownership exhibits a distinct pattern, increasing in the middle quartiles (2nd and 3rd) and declining in the top quartile, suggesting that livestock may serve as a source of income or sustenance for lower- and middle-income households. In comparison, wealthier households may prioritise other asset classes or have less need for livestock.

Ownership of Possession assets does not show any significant change across the income quartiles. A possible explanation is that Possession assets likely represent essential durable goods, such as furniture and appliances, needed for everyday living. Regardless of income level, most households might prioritise owning these necessities. Secondly, durable goods can last for several years. Lower-income households may purchase slightly less expensive versions of these items, but they still own similar categories of possessions. Additionally, replacement cycles for these goods might be longer for lower-income households, contributing to similar ownership rates across income quartiles. Perhaps the most basic needs for possessions are met at a certain point, and additional income does not necessarily translate to a significant increase in the quantity or type of these goods owned.

Asset accumulation patterns shift throughout life (Gruijters et al., 2023; Parker et al., 2022). Analysing ownership by age groups can highlight challenges younger generations face or disparities in wealth accumulation across generations. Table 3.5 presents asset ownership rates by age group of household heads. The table reveals that asset ownership increases with age but declines slightly after age 65, with a few exceptions. These exceptions include ownership of real estate (excluding owner-occupied homes) and livestock, which increase continuously, and bank account ownership, which declines gradually. Possession assets show no significant change across age groups. Most other assets, including owner-occupied homes, unincorporated businesses, stocks, vehicles, and superannuation, follow a general pattern of increasing with age before declining after the age of 65.

Table 3.5: Ownership in Asset Classes by Age Groups

	Age-Group of Household Head					
Household Assets	15 - 35	35 - 44	45 - 54	55 - 64	65 - Above	All Households
Owner-occupied House	56.7%	66.2%	66.8%	65.5%	60.7%	62.6%
Real Estate-excl Home	12.5%	20.6%	27.3%	32.6%	37.8%	24.3%
Unincorporated Business	2.6%	4.5%	4.9%	5%	2.7%	3.8%
Stocks	0.4%	0.4%	0.8%	0.8%	0.7%	0.6%
Bank Balance	55%	55.5%	54.7%	51.4%	45.9%	53%
Vehicles	9.5%	18.4%	20%	19.7%	17%	16.2%
Superannuation	6.8%	11.1%	12.7%	10.1%	6.3%	9.3%
Livestock	2.3%	3.7%	8.2%	11.6%	14.1%	7.1%
Possessions (durables)	98.4%	97.9%	97%	96.9%	97.4%	97.6%

Notes: Source: Own computation from waves 4 and 5 using NIDS weights

Table 3.5 provides insights into wealth accumulation across generations. Generally, ownership of most assets increases with age, reflecting a lifetime of earning, saving, and investing. However, ownership of most assets, except for real estate (excluding owner-occupied homes) and livestock, declines slightly after the age of 65. We can attribute this decline to several factors. During retirement, individuals may decumulate assets to fund their retirement lifestyle. Additionally, some assets may be transferred to younger generations through inheritance, and older individuals may sell riskier assets, such as stocks or businesses, and invest in safer options due to increased risk aversion.

The continuous increase in real estate ownership (excluding owner-occupied homes) and livestock with age can be attributed to the tendency of wealthier individuals to continue acquiring investment properties for income generation, even after retirement. Moreover, livestock ownership may be more common among older generations living in rural areas. The constant ownership of possession assets across age groups suggests these assets fulfil essential needs throughout life, aligning with findings from income analysis.

Education can influence access to financial literacy and higher-paying jobs, impacting asset accumulation (Estrada-Mejia et al., 2020; Seja et al., 2024). Analysing ownership patterns by education level can reveal knowledge gaps or limitations in opportunity. Table 3.6 shows asset ownership rates by level of education of household heads.

Table 3.6: Ownership in Asset Classes by Level of Education

	Education Level of Household Head							
Household Assets	No education	Primary	Secondary	Training-no G12	Training with G12	Bachelor	Higher Degree	All Households
Owner-occupied House	53.5%	59.7%	63.2%	67.1%	68.9%	74.2%	82.7%	62.6%
Real Estate-excl Home	41.2%	30.6%	18.5%	18.5%	18.5%	25.5%	39.8%	24.3%
Unincorporated Business	2.3%	3.3%	3.6%	5.6%	4.8%	8.2%	13.3%	3.8%
Stocks	0%	0%	0.3%	0.5%	1.4%	6.4%	14.3%	0.6%
Bank Balance	33.1%	40.7%	54.4%	66.9%	75.4%	85.8%	85.7%	53%
Vehicles	5.1%	6.8%	13.4%	20.9%	37.6%	63.8%	83.7%	16.2%
Superannuation	1.5%	3.1%	7.1%	12.6%	24.4%	44.3%	52%	9.3%
Livestock	17.2%	11.2%	4.6%	3.2%	2.3%	2.1%	2%	7.1%
Possessions (durables)	98.4%	98.1%	97.6%	97.2%	97%	96.3%	91.8%	97.6%

Notes: Source: Own computation from waves 4 and 5 using NIDS weights

Generally, ownership of most assets, such as owner-occupied homes, businesses, stocks, bank accounts, vehicles, and superannuation, tends to increase with education. However, there are exceptions to this trend. Real estate ownership, excluding owner-occupied houses, decreases from 41% for households with no education to 18.5% for those with secondary education, then rises to 39.8% for those with higher degrees. This U-shaped pattern suggests that individuals with no formal education may invest in smaller, local real estate, while those with higher degrees may invest in larger properties. Those with secondary education might lack the capital for real estate investments or prioritise other savings uses.

Livestock ownership drops from 17.2% for households with no education to 2% for those with higher degrees, possibly because higher education leads to urban jobs where livestock ownership is uncommon, and wealthier individuals prefer other investments. Possessions also show a slight decline, from 98.4% for households with no education to 91.8% for those with higher degrees. Despite this, possession assets remain the most owned. This trend suggests that while higher education does not necessarily increase the number of possessions, it may reflect a preference for higher-quality items.

Overall, these findings highlight the significant role education plays in wealth accumulation. Policies promoting education can help reduce wealth inequality. However, the relationship between education and asset ownership is complex, as specific asset types reveal varying investment strategies and priorities. Further exploration could investigate the U-shaped pattern of real estate ownership, analyse the quality and types of possession assets across different education levels, and examine the role of financial literacy programs alongside education in empowering wealth accumulation. By understanding how education affects asset ownership, policymakers can design targeted interventions to promote financial inclusion and bridge the wealth gap.

Table 3.7 shows how employment status, marital status, and gender influence patterns of asset ownership.

Table 3.7: Ownership in Asset Classes by Employment Status, Marital Status and Gender

	Employment status		Marital status		Gender		
Household Assets	Unemployed	Employed	Single	Married	Female	Male	All Households
Owner-occupied House	61.7%	63.4%	59.3%	67.7%	61.6%	64%	62.6%
Real estate-excl Home	29.2%	19.5%	23.4%	25.7%	26.4%	21.5%	24.3%
Unincorporated Business	1.4%	6.2%	2.9%	5.2%	3%	4.9%	3.8%
Stocks	0.2%	1%	0.3%	1%	0.3%	1%	0.6%
Bank balance	42.3%	63.5%	48.5%	59.9%	49%	58.3%	53%
Vehicles	10.5%	21.7%	9.1%	27%	10.9%	23.2%	16.2%
Superannuation	4.1%	14.3%	6.4%	13.7%	6.7%	12.6%	9.3%
Livestock	9.7%	4.6%	6%	8.8%	7.9%	6.1%	7.1%
Possessions (Durables)	97.4%	97.9%	98%	97%	97.4%	97.9%	97.6%

Notes: Source: Own computation from waves 4 and 5 using NIDS weights

Employment Status**:** Employed households generally own more assets, as employment provides income for saving and investment (Lindh & Ohlsson, 1998). However, unemployed households show higher ownership rates for real estate (excluding owner-occupied houses) and livestock. This may be because retirees, who are often unemployed, invest in real estate for income generation, or because unemployed individuals might live in rural areas where real estate and livestock ownership are more prevalent.

Marital Status**:** Married-headed households tend to own more assets compared to single-headed households (Anglade et al., 2022; Giannikos & Korkou, 2024), likely due to the presence of dual incomes and shared household expenses, which facilitate greater savings and investment. However, ownership of possession assets shows only a marginal difference between married and single households, indicating that basic household needs are less dependent on marital status.

Gender**:** Male-headed households generally own more assets, potentially due to the gender pay gap and traditionally higher earning potential for men (Anglade et al., 2022). However, female-headed households show slightly higher ownership rates for real estate (excluding owner-occupied houses) and livestock. Possession assets follow the general trend, with male-headed households having marginally higher ownership rates.

Location significantly influences asset ownership, as housing costs and access to financial services vary across different areas (Arundel & Hochstenbach, 2020). Analysing ownership patterns by rural/urban regions reveals geographic disparities. Table 3.8 examines asset ownership in Traditional Authority Areas (TAAs), Urban, and Farm Areas.

Table 3.8: Asset Ownership by Location Areas

	Location where Household Resides			
Household Assets	TAAs	Urban	Farms	All Households
Owner-occupied House	61.6%	65.2%	43.3%	62.6%
Real Estate-excl Home	32.1%	19.9%	19.1%	24.3%
Unincorporated Business	3.7%	4%	3.2%	3.8%
Stocks	0.1%	1%	0.3%	0.6%
Bank Balance	43.2%	59.3%	51.1%	53%
Vehicles	7.8%	21.7%	14%	16.2%
Superannuation	4.5%	12.7%	5.1%	9.3%
Livestock	16.9%	0.9%	8.2%	7.1%
Possessions (durables)	98.2%	97.1%	99%	97.6%

Notes: Source: Own computation from waves 4 and 5 using NIDS weights

Households in urban areas predominantly own most assets, including owner-occupied houses, businesses, stocks, bank accounts, vehicles, and pensions. Urban areas offer more job opportunities and higher-paying jobs, increasing disposable income for saving and investment. Additionally, urban areas provide better access to financial services, with a higher concentration of banks, investment firms, and other financial institutions, facilitating wealth accumulation.

TAA leads in real estate and livestock ownership. In TAAs, land inheritance is more common, and livestock rearing is often a subsistence activity. Livestock ownership holds cultural significance in some TAA communities. In farm areas, livestock ownership remains high, but it is second to that of TAAs, underscoring the importance of livestock in agricultural activities. Livestock ownership is least common in urban areas, as space and resources for raising livestock are limited.

These results highlight significant geographic disparities in asset ownership. Urban residents have a clear advantage in wealth accumulation across most asset classes. Policies aimed at reducing wealth inequality should consider the geographic location to address the challenges faced by rural populations, including access to financial services, job opportunities, and investment options. Investigating the availability and accessibility of financial services in different areas is crucial. The dominance of livestock ownership in TAAs and farm areas reflects rural livelihood strategies. Policies supporting livestock management practices or value-added products from livestock could benefit rural communities.

The majority race in South Africa may face historical or systemic barriers to wealth accumulation (Cooper, 2007; Seekings, 2008; Seekings & Nattrass, 2008). Analysing their asset ownership patterns can identify areas for policy intervention. Table 3.9 presents asset ownership by racial groups: Africans, Coloureds, Indians, and Whites.

Table 3.9: Ownership in Asset Classes by Race

	Race of Household Head				
Household Assets	African	Coloured	Indian	White	All Households
Owner-occupied House	61.6%	60.3%	73%	80.9%	62.6%
Real Estate-excl Home	25.3%	19.5%	19%	21.9%	24.3%
Unincorporated Business	3.7%	2.3%	7.6%	9.5%	3.8%
Stocks	0.2%	0.4%	1.7%	6.9%	0.6%
Bank Balance	51.1%	51.7%	67.5%	82.7%	53%
Vehicles	11.4%	19%	46%	77.4%	16.2%
Superannuation	7.1%	12.2%	13.1%	34.7%	9.3%
Livestock	8.5%	1.2%	0.4%	1%	7.1%
Possessions (durables)	98.1%	96.4%	95.4%	93.5%	97.6%

Notes: Source: Own computation from waves 4 and 5 using NIDS weights

Asset Ownership Patterns are such that whites predominantly own most assets, including owner-occupied houses, unincorporated businesses, stocks, bank accounts, vehicles, and superannuation. Indians follow Whites in asset ownership. Coloureds come third, while Africans are last in owning most of these assets. This pattern suggests that there have been and continue to be historical and ongoing disparities in wealth accumulation. African majorities might face historical barriers like slavery, discriminatory lending practices, limited access to property rights, hindering wealth accumulation, or systemic inequalities whereby unequal access to education, employment opportunities, and financial services can perpetuate wealth gaps across generations.

Possessions show a reversal of this pattern, with Africans leading at 98.1%, Coloureds coming second at 96.4%, Indians third at 95.4%, and Whites last at 93.5%, aligning with the above finding that possession assets represent essential needs, which most households prioritise regardless of their wealth level. For Real Estate (excluding owner-occupied houses), Africans dominate with 25.3% ownership, followed by Whites at 21.9%, Coloureds at 19.5%, and Indians at 19%. Livestock Ownership shows that Africans lead with 8.5%, Coloureds are second at 1.2%, Whites come third at 1%, and Indians are last at 0.4%, which aligns with the dominance of livestock ownership in rural areas, where Black African and Coloured populations might be more concentrated.

These patterns highlight a significant racial wealth gap, where minority groups hold a disproportionate share of wealth compared to the Black African majority, suggesting that policies aimed at addressing wealth inequality need to be transformative and specifically target the challenges faced by the Black African majority. This could include affirmative action programs that promote equitable access to education, quality employment opportunities, and financial services for Black South Africans, as well as land reform policies that address historical land dispossession and facilitate land ownership for Black South Africans.

3.3.3 Discussion of Descriptive Statistics

The distribution of asset ownership highlights stark inequalities. Bank accounts and owner-occupied housing are the most prevalent among low- and middle-income households, while equities and unincorporated businesses are nearly absent (less than 2%). In contrast, wealthier households hold diversified portfolios, consistent with modern portfolio theory (Markowitz, 1952) and a decline in relative risk aversion (Gollier, 2002). In comparison to advanced economies (Campbell, 2006; Guiso & Sodini, 2013), South African households exhibit significantly lower participation in risky financial assets. Barriers such as high entry costs, limited financial literacy, and lack of trust in formal institutions (Lusardi & Mitchell, 2014; Nyakurukwa & Seetharam, 2024) help explain this gap. Therefore, expanding affordable and accessible investment products, alongside targeted financial literacy programs, could reduce entry barriers into financial markets for low-wealth households.

The financial vs. non-financial balance shows South Africa's distinctive household finance structure. Poorer households rely on possessions and livestock, while the wealthy dominate financial assets. This pattern reflects the realities of developing countries (Oluwatayo & Babalola, 2020), where non-financial assets serve as savings and informal insurance. However, such assets are illiquid, leaving poor households without flexible liquidity. Wealthier households, in contrast, can leverage financial diversification for stability and growth. Therefore, implementing policies to expand access to savings products with flexible liquidity, such as low-fee accounts or micro-investment platforms, could help low-income households transition from illiquid tangible assets to safer financial holdings.

These descriptives also indicate substitution between tangible asset holdings and financial risk-taking. Households with significant livestock or vehicles hold fewer risky financial assets, consistent with the background risk hypothesis (Blanchett & Guillemette, 2019; Yao & Zhang, 2005). These informal, risky holdings crowd out financial participation, amplifying inequality: wealthier households can carry both tangible and risky financial assets, while poorer households cannot. This implies that strengthening agricultural insurance, vehicle credit markets, and informal savings cooperatives could reduce background risks and free up capacity for low-wealth households to enter formal financial markets.

Asset allocation also varies significantly across different racial groups, educational backgrounds, and geographic regions. White and highly educated households exhibit stronger participation in financial markets, whereas Black and rural households tend to remain concentrated in low-yield tangible assets. These disparities align with both South African evidence (Ngwenya & Paas, 2012; Von Fintel & Orthofer, 2020) and global findings (Lusardi & Mitchell, 2014), underscoring the role of historical exclusion, structural inequality, and informational barriers. Therefore, expanding rural banking infrastructure, integrating financial literacy into education, and targeted inclusion strategies for historically disadvantaged groups could be key to reducing structural inequality in household finance.

The Descriptives also suggest lifecycle patterns: younger households hold fewer risky assets, while older households show higher—but uneven—participation. This partially reflects life-cycle predictions (Modigliani & Brumberg, 1954), but deviations are visible, as Black and rural households fail to follow expected wealth-accumulation trajectories (Ngwenya & Paas, 2012). Retirement savings schemes and tailored financial advice could help correct distorted lifecycle patterns, ensuring that disadvantaged households can accumulate assets over time.

In summary, the descriptive evidence highlights clear patterns of household portfolio allocation in South Africa, which align with but also extend existing theoretical insights. As summarised in Table 3.10, wealthier households diversify into riskier financial assets in line with portfolio theory, while poorer households remain concentrated in possessions and livestock, reflecting the role of informal assets as a form of insurance. The findings also illustrate substitution between tangible assets and formal financial risk-taking, consistent with the background risk hypothesis. Importantly, disparities along racial, educational, and geographic lines underscore that portfolio allocation decisions are embedded in historical and structural inequalities, rather than occurring in a neutral environment. Finally, lifecycle dynamics appear, but with deviations unique to the South African context, where younger households underinvest and older disadvantaged households lack asset accumulation. Taken together, these patterns reinforce both the relevance of established household finance theory and the need for context-specific policies to broaden financial inclusion and support equitable wealth building.

Table 3.10: Summary of Descriptive Findings, Theoretical Link and Policy Implications

Finding	Theoretical Link	Policy Implications
Concentration of risky assets (stocks, businesses) among the wealthiest households	Modern Portfolio Theory (Markowitz, 1952); declining relative risk aversion (Gollier, 2002)	Broaden access to investment products (e.g., low-fee funds, micro-investing platforms) and improve financial literacy.
Poor households concentrated in possessions & livestock	Non-financial assets as informal savings/insurance (Oluwatayo & Babalola, 2020)	Promote flexible, low-cost savings instruments to shift households from vulnerable tangible assets to safer financial holdings.
Substitution between tangible assets and financial risk-taking	Background risk hypothesis (Yao & Zhang, 2005; Blanchett & Guillemette, 2019)	Expand agricultural insurance, rural credit, and savings cooperatives to reduce reliance on risky informal assets.
Strong racial, educational, and geographic disparities	Structural inequality and financial exclusion (Ngwenya & Paas, 2012; Von Fintel & Orthofer, 2020)	Targeted policies: rural banking infrastructure, financial literacy in schools, and inclusion programs for historically disadvantaged groups.
Lifecycle patterns with deviations (young households underinvest, older Black/rural households lack accumulation)	Life-cycle hypothesis (Modigliani & Brumberg, 1954) with South African deviations	Strengthen retirement savings, expand employer-based pension schemes, and tailor advice for low-wealth/rural households.
High ownership of essential possession assets across all groups	Essential consumption goods (basic needs; consistent with Engel's law dynamics)	Limited policy scope—suggests a "wealth floor" in essentials; interventions should focus on enabling transition to productive assets.

3.3.4 Composition and Construction of Risk Classes

It is imperative for this chapter to examine the risk profiles of household portfolios across the wealth levels. Since the dataset provides amounts invested in each asset but not their actual returns, a traditional mean–variance approach, as proposed by Markowitz (1952), is not feasible. Instead, I adopt a classification strategy widely used in household finance literature, grouping assets into low-risk, moderate-risk, or high-risk categories.

It is important to note, however, that risk classifications developed in global contexts may not fully align with the South African setting. Differences in political, economic, and financial systems, alongside the significance of informal and subsistence activities, may alter the relative risk profiles of certain assets. For example, livestock plays a more prominent role in household livelihoods and resilience strategies in South Africa compared to developed economies. Therefore, the risk categorisation presented here should be interpreted cautiously, with the understanding that country-specific dynamics may influence the perceived risk of assets.

Moreover, distinguishing between safe and risky assets is inherently challenging, as few assets are completely safe or entirely risky (Carroll, 2000). In the literature, financial assets are often classified as follows: equities are "risky," money market accounts are "safe," and other instruments (bonds, pensions, life insurance) are "fairly safe" (Barasinska et al., 2009; Bucciol & Miniaci, 2015; Carroll, 2000; Kochaniak, 2017, 2020; Mullahy, 2015). Some studies expand the risky category to include non-financial assets such as unincorporated businesses and real estate[10] (Bucciol & Miniaci, 2015; Kochaniak, 2020). This study builds on these classifications by adapting them for South Africa, incorporating liquidity, volatility, and protection against loss into the categorisation of non-financial assets.

Owner-occupied houses represent tangible assets with stable value over time, providing shelter, a basic need, and collateral for loans. Some studies suggest that owner-occupied housing serves as a buffer, enabling households to increase their equity share and participate in the stock market (Iwaisako, 2009). However, risky investments would decline for leveraged housing with commitment expenditures, such as mortgage payments (Cho, 2014; Fratantoni, 2001). Due to its feature of a buffer stock, I classify owner-occupied housing as a low-risk asset.

Essential household items are possessions with a relatively low risk of value depreciation, particularly when well-maintained. Additionally, manufacturers often provide guarantees for a certain period, indicating that these items are considered low-risk. Support for this classification is provided by evidence of substitution between household durables and liquid assets throughout consumers' life cycles (Fernández-Villaverde & Krueger, 2011). Since liquid assets are already considered low-risk, durable goods belong in this category, as they serve as substitutes for liquid assets.

Vehicles provide practical utility and convenience, but also carry financial risks. They tend to lose value quickly and incur ongoing costs, such as insurance and maintenance. They are generally classified as

[10] In this study real estate includes any other property except owner-occupied house. NIDS provides real assets, which comprise owner-occupied houses plus any other property. Because of differences in the inherent risk, I have disaggregated real assets into owner-occupied houses and real estate.

moderate-risk assets, as they are not entirely safe or high-risk. Their characteristics fall between the low-risk and high-risk categories (Martins, 2023).

Livestock can generate income or subsistence benefits, but are vulnerable to diseases, weather events, market price fluctuations, and management costs. This vulnerability results in a moderate-risk classification. According to Ogada et al. (2020), livestock is a form of savings that bridges household income gaps and offers better resilience than other household possessions. However, due to the inherent risks, this study categorises it as a moderate risk.

This categorisation does not imply that all assets within the same class face identical risk, but rather that they share broadly similar profiles. Some degree of subjectivity is unavoidable, particularly in contexts such as South Africa, where assets have additional social and livelihood dimensions. The classification should therefore be read as a heuristic device rather than an absolute ranking. Table 3.11 summarises the classification of nine asset classes into low-risk, moderate-risk, and high-risk categories.

Table 3.11: Classification of Household Assets by Inherent Risk

Low risk	Moderate risk	High risk	References
Bank account balance	Superannuation	Unincorporated Business Stocks Real Estates	(Barasinska et al., 2009; Bucciol & Miniaci, 2015; C. Carroll, 2000; Kochaniak, 2017, 2020; Mullahy, 2015).
Owner-occupied house Possessions	Vehicles Livestock		(Cho, 2014; Fernández-Villaverde & Krueger, 2011; Fratantoni, 2001; Iwaisako, 2009; Martins, 2023; Ogada et al., 2020)

Notes: The last column is a list of consulted studies that give an idea of the levels of inherent risk. While categorisation in the first row is well established in the literature, some degree of subjectivity is inherent in the second-row categorisation, necessitating a cautious interpretation of results.

Table 3.12 provides insight into the distribution of households' wealth allocation among each category and the percentage of households falling under each category. It displays the mean and median share of investment in each risk category, as well as the percentage of households with no wealth, partial wealth, or all their wealth allocated to each category.

Table 3.12: Shares of Household Wealth by Risk Class

Category	Mean	Median	HH with 0% share	HH with 100% share	HH with 0%<x<100%
Low risk	78.06%	99.99%	0%	42.32%	55.11%
Moderate risk	8.95%	0%	69.99%	0%	30.01%
High risk	12.98%	0%	73.33%	0%	26.67%

Notes: HH with 0% share (no wealth). HH with 100% share (all wealth). HH with 0%<x<100% (partial wealth).
Source: Own computation from waves 4 and 5 using NIDS weights.

The average and median households hold most of their wealth in the low-risk category, which I expected because possession assets, the modal type, fall into this category. The distributions for moderate-risk and high-risk assets are skewed to the right, with median shares much lower than mean shares—median values equal zero. Regarding the percentage of households in each category, no households allocate 100% of their wealth to moderate and high-risk classes, and approximately 70% or more do not hold any of these classes at all (0% share). In comparison, approximately 30% and 27% have some wealth in moderate and high-risk classes (0% < x < 100). Regarding the low-risk class, 42.32% of households hold all their wealth in the low-risk class, and no households have zero shares of the low-risk class. Approximately 55% of individuals have some portion of their wealth allocated to the low-risk class.

Table 3.12 shows that a significant number of corner values exist for each share, particularly for moderate and high-risk classes, with over 70% of the households not participating in them, and for the low-risk class, with over 40% holding all wealth. As explained in Section 3.3.6 below, the chosen modelling strategy effectively accommodates this prevalence of corner values.

3.3.5 Covariates and Descriptive Analysis of Portfolio Shares

This section provides an overview of the explanatory variables in the regression of portfolio shares of the three risk categories. My variable of interest is household wealth. However, I also control for various covariates commonly used in household portfolio literature (Mullahy, 2015; Kochaniak, 2017, 2020; Guiso et al., 2002; Iwaisako, 2009; Ito et al., 2017). Table 3.13 describes these covariates.

Table 3.13: Description of Covariates Used in Regressions

Variable	Description
Net Worth	Household Net Worth
Wealth quintiles	Five groups of households, ordered by Net Worth.
Log of Income	Logarithm of Households' total monthly income
Life insurance	Dummy variable for whether at least one Household member has life insurance
Happiness	Feelings of HH head compared to 10 years ago, 0. Less happy, 1. Same, 2. Happier
Stokvel	Dummy variable for at least one Household member has joined a stokvel.
Household size	Number of household members
Household size square	Square of the number of household members
Year Dummy	Dummy for observations in the year 2017. The year 2014 is the base
Age	Age of the Household head
Age-square	Square of the age of the Household head
Male	Dummy variable for the gender of the Household head
Married	Dummy variable for whether the Household head is married or single
Location	Geographical locations: 1. Traditional, 2. Urban, and 3. Farms
Race	Race of Household head: 1. African, 2. Coloured, 3. Asian/Indian, 4. White
Employed	Dummy variable for whether the Household head is employed or unemployed
Self-employed	Dummy variable equal to 1 if the Household is self-employed, and 0 otherwise
Years of education	Number of years of education of the Household head

Note: All socioeconomic characteristics are that of the household head. This includes happiness.

The key variable is household net worth and net worth quintiles. However, I control for household income levels, as per the literature. Additionally, I include standard demographic characteristics of the household head, such as age, gender, marital status, household size, race and geographical location. I also account for education level and employment status. Additionally, I control for life insurance and stokvel membership. The literature review provides an explanation for the inclusion of these variables. Table 3.13 defines each covariate, and Table 3.14 provides their summary statistics.

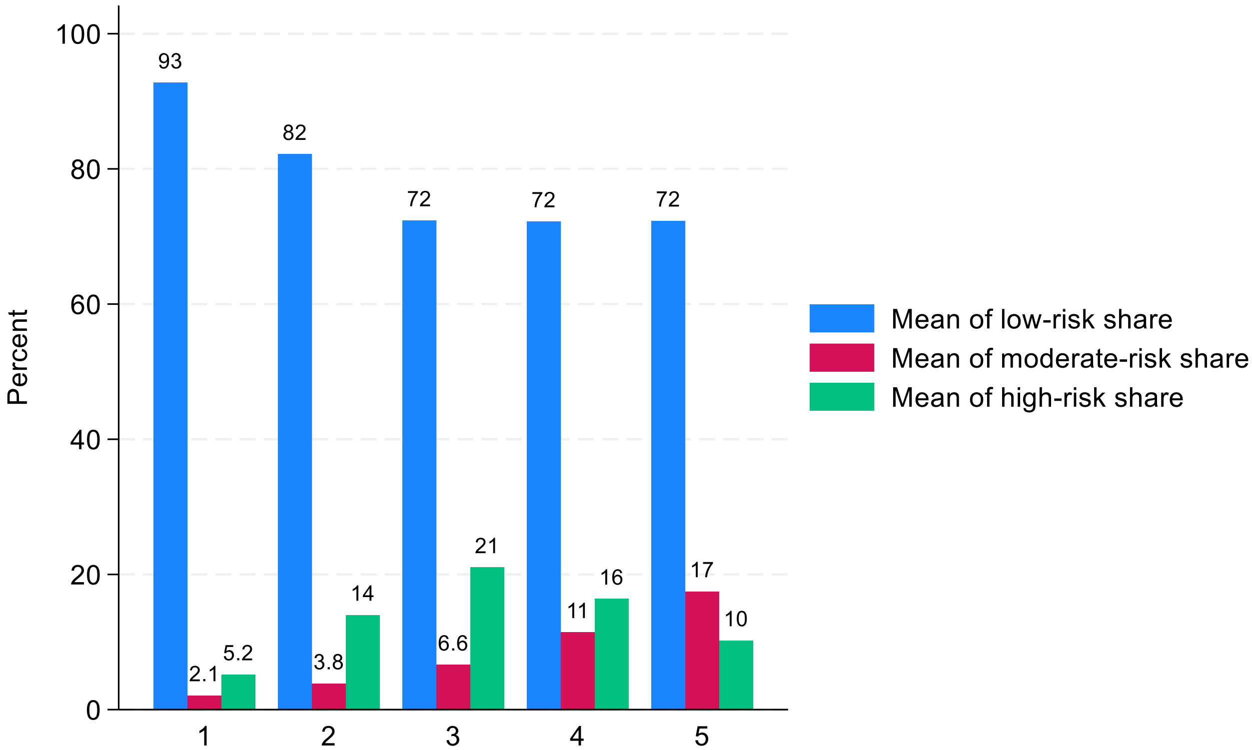
Table 3.14: Summary Statistics of the Covariates

Variable	Obs	Mean	Std. Dev.	Min	Max
Net worth	19638	R493375.1	R5634911.2	-11082574	5.765e+08
Net worth Quintiles	19638	3.0	1.414	1	5
Monthly income	19638	R9148.5	R26095.35	2.265	2607565.5
Life-insurance	18990	.135	.342	0	1
Happiness	18961	1.409	.764	0	2
Joined Stokvel	19025	.136	.342	0	1
Household size	19640	3.863	2.732	1	31
Household size square	19640	22.386	35.82	1	961
Age	19637	46.631	16.544	7	110
Age square	19637	2448.13	1660.908	49	12100
Male	19640	.427	.495	0	1
Married	19617	.395	.489	0	1
Location	19640	1.698	.575	1	3
Race	19638	1.304	.739	1	4
Employed	19606	.506	.5	0	1
Self-employed	8768	.114	.317	0	1
Years of education	19561	8.51	4.439	0	17

Note: Own computation using NIDS weights. I adjusted all the monetary values to the March 2017 prices.

Before presenting the estimation strategy, I explore the relationship between portfolio composition and the explanatory variable of interest by plotting the mean shares against different levels of household net worth. While this pattern cannot be interpreted as causal due to potential distortions from other factors correlated with net worth and portfolio makeup, it provides a helpful picture of the data.

Figure 3.1: Portfolio Shares by Net Worth Quintiles

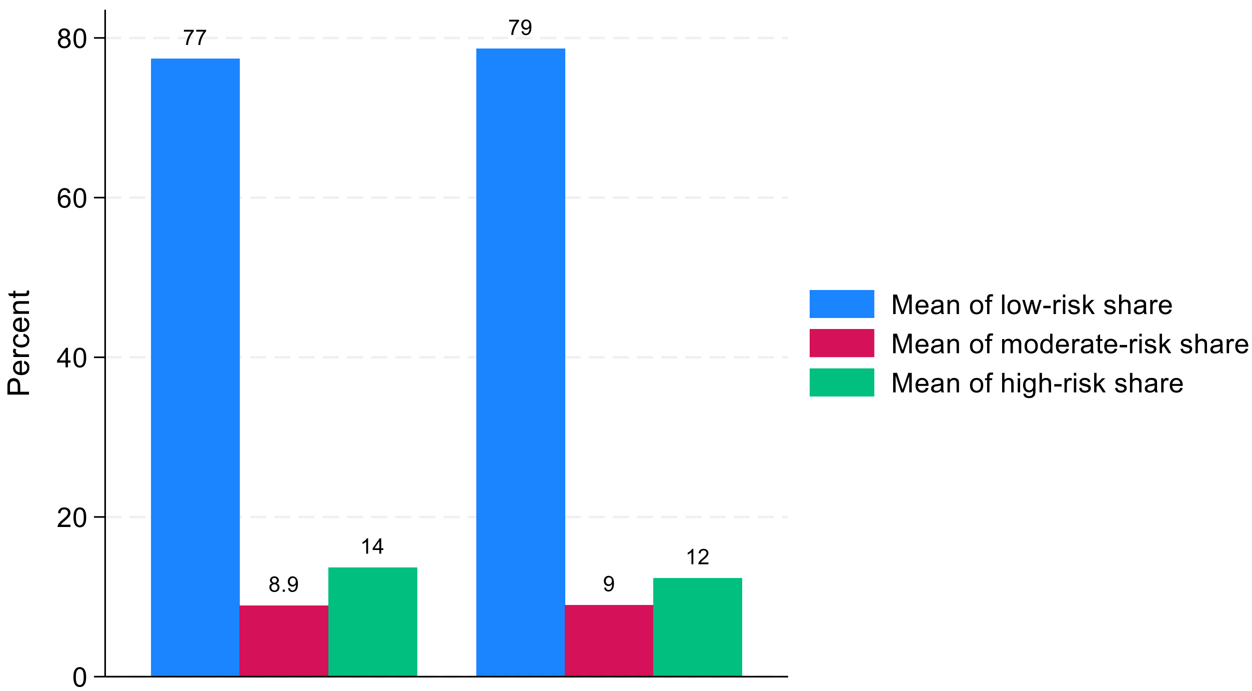


Source: Own computation using NIDS Weights (Pooled over 2014 and 2017)

Figure 3.1 shows the average shares for each risk class across quintiles of household net worth. The portfolio composition looks riskier in the middle than at the low and high ends of the net worth distribution. For instance, the share of the high-risk category increases from 5.2% in the first quintile to 21% in the third quintile, after which it falls to 16% and 10% in the fourth and fifth quintiles, respectively. The share of the moderate-risk category increases continuously across the net worth distribution. In contrast, the share of the low-risk category decreases from 93% in the first quintile to 72% in the middle quintile, after which it stays stable across the net worth distribution. According to Figure 3.1, we should expect a positive effect of household wealth on the shares of moderate- and high-risk assets, but a negative effect on the share of the low-risk category.

Figure 3.2 illustrates the average shares of each risk class over 2014 and 2017. There is a slight change in these portfolio shares between the two years. The share of low-risk assets increased slightly from 77% in 2014 to 79% in 2017, while the share of moderate-risk assets remained almost unchanged. The share of high-risk assets decreased slightly from 14% in 2014 to 12% in 2017.

Figure 3.2: Portfolio Shares by Years



Source: Own computation using NIDS weights

3.3.6 Empirical Estimation Strategy

At this juncture, I explain how I model the determinants of the three portfolio shares in Tables 3.10 and 3.11. The goal is to determine how household wealth influences households' holdings of the three portfolio shares. The analysis follows Mullahy (2015) and Murteira and Ramalho (2016), who modelled several shares in a joint framework via a multivariate fractional response model. When applying the logit link function, this is referred to as the Fractional Multinomial Logit (FMLOGIT) model. To model a multivariate framework of J different risk categories, I denote a share of j^{th} category held by i^{th} household during t^{th} period as y_{ijt}.

This study forms three specifications of FMLOGIT. The first specification is pooled FMLOGIT, which ignores unobserved individual heterogeneities that may affect y_{ijt}. The second is FMLOGIT in the context of Correlated Random Effects (CRE), which deals with unobserved heterogeneities that may not only affect y_{ijt} but may potentially bias the results. The third specification also addresses unobserved heterogeneities, but controls for endogeneity through two-step procedures known as the Control Function Approach (CFA).

3.3.6.1 Pooled FMLOGIT Model

I start a pooled FMLOGIT model from the following baseline specification:

$$y_{ijt} = \beta_{0j} + \beta_{1j} networth_{it} + \sum_{k=1}^{K} \gamma_{jk} x_{kit} + \delta_j wave_5 + \varepsilon_{ijt} \tag{3.1}$$

where:

- y_{ijt} is the fraction of total assets allocated to the category j ($j = 1, 2, 3$) by household i at period t, where $t = 0{,}1$ for two periods.
- $wave_5$ is an indicator variable for the wave five period (=1 if wave 5 and 0 if wave 4).
- $networth_{it}$ is the wealth of the household i in year t. β_{1j} captures the effect of household wealth on the fraction of total assets allocated to j^{th} category.
- β_{0j} is the mean share of the base category. The base is the share of low-risk assets in this study.
- X_{it} represents control variables such as household demographics, income, education, etc.

- ε_{ijt} is the error term.

Equation (3.1) is a linear system of J asset categories (J equations) and would effectively be an extension of the linear probability model (LPM), which has shortcomings (Brown et al., 2021; Kawasaki & Lichtenberg, 2014). For instance, LPM will not guarantee that $0 \leq E(y_{ijt}|\boldsymbol{x}) = \boldsymbol{x}'\beta_j \leq 1$. It would also be unable to handle boundary observations of 0 or 1 as Table 3.12 suggests that in this dataset, Pr $(y_{ijt} = 0|\boldsymbol{x}) \geq 0$, and Pr $(y_{ijt} = 1|\boldsymbol{x}) \geq 0$; and would likely embody heteroskedasticity in ε_{ijt}. Therefore, a suitable modelling strategy is the FMLOGIT, which is a joint estimation framework. It takes the following specification:

$$E[y_{ijt}|\boldsymbol{x}] = \Lambda(\boldsymbol{x}\beta_j) = \frac{\exp{(\boldsymbol{x}\beta_j)}}{\sum_{h=1}^{3} \exp{(\boldsymbol{x}\beta_h)}]} \tag{3.2}$$

Here $\boldsymbol{x}$ is a vector of household characteristics, household net worth, and time indicators on the right-hand side of (3.1). The model ensures that the predicted value of portfolio shares in each category ($j = 1, 2, 3$) lies between 0 and 1 and sums up to 1. Following Mullahy (2015) and Murteira and Ramalho (2016), the estimation of the conditional mean of all shares jointly is based on the quasi-maximum likelihood estimator for the multinomial logit specification (Kochaniak, 2020). The likelihood function is as follows:

$$L_i(\beta_j) = \prod_{j=1}^{3} E[y_{ijt}|\boldsymbol{x}]^{y_{ijt}} \tag{3.3}$$

The sum of the individual maximum log-likelihood to obtain the estimator $\hat{\beta}$ is as follows:[11]

$$\hat{\beta}_j = \arg max_\beta \sum_{i=1}^{n} logL_i(\beta_j) \tag{3.4}$$

[11] Maximization of (3.4) is readily conducted in STATA using the command ***fmlogit*** (M. Buis, 2017; M. L. Buis, 2008)**.**

Murteira and Ramalho (2016) warned that applying the fractional multinomial logit model gives rise to the problem of the independence of irrelevant alternatives (IIA). However, as Kochaniak (2020) suggested, in this type of study, where each household's shares add up to one, we can perceive the problem as of marginal importance.

3.3.6.2 FMLOGIT with Unobserved Heterogeneity

The pooled FMLOGIT does not consider the effects of unobserved heterogeneities. To allow time-invariant unobserved heterogeneity, I modify the equation (3.2) by including c_i (unobserved omitted factors) as follows:

$$E\left[y_{ijt}\middle|\boldsymbol{x},\bar{\boldsymbol{Z}},\boldsymbol{c_i}\right] = \Lambda\left(\boldsymbol{x}\beta_j + \varphi_j\bar{Z}_i\right) = \frac{\exp\left(\boldsymbol{x}\beta_j + \varphi_j\bar{Z}_i\right)}{\sum_{h=1}^{3}\exp\left(\boldsymbol{x}\beta_h + \varphi_j\bar{Z}_i\right)]} \tag{3.5}$$

Equation (3.5) includes the vector $\bar{Z}_i$, a subset of explanatory variables averaged over time for each household. Ideally, $\bar{Z}_i$ should include the time means of all time-varying variables (Papke & Wooldridge, 2008). However, in this case, other variables besides household net worth and income vary very little over the period under consideration. Additionally, unobserved and omitted factors, such as risk attitudes, are likely to influence the average household's net worth and income. Specifically, there are two reasons for including $\bar{Z}_i$ in (3.5). First, these variables may introduce endogeneity problems, as household wealth and income could be biased due to unobserved effects in the error terms of the portfolio share equation. Risk attitudes can significantly impact household wealth, income, and asset allocation decisions. Second, incorporating fixed effects in a panel model poses practical challenges when estimating nonlinear models, mainly due to the difficulty of managing numerous dummy variable coefficients (Wooldridge, 2014). To address endogeneity and the challenge of including fixed effects in the FMLOGIT model, I use the correlated random effects (CRE) or Chamberlain-Mundlak approach when estimating Equation (3.5). This method assumes that some explanatory variables correlate with unobservable variables. This approach computes the fixed effects estimator as a pooled estimator, incorporating the time averages of covariates as additional explanatory variables (Wooldridge, 2019).

3.3.6.3 Control Function Approach (CFA)

The CRE approach will be limited if the unobserved omitted factors include time-varying variables, such as financial literacy. Additionally, possible feedback between portfolio shares (y_{ij}) and household net worth (w_i) can still cause endogeneity problems as w_i and the unobservable factors, c_i are still correlated. I employ the control function approach (CFA) to address this endogeneity problem. CFA modifies the CRE approach by including extra regressors in estimating equation (3.5), so the remaining variation in household net worth would be uncorrelated with the unobservables. Therefore, I now rewrite equation (3.5) as follows:

$$\begin{aligned} E\left[y_{ijt}\middle|\boldsymbol{x}\right] = E\left[y_{ijt}\middle|Z_{1it}, w_{it}, c_i\right] &= \Lambda\left(Z_{1it}\beta_j + \gamma_j w_{it} + \varphi_j \bar{Z}_{1i} + c_i\right) \\ &= \frac{\exp\left(Z_{1it}\beta_j + \gamma_j w_{it} + \varphi_j \bar{Z}_{1i} + c_i\right)}{\sum_{h=1}^{3} \exp\left(Z_{1it}\beta_h + \gamma_h w_{it} + \varphi_j \bar{Z}_{1i} + c_i\right)} \end{aligned} \tag{3.6}$$

Where Z_1 is a vector of all exogenous variables, including a constant but excluding potential instruments. The following conditions ensure that the remaining variation in w_i is uncorrelated with c_i:

$$\begin{aligned} &w_{it} = Z\pi = Z_{1it}\pi_1 + Z_{2it}\pi_2 + v_{it} && \text{(a)} \\ &c = \rho v + e && \text{(b)} \\ &D(e|Z, v) = D(e) && \text{(c)} \end{aligned} \tag{3.7}$$

$\boldsymbol{Z_2}$ is a subset of exogenous variable $\boldsymbol{Z}$ excluded from (3.6) and works as an instrument for household net worth, w_{it}. In this dataset, I consider the socioeconomic status (SES) of parents of household heads to be potential instruments for household net worth. Specifically, I used parental education attainment and parents' job types as instruments. Parents' educational attainment could be correlated with wealth transfer to their children, influencing household wealth. Additionally, I argue that parental education would not directly affect current asset choices. It may influence financial literacy but not specific investment decisions.

Regarding job types, I argue that if parents held high-paying, stable jobs (e.g., doctors, lawyers, etc), it might indicate higher wealth they could potentially transfer to their children. Like education, I argue that this does not directly influence current asset allocation decisions. These parents could only instil saving habits but not specific investment preferences.

Part (a) of (3.7) is the reduced form of the endogenous variable, w_i and (π_1, π_2) are reduced form parameters. Part (b) is a linear projection of unobserved factors c on υ, the reduced form error in part (a), and it is the control function. It shows that if there is any correlation between w_i and c_i, it can only come from υ_i. ρ shows how much w is correlated with c, and consequently tells whether w is endogenous. Part (c) of (3.7) shows that e is independent of (Z, υ). Then the mean function (3.6) should also be conditional on reduced form error υ, which is a control function as follows:

$$\begin{aligned} E\left[y_{ijt}\middle|\boldsymbol{x}\right] = E\left[y_{ijt}\middle|Z_{1it}, w_{it}, \upsilon_{it}\right] &= \Lambda\left(Z_{1it}\beta_j + \gamma_j w_{it} + \varphi_j \bar{Z}_{1i} + \rho_j \upsilon_{it}\right) \\ &= \frac{\exp\left(Z_{1it}\beta_j + \gamma_j w_{it} + \varphi_j \bar{Z}_{1i} + \rho_j \upsilon_{it}\right)}{\sum_{h=1}^{3} \exp\left(Z_{1it}\beta_h + \gamma_h w_{it} + \varphi_j \bar{Z}_{1i} + \rho_j \upsilon_{it}\right)} \end{aligned} \tag{3.8}$$

Since υ_{it} is unobserved, a simple way to estimate parameters of (3.8) is to replace υ_{it} with its consistent estimate $\hat{\upsilon}_{it}$ which are residuals obtained from regression part (a) of (3.7). Therefore, I follow the two-step procedure as follows:

1. Obtain OLS residuals $\hat{\upsilon}_{it}$ from the regression of w_{it} on Z_{1it} and Z_{2it}. Essentially, I run an OLS for each of the two periods under consideration rather than a pooled OLS.
2. Apply pooled Fractional Multinomial Logit of $(y_{1it}, y_{2it}, y_{3it})$ on Z_{1it}, w_{it}, $\bar{Z}_i$, and $\hat{\upsilon}_{it}$ to estimate β, γ, φ_j, and ρ.

Rejection of the null hypothesis that $\rho = 0$ means that w is indeed endogenous. Otherwise, there is no endogeneity problem, in which case γ will be identical to the net worth coefficients in (3.6). This is a robust Hausman's (1978) test for endogeneity (Papke & Wooldridge, 2008; Wooldridge, 2019).

3.4 EMPIRICAL RESULTS AND DISCUSSION

Below are the regression results for the multivariate models discussed in Section 3.3.6. Since these models are nonlinear, the estimated coefficients do not provide clear insights into the effect of a covariate on the mean of portfolio shares. Therefore, I only report the computed marginal effects. These marginal effects sum to zero over the three portfolio shares, reflecting the reallocation of assets in a portfolio. The covariates used in each model are those described in Table 3.13.

3.4.1 Pooled Model

Table 3.15 presents the marginal effects of the fractional multinomial logit (FMLOGIT) model, pooled over 2014 and 2017. The reported standard errors in parentheses are based on bootstrapped standard errors with 500 replications.

Table 3.15: Marginal Effects of Pooled FMLOGIT Model

VARIABLES	Low risk	Moderate risk	High-risk
Log of household net worth	-0.006***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Log of Household Income	-0.049***	0.051***	-0.002
	(0.005)	(0.004)	(0.004)
Having life insurance vs not	-0.070***	0.070***	-0.000
	(0.008)	(0.005)	(0.007)
Happiness: Reference (Less happy than 10yrs ago)			

1. As Happy as 10 years ago	0.021*	-0.009	-0.012
	(0.012)	(0.009)	(0.010)
2. Happier than 10yrs ago	-0.008	0.012	-0.004
	(0.010)	(0.008)	(0.008)
Having Stokvel vs not	0.019**	-0.001	-0.018**
	(0.009)	(0.006)	(0.008)
Education years	-0.001	0.004***	-0.003***
	(0.001)	(0.001)	(0.001)
Employed vs Unemployed	-0.002	0.000	0.002
	(0.016)	(0.014)	(0.012)
Self-employed vs Not	-0.010	-0.042***	0.051***
	(0.009)	(0.008)	(0.007)
Household size	0.005	-0.006**	0.000
	(0.004)	(0.002)	(0.003)
Household size square	-0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)
Age	-0.016***	0.007***	0.009***
	(0.002)	(0.002)	(0.002)
Age square	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Male vs Female	-0.024***	0.034***	-0.010*
	(0.008)	(0.005)	(0.006)
<u>Race: Reference (African)</u>			
2. Colored	-0.001	0.017**	-0.016**
	(0.010)	(0.007)	(0.008)
3. Indian	0.057**	-0.039***	-0.018
	(0.022)	(0.013)	(0.021)
4. White	0.033**	-0.030***	-0.003
	(0.014)	(0.008)	(0.012)
Married vs Unmarried	-0.021***	0.018***	0.003
	(0.008)	(0.006)	(0.006)
<u>Location: Reference: (Traditional Authority Area)</u>			
2. Urban	0.031***	-0.008	-0.022***
	(0.009)	(0.006)	(0.007)

3. Farms	0.025*	-0.005	-0.020*
	(0.015)	(0.011)	(0.011)
Year dummy (2017 vs 2014)	0.004	0.005	-0.009*
	(0.006)	(0.005)	(0.005)
Observations	8,019	8,019	8,019

Notes: This table presents Marginal Effects based on the pooled FMLOGIT Model, where shares of Low-risk, Moderate-risk and High-risk assets are dependent variables jointly estimated. All Household characteristics are those of the Household head, and for those that are categorical, the base/reference category is written in parentheses. Bootstrapped Standard errors with 500 replications are in parentheses. ***, **, and * indicate 1%, 5%, and 10% levels of significance respectively.

Source: Own computation, Rand values adjusted to March 2017 prices.

The results from the pooled FMLOGIT Model provide further insights into the relationship between wealth and asset allocation behaviour in South Africa, statistically reinforcing the picture observed in Figure 3.1. An increase in household net worth significantly reduces the share of low-risk assets while considerably increasing the share of moderate-risk and high-risk assets. This statistically significant shift in asset allocation as wealth rises suggests that risk aversion diminishes with increasing wealth. Wealthier households appear more comfortable incorporating riskier assets into their portfolios. These findings align with existing literature regarding the link between wealth and portfolio choice (Gollier, 2002; Kochaniak, 2017, 2020).

The results affirm the general trend and quantify the magnitude of the shift. A 1% increase in household wealth decreases the share of low-risk assets by approximately 0.6% and increases the shares of moderate-risk and high-risk assets by around 0.3% and 0.3%, respectively. Several explanations may account for this trend. Wealthier households may prioritise assets with greater growth potential, such as those in the moderate and high-risk categories, to achieve long-term financial objectives, including retirement or wealth accumulation. Moreover, having a larger wealth base might provide a buffer against potential losses from riskier investments, making them more willing to accept some risk.

Regarding the control variables, as income increases, households allocate less to low-risk assets (-4.9%) and prioritise assets with moderate risk (5.1%). Life insurance is associated with a lower share of the low-risk category (-7%) but a higher share of the moderate-risk category (7%). Having life insurance has no significant effect on the shares of the high-risk category. Life insurance appears to serve as a safety net, enabling individuals with life insurance to invest in riskier assets for potential growth while maintaining a low-risk foundation.

Social networks also influence investment behaviour. Being a member of a Stokvel, an informal savings group, is associated with a higher share of low-risk assets (1.9%) and a lower share of high-risk assets (-1.8%). This suggests Stokvels might promote financial discipline and encourage saving in low-risk options. This result contradicts the finding that Stokvel membership has no significant effect on stock market participation (Nyakurukwa & Seetharam, 2024).

Contrary to previous studies (Delis & Mylonidis, 2015; Kollamparambil, 2020; Sachdeva & Lehal, 2023), emotional well-being does not appear to influence investment decisions. Education level also influences asset allocation (Biyase et al., 2019; Black et al., 2018). Counterintuitively, years of education have a positive effect on moderate-risk categories but a negative effect on the high-risk category. This result could be due to educated individuals' focus on financial security, leading them to prioritise moderate-risk assets and their growth potential. Self-employment is associated with a larger share of high-risk assets (5.1%) but a lower share of moderate-risk assets (-4.2%). Being married is associated with a lower share of low-risk assets and a higher share of moderate-risk assets. Marital status has no significant effect on the share of high-risk assets.

An interesting gender difference emerges in risk preferences. Male-headed households hold a higher share of moderate-risk assets, a lower share of low-risk assets, and a surprisingly lower share of high-risk assets than female-headed households. For low and moderate-risk categories, this result is as expected. However, for the high-risk category, the result contradicts previous findings, which have shown that male investors are more risk-tolerant than female investors (Dickason & Ferreira, 2018). Nonetheless, the result suggests potential gender differences in risk tolerance or household financial decision-making processes.

Household size also influences investment choices (Biyase et al., 2019; Dickason & Ferreira, 2018). An additional member in the household is associated with a decrease in the share of moderate-risk assets. Household size appears to have no significant impact on the shares of low and high-risk assets. The age of the household head has a quadratic relationship with the portfolio shares, reflecting the life-cycle hypothesis in investments. An additional year of the household head's age is associated with a decline in the share of low-risk assets until a minimum point, after which it begins to increase. However, an additional year of household age is associated with an increase in the shares of moderate- and high-risk assets until a maximum point, after which they start to decrease. The share of low-risk assets follows a U-shaped curve with age, reflecting a shift towards low-risk assets for security reasons in later years. In contrast, the shares of moderate-risk and high-risk assets increase with age up to a point and then decrease, possibly due to growing risk aversion as individuals approach retirement.

Racial background also influences asset accumulation (Biyase et al., 2019; Seekings, 2008; Seekings & Nattrass, 2008). Compared to Africans, Coloureds hold a larger share of moderate-risk assets and a smaller share of high-risk assets, while Indians and Whites hold a larger share of low-risk assets but a smaller share of moderate-risk assets. Regarding high-risk assets, there is no significant difference between Indians and Africans, as well as between Whites and Africans. This not only contradicts the descriptive finding above but is also contrary to expectations, which is surprising given the historical and ongoing socioeconomic inequalities.

Finally, geographic location matters. Residents of urban areas have a higher share of low-risk assets but a lower share of high-risk assets than residents of Traditional Authority Areas (TAA). This result could be due to easier access to low-risk financial products in urban areas alongside a potentially more conservative investment culture. Residents of farms show a similar pattern to those of urban areas.

3.4.2 Correlated Random Effects Model

The asset allocation analysis in section 3.4.1 employed a pooled FMLOGIT model. While it provided valuable insights, a potential limitation is that it does not account for unobserved heterogeneities—unmeasured characteristics of households that might influence their asset allocation decisions. If these unobserved factors correlate with the included variables (e.g., household net worth), the results in Table 3.15 will be biased.

I implemented a Fixed-Effects or Correlated Random Effects (CRE) model using the FMLOGIT framework (as outlined in equation (3.5)) to address this limitation. This approach utilises changes in household covariates over time to identify their effects. By focusing on deviations from a household's time average for each variable, the CRE model helps control for unobserved heterogeneities.

It is essential to compare the fixed effects (FE) and random effects (RE) through the null hypothesis $H_0: \varphi_j = 0$ from the equation (3.5). The rejection of the null favours FE, which confirms that it is appropriate for the CRE model. This is because the time averages of certain variables, specifically household income, are statistically significant. However, most of them, such as the average net worth and average years of education over time, are insignificant. Therefore, results in Table 3.16 exclude those that are insignificant to reduce multicollinearity and enhance efficiency (Wooldridge, 2019). Interestingly, the results of the pooled and CRE models in Table 3.16 appear similar, suggesting that unobserved heterogeneities might not be a significant concern in this analysis. The observed effects of household wealth on asset allocation hold even after controlling for these unobserved factors.

Overall, the analysis underscores the importance of accounting for unobserved heterogeneities and utilising suitable models, such as the CRE-FMLOGIT, to obtain more robust results. However, the close similarity between the pooled and CRE models suggests that the core findings about wealth and risk-taking behaviour remain valid.

Table 3.16: Marginal Effects for FMLOGIT Model under Correlated Random Effects

VARIABLES	Low risk	Moderate risk	High-risk
Log of household Net Worth	-0.006***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Log Monthly income	-0.021*	0.018**	0.003
	(0.011)	(0.009)	(0.009)
Time Mean of Monthly Income	-0.032***	0.038***	-0.006

	(0.012)	(0.009)	(0.009)
Having life insurance vs Not	-0.069***	0.069***	-0.000
	(0.008)	(0.006)	(0.007)
<u>Reference: Less happy than 10yrs ago</u>			
1. As happy as 10 years ago	0.021*	-0.009	-0.012
	(0.012)	(0.009)	(0.009)
2. Happier than 10yrs ago	-0.008	0.012	-0.004
	(0.011)	(0.008)	(0.008)
Having Stokvel vs Not	0.020**	-0.002	-0.018**
	(0.010)	(0.007)	(0.007)
Education years	-0.001	0.004***	-0.003***
	(0.001)	(0.001)	(0.001)
Employed vs Unemployed	-0.002	0.000	0.002
	(0.017)	(0.014)	(0.013)
Self-employed vs Not	-0.010	-0.041***	0.051***
	(0.010)	(0.008)	(0.007)
Household size	0.006	-0.006**	0.000
	(0.004)	(0.002)	(0.002)
Household size square	-0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)
Age	-0.016***	0.007***	0.009***
	(0.002)	(0.002)	(0.002)
Age square	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Male vs Female	-0.024***	0.033***	-0.010*
	(0.008)	(0.005)	(0.006)
<u>Race: Reference (African)</u>			
2. Colored	-0.000	0.017**	-0.016**
	(0.010)	(0.007)	(0.008)
3. Indian	0.059**	-0.040***	-0.019
	(0.023)	(0.014)	(0.022)
4. White	0.035***	-0.031***	-0.004
	(0.013)	(0.008)	(0.012)
Married vs Single	-0.020**	0.017***	0.003

	(0.008)	(0.006)	(0.006)
Location: Reference: (Traditional Authority Area)			
2. Urban	0.031***	-0.009	-0.022***
	(0.009)	(0.007)	(0.007)
3. Farms	0.027*	-0.007	-0.019
	(0.015)	(0.011)	(0.012)
Year dummy (2017 vs 2014)	-0.002	0.018***	-0.016**
	(0.008)	(0.006)	(0.007)
Time mean (proportion of 2017 obs)	0.012	-0.030***	0.019*
	(0.014)	(0.010)	(0.011)
Observations	8,019	8,019	8,019

Notes: This table presents Marginal Effects based on the Fractional Multinomial Logit Model, which allows for unobserved heterogeneities using a correlated random effects model. All household characteristics are represented by those of the household head. Bootstrapped Standard errors with 500 replications are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Source: Own computation, Rand values adjusted to March 2017 prices.

3.4.3 Control Function Approach

Both pooled and CRE models assume that none of the covariates correlates with idiosyncratic error. Though CRE allows unobserved heterogeneity to correlate with the regressors, it does not necessarily address potential endogeneity between household wealth and asset allocation. I employed a two-step control function approach (CFA), where, in the first step, I ran a household net worth regression using exogenous variables, including parental socioeconomic status[12], and obtained a control function. The coefficient of the control function is insignificant for the three risk categories (see Table 3.17). I fail to reject the hypothesis that household wealth is exogenous at all significance levels.

Table 3.17: Marginal Effects of FMLOGIT using the Control Function Approach

VARIABLES	Low	Moderate	High

[12] We believe that the socioeconomic status of parents of the household head can directly influence the household net worth, but not the portfolio preferences. This socioeconomic status includes mothers' and fathers' education and their job types.

Log of household Net worth	-0.007**	0.005**	0.002
	(0.003)	(0.002)	(0.003)
Time Mean of household Net worth	0.003	-0.002	-0.000
	(0.003)	(0.002)	(0.003)
Log of household monthly income	-0.014	0.020	-0.006
	(0.022)	(0.015)	(0.017)
Time Mean of Monthly Income	-0.018	0.016	0.002
	(0.023)	(0.016)	(0.018)
Having life insurance vs Not	-0.060***	0.063***	-0.003
	(0.013)	(0.010)	(0.010)
Reference: Less happy than 10yrs ago			
1. As happy as 10 years ago	0.002	0.002	-0.003
	(0.021)	(0.015)	(0.016)
2. Happier than 10yrs ago	-0.020	0.028**	-0.008
	(0.017)	(0.013)	(0.014)
Having Stokvel vs Not	0.011	0.006	-0.017
	(0.017)	(0.013)	(0.013)
Education years	-0.023	0.005	0.018
	(0.017)	(0.014)	(0.012)
Time Mean of education years	0.017	0.001	-0.018
	(0.017)	(0.014)	(0.012)
Employed vs Unemployed	-0.031**	0.034***	-0.003
	(0.014)	(0.012)	(0.011)
Household size	-0.001	0.011	-0.009
	(0.017)	(0.012)	(0.013)
Time Mean of household size	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.000)
Household size square	0.009	-0.015	0.005
	(0.016)	(0.011)	(0.013)
Age	-0.018***	0.010***	0.008***
	(0.003)	(0.002)	(0.002)
Age square	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Male vs Female	-0.017	0.023**	-0.006
	(0.013)	(0.009)	(0.009)
Race. Reference (African)			
2. Colored	-0.009	0.041***	-0.032**
	(0.019)	(0.015)	(0.012)
3. Indian	0.045	-0.007	-0.038*
	(0.034)	(0.025)	(0.023)
4. White	-0.027	0.002	0.025
	(0.020)	(0.015)	(0.017)
Married vs Single	-0.020	0.017	0.003
	(0.014)	(0.011)	(0.011)
Reference: Traditional Authority Area			
2. Urban	0.064***	-0.032**	-0.032**
	(0.019)	(0.015)	(0.014)
3. Farms	0.090***	-0.080***	-0.010

	(0.031)	(0.023)	(0.025)
Year dummy (2017 vs 2014)	0.001	-0.002	0.001
	(0.012)	(0.009)	(0.009)
Control Function	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Observations	2,486	2,486	2,486

Notes: This table presents Marginal Effects based on the Fractional Multinomial Logit Model, allowing unobserved heterogeneities and using a control function approach to deal with endogeneity. All Household characteristics are that of the Household head. Bootstrapped Standard errors with 500 replications are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.
Source: Own computation, Rand values adjusted to March 2017 prices.

The results from the CFA revealed that the effect of household wealth on household asset allocation decisions remains valid across low-risk, moderate-risk, and high-risk categories, as suggested by both the pooled and CRE models. Overall, the analysis highlights the importance of considering unobserved heterogeneities and endogeneity when analysing relationships between variables that may influence each other, such as wealth and asset allocation decisions. By employing these techniques, the study provides a more robust understanding of the relationship between wealth and the asset allocation behaviour of South Africans.

3.4.4 Probability of Risk-Taking

In Table 3.12, 42.32% of households hold all their wealth in low-risk assets, which indicates that the percentage of households with at least one risky asset is 57.68%. Therefore, we define a binary variable that equals one if a household has at least one risky asset in its portfolio (either moderate-risk or high-risk) and zero otherwise. We then apply a logit or probit model to analyse how the covariates in sections 3.4.1, 3.4.2, and 3.4.3 above affect the likelihood of having at least one risky asset in the portfolio. This also serves as a robustness check for the previous analysis. Table 3.18 presents the results.

Table 3.18: Marginal Effects of the Logit Model for the Likelihood of Risk-Taking

VARIABLES	Pooled	CRE	CFA
Log of household Net worth	0.017***	0.013***	0.009**
	(0.001)	(0.002)	(0.005)
Time Mean of household Net worth		0.006**	0.004
		(0.002)	(0.005)
Log of household monthly income	0.082***	0.025**	0.028
	(0.005)	(0.012)	(0.031)
Time Mean of Monthly Income		0.066***	0.043
		(0.012)	(0.033)
Having life insurance vs Not	0.120***	0.116***	0.088***
	(0.012)	(0.012)	(0.023)
Reference: Less happy than 10yrs ago			
1. As happy as 10 years ago	-0.003	-0.002	0.043
	(0.011)	(0.011)	(0.032)
2. Happier than 10yrs ago	0.016*	0.014	0.070**
	(0.010)	(0.009)	(0.027)
Having Stokvel vs Not	-0.011	-0.011	0.012
	(0.011)	(0.010)	(0.025)
Education years	0.000	0.014	0.004
	(0.001)	(0.010)	(0.024)
Time Mean of education years		-0.015	0.007
		(0.010)	(0.024)
Employed vs Unemployed	0.016**	0.016**	0.023
	(0.008)	(0.008)	(0.023)
Household size	0.002	0.006	-0.013
	(0.003)	(0.006)	(0.020)
Time Mean of household size		-0.005	0.002
		(0.005)	(0.019)
Household size square	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.001)
Age	0.010***	0.009***	0.017***
	(0.001)	(0.001)	(0.004)
Age square	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Male vs Female	0.012*	0.011	0.060***
	(0.007)	(0.008)	(0.019)
Race. Reference (African)			
2. Colored	-0.022**	-0.023**	-0.015
	(0.011)	(0.011)	(0.028)
3. Indian	-0.005	-0.015	0.037
	(0.032)	(0.033)	(0.068)
4. White	0.149***	0.138***	0.140***
	(0.021)	(0.021)	(0.032)
Married vs Single	0.056***	0.054***	0.032
	(0.008)	(0.008)	(0.021)
Reference: Traditional Authority Area			

2. Urban	-0.087***	-0.088***	-0.062***
	(0.008)	(0.008)	(0.023)
3. Farms	-0.105***	-0.105***	-0.075
	(0.015)	(0.015)	(0.046)
Year dummy (2017 vs 2014)	-0.039***	-0.037***	0.008
	-0.087***	-0.088***	-0.062***
Time mean (Proportion of 2017 obs)		0.001	
		(0.015)	
Control Function			0.000
			(0.000)
Observations	18,633	18,633	2,605

Notes: This table presents Marginal Effects based on the Logit Model of pooled CRE, allowing for unobserved heterogeneities, and using a control function approach to deal with endogeneity. The dependent variable is a dummy equal to 1 if a household owns at least one risky asset and 0 otherwise. All Household characteristics are that of the Household head. Bootstrapped Standard errors with 500 replications are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Source: Own computation, Rand values adjusted to March 2017 prices.

The first observation is that the control function is insignificant, leading to the non-rejection of the null hypothesis that household net worth is exogenous. Therefore, as previously stated, the results of the CFA approach can be disregarded. The second issue is the realisation that time averages of time-varying variables are significant, supporting FE or CRE as before. Thus, it is not surprising that the coefficients under the pooled model are generally slightly higher than those of the CRE model. However, this difference is insufficient to alter the conclusions already drawn regarding the effect of household wealth on asset allocation decisions. The results also confirm the categorisation of assets into three risk categories. The influence of household wealth on allocation decisions among the three risk categories corresponds with the effect of household wealth on the probability of assuming risk.

3.4.5 Discussion of FMLOGIT Results

The pooled FMLOGIT regression results offer strong evidence on how household wealth and related factors influence asset allocation across low-, moderate-, and high-risk categories. By connecting these findings with the theoretical framework and previous empirical evidence, this section places the results within the broader literature on household finance, risk behaviour, and inequality.

Household net worth has a statistically significant influence on portfolio allocation. As wealth increases, the proportion of low-risk assets decreases, while investments in both moderate- and high-risk categories increase. This result confirms the descriptive evidence and aligns with the declining relative risk aversion hypothesis (Arrow, 1965; Pratt, 1964), which suggests that wealthier households are willing to accept greater financial risk. It also supports the findings of Gollier (2002) and Kochaniak (2017, 2020), who show that higher wealth prompts a shift from safe to riskier assets.

The result also aligns with the Life-Cycle Hypothesis (Modigliani & Brumberg, 1954) and Modern Portfolio Theory (Markowitz, 1952). Wealthier households—especially those in middle or later life stages—may prioritise portfolio growth by diversifying into moderate- and high-risk assets, while their larger wealth base cushions them from downside risk. In the South African context, where wealth inequality is stark, this suggests that wealthier households are both willing and able to pursue higher-return investment opportunities. This dynamic contributes to the widening wealth gap, as lower-wealth households remain locked to conservative asset choices.

Household income also plays a role, shifting portfolios from low-risk to moderate-risk assets. This supports Cocco's (2005) argument that stable income lowers participation costs and liquidity constraints, allowing for more risk-taking. The finding also aligns with the Permanent Income Hypothesis (Friedman, 1957), which posits that stable, long-term resources foster forward-looking investment strategies.

Life insurance coverage decreases low-risk allocations while increasing moderate-risk holdings. This aligns with the concept of background risk (Cardak & Wilkins, 2009; Gomes & Michaelides, 2005). By offering a financial safety net, life insurance enables households to assume more financial risk elsewhere in their portfolios. Notably, this implies that access to formal risk-mitigation products can significantly influence household portfolio decisions, particularly for middle-income households that balance protection with growth.

Conversely, membership in a stokvel—an informal savings group—tends to increase low-risk allocations and decrease high-risk ones. This underscores the role of social networks and informal finance in influencing behaviour. While stokvels promote financial discipline and facilitate risk-sharing within communities, they may also reinforce conservative saving habits, thereby limiting exposure to higher-return investments. This contrasts with Nyakurukwa and Seetharam (2024), who find little effect of stokvels on stock market participation, suggesting that their impact may differ across financial domains.

Education shifts portfolios towards moderate-risk assets but away from high-risk ones, which is an unexpected outcome. While the literature generally associates higher education and financial literacy with riskier portfolios (Black et al., 2018; Lusardi & Mitchell, 2014), this result may reflect a preference among educated South Africans for cautious risk-taking. Education can promote financial sophistication and diversification, but it may also encourage a cautious attitude towards very high-risk assets.

Employment status has mixed effects: while there is no significant difference between employed and unemployed, self-employed households hold a larger share of high-risk assets but fewer moderate-risk ones. This aligns with the entrepreneurial nature of self-employment, where households may be used to taking on greater financial risk (Heaton & Lucas, 2000). Being married increases allocations to moderate-risk assets, consistent with the idea that marriage provides financial stability and shared risk management, enabling households to tolerate more risk (Biyase et al., 2019).

Age effects follow a nonlinear, quadratic pattern that generally supports the Life-Cycle Hypothesis. Younger and older households tend to prefer low-risk assets, whereas middle-aged households allocate more to moderate- and high-risk categories. This reflects the interaction of wealth accumulation, income stability, and retirement planning over the life cycle (Ameriks & Zeldes, 2011; Campbell, 2006). However, the South African context complicates this view: structural inequalities in access to financial products mean that age effects may overlap with cohort effects linked to historical disadvantages.

The gender results are striking. Male-headed households allocate more to moderate-risk assets and less to low-risk assets, consistent with the literature on higher male risk tolerance (Dickason & Ferreira, 2018; Felton et al., 2003). Yet unexpectedly, men hold fewer high-risk assets than female-headed households. This divergence from international evidence suggests that gendered financial behaviour in South Africa may reflect household decision-making dynamics rather than individual preferences. Women heading households may invest in high-risk assets out of necessity—seeking higher returns to compensate for limited income and wealth—rather than greater tolerance for risk per se. This nuance highlights the importance of context-specific interpretations of gendered behaviour.

Race significantly influences portfolio allocation, reflecting South Africa's persistent inequalities. Compared to African households, Coloured households tend to favour moderate-risk assets but avoid high-risk ones, while Indian and White households allocate more to low-risk assets. These results differ from expectations, as one might assume that greater risk diversification would be observed among historically wealthier groups. Instead, the findings may indicate a "wealth preservation" motive: historically advantaged groups might rely on safer financial products to protect their accumulated wealth (Seekings & Nattrass, 2008). Conversely, African households, with lower initial wealth, may diversify more aggressively when opportunities arise, even from a smaller asset base.

Location also plays a role. Urban and farm households hold larger shares of low-risk assets than those in traditional authority areas, while simultaneously holding fewer high-risk ones. This is counterintuitive, as urban households typically have greater access to financial products. The results may reflect cultural preferences for safety in formal markets or institutional biases in product design that limit urban households' exposure to higher-return investments. Conversely, households in traditional authority areas may diversify more out of necessity, reflecting limited access to formal low-risk savings instruments.

Taken together, these results illustrate that while wealth remains the main factor influencing riskier asset holdings—aligning with theory and international evidence—household behaviour in South Africa is influenced by a wider set of factors, including income stability, access to insurance, informal financial institutions, education, demographic characteristics, and persistent structural inequalities. Theoretical predictions regarding declining relative risk aversion, life-cycle changes, and diversification are generally supported, but South Africa's unique context of inequality and financial exclusion introduces significant deviations. These findings suggest that theories of household portfolio choice should be adapted to account for the structural and institutional realities of emerging markets. Wealth and income guide the overall direction of portfolio adjustments, but social networks, cultural practices, and historical legacies influence the degree of risk-taking.

3.5 CONCLUDING REMARKS

This study has analysed household asset allocation across the wealth distribution in South Africa, with a particular focus on how wealth affects the composition of both financial and non-financial portfolios. Using waves 4 and 5 of the National Income Dynamics Study (NIDS) and applying a fractional multinomial logit (FMLOGIT) model, the analysis revealed insights into the relationship between wealth, household characteristics, and portfolio choices in a context of persistent inequality.

The descriptive findings highlighted significant differences in asset ownership and composition across the wealth distribution. While high-wealth households possessed diversified portfolios including property, vehicles, financial assets, and retirement funds, lower-wealth households were mostly limited to tangible necessities and informal savings methods. These patterns reflected both the lasting legacy of apartheid, which restricted asset accumulation for the majority, and the unequal access to financial markets that continues to shape the post-apartheid economy.

The regression results confirmed that wealth is the strongest determinant of portfolio composition, consistent with established theories of declining relative risk aversion (Arrow, 1965; Pratt, 1964) and portfolio diversification (Markowitz, 1952). Increases in net worth were associated with a reduced reliance on low-risk assets and a greater allocation to moderate- and high-risk categories. These findings echoed international evidence (Guiso & Sodini, 2013; Kochaniak, 2020) but also showed unique dynamics in the South African context. For example, informal savings groups (stokvels) played a distinctive role in shaping behaviour, reinforcing the conservative risk stance of lower-income households, while formal instruments, such as life insurance, were associated with an increased willingness to hold riskier assets.

Demographic factors, including age, education, gender, and location, further influenced portfolio outcomes, often aligning with life cycle and human capital theories but also diverging due to structural inequalities. Urban households, despite greater access to financial products, often displayed a preference for safer assets, highlighting the impact of historical exclusion, trust in institutions, and background risk in shaping choices. Similarly, effects related to gender and race suggest that social and cultural constraints continue to influence the allocation of wealth across different assets.

Overall, the chapter makes three main contributions. First, it broadens household finance research by applying it to a developing country context, moving beyond the focus on financial assets to include the entire household balance sheet. Second, it illustrates how extreme inequality influences portfolio allocation, with wealthier households able to diversify effectively, while poorer households are constrained by necessity and limited access. Third, it emphasises the importance of informal institutions alongside formal ones, offering a more comprehensive view of household asset allocation in South Africa.

For policy, the findings highlight the importance of targeted financial inclusion strategies. Expanding access to formal financial products, enhancing financial literacy, and building trust in financial institutions could increase opportunities for lower-wealth households. At the same time, recognising the integral role of informal savings mechanisms suggests that inclusive policies should support, rather than replace, these existing practices.

Finally, this research highlights several pathways for future study. Longitudinal analysis of portfolio dynamics could provide insights into mobility and persistence in household financial behaviour. Further exploration of behavioural factors, such as trust, risk perceptions, and intergenerational wealth transfer, would enhance the understanding of the mechanisms behind allocation decisions. Comparative research with other developing countries could determine whether South Africa's experience is unique or indicative of broader patterns in unequal economies.

By integrating theory, empirical analysis, and policy relevance, this study enhances understanding of household asset allocation in unequal societies. It shows that although standard models of portfolio choice remain informative, their application is fundamentally shaped by inequality, history, and institutional context.

CHAPTER 4: HOUSEHOLD ASSET HOLDING DIVERSIFICATION ACROSS WEALTH DISTRIBUTION IN SOUTH AFRICA

4.1 INTRODUCTION

Diversifying household assets is vital for stabilising finances, reducing risks, and building wealth. The way households allocate resources across different asset classes affects their financial resilience and long-term economic health (Lhabitant, 2017). In South Africa, where wealth inequality ranks among the highest globally (SA-TIED, 2020), understanding household asset diversification is essential for policymakers and researchers. Despite its significance (Rubens et al., 1998), there has been limited research on how South African households allocate their assets and the factors that influence these choice decisions.

To address this gap, this chapter analyses household asset diversification across wealth levels using data from the National Income Dynamics Study (NIDS) survey. NIDS is especially suitable for this research for several reasons. First, it is South Africa's first nationally representative survey panel dataset, covering households across different income and wealth brackets, thus capturing heterogeneity in financial behaviour. Second, its detailed information on household balance sheets—including housing, financial, business, and other non-financial assets—enables a comprehensive analysis of portfolio composition. Third, its longitudinal structure allows the study to examine how diversification patterns develop over time and respond to shocks or changing life events. These strengths make NIDS particularly relevant for investigating household portfolio choices in a highly unequal society such as South Africa.

This study aims to examine the level of diversification of asset portfolios held by South African households by addressing the following key questions:

1. How diversified are the asset portfolios of South African households at different wealth levels?
2. What demographic and socioeconomic factors affect the level of portfolio diversification?
3. Do more diversified portfolios help households withstand adverse life events?

The life-cycle hypothesis suggests that households strategically allocate their income and wealth to meet various savings goals, including retirement, emergency funds, and passing on wealth to future generations, while also balancing their immediate consumption needs (Bodie et al., 2009). Households pursue these financial objectives by investing in diverse assets, with diversification being a key strategy to reduce risk (Chhabra, 2005; Lhabitant, 2017). The structure of household assets, which includes housing and financial assets, differs notably from the portfolios of most households, which are predominantly composed of housing assets (Bricker et al., 2019b). This lack of diversification can leave households vulnerable during economic downturns or unexpected financial shocks (Bricker et al., 2019).

Disparities in asset diversification exist across various wealth levels. Households with lower wealth face more challenges when diversifying their assets compared to wealthier ones (Wei et al., 2019). Low-wealth households tend to hold more liquid assets, while wealthier households often invest in riskier assets such as stocks and private businesses (Wei et al., 2019), indicating that wealth distribution is a key factor in diversification. In South Africa, where wealth inequality persists (Chatterjee et al., 2022), understanding household asset diversification is essential for creating policies that promote equity and economic stability. Moreover, a household's willingness to accept investment risk is a significant predictor of their diversification strategy, along with other socioeconomic factors (Barasinska et al., 2008). Short-term concerns about job security or health can also result in low asset diversification (Mariotti et al., 2015; Palia et al., 2014). Households operating within diverse financial markets may encounter constraints due to ineffective information channels, which may influence their diversification choices (Mariotti et al., 2015).

This study provides new insights into how South African households at various wealth levels diversify their asset portfolios. Using NIDS data, the study assesses asset diversification across seven asset classes. The analysis explores how household wealth, demographics, and socioeconomic factors influence diversification patterns. By examining the relationship between wealth distribution and asset allocation, this research provides valuable insights into the financial behaviour of South African households. The findings can inform policies aimed at reducing economic disparities, enhancing financial resilience, and promoting equitable wealth distribution. Additionally, the study contributes to a broader understanding of household finance by revealing how diversification can help mitigate the effects of adverse life events, thereby improving the financial well-being of households across different wealth tiers.

The rest of this chapter is organised as follows: Section 4.2 discusses the theoretical underpinnings and literature review, Section 4.3 presents the data, variables, and estimation techniques, Section 4.4 discusses the empirical results, and Section 4.5 concludes.

4.2 THEORETICAL UNDERPINNINGS AND LITERATURE REVIEW

Several theories and conceptual frameworks offer valuable insights into household asset diversification. A foundational theory in this domain is Markowitz's (1952) portfolio theory, which explains the relationship between risk and return in investment decisions. The theory demonstrates that investors can maximise expected returns for a given level of risk by holding a portfolio of assets that are imperfectly correlated.

For households, diversification thus reduces vulnerability to shocks and enhances financial resilience. Households with more diversified portfolios are therefore more likely to accumulate wealth and achieve long-term stability than those with concentrated holdings (Mariotti et al., 2015). Portfolio theory consequently suggests a positive association between household wealth levels and the degree of diversification.

The lifecycle hypothesis, developed by Modigliani and Brumberg (1954), further extends this understanding by emphasising the temporal dimension of asset accumulation and diversification. It posits that individuals move through predictable stages—early career, mid-career, and retirement—each of which shapes saving behaviour, risk tolerance, and asset choices (Feiveson & Sabelhaus, 2019). Younger individuals with longer horizons tend to invest in riskier and more diverse assets, while older individuals typically adopt conservative strategies. Moreover, intergenerational transfers enable wealthier households to diversify their assets earlier in life, thereby reinforcing wealth inequality across generations (Modigliani, 1988).

Asset poverty theory (Sherraden, 1990; Sherraden & Gilbert, 2016) introduces a structural dimension by emphasising the absence of financial and non-financial assets essential for household security. Asset-poor households, often excluded from formal credit and financial markets, struggle to build diversified portfolios. Institutional theory complements this by demonstrating how property rights, access to credit, and welfare policies shape households' capacity to accumulate and diversify wealth (Wilson, 2011). In contexts such as South Africa, where historical exclusion and inequality have left enduring imbalances in asset ownership, these theories are particularly relevant.

Human Capital Theory (Becker, 1964) underscores the role of education, skills, and experience in influencing household income and subsequent asset choices. Investments in human capital can translate into higher earnings and a greater ability to diversify portfolios (Mariotti et al., 2015; Worthington, 2009). Finally, Social Capital Theory highlights the role of networks, norms, and trust in facilitating access to resources, information, and opportunities that shape asset allocation (Asmamaw et al., 2019). These theoretical perspectives converge on a critical insight: household asset diversification is not merely an outcome of wealth but also shaped by life-cycle dynamics, structural inequalities, human capital, and social networks.

A broad body of empirical literature across countries has documented the determinants of household asset diversification. In the United States, Caner and Wolff (2004) and Wolff (2012) demonstrate that wealthier households hold a diverse mix of stocks, bonds, and business equity, whereas poorer households tend to be concentrated in real estate or debt. Goetzmann and Kumar (2008) further highlight life-cycle effects, with older households reducing exposure to risky assets by diversifying holdings more broadly.

In China, Wu et al. (2022) find that cognitive ability is positively associated with diversification, while Peng et al. (2022) identify education, financial literacy, and urban residence as significant determinants. Wealthier households hold a diverse range of financial assets, whereas poorer ones remain overexposed to housing. In India, Chakrabarty and Mukherjee (2021) utilise Theil's entropy index to demonstrate that financial inclusion enhances diversification, resulting in higher household welfare. Similarly, studies in Australia reveal that income, education, risk tolerance, and access to financial markets are key drivers of diversification (Mariotti et al., 2015). Across these contexts, wealthier households consistently demonstrate broader asset allocation, highlighting wealth as a central determinant of diversification.

Compared with international literature, South African evidence remains limited and fragmented. Ngwenya and Paas (2012) explore lifecycle effects on financial product ownership across racial groups, finding evidence of diversification among white households in middle life stages, but to a lesser extent among other groups. Ebenezer and Abbyssinia (2018) examine livelihood diversification in the Eastern Cape and show that its effectiveness in reducing poverty depends on access to resources and institutional support. Tita & Aziakpono (2017) and Mahalika et al. (2023) find that improved access to financial services enhances diversification and reduces household poverty. Alemu (2012) highlights gendered barriers to asset accumulation and diversification, while Sikhunyana et al. (2020) investigate livelihood diversification among poor households, showing how survival strategies shape household portfolios.

While these studies offer valuable insights, they exhibit several limitations. First, most focus on livelihood diversification (income sources, survival strategies) rather than systematic household asset portfolios. Second, they tend to emphasise poverty reduction rather than the broader dynamics of diversification across the wealth distribution. Third, empirical analyses are often restricted to specific provinces, demographic groups, or narrow asset classes, which limits generalizability. Finally, the interaction between diversification and households' ability to withstand adverse life events remains underexplored.

The reviewed literature highlights clear international evidence on how wealth and socioeconomic factors influence household diversification, while also revealing notable gaps in the South African context. Specifically:

- Lack of systematic measurement: Existing South African studies rarely capture asset diversification across multiple asset classes, leaving the broader structure of household portfolios unexplored.

- Wealth-distribution focus: No studies explicitly examine how asset diversification varies across the wealth distribution, despite South Africa's extreme inequality.
- Resilience to shocks: The extent to which diversification enhances household resilience to life events has received limited attention.
- Integration of determinants: Prior research often isolates factors such as financial inclusion or gender, but does not systematically integrate wealth, demographic, and socioeconomic variables in explaining diversification.

This study aims to address these gaps by utilising the National Income Dynamics Study (NIDS) dataset to measure household asset diversification across seven distinct asset classes. It examines how demographic and socioeconomic characteristics shape diversification across the wealth distribution and assesses whether diversified portfolios help households withstand adverse life events. In doing so, it contributes to the literature on household finance in South Africa by linking diversification patterns to inequality, financial inclusion, and resilience, thereby offering evidence relevant for both academic inquiry and policy design.

4.3 DATA, VARIABLES AND ESTIMATION TECHNIQUES

4.3.1 Data

The chapter relies on the fourth and fifth waves of NIDS data, just as the previous two chapters do. Unlike other waves, these are particularly relevant for analysing household asset-holding diversification in South Africa because they capture household possessions such as durable goods. Household possessions can offer valuable insights into the patterns of asset ownership in South Africa. Differential access to durable goods and other household possessions may be attributable to income, education, and other socioeconomic disparities (Biyase et al., 2019). The fifth wave is particularly significant because it was the most recent before the COVID-19 pandemic. It allows examining household assets and well-being shortly before this significant economic shock. Such information is crucial for understanding household resilience or vulnerability shortly before this economic shock.

4.3.1.1 Data Handling and Scaling

The dataset combines variables expressed in different units—monetary values (e.g., net worth, income, financial assets, livestock, and vehicles), categorical indicators (e.g., gender, race, marital status, and employment status), and dimensionless indexes (e.g., diversification index). To ensure comparability across scales, all monetary variables were converted into real South African Rand (ZAR) using the consumer price index (CPI) with a base year of March 2017.

Relative measures, such as the net worth-to-median ratio, were created to position households within the wealth distribution on a scale-free basis, reducing heterogeneity in absolute values. Index measures, including the diversification index, are inherently unitless and thus directly comparable across households. These steps ensure that the econometric models treat variables of different dimensions consistently, avoiding distortions caused by scale differences. The detailed data dictionary (Appendix C) provides definitions, units, and dimensionality for all variables used in the analysis.

4.3.1.2 Strengths and Limitations of the NIDS Dataset

The National Income Dynamics Study (NIDS) offers a vital resource for analysing household behaviour in South Africa. Its panel structure enables the tracking of households and individuals over time, facilitating the study of changes in wealth accumulation, asset diversification, and vulnerability to shocks. The survey's detailed household-level data captures a broad spectrum of economic and demographic variables, including financial and non-financial assets, income, employment, and social factors. This extensive data set makes it well-suited for exploring the determinants and impacts of asset diversification.

However, some limitations need to be recognised. Attrition across waves is significant and could bias results if households that drop out differ systematically from those that stay. Recall bias may influence self-reported data, especially on income, asset values, and adverse life events. Additionally, informal sector activities and assets—which are vital to the livelihoods of many South Africans—may be underreported or measured inconsistently. While weighting adjustments and robustness checks can help reduce these issues, they cannot completely eliminate them. Nevertheless, NIDS remains the most comprehensive nationally representative panel dataset available for South African households, and its strengths outweigh its limitations for this study. However, results should be approached with caution, considering these data-related challenges.

4.3.2 Variables

The main variables I use in this chapter are indicators of household asset-holding diversification and wealth distribution in South Africa, as well as the socioeconomic characteristics of the households. Table 4.1 presents a description of these variables.

Table 4.1: Variable Description

VARIABLES	DESCRIPTION
Diversification index	Index of 7 distinct asset classes ranging from 0 to 1
Diversification level	Categorical variable: 1=Under diversified. 2=Moderately diversified. 3=Fully diversified

Net worth	Total Assets minus Total Debts
Net worth-median ratio	A ratio of net worth/median net worth indicates the position of a household in terms of wealth distribution.
Household income	Household monthly total income
Debt-to-Assets ratio	Total debt/total assets
Self-employed	1=self-employed and 0=otherwise
Life-insurance?	Have life insurance? 1= Yes, 0=No
Household size	Number of household members
Age	Age of household head
Age square	Square of the Age of the household head
Education years	Education years of the household head
Gender	1=male, 0=female
Race	1=African, 2= coloured, 3=Asian/Indian, 4=White
Marital status	1= partner Household head, 0= single Household head
Employment status	1=employed and 0=unemployed
Geographical location	1=Traditional Authority Area (TAA), 2=Urban, 3=Farms

Household Asset Holding Diversification: I construct two indicators of household asset holding diversification from seven asset classes provided in NIDS—the diversification index and three categories of diversification levels. NIDS contains the value of assets that a household owns, including financial assets (such as stocks, unit trusts, and bank accounts), physical assets (such as real estate, livestock, durables, and vehicles), and other assets (such as business assets and retirement annuities). Table 4.4 presents the summary statistics of the assets I utilise to construct both measures of asset diversification.

Wealth Distribution: I calculate the wealth distribution by dividing each household's net worth by the median net worth, where net worth is the excess of household assets over liabilities. The ratio of household net worth to the median shows each household’s relative position, indicating whether it is above or below the “typical” level of wealth. I adopt this approach from Szymborska (2019), who used the ratio as a proxy for income distribution to assess household positions relative to the median. This method offers a clearer picture of a "typical" household's wealth than a simple mean, which can be heavily skewed by a few households with extremely high wealth values (Lavine, 2012). It is especially relevant in contexts of high wealth inequality, where traditional mean calculations can substantially misrepresent the financial standing of most households (Dräger et al., 2023). This is crucial because, in nations like South Africa, where a small fraction of the population holds a disproportionate share of total wealth (Orthofer, 2016), the median provides a more reliable indicator of central tendency for wealth distribution (Assouad, 2023).

The ratio is my primary focus among other regressors as I examine how wealth distribution affects asset-holding diversification. To ensure robustness, I also construct wealth quartiles based on household net worth. This alternative classification offers a categorical view of the distribution, enabling me to assess whether the results are sensitive to the choice of relative measure. Consistency across both specifications strengthens the validity of the findings. Other regressors include economic variables such as household income, debt-to-asset ratio, education, and employment status, as well as demographic variables like age, marital status, gender, and race.

4.3.3 Diversification Measures

Herfindahl-Hirschman Index/Gini-Simpson Index

I adopt the asset diversification measure used by Mariotti et al. (2015). This measure indicates the extent to which households diversify their assets across different asset classes. It applies the Herfindahl-Hirschman Index (HHI), which calculates the degree of concentration or diversification across asset classes. HHI is commonly used in industrial organisations to measure market concentration, but can also be applied to household asset-holding diversification. It sums the squares of the market shares (but in this case, the asset shares) of each household in the NIDS sample:

$$HHI = \sum_{i=1}^{k} s_i^2 = \left(\frac{value\ of\ asset_1}{value\ of\ all\ assets}\right)^2 + \cdots + \left(\frac{value\ of\ asset_k}{value\ of\ all\ assets}\right)^2 \tag{4.1}$$

Where: s_i is the share of k^{th} asset for each household asset portfolio.

The resulting value of the HHI ranges from $1/k$ for perfect diversification (i.e., a household holds equal shares of all k assets) to 1 for perfect concentration (i.e., a household has only one asset). A higher HHI indicates a greater concentration of assets (less diversification), while a lower HHI suggests a more diversified portfolio of household assets. A more reasonable measure is the Gini-Simpson index (GSI). It modifies the HHI such that an index of zero indicates those who choose not to diversify at all. The following calculates GSI:

$$GSI = 1 - \sum_{i=1}^{k} s_i^2 \tag{4.2}$$

A higher GSI indicates greater asset diversification, while a lower GSI indicates lower asset diversification. I calculate GSI for the following seven household asset classes: *real estate, business assets, financial assets, retirement annuities, livestock, vehicles*, and *possessions*.

The use of HHI or GSI reflects how the wealth is spread across several assets—it does not reflect risk diversification. Hence, some researchers termed it a "naïve diversification measure" (Barasinska et al., 2009). The second measure of diversification tries to incorporate assets with their inherent risks.

A Measure Based on Risk Level

I construct the second measure of asset diversification following Barasinska et al. (2009). The measure accounts for the number of assets and their degree of risk diversification in a portfolio. To construct this second measure, I disaggregate real estate into owner-occupied[13] houses and other property and financial assets, including bank accounts and stocks, to now comprise a total of nine asset classes: real estate, stocks, business assets, bank accounts, vehicles, owner-occupied houses, possessions, livestock, and retirement annuities. Then, I categorise these assets into low-risk, moderate-risk, and high-risk categories, as described in Section 3.3.2 above. I justified this classification under section 3.3.2. Table 4.2 shows the asset classification by risk levels.

Table 4.2: Asset Classification by Risk Levels

Low risk	Moderate risk	High risk
Bank account balance	Vehicles	Unincorporated Business
Possessions	Livestock	Stocks
Owner-occupied house	Superannuation	Real Estates

The second measure involves determining the diversification level by identifying asset ownership across the three classes. It considers portfolios comprising assets from all three risk classes *fully diversified*, while those comprising assets from just one category are *under-diversified*. Finally, the measure considers portfolios containing assets from any two of these categories as *moderately diversified*. Therefore, this measure of diversification becomes an ordered categorical variable of three levels, as presented in Table 4.3. 1=*Under-diversified*, 2=*Moderately diversified*, and 3=*Fully diversified*.

Table 4.3 presents the distribution of households by the three levels of asset diversification. Values in the upper part of Table 4.3 indicate that the majority of households (over 50%) held under-diversified portfolios in 2014 and 2017. Approximately 35% of households held moderately diversified portfolios over the

[13] The reason for disaggregating is that owner-occupied house is viewed as having different risk from other property as articulated in chapter 3. The same goes for bank account balance and the stocks. Thie disaggregation raises the total number of assets provided in NIDS from 7 to 9.

past two years. The lowest proportion of households (11% and 13.5% in 2014 and 2017, respectively) holds fully diversified portfolios.

The bottom part of Table 4.3 indicates that households tend to prefer safety. From 2014 to 2017, all households with under-diversified portfolios preferred low-risk assets, and no households preferred moderate or high-risk assets. Additionally, for 2014, 45% of those with moderately diversified portfolios prefer a combination of low-risk and moderate-risk assets, and about 55% prefer a combination of low and high-risk assets. However, with 2017 data, 52% prefer a combination of low-risk and moderate-risk assets, while 48% prefer a moderate-risk combination of low-risk and high-risk assets. No households preferred a high-risk combination that included moderate- and high-risk assets. The proportion of those whose portfolios are quite diversified, combining moderate and high-risk assets, is nil.

Table 4.3: Summary of Diversification Measure of Categorical Levels

Portfolio Types	Year 2014	Year 2017
1. Under diversified (% households holding any single class)	54	51.9
2. Moderately diversified (% households holding any two classes)	35	34.6
3. Fully diversified (% households holding all classes)	11	13.5
Total	100	100

Portfolio Types (Classified by Risk)		Asset Classes Owned: Low	Moderate	High	Year: 2014(%)	2017(%)
Under diversified portfolios	Low	1	0	0	100	100
	Moderate	0	1	0	0	0
	High	0	0	1	0	0
Total					100	100
Moderately diversified portfolios	Low	1	1	0	45	52
	Moderate	1	0	1	55	48
	High	0	1	1	0	0
Total					100	100
Fully diversified portfolios		1	1	1	100	100

Note: "1" indicates ownership of a particular risk class, and "0" denotes non-ownership.

4.3.4 Link between Theory and Empirical Specification

The theoretical foundation of this study rests on three complementary perspectives: portfolio theory, life cycle theory, and risk management theory. Portfolio theory (Markowitz, 1952; Wagner & Lau, 1971) posits that diversification across uncorrelated assets reduces overall risk for a given expected return. Household portfolios that spread wealth across asset classes should therefore exhibit greater resilience to shocks. This motivates the use of indices such as the Herfindahl-Hirschman Index (HHI) and its transformation, the Gini-Simpson Index (GSI), which quantify the degree of concentration versus diversification. These indices provide a tractable way to operationalise the theoretical construct of diversification in empirical analysis.

Life-cycle theory (Gomes & Michaelides, 2005; Modigliani & Brumberg, 1954) emphasises that portfolio choices vary with age, income, and wealth accumulation. To reflect this heterogeneity, households are placed along the wealth distribution (via quartiles and median ratios), and demographic and economic covariates are incorporated into the model. This ensures that the empirical models account for structural differences in asset allocation driven by life-cycle motives.

Finally, risk-management theory emphasises that resilience depends not only on the number of assets held but also on exposure to different risk levels (Araújo et al., 2022). This justifies the development of a categorical diversification measure encompassing low-, moderate-, and high-risk asset classes. The ordered logit/probit model naturally follows, as it estimates the likelihood of households being under-, moderately-, or fully diversified, consistent with the ordered nature of resilience levels suggested by the theory. Empirically, the fractional logit model for GSI and the ordered choice model for risk-based diversification directly operationalise these theoretical constructs. By linking wealth distribution, demographic and economic controls, and diversification indices, the specifications test the central proposition that asset allocation decisions—guided by portfolio optimisation, life-cycle motives, and risk-management considerations—systematically shape household financial resilience.

4.3.5 Estimation Techniques

I utilise the Fractional Regression Model (FRM) to analyse how household wealth distribution affects asset-holding diversification. FRM is suitable when the dependent variable, GSI, takes values between 0 and 1. Papke & Wooldridge (1996) introduced the FRM, which they extended to panel data in Papke and Wooldridge (2008) . I start with the following specification, which helps explain how wealth distribution influences asset-holding diversification.

$$\begin{aligned} GSI_{it} = \beta_0 + \beta_1 Q2_{it} + \beta_2 Q3_{it} + \beta_3 Q4_{it} + \beta_4 wave_5 + \beta_5 (Q2_{it} \times wave_5) \\ + \beta_6 (Q3_{it} \times wave_5) + \beta_7 (Q4_{it} \times wave_5) + \gamma X_{it} + \varepsilon_{it} \end{aligned} \tag{4.3}$$

where:

- GSI_{it} is an index of seven asset classes j (j=1, 2,…,7) of household i at period t, where t=0,1 for two time periods.
- $Q2_{it}$, $Q3_{it}$, and $Q4_{it}$ are indicator variables representing the second, third, and fourth quartiles of net worth for household *i* at period *t*, respectively. These categories indicate where a household stands in the wealth distribution. Another version of this model will use a ratio of net worth to median net worth, rather than net worth quartiles. These two versions will provide a comprehensive picture of how asset-holding diversification and wealth distribution are related.
- $wave_5$ is an indicator variable for the wave five period (=1 if wave 5 and 0 if wave 4).

- $\beta_1, \beta_2, and\ \beta_3$ indicate how asset diversification for households in each quartile differs from that of the reference group. This difference can be attributed to variations in wealth levels, but it may also be due to unobservable factors that influence asset diversification and wealth.
- β_4 indicates a change in asset diversification between Wave 4 and Wave 5.
- β_5, β_6, and β_7 indicate how changes in asset diversification for households in each quartile differ from the reference category (first quartile) over the Wave 5 period. This difference isolates the causal effects of wealth from the impact of time-invariant unobservable factors.
- X_{it} represents control variables such as household demographics, income, education, etc.
- ε_{it} is the error term.

4.3.6 Fractional Logit/Probit Model for GSI

Specification (4.3) is linear and does not guarantee that $0 \leq E(GSI_{it}|X) \leq 1$. I, therefore, apply the following modification following Papke & Wooldridge (1996), where X denotes all covariates on the right-hand side of (4.3), and Y denotes GSI.

$$E(Y|X) = G(X\theta) \tag{4.4}$$

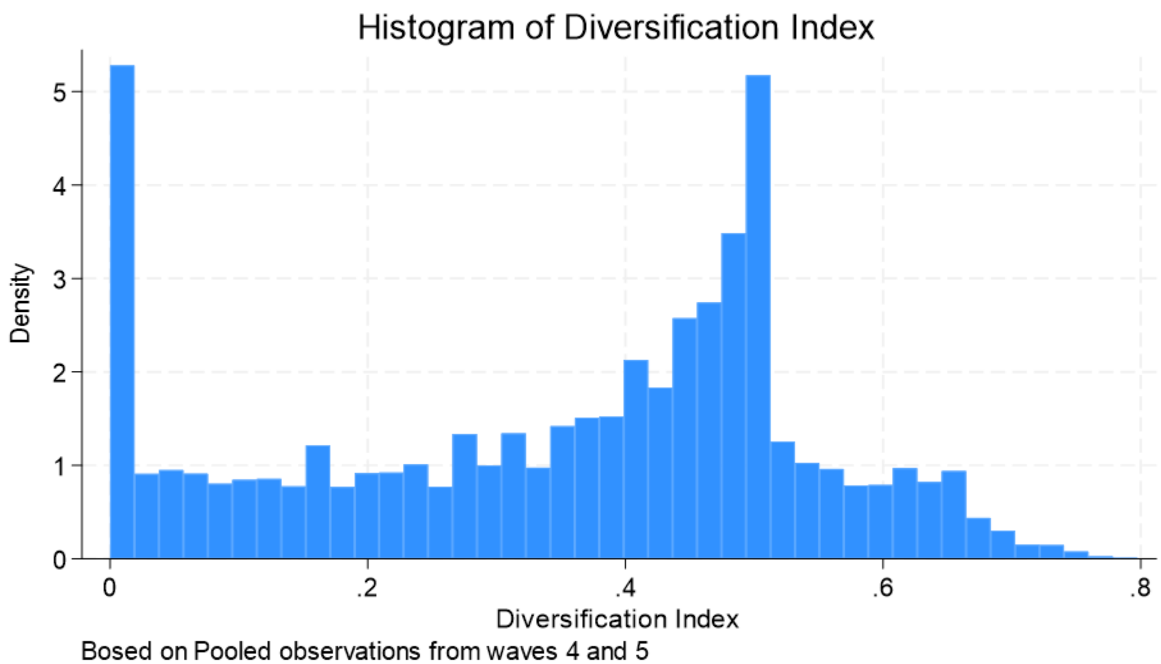
Where, $G(.)$ is a known nonlinear function satisfying $0 < G(.) < 1$, and its specification can be any cumulative distribution, such as logit and probit. $\theta = (\boldsymbol{\beta},\ \boldsymbol{\gamma})'$ is a vector of parameters of (4.3) to be estimated. Papke & Wooldridge (1996) showed that, although nonlinear least squares (NLS) could give consistent estimates for θ, it is more efficient to assume a Bernoulli distribution for Y conditional on X and estimate the parameters θ by maximising the quasi-likelihood function:

$$LL(\theta) = ylog[G(X\theta)] + (1 - y)\log[1 - G(X\theta)] \tag{4.5}$$

As the Bernoulli distribution is a member of the linear, exponential family, the resulting quasi-maximum likelihood (QML) estimator for θ will always be consistent, regardless of the true distribution of Y conditional on X, provided that (4.3) is correctly specified (see Gourieroux, Monfort and Trognon, 1984 quoted in Ramalho & da Silva, (2009)).

Figure 4.1 shows the histogram of the diversification index (Y), which reveals a bunch of households with zero diversification index. i.e. households holding just one asset. Therefore, there is a likelihood of two decision processes. Firstly, a household decides whether to diversify ($Y = 0$ or $Y > 0$). Secondly, conditional on having decided to diversify, the household chooses how much to diversify ($0 < Y < 1$). If two different processes guide the household in making these two decisions, the theta estimates, $\hat{\theta}$ will be biased (Buis, 2010). However, there is no reason to believe that two different processes govern the decisions.

Figure 4.1: Histogram of Diversification Index (GSI)



4.3.7 Ordered Logit or Probit Model

The second measure of the dependent variable is asset diversification levels: 1. *Under-diversified*, 2. *Quite diversified,* and 3. *Fully diversified*. Ordered Probit and Ordered Logit models are standard statistical models used to analyse the relationship between a dependent variable that takes on values of ordered alternatives and one or more independent variables. The basic idea behind both models is to estimate the probability of the dependent variable taking on a specific value, given the values of the independent variables. To illustrate, I assume an index model for a single latent variable, y*, which is unobservable but known only when it crosses thresholds.

$$y_i^* = X_i'\beta + u_i \tag{4.6}$$

$$y_i = j \quad if \quad \alpha_{j-1} < y_i^* \leq \alpha_j$$

where $j = 1, \dots, J$ is the number of alternatives, and α is the cutoff point between the alternatives. The probability that household *i* will select alternative *j* is:

$$p_{ij} = p(y_i = j) = p(\alpha_{j-1} < y_i^* \leq \alpha_j) = F(\alpha_j - X_i^*\beta) - F(\alpha_{j-1} - X_i^*\beta) \qquad (4.7)$$

The difference between the Probit and Logit models lies in their assumptions about the distribution of the error term in the model. In the ordered Probit model, the error term is assumed to follow a normal distribution. The model estimates the coefficients of the independent variables in such a way as to maximise the likelihood of the observed data, given the normal distribution of the error term. In the ordered Logit model, the error term assumes a logistic distribution, and F is the logistic cumulative density function (CDF); $F(z) = e^z/(1 + e^z)$The model estimates the coefficients of the independent variables to maximise the likelihood of the observed data, given the logistic distribution of the error term. Both models produce estimates of the coefficients of the independent variables, which I interpret as the effect of each independent variable on the probability of choosing the specific level of diversification.

4.3.8 Diversification and Resilience-DiD Strategy

Diversification, which spreads investments across various asset classes, reduces risk and enhances financial resilience. This section explores the strategy for analysing how diversification can mitigate the impact of adverse life events.

The portfolio theory suggests that diversified investments reduce risk and improve returns. Households with diversified portfolios are better equipped to withstand economic shocks (Wagner & Lau, 1971). The fundamental concepts of portfolio theory—risk, return, diversification, and asset allocation—underscore that by investing in different asset classes, households can reduce risk because the returns on these assets are often not perfectly correlated, meaning that gains in one asset can offset losses in another.

The life-cycle theory posits that individuals accumulate wealth throughout their lives to meet future needs, and diversification is essential for ensuring financial security during different life stages (Gomes & Michaelides, 2005). Individuals' risk tolerance and investment goals change through various life stages. For instance, younger households may invest more in equities and growth-oriented assets, seeking higher returns. As they retire, they may shift their investments towards more conservative assets, such as bonds, to reduce risk and generate a stable income.

Diversification also acts as a risk management strategy, protecting households from unexpected events such as job loss, illness, or natural disasters (Araújo et al., 2022). Risk management involves assessing potential risks, mitigating them, and building resilience to withstand them. By diversifying investments across different asset classes, households can reduce the concentration of risk and improve their financial resilience. For example, a household facing job loss might diversify its income by investing in rental properties or starting a small business, thereby cushioning the financial impact of unemployment.

These three theoretical frameworks—portfolio theory, life-cycle theory, and risk management—provide a robust foundation for understanding how asset diversification enhances household resilience and financial well-being. Together, they offer a comprehensive view of the factors influencing asset allocation decisions and the benefits of diversification. This subsection aims to develop a methodology for addressing the final question: Can diversification mitigate the impact of adverse life events on households?

While research in South Africa has explored poverty, inequality, and livelihood strategies (Alemu, 2012; Ebenezer & Abbyssinia, 2018; Sikhunyana et al., 2020), none has directly examined whether asset diversification enhances resilience to adverse shocks. This section addresses this gap by analysing the impact of adverse life events on the net worth of households with diversified portfolios compared to non-diversified portfolios.

The longitudinal nature of NIDS enables an analysis of how wealth changes in households that have encountered unexpected adverse life events compared to those that have not. By examining fully diversified versus less-than-fully diversified households, this study evaluates household resilience to adverse shocks. Specifically, this section utilises a difference-in-difference (DiD) strategy to compare the effects of adverse shocks on net worth between households with diversified asset portfolios and those without. The central research question is: "How do negative life events impact net worth in households with these two levels of asset diversification?" The aim is to quantify the effects of adverse shocks on net worth between households holding fully diversified asset portfolios and those that do not.

NIDS data includes whether a household experienced adverse life events in the past 24 months, which is crucial for constructing the treatment variable. The treatment variable is coded as 1 if a household experienced an adverse event in Wave 5 but not in Wave 4, and 0 otherwise. This is compared to a control group of households that never experienced any adverse events in either period. Another critical variable indicates whether a household is fully diversified. I code 1 for households holding at least one asset across the three risk classes (low-risk, moderate-risk, and high-risk) and 0 otherwise. The interaction between these variables will reveal the differential impact of adverse shocks on net worth changes between fully diversified households and those that are not. The DiD strategy outlined below will guide this analysis.

4.3.8.1 Difference in Differences Strategy

To identify households that experienced adverse life events, NIDS asked whether the respondents experienced the following adverse life events during the past twenty-four months:

- Theft, fire, or destruction of household property.
- Widespread death or disease of livestock.
- Major crop failure.
- Any other adverse event, including loss of income, death of household members, health issues, etc.

The interest is to determine how the impact of these adverse events differs between households holding diversified portfolios and those holding non-diversified portfolios. In that way, we can evaluate whether diversification provides a buffer against unexpected adverse events.

The DiD approach is a statistical technique used to estimate causal relationships by comparing the changes in outcomes over time between a group exposed to a treatment (in this case, households experiencing adverse life events) and a control group (households that did not experience such events). This method helps isolate the effect of the treatment by controlling for time trends that might affect both groups similarly.

In the context of this study, DiD is particularly suitable for analysing how adverse life events impact the net worth of households with varying levels of asset diversification. The DiD approach leverages the longitudinal nature of the NIDS data, which tracks households over time, allowing for a before-and-after comparison of the impact of adverse shocks.

By applying DiD, we can more accurately assess whether households with diversified asset portfolios are more resilient to wealth erosion following adverse shocks than those with non-diversified portfolios. This methodology helps control for potential confounding factors that could influence wealth changes over time, ensuring that the observed differences are more likely attributable to the diversification of asset holdings rather than other external factors.

The implementation of the DiD strategy requires the following grouping of the households:

Treatment and Control Groups:

- *Treatment Group*: Households that experienced an adverse life event in Wave 5 but did not experience such in Wave 4 of the NIDS.
- *Control Group*: Households that did not experience an adverse life event in both waves.

Diversification Indicator:

A household's diversification status is categorised as diversified or under-diversified based on asset holdings. A binary indicator variable equals 1 if the household holds a fully diversified portfolio across the three risk classes identified above and 0 if it is less than fully diversified.

Interaction Term:

The DiD model includes an interaction term between the treatment indicator (whether a household experienced an adverse life event) and the diversification indicator (whether a household is diversified). This interaction term captures the differential impact of adverse life events on wealth changes for households that are diversified versus those that are not.

The basic DiD model is as follows:

$$\begin{aligned} y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Treatment_i + \beta_3 (Post_t \times Treatment_i) + \beta_4 Diversified_i \\ + \beta_5 (Post_t \times Diversified_i) + \beta_6 (Treatment_i \times Diversified_i) \\ + \beta_7 (Post_t \times Treatment_i \times Diversified_i) + \beta_8 X_{it} + \varepsilon_{it} \end{aligned} \tag{4.8}$$

Where y_{it} is the net worth of the household *i* at time *t*.

$Post_t$ is an indicator variable equal to 1 for the post-treatment period (wave 5) and 0 for the pre-treatment period (wave 4).

$Treatment_i$ is an indicator variable equal to 1 if the household experienced an adverse life event in Wave 5 but not in Wave 4, and 0 otherwise.

$Diversified_i$ is an indicator variable equal to 1 if the household portfolio is diversified and 0 if under-diversified.

X_{it} represents the socio-economic and demographic characteristics of households.

The interpretation of coefficients is as follows:

β_0: The average net worth of the control group in 2014.

β_1: The change in the average net worth over time for the control group.

β_2: The difference in the average net worth between the treated and control groups in 2014.

β_3: The DiD estimator representing the negative shocks' impact on net worth, regardless of diversification.

β_4: The difference in net worth between diversified and non-diversified households in 2014.

β_5: The change in the average net worth over time for diversified households in the control group.

β_6: The difference in the average net worth between diversified and non-diversified households in the treated group in 2014.

β_7: The triple interaction term illustrates the differential impact of negative shocks on net worth for diversified households compared to non-diversified ones. This coefficient is crucial for addressing the third question regarding whether diversification protects against adverse shocks. If this coefficient is statistically significant and negative, it indicates that the detrimental effect of shocks on net worth is more pronounced for households with a fully diversified portfolio than for those without. Conversely, suppose it is statistically significant and positive. In that case, it suggests that the negative impact of shocks on net worth is less severe (or even positive) for fully diversified households compared to their non-diversified counterparts. If it is not significant, there is no evidence to imply that diversification moderates the impact of shocks.

The DiD strategy has several advantages, one of which is that it controls for Unobserved Time-Invariant Factors. By comparing changes within households over time, the DiD method controls for unobserved factors that might influence wealth but do not change over time, such as household attitudes towards risk or cultural factors. DiD accounts for common time trends, controlling for trends that affect all households similarly, such as macroeconomic conditions or policy changes. More importantly, it focuses on Causal

Inference: By comparing the treatment and control groups before and after the negative shock, DiD provides stronger evidence of causality than simple cross-sectional analyses.

However, the following challenge requires consideration: Parallel Trends Assumption. A fundamental assumption in DiD is that the treatment and control groups would have followed parallel paths over time in the absence of the treatment. Any deviation from this assumption can bias the results. Given only these two waves (4 and 5), testing for the parallel trend assumption is impractical, a caveat we shall bear in mind when interpreting the results. Nonetheless, the DiD methodology is suitable for assessing how asset diversification influences household resilience to financial shocks. It provides a robust framework for understanding the impact of adverse life events on wealth across different levels of asset diversification.

4.4 RESULTS AND DISCUSSION

4.4.1 Descriptive Results

The analysis starts by summarising household assets, asset diversification, and wealth distribution using mean, median, and standard deviation measures, based on pooled data from waves 4 and 5 of the NIDS dataset. The mean and median values of the asset diversification index are 0.35 and 0.40, respectively, with a range from zero (least diversified household) to 0.80 (most diversified household). The discrepancy between the mean and median likely reflects the presence of extreme observations that lower the mean, while the median remains robust to such outliers. Furthermore, when the mean exceeds the median, as seen in the data for all assets and net worth, it indicates positive skewness in the distribution, suggesting that a few high-value outliers have a disproportionate impact on the mean and contribute to wealth inequality. (Table 4.4 provides a summary of these findings.)

Table 4.4: Summary of Assets, Net Worth and Diversification Index

	N	Mean	SD	Min	Median	Max
Diversification index	19021	.35	.20	0	.40	.80
Real estates	15771	357198.05	2545245	1.00	57522.52	2.073e+08
Business assets	748	335830.91	2759516	33.00	13830.33	54995692
Financial assets	10337	54730.13	3420224.2	1	791.32	3.443e+08
Vehicles	3148	130117.88	242608.15	1.12	70054.86	8385535
Livestock	1391	46216.73	133367	2.2	14314.85	3079758.8
Retirement annuities	1803	997173.24	13696661	1.148	157084.78	5.742e+08
Possessions	19020	82754.895	999968.66	1.148	22581.787	1.250e+08
Total assets	19021	532838.05	5751972	51.86	82493.54	5.767e+08
Net worth	19638	493375.1	5634911.2	-11082574	75536.34	5.765e+08
Net worth/Median	19638	6.772	80.939	-167.923	1.045	8735.35
Net worth deciles	19638	5.5	2.873	1	5	10
Household income	19638	9148.5	26095.35	2.265	4703.683	2607565.5

Note: Pooled observations over waves 4 &5 and Rand values adjusted to March 2017 prices.

The analysis shows that private business and livestock assets are the least held, with only 748 and 1391 households owning them. In contrast, household possessions, including durables, are most common, with 19,020 households, followed by real estate with 15,771. Mean values indicate that retirement annuities (R997,173), real estate (R357,198), and private business (R335,831) are the most valuable, while livestock (R46,217) and financial assets (R54,730) are the least valuable. These observations highlight how asset diversification may influence wealth inequality; low business ownership could limit diversification, though it can significantly boost wealth for owners. I examine how asset-holding diversity is related to wealth distribution, taking into account the socioeconomic characteristics of households.

Table *4.5* presents the breakdown of household asset-holding diversification by various household characteristics. The first column specifies the characteristics of the households, including their net worth and the median net worth ratio, while the second column represents a binary decision on whether households opted to diversify their assets. In other words, it indicates whether the households hold only one asset

($GSI = 0$) or more than one asset ($GSI > 0$). The third column provides information on the degree of asset diversification, depicted by the quartiles of the diversification index.

Table 4.5: Summary of Household Characteristics by Diversification Index

VARIABLES		The binary decision to diversify		Quartiles of diversification index for Households with GSI>*0* Only			
		GSI=0	*GSI>0*	1st	2nd	3rd	4th
Pooled observations (N)		1,480	17,541	5,723	4,676	4,432	4,332
Financial characteristics							
Net worth (R)		38,833	2,705,135	7,941,061	1,682,086	1,079,078	1,444,197
Net worth-to-median ratio		.42	30.78	108	23	15	19
Income (R)		6,663	25,743	22,779	32,164	22,400	27,485
Life insurance	Yes	3	14	9	13	10	22
(%)	No	97	86	91	87	90	78
Socioeconomic characteristics							
Age (years)		46	53	53	53	53	53
Education (Years)		8	10	10	10	9	11
Household size (N)		6	4	4	4	4	4
Gender (%)	Male	44	43	43	41	39	48
	Female	56	57	57	59	61	52
Marital status	Partner H.H.	75	59	31	39	38	49
(%)	Single H.H.	25	41	69	61	62	51
Race (%)	African	80	65	79	81	85	82
	Coloured	20	14	15	13	11	10
	Indian	0	1	1	1	1	1
	White	0	20	5	5	3	6
Location (%)	TAA	40	17	31	39	42	38
	Urban	20	81	63	56	53	57
	Farms	40	2	6	5	5	5
Employment	Employed	81	85	84	83	82	90
status (%)	Unemployed	19	15	16	17	18	10
Self-employed	Yes	5	12	9	12	10	16
(%)	No	95	88	91	88	90	84

Note: The table used the first measure of diversification, which is based on the Gini-Simpson index

When pooling observations across waves 4 and 5, 1480 households opted to hold only one asset, while 17,541 households chose to diversify their asset holdings. Among those who decided to diversify, the number of households decreases as the level of diversification increases, as indicated by the quartiles of the GSI. The average ratio of net worth to median net worth for households that do not diversify is 0.42, while those that diversify have an average ratio of 30.78, suggesting a positive association between position on the net worth distribution and the likelihood of diversifying. Regarding the degree of diversification, Figure 4.2 shows the relationship between the diversification index and net worth deciles. It indicates that asset-holding diversification generally increases with wealth distribution until the 70th percentile, after which it decreases slightly. This pattern suggests a quadratic relationship between the levels of diversification and the distribution of net worth. Specifically, households in the 70th net worth percentile have the most diversified portfolios. In contrast, those in the 10th decile have less diversified portfolios but may have held high-return assets.

Figure 4.2: Mean of Diversification Index (GSI) over Net Worth Deciles

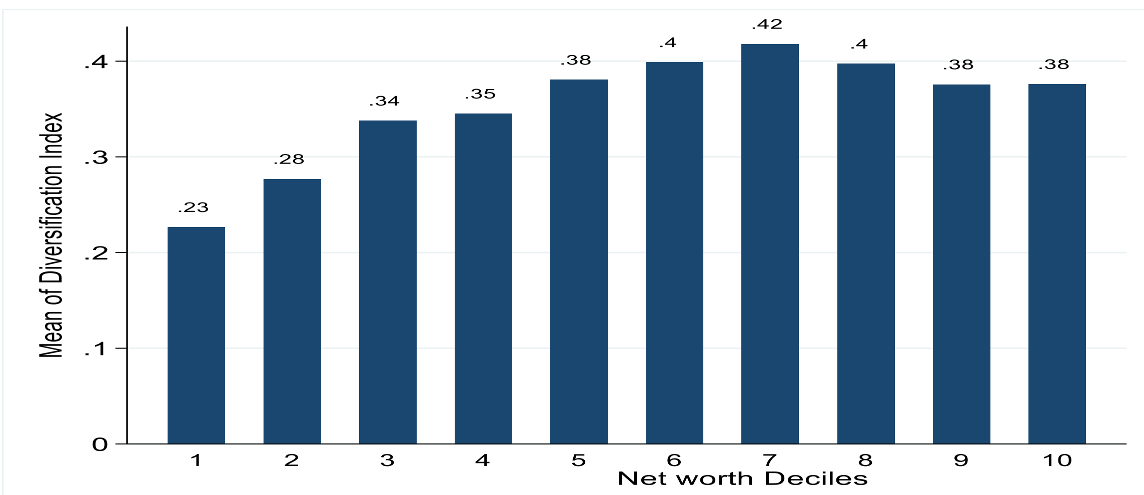
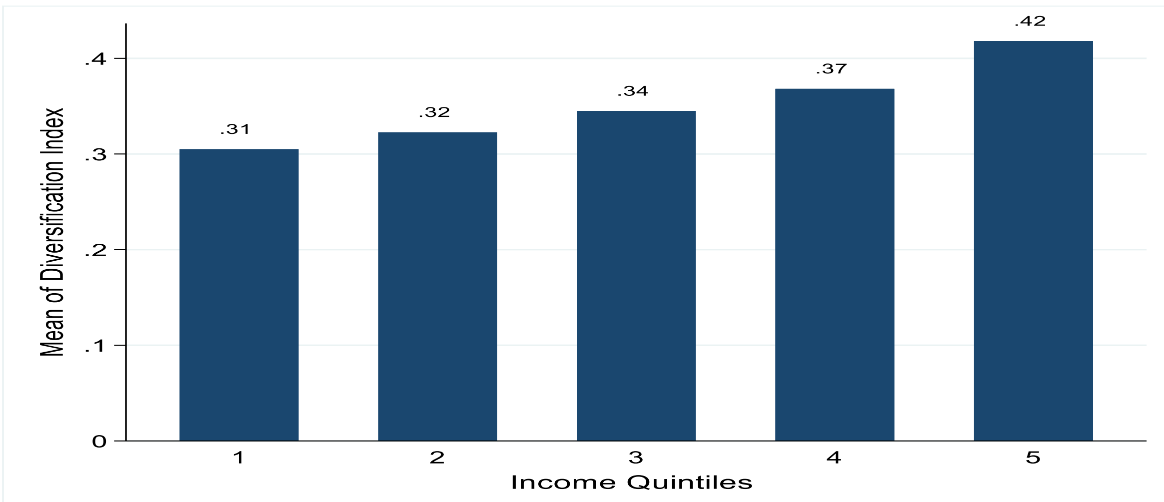


Table 4.5 reveals a positive association between household income and the likelihood of asset diversification. Specifically, households holding only one asset have an average monthly income of R6,663. In comparison, those holding more than one asset have an average income of R25,723, suggesting that an increase in income is associated with a higher likelihood of holding multiple assets and highlighting the role of income in increasing the affordability of accumulating more assets. Moreover, Figure 4.3 illustrates

that diversification steadily increases with income, indicating that higher incomes enable households to save more and finance additional investments. These findings underscore the critical role of income in driving asset accumulation and diversification.

Figure 4.3: Mean of Diversification Index (GSI) over Income Quintiles



The typical age of household heads exhibits a positive correlation with asset diversification. Specifically, the mean age for households possessing a single asset is 46 years, whereas it rises to 53 years for those with multiple assets, a trend observed across all quartiles of the diversification index (*Table 4.5*). Asset diversification tends to increase with age, reaching its peak in the 55-64 age group (Figure 4.4), followed by a slight decline, which suggests that older heads are more inclined to diversify their assets. Conversely, younger heads may prefer to invest in riskier assets to achieve higher returns, whereas older heads generally hold a larger proportion of low-risk assets to safeguard their wealth, often centred in their residential properties.

Figure 4.4: Mean of Diversification Index (GSI) by Age Groups

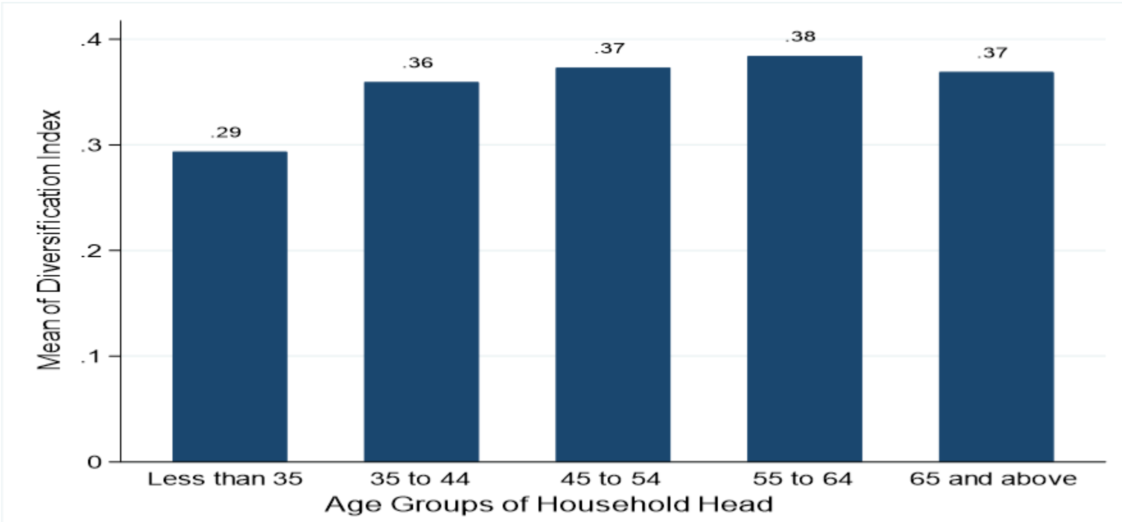


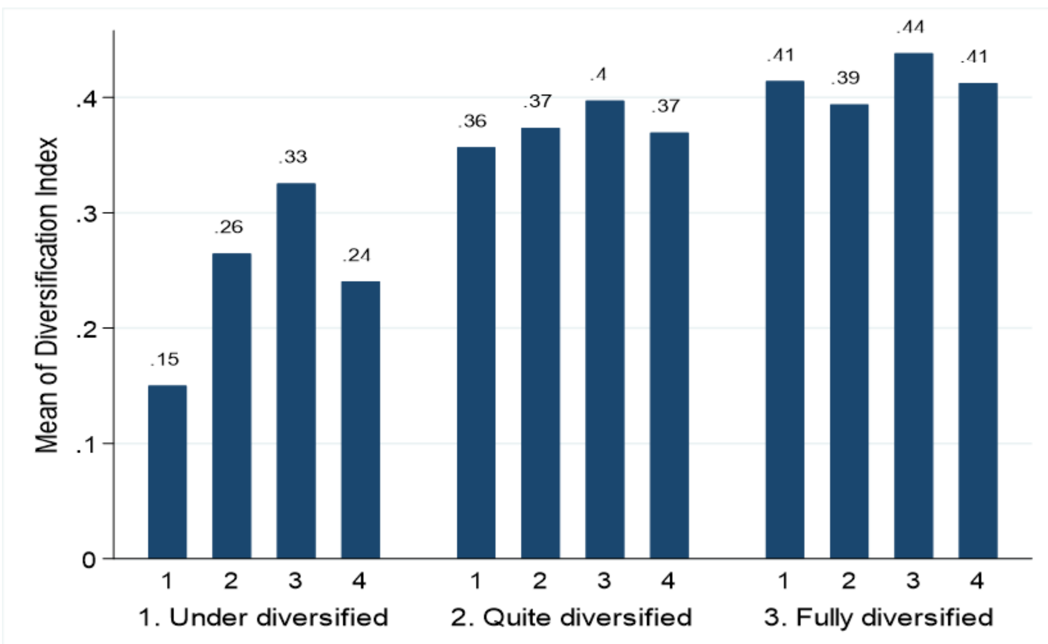
Table 4.5 reveals that the average years of education for heads of households with only one asset is 8, compared to an average of 10 years for those with more than one asset, suggesting that education level may play a role in household asset-holding diversification. Previous studies have also demonstrated a positive correlation between educational level and the diversification of household assets (Sierminska & Silber, 2020). This relationship may be due to the fact that higher levels of education are often associated with greater financial literacy and a deeper understanding of financial products and investment opportunities. With a better understanding of the financial market, households may be more likely to make informed decisions about their investments and diversify their portfolios across a range of assets such as stocks, bonds, and property. Additionally, Education level impacts asset diversification, as educated households tend to have higher-paying jobs and more opportunities to accumulate wealth, allowing them to invest in a broader range of assets.

The findings in Table 4.5 suggest that various characteristics, such as gender, marital status, race, employment status, and geographic location, may influence household asset diversification. Prior research has established significant differences in the level of diversification across these groups (Sierminska & Silber, 2020; Worthington, 2009). For instance, female-headed households tend to hold less diversified portfolios than male-headed households, potentially because of differences in income, risk aversion, and access to financial resources. Marital status is also a significant predictor of diversification, with married household heads demonstrating a greater propensity to diversify their portfolios than single or divorced household heads, possibly due to economies of scale resulting from the pooling of resources. Race also appears to play a role in asset-holding diversification, with non-white households having less diversified portfolios than White households, which may be due to differences in income, access to financial resources, and historical discrimination. Furthermore, Table 4.5 indicates that employment status and geographic location can affect asset-holding diversification. These findings suggest that various demographic factors can influence asset-holding diversification, highlighting the importance of considering such characteristics in analysing household asset-holding diversification.

Furthermore, Figure 4.5 and Figure 4.6 present a comparison of asset holdings among household wealth quartiles, highlighting substantial differences not only in the types and amounts of assets held but also in the levels of diversification. Figure 4.5 illustrates that households across different wealth quartiles possess varying levels of diversification, and within the same quartile, there are significant variations in diversification levels. For instance, households in the fourth quartile exhibit different degrees of diversification, ranging from under-diversification to full diversification. These outcomes demonstrate that wealth alone does not account for differences in household diversification levels.

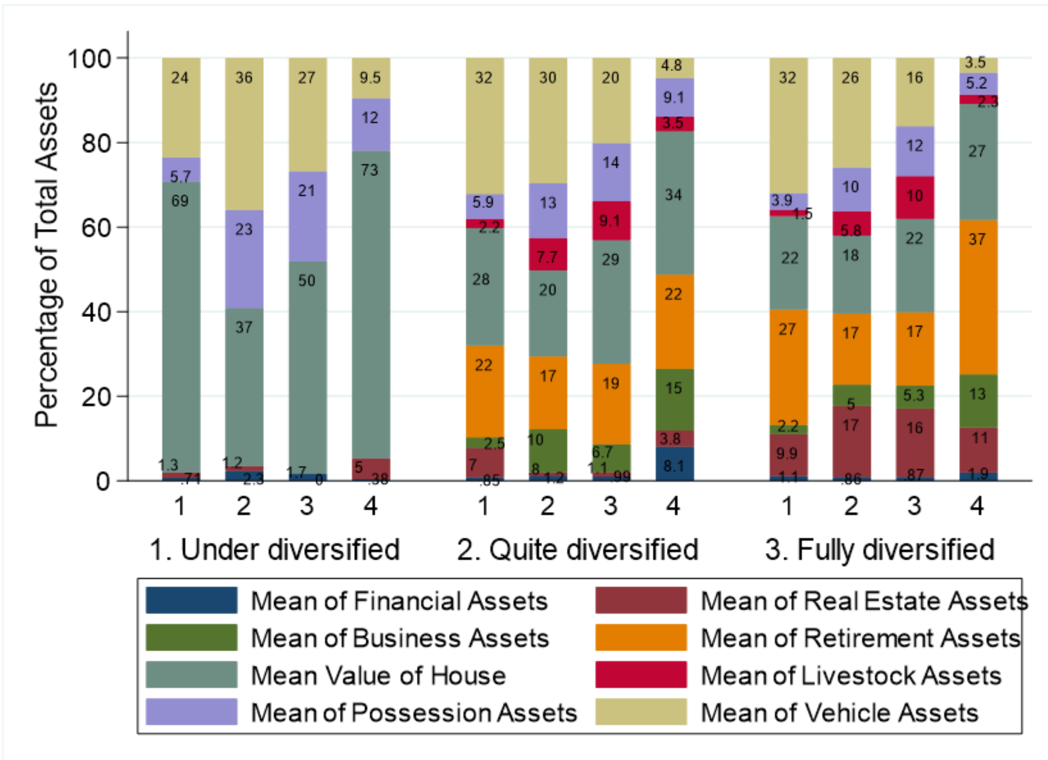
Several factors, including household characteristics, may also contribute to the differences in diversification levels among households within the same wealth quartile. Financially literate households with greater knowledge about investment opportunities may be more inclined to diversify their asset holdings. Similarly, households with a high tolerance for risk may be more willing to undertake significant investment risks by diversifying their asset holdings. In contrast, households with limited access to financial products and services may be less able to diversify their asset holdings (Tita & Aziakpono, 2017), even if they have a similar level of wealth.

Figure 4.5: GSI by Diversification Level and Wealth Quartiles



Moreover, Figure 4.6 illustrates that households within the same wealth quartile hold different types and amounts of assets in their portfolios. For example, households in the fourth quartile exhibit variations in the composition of their portfolios, with under-diversified portfolios mainly holding owner-occupied houses. In contrast, diversified portfolios contain a more significant share of retirement and business assets. These findings suggest that factors other than wealth may influence households' investment decisions. The regression results in Section 4.4.2 further corroborate the existence of these factors.

Figure 4.6: Asset Types and Amounts by Div. level and Wealth Quartiles



4.4.2 Fractional Regression Model Results

Table 4.6 presents the results of the fractional regression model (FRM), which examines factors influencing the diversification index. The focus is on the net worth variables as the interest is to analyse asset-holding diversification along the wealth distribution. Model 1 utilises a categorical variable with four quartiles of the net worth distribution to identify the household's position on the net worth distribution, with the 1st quartile serving as the reference group. Model 2 uses a continuous variable that determines the household’s position relative to the median position on the wealth distribution. This variable is a ratio of household net worth to median net worth. A ratio of 1 indicates that the household is in the middle of the wealth distribution. The ratios far greater than one indicate top-end positions, while those far less than one indicate bottom-end positions. Additionally, the visuals from Figure 4.2 suggest that I may need to include a quadratic term to capture the nonlinear effects of the wealth variable. The discussions following Table 4.6 focus solely on the marginal effects of these factors. Table B1 in Appendix B displays the original results, along with the necessary diagnostic tests.

Table 4.6: Marginal Effects from the Fractional Logit Model

	Fractional Logit Model	
VARIABLES	Model 1	Model 2
Net worth quartiles: Ref (1st quartile)		
2nd quartile	0.070***	
	(0.009)	
3rd quartile	0.109***	
	(0.009)	
4th quartile	0.073***	
	(0.010)	
Log (net worth/median)		0.051***
		(0.006)
Log (net worth/median) square.		-0.013***
		(0.001)
Log of household income	0.030***	0.041***
	(0.004)	(0.004)
Debt to assets ratio	-0.003	-0.000
	(0.003)	(0.004)
Being Self-employed	0.038***	0.048***
	(0.009)	(0.009)
Having Life-insurance	0.035***	0.039***
	(0.006)	(0.006)
Household size	0.012***	0.013***
	(0.003)	(0.003)
Household size square	-0.001***	-0.001***
	(0.000)	(0.000)
Age	0.006***	0.007***
	(0.002)	(0.002)
Age square	-0.000***	-0.000***
	(0.000)	(0.000)
Education years	0.001	0.002**
	(0.001)	(0.001)
Male vs Female	0.027***	0.027***
	(0.006)	(0.006)
Race: Ref (4. White)		
1. African	0.043***	0.020*
	(0.011)	(0.011)

2. Coloured	0.018	-0.006
	(0.013)	(0.013)
3. Indian/Asian	-0.021	-0.038
	(0.025)	(0.023)
Married vs Single	0.017***	0.018***
	(0.006)	(0.006)
Employed vs Unemployed	-0.009	-0.013
	(0.014)	(0.014)
Location: Ref (1. TAA)		
2. Urban	-0.015**	-0.019***
	(0.007)	(0.007)
3. Farms	-0.047***	-0.052***
	(0.013)	(0.014)
Year 2017 vs 2014	0.002	0.001
	(0.005)	(0.005)
Observations	5,082	5,082

Note: Robust Standard errors in parentheses: *** p<0.01, ** p<0.05, *p<0.1. In Model 1, the main regressor is net worth quartiles, with the first quartile serving as the reference group. Model 2's main regressor is the net worth ratio to median net worth.

The fractional logit model results provide valuable insights into the relationship between household asset diversification and wealth distribution in South Africa. The analysis confirms a positive relationship between wealth and asset diversification. As the positive and significant coefficient signs of net worth variables indicate, households in higher wealth quintiles tend to have more diversified portfolios than those in lower quintiles. Including a quadratic term in model 2 suggests a nonlinear relationship between wealth and diversification. While diversification initially increases with wealth, this effect may slightly diminish at higher wealth levels. The estimated marginal effects indicate that a 1% increase in the ratio of net worth to median net worth is associated with a 0.05 percentage point increase in the diversification index, suggesting a gradual increase in diversification with wealth.

These findings highlight the importance of wealth in facilitating asset diversification. Households with greater resources may have more flexibility to invest in a broader range of assets, reducing their risk exposure and potentially improving their financial outcomes. However, the coefficient of the square of the net worth-to-median net worth ratio is negative and significant, suggesting that as households move even further up the net worth distribution and become very wealthy, their portfolios may become less diversified, because very wealthy households may have a greater ability to invest in niche assets or engage in specialised investment strategies that are not accessible to the average investor. They may also be more able to tolerate risk and concentrate their investments on a few high-risk, high-reward assets.

The results further indicate that household income is positively correlated with the level of diversification. A 1% increase in household income increases the diversification index by 0.3 or 0.04 percentage points. The finding suggests that wealthier households are more likely to hold a diversified portfolio of assets, as they possess greater financial resources and are therefore better equipped to invest in a variety of assets. They are also likely to have a more diverse portfolio of assets, as wealthier households have a greater capacity to manage a more complex portfolio of assets and have access to a broader range of investment opportunities.

The results also indicate that *being self-employed* increases the diversification index by about 0.04, showing a positive effect of self-employment. The results could be due to the fact that self-employed individuals have more flexible income streams to invest in a diverse range of income-generating assets. For instance, they may invest in multiple businesses or projects concurrently, spreading their risk across various sources of income. Moreover, self-employed individuals may be more financially literate and better equipped to manage a more complex portfolio of assets. This result suggests that promoting self-employment and entrepreneurship may be an effective strategy for enhancing household asset diversification. Nevertheless, it is essential to acknowledge that self-employment may not be a viable or desirable option for everyone, and other factors, such as access to resources and opportunities, may also play a crucial role in determining household asset-holding diversification. Hence, further research is needed to comprehensively understand the underlying mechanisms responsible for this association.

The FRM results also indicate that households whose heads have *life insurance* exhibit a higher level of diversification index compared to those without life insurance. The two models produce consistent findings and are statistically significant. A plausible explanation for this outcome is that life insurance provides financial protection, allowing households to engage in more diversified and potentially lucrative income-generating assets. For instance, households with life insurance may feel more financially secure and, therefore, more inclined to invest in higher-risk, higher-return assets such as starting a business or investing in the stock market. These findings suggest that enhancing access to life insurance may be an effective strategy for promoting household asset-holding diversification. However, further research is needed to fully understand the mechanisms underlying this association.

The results indicate a quadratic relationship between *household size* and the diversification index, as measured by the number of household members. Specifically, the positive and significant coefficient of household size suggests that larger households tend to have higher levels of diversification. However, the negative and significant coefficient of the square of household size implies that the effect of household size on diversification is not linear. However, it somewhat diminishes as household size increases. This non-linear relationship suggests that the impact of household size on diversification is only positive up to a point, beyond which it becomes harmful. A possible explanation for this result is that larger households may have diverse needs that require a wider range of assets to meet those needs. However, as the household size increases, managing and maintaining a diverse range of assets may become increasingly challenging, resulting in diminishing returns in diversification. Additionally, larger households may have more limited resources available to diversify their asset holdings, which could explain why the effect of household size on diversification diminishes as household size increases.

Although Biyase et al. (2019) found no significant relationship between household size and asset poverty, this study finds that the relationship between household size and asset diversification is not linear. The result underscores the importance of considering the non-linear relationship between household size and diversification when designing policies and interventions to promote asset diversification among households.

The results reveal that the *age of the household head* has a quadratic relationship with the diversification index, as indicated by the positive and significant coefficient of age and the negative and significant coefficient of the square of age. This finding implies that the relationship between age and diversification is non-linear. The positive coefficient of age suggests that as the household head's age increases, the diversification index also increases, ceteris paribus. However, the negative coefficient of the squared term of age implies that the effect of ageing on diversification diminishes beyond a certain threshold. A possible explanation for this quadratic relationship is that younger household heads may have limited financial resources and, therefore, a narrower range of assets. In comparison, older household heads with more time to accumulate wealth may have a broader range of assets. However, beyond a certain age, factors such as retirement or health issues may limit the ability to accumulate or maintain assets, offsetting the effect of ageing on diversification.

The findings from Model 2 suggest that the household head's years of *education* have a positive effect on the diversification index. This association is significant at the 5% level. This result may be due to the fact that higher levels of education provide households with greater knowledge, skills, and resources, enabling them to engage in a broader range of income-generating activities. This finding is consistent with previous research, which demonstrates that education significantly reduces the likelihood of falling into asset poverty (Biyase et al., 2019). The positive association between education level and the diversification index suggests that individuals with higher levels of education are more likely to have diversified portfolios. This finding emphasises the importance of investing in education and human capital development to promote asset diversification and reduce wealth inequality. Policies to improve access to education, particularly for disadvantaged groups, can empower households to make informed financial decisions and build more resilient asset portfolios.

Regarding the *gender of the household head*, the results indicate that households headed by men have a higher diversification index than households headed by women. This result may be due to cultural norms and gender roles, which typically expect men to be the primary breadwinners and provide greater access to resources and income-generating opportunities. Additionally, male-headed households may appear more effective at diversifying their assets, which may be due to greater access to resources, networks, and cultural expectations regarding male economic roles. It is essential to note that these findings do not necessarily imply that one gender is inherently more adept at diversifying household assets. Instead, these results may reflect broader social and economic factors that influence household decision-making and access to resources.

These findings, along with previous research (Alemu, 2012; Ebenezer & Abbyssinia, 2018), emphasise the significance of considering gender dynamics and socio-cultural contexts when analysing household asset-holding diversification. Addressing gender inequalities and improving access to resources and opportunities for all households, irrespective of gender, may be crucial to promoting more equitable and diversified household asset portfolios.

The results for *race* are not as expected. The diversification index for African households appears to be significantly higher than that for White households. There is no significant difference between the diversification index of White households and Coloured and Indian households.

The unexpected finding that African households exhibit a higher diversification index than White households is intriguing and warrants further exploration. However, potential explanations may be that African households may have been forced to diversify their asset portfolios due to historical and ongoing economic challenges. Limited access to formal financial services and higher unemployment rates may have compelled them to explore alternative income-generating activities, leading to more diversified asset holdings. Additionally, more African households may be engaged in the informal sector, which requires greater flexibility and resourcefulness. This leads to more diversified asset holdings as individuals seek to navigate uncertain economic conditions. Cultural differences and traditional practices may also influence asset diversification strategies. For example, certain cultural groups may have a strong tradition of investing in livestock, land, or community-based assets, contributing to a more diversified portfolio.

The results indicate that households headed by *married individuals* exhibit a significantly higher diversification index than those headed by *single individuals*. We can attribute this outcome to several factors, including shared decision-making within the household, economies of scale, and enhanced access to resources and networks.

Regarding location, the results indicate that households in urban and farm areas have a significantly lower diversification index than those located in *Traditional Authority Areas* (TAA). One possible explanation for this result could be that urban and farm households rely more heavily on a limited number of assets for their livelihoods, which may discourage them from pursuing asset diversification. This outcome is consistent with earlier studies that have established that rural households in South Africa utilise various livelihood strategies, including agriculture, livestock rearing, and off-farm activities (Alemu, 2012; Sikhunyana et al., 2020).

This finding suggests that certain factors contribute to higher asset diversification levels in TAA households. In some TAA communities, for instance, land ownership is often communally managed, creating opportunities for households to invest in a diversified range of assets, including livestock, crops, and natural resources. Additionally, TAA communities may benefit from stronger social networks and community support systems, which facilitate the sharing of resources, skills, and knowledge related to investment and wealth accumulation. TAA households also tend to be extended households, comprising multiple generations living together, providing a more substantial resource pool for diversified portfolio investment.

Moreover, TAA households may also adhere to traditional savings practices, such as stokvels (informal savings clubs), which may provide credit and savings opportunities that facilitate investment in a diversified portfolio. Furthermore, TAA households may experience a lower cost of living than their urban and farm counterparts, leaving them with more disposable income to invest in diversified portfolios.

4.4.3 Ordered Logit Model Results

Table 4.7 presents the marginal effects of the ordered logit regression. Table B1, in Appendix B, the original results of the ordered logit regression are provided, along with the appropriate diagnostics that were conducted. To complement the FRM results, ordered logit regression provides additional insights when the measure of diversification is a categorical variable with three levels: under diversified (0), quite diversified (1), and fully diversified (2). The results are consistent with those presented in the FRM above. As expected, the marginal effects for each covariate sum to zero across the three levels of diversification.

Table 4.7: Marginal Effects from the Ordered Logit Model

	Model 1			Model 2		
VARIABLES	Under	Quite	Fully	Under	Quite	Fully
Quartiles: Ref (1st quartile)						
2nd quartile	-0.170***	0.131***	0.039***			
	(0.021)	(0.016)	(0.005)			
3rd quartile	-0.298***	0.211***	0.087***			
	(0.020)	(0.016)	(0.007)			
4th quartile	-0.386***	0.249***	0.136***			
	(0.022)	(0.017)	(0.007)			
Log (net worth/median net worth)				-0.103***	0.053***	0.05***
				(0.010)	(0.005)	(0.005)
Log (net worth/median net worth) square.				0.004	-0.002	-0.002
				(0.002)	(0.001)	(0.001)
Log of household income	-0.102***	0.047***	0.055***	-0.101***	0.052***	0.049***
	(0.008)	(0.004)	(0.004)	(0.008)	(0.005)	(0.004)
Debt to assets ratio	-0.001	0.001	0.001	-0.005	0.003	0.003
	(0.004)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)
Being Self-employed	-0.181***	0.083***	0.098***	-0.191***	0.099***	0.092***
	(0.017)	(0.008)	(0.009)	(0.018)	(0.009)	(0.009)
Having Life-insurance	-0.088***	0.040***	0.047***	-0.092***	0.048***	0.044***
	(0.012)	(0.006)	(0.006)	(0.012)	(0.007)	(0.006)
Household size	0.016**	-0.007**	-0.009**	0.012*	-0.006*	-0.006*
	(0.005)	(0.002)	(0.003)	(0.005)	(0.003)	(0.003)
Household size square	-0.001*	0.0004*	0.001*	-0.001	0.0004	0.0004

	(0.000)	(0.0002)	(0.000)	(0.0004)	(0.0002)	(0.0002)
Age	-0.014***	0.006***	0.008***	-0.017***	0.009***	0.008***
	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
Age square	0.0001**	-0.0001**	-0.0001**	0.0001**	-.0001***	-0.0001**
	(0.000)	(0.000)	(0.000)	(0.00004)	(0.000)	(0.000)
Education years	-0.001	0.0004	0.000	-0.0005	0.0003	0.0003
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Male vs Female	-0.040***	0.018***	0.022***	-0.043***	0.022***	0.0205***
	(0.012)	(0.005)	(0.006)	(0.012)	(0.006)	(0.006)
Race: Ref (4. White)						
1. African	0.025	-0.011	-0.014	-0.015	0.008	0.007
	(0.021)	(0.009)	(0.012)	(0.023)	(0.012)	(0.011)
2. Coloured	0.057*	-0.026*	-0.031*	0.018	-0.010	-0.008
	(0.024)	(0.011)	(0.013)	(0.026)	(0.014)	(0.012)
3. Indian/Asian	0.025	-0.011	-0.014	0.0032	-0.002	-0.002
	(0.047)	(0.021)	(0.026)	(0.049)	(0.026)	(0.023)
Married vs Single	-0.051***	0.023***	0.028***	-0.048***	0.025***	0.023***
	(0.012)	(0.006)	(0.007)	(0.013)	(0.007)	(0.006)
Employed vs Unemployed	0.041	-0.019	-0.0219	0.041	-0.021	-0.02
	(0.026)	(0.012)	(0.014)	(0.027)	(0.014)	(0.013)
Location: Ref (1. TAA)						
2. Urban	0.031*	-0.014*	-0.017*	0.040**	-0.020**	-0.02**
	(0.013)	(0.006)	(0.008)	(0.014)	(0.007)	(0.007)
3. Farms	-0.035	0.013	0.021	-0.010	0.005	0.005
	(0.024)	(0.009)	(0.015)	(0.025)	(0.012)	(0.014)
Year 2017 vs 2014	-0.005	0.0023	0.003	-0.002	0.001	0.001
	(0.010)	(0.005)	(0.006)	(0.011)	(0.006)	(0.005)
Observations	5082	5082	5082	5082	5082	5082

Note: Robust Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. In Model 1, the main regressor is net worth quartiles. In Model 2, the main regressor is the ratio of household net worth to median net worth.

Compared to households sitting in the first quartile of wealth distribution, households seated in the second quartile of wealth distribution have 17% less chance of selecting under-diversified portfolios, 13.1% more likely to select quite-diversified portfolios, and 3.9% more likely to choose fully diversified portfolios. A similar pattern is observed for households in the third and fourth quartiles compared to those in the first quartile, reinforcing the positive relationship between wealth and diversification previously observed in the analysis of the diversification index. Model 2's estimated marginal effects indicate that a 1% increase in the ratio of net worth to median net worth is associated with a decrease in the probability of under-diversification and an increase in the likelihood of choosing moderate and fully diversified portfolios. This result suggests that wealth is crucial in enabling households to adopt more diversified investment strategies.

Most other covariates appear to yield results consistent with those of the fractional logit model, suggesting that these findings are robust to different measures of asset diversification.

4.4.4 The Impact of Negative Life Events Across Diversification Levels

Table 4.8 presents results of the impact of adverse life events on household net worth. A constant represents the average net worth of the control group in 2014. The coefficient of the time variable indicates the change in average net worth over time for the control group and is insignificant. The coefficient of the treatment variable, which represents the difference in average net worth between the treatment and control groups in 2014, is also insignificant. However, the change in this difference, as indicated by the interaction between the time and treatment variables, is positive and significant. It becomes insignificant once we include controls, suggesting that some time-varying factors may have increased the average net worth of the treatment group.

The indicator for complete portfolio diversification remains positive and significant both with and without controls. It represents the average net worth difference between households that hold fully diversified portfolios and those with less than fully diversified portfolios in the control group during 2014. However, the change in this difference over time, as illustrated by the interaction between time and diversification, is insignificant without controls but negative and significant once controls are added, indicating a decline in the net worth of diversified households in the control group.

The interaction between treatment and diversification, which represents the difference between households holding fully diversified portfolios and those with less than fully diversified portfolios in the treatment group during 2014, is insignificant without controlling for other factors. However, this becomes negative and significant when controls are included. It illustrates that, prior to the shock (2014), the net worth of households holding fully diversified portfolios was lower than that of those with less diversified portfolios. Interestingly, the situation reverses after the shock (2017), as indicated by the triple interaction term. With controls, the coefficient of the triple interaction term is positive and significant at the 1% level. This indicates that the negative impact of shocks on net worth is less severe (or even positive) for households with fully diversified portfolios compared to those with less diversified portfolios.

A possible explanation for this result is that households holding fully diversified portfolios may recover more quickly or experience lower losses due to risk diversification across asset classes. Some may even have access to liquid financial assets, allowing them to buffer the shock. Households without diversification may experience significant declines in net worth due to their reliance on fewer assets. Therefore, a policy implication is that promoting financial literacy and encouraging diversification strategies could help households better withstand adverse shocks.

Table 4.8: The Impact of Negative Life Events on Household Net Worth

VARIABLES	Model 1 Without controls	Model 2 With controls
Constant	207,739.93***	-5130818.23***
	(55,288.73)	(1021309.39)
Post	45,355.24	-10,489.58
	(76,439.78)	(160,536.26)
Treatment	44,046.62	-110,005.61
	(177,299.18)	(401,083.99)
Post × Treatment	788,994.35***	273,794.13
	(253,249.11)	(544,503.16)

Diversified	786,351.93***	2505832***
	(186,231.72)	(376,221.03)
Post × Diversified	-207,285.20	-2417569.63***
	(242,412.77)	(457,712.67)
Treatment × Diversified	-667,866.20	-3008696.45**
	(524,357.36)	(1273647.81)
Post × Treatment × Diversified	92,563.20	5924365.79***
	(694,348.56)	(1545000.31)
Observations	10,737	1,372

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The net worth values are presented in levels that facilitate the interpretation of the coefficients as the average net worth for specific groups. They are Rand values adjusted to March 2017 prices.

The parallel trends assumption (PTA) is a fundamental requirement for Difference-in-Differences (DiD) estimation, ensuring that the treated and control groups would have followed the same trend in the absence of treatment. However, in this study, the inability to test the PTA empirically due to the limited number of periods does not necessarily undermine the validity of the analysis. Some theoretical considerations justify why the PTA may be of marginal importance in this context. Firstly, selection into treatment is mainly exogenous. I posit that negative shocks are random or exogenous, such as those arising from unexpected life events, natural disasters, or personal tragedies; thus, differences in net worth growth between the treated and control groups before the shock would be minimal. Exogeneity in treatment reduces the likelihood that pre-existing differences drive the estimated effects, thereby alleviating concerns about violations of the PTA. Meyer (1995) argues that when treatment is plausibly exogenous, deviations from strict parallel trends have less influence on DiD estimates.

Secondly, since PTA primarily concerns differences in trends rather than levels, even if the treated and control groups displayed different baseline levels of net worth in 2014, the main issue is whether their trends differed. Given that net worth is influenced by broad economic conditions (e.g., GDP growth, inflation, market trends), it is reasonable to assume that, in the absence of shocks, all households would have been similarly affected by these macroeconomic factors. Angrist and Pischke (2009) emphasise that the validity of DiD relies more on the similarity of trends than on equal baseline levels, which can often be accounted for through covariate adjustments. Since pre-trend data are unavailable, controlling for household-level characteristics, such as income, education, and employment status, helps reduce bias from potential trend differences. If these characteristics are similar across groups at baseline, it is less likely that differential pre-treatment trends existed. Imbens and Wooldridge (2009) suggest that including co-variates in difference-in-differences (DiD) models enhances robustness when pre-trend validation is in-feasible.

Essentially, my primary interest is to ascertain whether the impact of adverse shocks differs between households with diversified portfolios and those without. The regression model captures this with the triple interaction term (Time × Treated × Diversified). This interaction term essentially compares the rel-ative change in net worth between the diversified and non-diversified groups within the treated group. Even if the treated and control groups had different pre-treatment trends, the relative difference in how the shock affected diversified versus non-diversified households might still be valid, provided that the diversification effect is consistent across the two groups. Effectively, the question is, "Did diversification alter the relative impact of the shock, regardless of the overall trend?" To provide a more conceptual analogy for my position, we can think of it like comparing the effectiveness of a new medicine in two hospitals. Even if the hospitals have different baseline patient outcomes, we can still compare the relative improvement in patient outcomes between the two hospitals after administering the medicine. The overall level of patient outcomes might differ, but the relative effect of the medicine is what truly matters.

This justification does not render the PTA irrelevant in this study. It merely illustrates that the core findings may still be interpretable with this caveat. The lack of pre-trend data to validate PTA remains a significant limitation that this study must acknowledge.

A further caveat to acknowledge is that the inability to empirically test the parallel trends assumption, due to the lack of pre-treatment data, restricts the internal validity of the estimates, as it cannot be confirmed whether the treatment and control groups would have followed similar trajectories in the absence of diversification differences. Although covariate adjustments and theoretical justification mitigate this concern to some extent, they do not completely replace empirical validation. Beyond internal validity, concerns also extend to external validity. The NIDS data offer nationally representative coverage, but the results may not generalise to all household contexts. For instance, unobserved heterogeneity—such as differences in access to informal insurance networks, social capital, or exposure to localised shocks—may influence diversification behaviour in ways not captured by the survey. Moreover, the South African setting, characterised by deep historical inequalities and unique institutional arrangements, may limit the applicability of findings to other developing or emerging economies.

Taken together, these caveats suggest that while the DID estimates offer indicative evidence of the protective role of diversification, they should be interpreted with caution. The results emphasise associations rather than definitive causal effects, and the findings are best understood as context-specific rather than universally generalisable. Future research should utilise richer longitudinal data with multiple pre-treatment periods to strengthen internal validity and explore cross-country comparisons to assess external validity.

4.4.5 Discussion of Empirical Results

The empirical results of this study offer important insights into the dynamics of household asset allocation in South Africa. By combining descriptive evidence, regression analysis, and Difference-in-Differences estimates, the findings collectively emphasise the roles of wealth distribution, education, gender, rural–urban divides, and diversification in fostering resilience. This section interprets these results in light of theoretical expectations and places them within the broader empirical literature, both internationally and locally.

4.4.5.1 Wealth and Diversification

The results confirm that household wealth has a significant influence on asset diversification. Wealthier households tend to hold portfolios comprising financial assets, retirement savings, and business interests, whereas poorer households are often focused on housing, possessions, or livestock. These findings align with portfolio theory (Markowitz, 1952), which suggests that higher wealth levels broaden the range of investment options by reducing liquidity constraints and spreading risk.

International studies support this wealth–diversification gradient. Wei et al. (2019) demonstrate that wealthier Chinese households invest more heavily in risky but high-return assets, while low-wealth households remain in liquid, low-yield assets. Bricker et al. (2019b) similarly highlight that U.S. household portfolios are dominated by housing at the lower end of the distribution. South African households exhibit the same structural bias, with poorer households disproportionately locked into single-asset holdings—typically housing or informal assets—due to limited access to formal financial markets. The South African context, however, amplifies these disparities. The legacy of apartheid systematically excluded the majority population from wealth accumulation opportunities (Chatterjee et al., 2020), resulting in present-day wealth concentration among a small minority (SA-TIED, 2020). As a result, diversification patterns are not merely individual choices but reflect the structural inequalities underpinning South Africa's wealth distribution.

4.4.5.2 Education and Human Capital Theory

Education emerges as a significant predictor of diversification. Households with higher educational attainment show a greater ability to spread risk across multiple assets. This aligns with human capital theory (Becker, 1964), which emphasises education as a way to improve financial literacy, risk awareness, and long-term planning skills. In developed economies, Worthington (2009) and Lusardi & Mitchell (2014) stress that financial literacy is vital for effective portfolio diversification.

The evidence from South Africa suggests a similar pattern, albeit intensified by the significant disparities in access to education. The unequal distribution of educational opportunities, rooted in apartheid policies, continues to influence intergenerational outcomes (Mosomi & Wittenberg, 2020). Therefore, differences in diversification according to education level reflect not only personal ability but also systemic gaps in access to financial knowledge and resources. These findings highlight the importance of financial education policies. Initiatives focused on improving financial literacy and investment knowledge could enable lower-wealth households to diversify more successfully, helping to reduce the financial resilience gap between richer and poorer households.

4.4.5.3 Gender Disparity in Diversification

The regression results indicate that female-headed households are notably less diversified than their male-headed counterparts. This finding is consistent with global evidence documenting the gender gap in financial participation (Cupák et al., 2021; Denton & Boos, 2007; Meriküll et al., 2021). Women tend to be more risk-averse, have limited access to financial products, and face cultural and institutional barriers that restrict their ability to engage with diversified asset markets.

In South Africa, these barriers are especially significant. Dickason & Ferreira (2018) found that men are more risk-tolerant than women, while Dhlembeu et al. (2022) observed that gender inequality in financial literacy and asset ownership reinforces broader income and wealth disparities. The observed results confirm that South African women continue to face structural disadvantages in asset accumulation, which limits their ability to adopt diversification strategies that could otherwise reduce financial risk. Addressing this gap requires more than financial literacy; it involves overcoming systemic barriers such as gendered labour market inequalities, unequal inheritance practices, and limited access to credit.

4.4.5.4 Rural-Urban Divide in Diversification

Contrary to much of the international literature (Galster & Wessel, 2024), the results indicate that urban and farm households are less diversified than households in Traditional Authority Areas (TAAs). This finding suggests that the South African context departs from the standard rural–urban divide often reported in developing countries, where rural households are typically seen as constrained in their diversification options. One possible explanation is that households in TAAs rely on multiple livelihood and asset strategies, including livestock, informal savings groups (stokvels), small-scale enterprises, and remittances. These diversified strategies may arise out of necessity, as TAA residents face greater vulnerability to shocks and limited formal employment opportunities (Sikhunyana et al., 2020). In contrast, urban households may concentrate their wealth in fewer asset classes, most notably housing, which dominates urban household portfolios and reduces measured diversification. Farm households' lower diversification is also consistent with the high asset specificity of agricultural investment, where resources are tied to land, equipment, or livestock, leaving little room for broader financial or business asset accumulation (Mathinya et al., 2023).

This result aligns with evidence from Ebenezer and Abbyssinia (2018), who found that livelihood diversification in South Africa is context-specific and often more extensive in areas where formal employment and financial services are scarce. It also reinforces the argument that rural households may adopt **"**survivalist diversification**"** strategies to mitigate vulnerability, whereas urban households, though wealthier in absolute terms, may remain concentrated in a narrow range of assets (Gebru et al., 2018; Tadele, 2021). Thus, the South African case illustrates that diversification does not always follow a simple rural–urban gradient; instead, it reflects the complex interplay of market access, institutional structures, and household necessities (Mathinya et al., 2023; Vilakazi et al., 2025).

4.4.5.5 Diversification and Household Resilience

The Difference-in-Differences results indicate that households with diversified portfolios experience smaller wealth losses when faced with adverse life events, although the estimates lack strong statistical precision. This finding aligns broadly with risk management theory (Wagner & Lau, 1971), which stresses diversification as a strategy to buffer against shocks. Similar results are observed in international contexts. For example, Araújo et al. (2022) find that diversified households in Brazil are more resilient to income shocks. In South Africa, where households are highly exposed to unemployment, health shocks, and macroeconomic volatility, the role of diversification in stabilising household wealth is particularly important.

Nonetheless, the methodological limitations of the DiD approach—particularly the inability to verify parallel trends—necessitate cautious interpretation. The results should be regarded as indicative evidence rather than definitive proof of causality. This highlights the need for future research employing longer time-series data or natural experiments to more rigorously evaluate the causal impact of diversification on resilience.

4.4.5.6 Synthesising Theory and Policy Implications

Overall, the findings demonstrate that structural inequalities of wealth, education, gender, and geography shape asset diversification in South Africa. While wealthier, better-educated, and male-headed households can diversify more broadly and gain protective benefits, poorer, less-educated, and female-headed households remain constrained in their options. Interestingly, households in Traditional Authority Areas (TAAs) appear more diversified than their urban and farm counterparts, not because of better access to financial markets but as a necessity-driven response to risk and the lack of formal insurance. This demonstrates that diversification in South Africa does not always indicate financial opportunity but can also be a strategy for resilience against structural exclusion.

These patterns have significant theoretical and policy implications. Portfolio theory helps explain the diversification advantage of wealthier households, while life-cycle theory captures age and education-related differences. Risk management theory, in turn, clarifies the resilience-driven diversification of TAA households. Together, these perspectives stress the need for policies that address the uneven access to diversification. Progressive wealth redistribution and asset transfer programmes could broaden the asset base of lower-wealth households, while targeted financial education initiatives—especially for women and lower-income groups—could encourage more inclusive financial strategies. Gender-sensitive policies that address credit access and inheritance rights are also vital. By examining household asset allocation within South Africa's broader socio-economic inequalities, this study demonstrates both the advantages and the limitations of diversification as a pathway to resilience and reduced inequality.

4.5 CONCLUDING REMARKS

This chapter investigated the level of asset portfolio diversification among South African households, examining its relationship with wealth, demographic factors, and resilience to adverse life events. Utilising fractional logit and ordered logit models, we found a positive, albeit diminishing, association between wealth and diversification at very high wealth levels. A 1% increase in the net worth-to-median net worth ratio leads to a 0.05 percentage point increase in the diversification index. Household income, self-employment, life insurance, household size (up to a point), age, education, and marital status positively influence diversification. Rural households in Traditional Authority Areas exhibit greater diversification compared to urban and farm areas. Crucially, diversified portfolios provide a buffer against adverse life events; households holding fully diversified portfolios tend to experience less severe declines in net worth.

A significant limitation is the absence of pre-treatment data to empirically test the assumption of parallel trends in the difference-in-differences analysis. While theoretical justifications and covariate controls were implemented, the lack of direct validation weakens the causal inference. Additionally, the study relies on self-reported data, which may be subject to recall bias or measurement error.

The findings underscore the importance of promoting financial literacy and access to diverse investment opportunities, particularly for lower-wealth households. Policies should aim to reduce barriers to financial markets and encourage the adoption of diversification strategies. Promoting self-employment and entrepreneurship can also enhance portfolio diversification. Targeted financial education programmes, especially in rural areas and for women, are crucial for improving financial decision-making. Policies should address gender inequalities and cultural norms that limit women's access to resources. Interventions should consider the non-linear relationship between household size and diversification. Furthermore, policies should recognise the unique diversification patterns in Traditional Authority Areas and leverage existing community-based financial practices, such as stokvels.

Beyond the empirical patterns, these findings can be situated within broader theoretical debates. Portfolio theory helps explain why wealthier households diversify more effectively, as they possess both the resources and risk tolerance to invest across asset classes. Life-cycle theory explains how diversification changes with age and education, reflecting shifting financial needs and capacities throughout the household life course. Yet, risk management theory sheds light on the paradoxical case of Traditional Authority Area households, whose higher diversification arises less from opportunity and more from necessity in the absence of formal insurance or reliable credit. This suggests that diversification in South Africa cannot always be interpreted as a sign of financial sophistication but must be contextualised as a coping mechanism in structurally constrained environments.

By embedding household financial behaviour within South Africa’s deep structural inequalities, this study underscores both the potential and the limitations of asset diversification as a pathway to resilience.

Wealthier, urban, and male-headed households diversify by choice, whereas poorer, rural, and female-headed households often diversify out of necessity. This divergence has important policy implications: efforts to promote inclusive financial development must address the barriers of wealth, gender, and geography that condition households' ability to pursue diversification as a proactive rather than reactive strategy.

Longitudinal studies are necessary to investigate the dynamic nature of portfolio diversification and its long-term impact on financial resilience. Future research could investigate the role of specific asset classes, such as informal savings groups or digital financial services, in enhancing diversification. Further research could explore the impact of financial literacy interventions on diversification behaviour across different socioeconomic groups. Finally, exploring the impact of macroeconomic shocks on diversified portfolios using richer datasets, including pre-treatment data, would provide more robust evidence.

Appendix B Chapter 4

The regression results from the Fractional Response Model and the Ordered Logit Model. For the Fractional Response Model, we have used the Generalised Linear Model (`glm`) command in Stata, specifying the `family(binomial)` and `link(logit)` options, and notably, using `vce(robust)` to account for the quasi-likelihood nature. Since `glm` fits a quasi-likelihood model (Fractional Logit), our diagnostics concentrated on model specification and the robustness of standard errors rather than traditional log-likelihood tests. While the `family (binomial)` and `link (logit)` define the model, `vce(robust)` is essential for obtaining accurate standard errors for this quasi-likelihood estimator, which effectively manages potential overdispersion (although this is not directly tested, it is adjusted for). For the specification test, we applied the `linktest` to verify that the model is correctly specified.

To validate the ordered logit model, several diagnostic checks were performed. Multicollinearity was assessed using the Variance Inflation Factor (VIF), with all values well below the usual threshold of 10, indicating no serious multicollinearity. Model fit was evaluated using a pseudo-R-squared value, which demonstrated acceptable explanatory power for household-level cross-sectional data. A likelihood ratio test confirmed that the model significantly outperforms the null model. Robust standard errors were used to address potential heteroskedasticity. Lastly, alternative specifications (ordered probit) yielded results consistent with the baseline ordered logit estimates, reinforcing the robustness of the findings.

Table B1: Main Results of FRM and Ordered Logit Models

	Fractional Logit Model		Ordered Logit Model	
VARIABLES	Model 1	Model 2	Model 1	Model 2
Net worth quartiles: Ref (1st quartile)				
2nd quartile	0.310***		0.856***	

	(0.042)		(0.108)	
3rd quartile	0.475***		1.476***	
	(0.040)		(0.104)	
4th quartile	0.322***		1.933***	
	(0.044)		(0.110)	
Log (net worth/median)		0.220***		0.578***
		(0.027)		(0.058)
Log (net worth/median) square.		-0.055***		-0.022*
		(0.005)		(0.012)
Log of household income	0.128***	0.175***	0.603***	0.563***
	(0.018)	(0.019)	(0.048)	(0.049)
Debt to assets ratio	-0.014	-0.001	0.007	0.030
	(0.012)	(0.018)	(0.022)	(0.026)
Being Self-employed	0.165***	0.210***	1.066***	1.066***
	(0.038)	(0.038)	(0.100)	(0.101)
Having Life insurance	0.152***	0.168***	0.516***	0.514***
	(0.027)	(0.027)	(0.070)	(0.070)
Household size	0.051***	0.057***	-0.094***	-0.066**
	(0.013)	(0.014)	(0.030)	(0.030)
Household size square	-0.003***	-0.004***	0.005**	0.004*
	(0.001)	(0.001)	(0.002)	(0.002)
Age	0.027***	0.030***	0.082***	0.093***
	(0.008)	(0.008)	(0.021)	(0.021)
Age square	-0.000***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Education years	0.006	0.010**	0.005	0.003
	(0.004)	(0.004)	(0.011)	(0.011)
Male vs Female	0.115***	0.116***	0.236***	0.238***
	(0.026)	(0.026)	(0.068)	(0.067)
Race: Ref (4. White)				
1. African	0.189***	0.087*	-0.146	0.083
	(0.050)	(0.050)	(0.123)	(0.127)
2. Coloured	0.082	-0.028	-0.338**	-0.100
	(0.056)	(0.057)	(0.141)	(0.144)
3. Indian/Asian	-0.097	-0.170	-0.150	-0.018
	(0.117)	(0.107)	(0.274)	(0.275)
Married vs Single	0.075***	0.080***	0.299***	0.267***
	(0.027)	(0.027)	(0.071)	(0.070)
Employed vs Unemployed	-0.038	-0.057	-0.239	-0.227
	(0.060)	(0.060)	(0.154)	(0.151)
Location: Ref (TAA)				
2. Urban	-0.064**	-0.081***	-0.184**	-0.223***
	(0.029)	(0.029)	(0.080)	(0.079)
3. Farms	-0.207***	-0.228***	0.209	0.057
	(0.059)	(0.061)	(0.145)	(0.142)
Year 2017 vs 2014	0.010	0.004	0.030	0.011
	(0.023)	(0.023)	(0.061)	(0.060)
α1			8.429***	8.053***

			(0.613)	(0.602)
α2			11.328***	10.985***
			(0.623)	(0.613)
Constant	-2.942***	-3.229***		
	(0.231)	(0.232)		
Observations	5,082	5,082	5,082	5,082

Notes: Robust Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. In Model 1, the main regressor is net worth quartiles. In Model 2, the main regressor is the ratio of household net worth to median net worth.

Difference-in-Differences regression is a method for analysing the impact of negative life events on the net worth of households with fully diversified portfolios compared to those without.

Table B2: Difference in Differences Regression with and without covariates

VARIABLES	Model 1 Without controls	Model 2 With controls
Post	45,355.24	-10,489.58
	(76,439.78)	(160,536.26)
Treatment	44,046.62	-110,005.61
	(177,299.18)	(401,083.99)
Post × Treatment	788,994.35***	273,794.13
	(253,249.11)	(544,503.16)
Diversified	786,351.93***	2505832***
	(186,231.72)	(376,221.03)
Post × Diversified	-207,285.20	-2417569.63***
	(242,412.77)	(457,712.67)
Treatment × Diversified	-667,866.20	-3008696.45**
	(524,357.36)	(1273647.81)
Post × Treatment × Diversified	92,563.20	5924365.79***
	(694,348.56)	(1545000.31)
Mother's years of education		29,786.343
		(30,183.328)
Mother's type of Job		71,902.605***
		(27,466.433)
Father's years of education		47,804.202
		(30,151.923)
Father's type of Job		20,353.979
		(28,657.747)
Race: (Ref: 1. African)		
2. Coloured		119,444.536
		(210,831.287)
3. Indian/Asian		438,140.867

		(603,357.429)
4. White		1943141.420***
		(289,787.681)
Location: (Ref: 1. Traditional Authority Areas-TAA)		
2. Urban		-130,792.256
		(198,513.507)
3. Farms		228,140.202
		(362,600.870)
Male vs Female		371,862.931**
		(164,054.298)
Married vs Single		61,180.215
		(180,131.205)
Employed vs Unemployed		-513,314.444***
		(182,910.878)
Age		7,850.658
		(32,168.887)
Age Square		39.630
		(343.719)
Household size		89,181.664
		(88,780.390)
Household size square		-10,242.931
		(7,123.846)
Log household income		303,745.813***
		(94,891.365)
Education Years		83,206.929**
Being a member of Stokvel		309,139.937
		(207,593.037)
		(34,024.728)
Constant	207,739.93***	-5130818.23***
	(55,288.73)	(1021309.39)
Observations	10,737	1,372

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The net worth values are in levels that allow for the interpretation of the coefficients as the average net worth for specific groups. They are Rand values adjusted to March 2017 prices.

Appendix C Data Dictionary of Key Variables

Table C 1: Data Dictionary of Key Variables

Variable	Definition	Unit / Scale	Dimensionality	Notes
Net worth	Household assets minus liabilities	South African Rand (ZAR), continuous	Monetary	Converted to real terms using CPI (March 2017).
Net worth-to-median ratio	Household net worth divided by the sample median	Dimensionless ratio	Relative scale	Used to position households within wealth distribution.
Income	Total household monthly income	ZAR, continuous	Monetary	Converted to real terms using CPI (March 2017).
Debt-to-assets ratio	Household total debts divided by total assets	Dimensionless ratio	Relative scale	Used as a continuous variable in regressions
Life insurance	Any household member covered by Life insurance	Binary (1 = yes, 0 = no)	Categorical	Used as a dummy in regressions
Education	Number of years of educational attainment of the household head	Years, continuous	Continuous	Used as a continuous variable in regressions
Employment status	Household head employment status	Binary (1 = employed, 0 = not)	Categorical	Used as a dummy in regressions
Self-employment status	Household head employment status	Binary (1 = self-employed, 0 = not)	Categorical	Used as a dummy in regressions
Location	Geographical location where the household resides	1= Traditional Authority Area, 2= Urban, 3= Farms	Categorical	Used as one of the control variables in regressions.
Year	Year of survey wave	Binary (1= 2017, 0=2014)	Categorical	Used as a dummy in regressions
Demographics	Age, gender, marital status, household size	Mixed (years, binary, categorical, integer)	Various	Part of control variables in regressions

Livestock	Value of household livestock holdings	ZAR, continuous	Monetary	Converted to real terms using CPI (March 2017).
Vehicles	Value of household-owned vehicles	ZAR, continuous	Monetary	Converted to real terms using CPI (March 2017).
Business assets	Value of unincorporated business	ZAR, continuous	Monetary	Converted to real terms using CPI (March 2017).
Real estate	Value of non-primary residential property	ZAR, continuous	Monetary	Converted to real terms using CPI (March 2017).
Owner-occupied housing	Value of the household's primary dwelling	ZAR, continuous	Monetary	Converted to real terms using CPI (March 2017).
Retirement annuities	Value of pensions/superannuation	ZAR, continuous	Monetary	Converted to real terms using CPI (March 2017).
Possessions	Value of durable goods	ZAR, continuous	Monetary	Converted to real terms using CPI (March 2017).
Bank balance	Value of money in a Bank account	ZAR, continuous	Monetary	Converted to real terms using CPI (March 2017).
Stocks	Value of the Household's shares or unit trusts	ZAR, continuous	Monetary	Converted to real terms using CPI (March 2017).
Diversification index (GSI)	$1 - \sum (asset\ share)^2$	0–1 index, continuous	Dimensionless	Higher values = more diversified.
Diversification (categorical)	Diversification across risk classes	Ordered (1=Low, 2=Moderate, 3=High)	Categorical	Ordered logit/probit models.
Adverse life event	The household experienced an event in the past 24 months	Binary (1 = yes, 0 = no)	Categorical	Used in DiD models.

CHAPTER 5: SUMMARY AND CONCLUDING REMARKS

5.1 INTRODUCTION

The wealth of individuals, households, and society has a significant influence on public budgets, policy choices, and political stability. Consequently, understanding household financial decision-making is crucial, as these decisions have a direct impact on both short-term and long-term wealth outcomes. This thesis explores the complex relationship between household finance and wealth inequality by analysing the role of household balance sheet components and characteristics in wealth disparity, the connection between asset allocation and wealth distribution, the link between diversification and wealth equality, and the impact of life events on wealth across different levels of diversification. By quantifying these relationships, policymakers, financial planners, and educators can better identify societal segments that are underutilising their wealth-building potential or are less resilient to adverse events.

This chapter presents a comprehensive discussion of the thesis, encompassing its theoretical and empirical contributions, significance, implications, recommendations, limitations, and potential directions for future research. It is organised into five sections. Section 5.2 provides a general overview of the thesis. Section 5.3 assesses the importance of the thesis, emphasising its contribution to the academic field and the distinctiveness of its methodology. Section 5.4 considers the implications of the findings and makes policy recommendations. The final section, Section 5.5, outlines the limitations of the research and suggests avenues for future investigation.

5.2 THESIS SUMMARY

Chapter 1 sets out the motivation for the thesis. South Africa grapples with persistent wealth inequality, exacerbated by historical inequities. This thesis examines the relationship between household finance and wealth distribution, with a focus on balance sheet components, portfolio choices, and asset diversification. Understanding these factors is crucial for addressing wealth inequality and promoting economic fairness.

Chapter 1 also provided a brief overview of the theoretical foundations of household consumption, saving, and investment decisions. It examined the factors influencing wealth accumulation and distribution, highlighting the roles of life-cycle theory, portfolio theory, and behavioural economics. The chapter stressed the unequal access to financial resources and opportunities that contribute to wealth inequality. While Modern Portfolio Theory (MPT) offers a framework for optimising asset allocation, factors such as financial expertise, risk tolerance, and minimum investment requirements can restrict its effectiveness for less wealthy households. With an understanding of these theoretical concepts, subsequent chapters carried out empirical investigations into the relationship between household finance and wealth inequality.

Household finance significantly influences wealth accumulation. However, comprehensive research on this subject in South Africa remains scarce. This thesis aims to address this gap by exploring how household balance sheets, investment choices, and asset diversification contribute to wealth inequality. The study uses the National Income Dynamics Survey (NIDS) to examine household wealth accumulation and financial decisions. The results provide valuable insights into the factors that drive wealth inequality and suggest potential policy measures. The thesis adds to the ongoing discussion on economic inequality in South Africa by analysing the relationship between household finance and wealth distribution.

Chapter 2, motivated by the fact that wealth inequality in South Africa is a pressing issue, with a significant concentration of wealth in the hands of a small percentage of the population, investigates the role of household balance sheet components and characteristics in perpetuating wealth inequality. Using RIF regression, the chapter identifies key drivers of inequality, including specific assets and liabilities contributing to disparities. Additionally, the chapter examines the impact of household characteristics such as age, education, and location on wealth inequality. These findings emphasise the intricate relationship between household finances and wealth distribution in South Africa. Understanding these factors is essential for developing effective policies to address inequality and promote economic fairness.

Chapter 3 examined the relationship between wealth and asset allocation decisions in South Africa, using NIDS data and the fractional multinomial logit (FMLOGIT) model. The chapter revealed that wealthier South Africans tend to have a higher risk tolerance, allocating a larger proportion of their wealth to moderate- and high-risk assets. Other factors, including income, life insurance, Stokvel membership, emotional well-being, education, employment, marital status, household size, age, race, and geographic location, also influence asset allocation choices.

While unobserved characteristics may influence asset allocation decisions, the CRE model confirms that unobserved heterogeneity does not significantly alter the main findings, validating the results of the pooled FMLOGIT model. Similarly, the CFA analysis indicates that household wealth is exogenous, strengthening the robustness of the observed relationship between wealth and asset allocation. The logit model further supports the conclusions, showing that the likelihood of investing in riskier assets increases with wealth, thereby confirming the classification of asset categories.

These findings have important implications for policymakers and financial institutions. Customised financial literacy programmes and investment products can foster financial inclusion and improve the financial well-being of South Africans across all wealth levels. By understanding the various factors that influence asset allocation, policymakers can develop more effective interventions to support informed investment choices and encourage economic prosperity.

Chapter 4 examined the factors affecting asset diversification in South Africa using NIDS data. The chapter identified a curvilinear relationship between wealth and diversification, with households in the upper-middle wealth range showing the most diverse portfolios. Additionally, several socioeconomic and demographic factors, including income, household size, education, age, life insurance, self-employment, marital status, gender, and residence in Traditional Authority Areas, are positively associated with asset diversification. These findings imply that policies promoting these factors can directly foster greater asset diversification.

Crucially, diversified portfolios offer a buffer against negative life events; households with fully diversified portfolios tend to experience less severe declines in net worth. Households with such portfolios are better equipped to withstand shocks and preserve or grow their wealth. These findings emphasise the importance of asset diversification as a protective measure against financial hardship. By addressing the factors that influence diversification and promoting policies that support financial inclusion and reduce inequalities, South Africa can foster a more equitable and resilient financial landscape.

5.3 THESIS CONTRIBUTIONS

The significant contributions of the thesis to the literature on household finance are threefold. First, recognising the skewed focus of existing literature on household finance towards the developed world, the emphasis on South Africa has broadened the perspective on developing countries. This thesis enhances our understanding of household asset portfolios, wealth accumulation, diversification, and resilience, adding another layer to the comprehension of wealth inequality. Additionally, the relatively recent availability of a shorter time series for the wealth module in NIDS data makes this study one of the first longitudinal analyses of financial decisions among South African households. Therefore, it was possible to assess the causal impact of adverse life events. However, the availability of more extended time series will greatly benefit future research.

Second, constructing indicators of diversification and treatment variables using adverse life events was a novel contribution in South Africa. These indicators establish a crucial link between asset diversification and adverse economic shocks. Consequently, the benefits of asset diversification were straightforward to evaluate and test. Analysing the differential impact of adverse life events on households with varying diversification levels assesses how diversification offers resilience against adverse shocks. The life events discussed include theft, fire, destruction of household property, livestock deaths or widespread disease, major crop failures, and the death of household members. Households holding diversified portfolios were able to maintain or even increase their net worth during these events.

Thirdly, the study comprehensively analysed the factors driving wealth inequality in South Africa, focusing on household balance sheet components and demographic characteristics. The study employed the Recentred Influence Function (RIF) regression to identify key contributors to inequality. Business assets emerge as a significant driver of wealth concentration, while real estate has a more equalising effect. Debt, particularly consumer debt, can exacerbate inequality. Demographic factors, including race, education, and employment status, also play a significant role. Understanding these factors is essential for policymakers seeking to address wealth inequality. Policymakers can foster a more equitable and inclusive society by promoting entrepreneurship, expanding access to education, and promoting financial inclusion.

5.4 IMPLICATIONS AND RECOMMENDATIONS

The findings of this study have important implications for public policymakers, financial planners, and financial educators. The analysis indicates that life-cycle stages, along with demographic, socioeconomic, and financial sophistication factors, influence household financial decisions more than traditional investment theory suggests, highlighting the need for targeted policies in several key areas:

Wealth Inequality: Policymakers should focus on promoting entrepreneurship, improving access to education, and expanding financial inclusion, especially for disadvantaged groups. Tackling these issues can help lessen wealth disparities, particularly among non-White populations and those excluded from business ownership.

Financial literacy: Tailored financial literacy programmes are vital, especially for middle-income households that are increasingly investing in moderate- and high-risk assets. These programmes can enable individuals to make informed decisions, reduce financial vulnerability, and foster broader wealth creation.

Asset Diversification: Promoting asset diversification is vital as it safeguards against adverse life events. Policies should encourage diversification, especially among lower- and middle-income households, through supporting income growth, education, and self-employment opportunities.

Risk Management: Creating investment products that suit various risk tolerance levels and wealth segments can promote financial inclusion. Understanding what influences asset allocation allows for more targeted interventions, thereby enhancing financial wellbeing across different demographic groups.

By tackling these areas, policymakers and financial institutions can build a more equitable and resilient financial environment in South Africa, decreasing reliance on welfare and improving household financial stability.

5.5 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This thesis explores the complex relationship between household finance and wealth inequality by examining the role of household balance sheet components and characteristics, the link between asset allocation and wealth distribution, the connection between diversification and wealth disparity, and the impact of life events on wealth across different levels of diversification. However, this does not come without notable caveats.

- The study's analysis of wealth inequality in South Africa examined a relatively short dataset period, which may not fully reflect long-term trends and dynamics in wealth distribution.
- Classifying household assets as low-, moderate-, and high-risk in asset allocation analysis is mainly subjective, especially for non-financial assets. This subjective categorisation may affect the accuracy of the results.
- Another limitation is the lack of pre-treatment data to empirically verify the assumption of parallel trends in the difference-in-differences analysis. Although theoretical justifications and covariate controls were used, the absence of direct validation undermines the causal inference.

To improve on the current findings, Future Research can consider the following avenues:

Extended Timeframe Analysis: Future studies should explore wealth distribution dynamics over extended periods to capture more comprehensive trends and changes in wealth inequality.

Intersectionality of Factors: Research should delve deeper into the intersectionality of demographic factors such as race, education, and employment status and their combined impact on wealth outcomes.

Objective Asset Categorisation: Developing an objective framework to categorise non-financial household assets by inherent risk would enhance the accuracy of future asset allocation studies.

Impact of Specific Shocks: Future research should investigate the effects of specific adverse life events on household net worth, with a focus on how these impacts vary across different demographic groups. Also, using richer datasets, including pre-treatment data, would provide more robust evidence.

Long-Term Consequences of Shocks: Investigating the long-term effects of adverse life events on wealth, particularly in relation to asset diversification, could provide deeper insights into household financial resilience.

Tailored Financial Products: Research could explore the development of financial products tailored to different risk tolerance levels and wealth segments, promoting broader financial inclusion.

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