An assessment of the factors influencing asset accumulation of South African rural households

by

Mzwandile Dayimane

Submitted in partial fulfilment of the requirements.

For the degree of.

Master of Science in Agric (Agricultural Economics)

Department of Agricultural Economics, Extension and Rural Development

Faculty of Natural and Agricultural Sciences

University of Pretoria

February 2024

ABSTRACT

Rural areas in South Africa are predominantly characterized by the presence of subsistence farming households, many of which face challenges related to limited asset ownership. While historical poverty reduction efforts have primarily focused on addressing income poverty, this approach overlooks the multifaceted nature of poverty experienced by rural communities. Scholars increasingly argue that poverty should not be solely defined by insufficient income or consumption but should also consider the absence of assets.

This study adopts an asset-centric perspective to investigate the factors influencing asset accumulation among rural households in South Africa. Particularly, it examines how participation in subsistence farming impacts asset accumulation, given the crucial role that asset ownership plays in ensuring a basic standard of living, especially when facing unpredictable fluctuations in income.

To conduct this research, data from South Africa's 2018 General Household Survey (GHS), conducted by Statistics South Africa, was utilized. The study focused on a subset of rural residents within the dataset.

The results of the Multiple Correspondence Analysis (MCA) reveal that the first component accounts for 57.2% of the overall variance, while the second component explains 12.3%. The asset index derived from the eigenvalues of the first component reveals a pattern wherein positive coefficients corresponded with assets associated with higher socio-economic status, such as ownership of computers, vehicles, and telephones. Conversely, negative coefficients were indicative of items reflecting lower living standards.

The study's findings highlights the significance of various factors in influencing household asset accumulation. Household engagement in subsistence farming, household size, income levels, the primary source of income, gender dynamics, and the age of the household head emerged as influential determinants. Both ordinary least squares (OLS) and Ordered Multinomial Logit regression models strongly supported these findings, with the latter based on asset wealth quintiles.

The research revealed that asset poverty is more prevalent in female-headed households compared to male-headed ones. In addition, households involved in subsistence farming exhibited higher levels of asset ownership, suggesting that this livelihood strategy has a positive impact on their overall well-being.

The study also highlights the crucial role of access to basic services such as transportation, information, and communication in enhancing households' resilience to economic shocks. Assets were identified as essential tools for coping with unforeseen challenges. Consequently, the study recommends the implementation of policies and strategies aimed at improving rural access to basic services, infrastructure, and land markets. Such measures have the potential to mitigate asset poverty and align with the government's rural development objectives.

Key words: Asset accumulation, Asset ownership, Asset poverty, Asset index, Multiple Correspondence Analysis.

DECLARATION

I declare that this mini dissertation is my original work, does not involve plagiarism or collusion and has not been submitted in partial or entirety for degree purposes to any other university. Where use has been made of the work of others it is duly acknowledged in the text.

....

Mzwandile Dayimane (Candidate)

As supervisor, I agree to submission of this dissertation for examination.

....

Moraka Nakedi Makhura (Supervisor)

DEDICATION

This dissertation is wholeheartedly dedicated to my late grandmother "Nohombile Nomalizo Dayimane" and my sister "Xoliswa Julia Dayimane" who dedicated their lives in continuously providing emotional, financial, and moral support in ensuring a decent education for me.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my profound gratitude to God the Father through my Lord Jesus Christ for His enduring mercy and unwavering guidance. Without His divine intervention, completing this dissertation would have been an insurmountable task, for His Word reminds us to "Commit your ways to the LORD, Trust in Him, And He shall bring it to pass."

I extend my heartfelt appreciation to everyone who contributed to the successful completion of this dissertation. Your invaluable input, time, and unwavering support played an indispensable role in this journey. I wish to offer my sincere thanks to the following individuals and institutions:

To my dedicated supervisor, Dr. Moraka Nakedi Makhura, your guidance and support from the inception of this study until its completion have been immeasurable. Your mentorship, motivation, and constructive feedback were instrumental in helping me organize my thoughts and navigate the challenges of this research. I am also grateful for your efforts in securing allowances and research funds on my behalf. Your commitment to my success is deeply appreciated, and may God continue to bless you abundantly.

I would like to express my gratitude to the National Research Fund (NRF) for their generous research funding throughout the year. Special thanks to Ncuthukazi Tshabalala from UP-NRF for her invaluable assistance in administering the funds.

My heartfelt appreciation goes to the Center of Collaboration on Economics of Agricultural Research and Development (CoC-EARD) for their multifaceted support, including funding and capacity building. The CoC Colloquium and writeshop provided me with valuable insights and suggestions, and I extend my thanks to all the CoC Management.

To my beloved family, particularly my sister, Xoliswa Dayimane, my nieces and nephews Asithandile, and Imibongo (Aluve), my siblings Sindiswa, and Tsepisang, and my uncle Andile, your unwavering perseverance and continuous support throughout my academic journey have been a source of strength. While it has been a long road, this dissertation stands as a testament to your unwavering support. I cherish and love you all, and I pray that God's blessings may abundantly grace your lives.

To my fellow colleagues and friends, including Reitumetse Happiness Morabe, Sandi Shumane, Light Ngobeni, Sukoluhle Mazwane and many others whose names I could not mention individually, I extend my sincere gratitude. Your love and support were deeply appreciated, and your presence made a significant difference.

Once again, thank you all immensely for your contributions, encouragement, and support throughout this journey. Your collective efforts have been instrumental in the successful completion of this dissertation!

Thank you all very much!

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

APPENDICES

ACRONYMS AND ABBREVIATIONS

DA	Demographic Analysis division
DFID	Department for International Development
DHS	Demographic and Health Survey
GHS	General Household Surveys
IC	Intergenerational Connections
ISR	Inverse Sampling Rate
LCH	Lifecycle Hypothesis
MCA	Multiple Correspondence Analysis
NGP	New Growth Path
NIDS	National Income Dynamics Study
PCA	Principal Component Analysis
PDHS	Pakistan Demographic and Health Survey
SEP	Socio Economic Position
Stats SA	Statistics South Africa
PSU	Primary Sampling Unit
ICT	Information and Communication Technology

CHAPTER 1: INTRODUCTION

1.1 Background

Is it possible for those entrenched in structural poverty to make progress over time? The answer lies in the dynamics of asset accumulation. The accumulation of assets plays a pivotal role in reducing poverty and enhancing resilience among rural households in South Africa. Traditional methods of poverty alleviation often fall short, whereas asset-based approaches offer more sustainable solutions (Global Economy and Development, 2006). Poverty can be understood in both monetary and non-monetary terms. In monetary terms, it relates to insufficient income, while in non-monetary terms, it encompasses factors such as limited access to public services, lack of private asset ownership, social isolation, and vulnerability to shocks, especially in a changing environment (Jansen, 2015).

In most low- and middle-income rural areas, the strong connection between poverty, food insecurity, and a low standard of living is well-recognized. However, the focus of poverty reduction policies has often centred on income poverty, neglecting other dimensions of poverty that impact rural households (Awotide et al., 2014). Awotide et al. (2014) contend that poverty should not be solely defined by the absence of income or consumption but should also consider the absence of assets. Scholars such as Barrett & Swallow (2006), Carter & Barrett (2006), and Awotide et al. (2014) argue that household well-being is more accurately assessed through asset ownership rather than income or consumption. They emphasise that “Asset ownership is less susceptible to random shocks and is likely to be a more stable indicator of household well-being, especially in less developed and developing countries where rural households heavily rely on rain-fed farming, resulting in weather-induced income volatility” (Awotide et al., 2014).

The level of asset possession within rural households can significantly impact their long-term food security, especially during off-seasons or when crop yields are compromised due to climate change. In such situations, a household’s ability to meet essential needs, including food, may hinge entirely on the sale of its assets.

The measurement of asset poverty in households is of utmost importance in demographic and economic analysis. It not only aids in assessing welfare and inequality within a society but also in understanding the influence of various wealth-related factors when used as control variables (Habyarimana et al., 2015). Economists, social scientists, and policymakers have long been concerned with measuring individual and household poverty (Hackman et al., 2021), particularly regarding how poverty and inequality impacts individual well-being (Hackman et al., 2021).

Asset poverty emerges as a particularly pertinent and crucial form of poverty, characterized by a household's inability to access sufficient wealth resources to meet basic needs within a specified timeframe (Awotide et al., 2014). Assets hold unique significance in assessing household well-being due to their lower susceptibility to fluctuations compared to income or expenditure (Awotide et al., 2014). Notably, a 2002 study by the Department for International Development (DFID) highlighted the pivotal role of asset ownership in the long-term livelihood strategies of rural households striving for improved well-being. Asset poverty quantifies the extent to which rural households possess a sufficient stock of assets to maintain a basic standard of living during temporary economic hardships. Asset-poor households, as per Awotide et al. (2014), typically lack the resources to invest in their future or provide basic support to household members during periods of economic instability.

This research investigates various factors influencing asset accumulation among rural households in South Africa, with a primary focus on building resilience through asset-based approaches. This study takes an innovative, non-monetary perspective on poverty assessment in South Africa, emphasizing asset accumulation as a key indicator of well-being for rural households.

1.2 Problem statement

Rural households in South Africa exhibit significant variability in terms of asset ownership and their interconnectedness with various socioeconomic factors. This variability raises critical questions about identifying those who are well-off and those who are impoverished, and how to accurately pinpoint the economically disadvantaged. It is essential to distinguish and target the most vulnerable to poverty and inequality, particularly households with limited asset ownership, in order to plan, execute, and monitor development programs and public services with fairness and effectiveness.

Despite numerous development strategies and substantial investments in poverty alleviation and wealth creation in South Africa, the country's poverty rate remains persistently high (Biyase et al., 2019). Even initiatives like the New Growth Path (NGP) have highlighted the enduring challenges of unemployment and poverty in South Africa, especially in rural areas

(Biyase et al., 2019). Alongside poverty alleviation and inequality concerns, the issues related to data and methodologies employed for gauging economic well-being are also under scrutiny.

Filmer & Pritchett (2001) proposed the utilization of asset indices as a viable alternative to conventional income and expenditure measurements for assessing household standards of living. The adoption of asset indices has become critical in providing detailed insights into socioeconomic disparities in economic well-being and the utilization of publicly provided services. According to Shaukat (2019), asset indices surpass income and consumption as more reliable predictors of living standards. Recently, researchers have increasingly turned to asset indices constructed from readily available data on household assets, household attributes, and access to services (Fomum & Jesse, 2017; Biyase et al., 2019; Biyase & Zwane, 2017; Jansen et al., 2015; Booysen et al., 2008; Filmer & Pritchett, 2001; Sahn & Stifel, 2000; Sahn & Stifel, 2003, and Habyarimana et al., 2015).

Asset indices offer a cost-effective method for measuring a household's long-term economic capacity. In many countries, asset indices have been instrumental in uncovering factors influencing poverty, wealth acquisition, and inequality. Additionally, asset indices have facilitated the identification of economic well-being disparities among families, both within and between nations, by categorizing households based on socioeconomic standings, thereby tailoring intervention efforts. An in-depth understanding of socioeconomic hierarchies informs targeted measures to enhance economic outcomes for those disproportionately disadvantaged. When employed as a measure of living standards, the asset-index allows for the identification of numerous demographic and socioeconomic variables associated with economic well-being. Nevertheless, research suggests that the utilization of asset indices as a tool, particularly in South Africa, has been limited, partly due to resource and data constraints.

While some researchers have employed asset indices in South Africa, including studies by Biyase et al. (2019); Biyase & Zwane (2017); Jansen et al. (2015); Booysen et al. (2008); Fomum & Jesse (2017); and Daniels et al. (2014), these investigations have not specifically focused on rural areas, where asset poverty is more prevalent. Consequently, these studies fail to provide a comprehensive understanding of rural asset poverty and the factors influencing asset accumulation in these settings. These prior studies aimed to identify variables contributing to multidimensional poverty and inequality across the country, encompassing both urban and rural households. Augustine (2015) examined the correlation between wealth and tribal authority areas, while Fomum & Jesse (2017) explored the relationship between asset accumulation and financial inclusion. To the best of our knowledge, no comprehensive study has thoroughly explored the socioeconomic and demographic determinants of asset accumulation among rural households in South Africa, with a particular focus on the impact of subsistence farming on asset accumulation.

In light of these research gaps and the persisting challenges of rural poverty, this study endeavours to address this dearth of literature. It aims to complement existing research on asset accumulation and ownership in rural areas and present a more holistic view of the socioeconomic and demographic factors influencing asset ownership and household economic well-being among rural households in South Africa. Specifically, this study investigates the influence of household engagement in subsistence farming on asset accumulation. This holds particular significance in rural households, where asset ownership assumes a pivotal role in sustaining adequate consumption levels amid income volatility and achieving overall well-being (Awotide et al., 2014).

3.5 Research question.

The study was guided by three research questions:

i. What are the key assets accumulated by rural households in South Africa?
ii. What are the factors influencing asset accumulation among rural households?
iii. What are the effects of demographic and socio-economic factors on asset accumulation?

3.5 Objectives of the study

The primary objective of this research was to investigate the factors affecting asset accumulation in the rural areas of South Africa.

1.4.1 Sub-objectives

To achieve the main objective, the following specific objectives were formulated for the study.

i. To examine the key assets that the rural households prioritize.
ii. To identify the socio-economic and demographic factors affecting asset accumulation.
iii. To assess the effects of demographic and socio-economic factors on asset accumulation.

1.5 Contribution of the study

This study will add to the corpus of information on asset accumulation and poverty dynamics in numerous ways. Firstly, the application of MCA in constructing the assets index by this study adds depth to the methodology, reinforcing the argument for innovative approaches in understanding and addressing wealth dynamics. Secondly, this research contributes significantly to the existing body of knowledge by providing insights into the factors that influence the accumulation of assets. Lastly, the findings of this study can serve as valuable information for policymakers, researchers, and practitioners, assisting them in developing targeted interventions and policies to promote asset accumulation and alleviate poverty.

1.6 Organization of the dissertation

Chapter 1 introduced the investigation and provides an overview of this dissertation, including the research context, specific research problem, research questions, objectives, sub-objectives, limitations, and contributions. Chapter 2 discusses the conceptual definitions and measurement approaches related to standards of living, asset accumulation and asset poverty. Specifically, the chapter focuses on the conventional unidimensional monetary measures and the broader multidimensional measures. Furthermore, the section also review existing literature on the factors influencing asset accumulation.

Chapter 3 outlines the methodology employed for gathering and analysing secondary data from the Stats SA (2018) General Household Survey (GHS) in South Africa. It details data collection tools, instruments, and the sampling technique used to collect quantitative data for this study. This chapter also elucidates the research approach and regression technique used to identify factors affecting asset accumulation in rural South African households. Chapter 4 presents descriptive analysis of household characteristics based on the responses that were captured on the survey. The descriptive statistics are summarised using tables and figures, and then discussed to present a comprehensive overview of demographic, regional, and socio-economic attributes within the rural South African population.

Chapter 5 presents and discuss the results obtained from the multivariate analysis that was conducted. Furthermore, the results obtained from the two approaches that were used in this research are compared. Chapter 6 provide recommendations and draw conclusions from the results obtained in this research. Additionally, effort is made to highlight how the results obtained from this research can be used to inform policy decisions and in filling the existing gap in the research and practice.

CHAPTER 2: REVIEW OF LITERATURE

2.1 Introduction

This chapter discusses the characteristics of rural subsistence farming households. Secondly, some conceptual definitions and approaches to the measurement of standards of living, welfare, and asset poverty. In this regard, the traditional money metrics and the more broad-based composite asset-index approaches are discussed. Additionally, the chapter also covers the literature on the determinants and factors affecting asset accumulation.

2.2 Characteristics of rural subsistence households

Going back in time, homestead backyard food gardening long existed. Rural residents founded, established, and subsequently relied on subsistence backyard food gardens in South Africa's former homelands as a result of improvement planning, homeland settlement laws, and, finally, apartheid (Christian & Obi, 2018). Christian & Obi (2018) cited Perry (2012), who characterized homestead backyard farming as a very old concept in which Bantu settlers in rural South Africa established their homesteads based on their proximity to natural resources, particularly water supplies. These residents were largely Agri-pastoral farmers who lacked passion. This arrangement was remarkable in that it supported both livestock and crop farming. Communal efforts were employed in doing several farming activities like planting, ploughing, weeding, and even harvesting, lowering production costs significantly. Furthermore, their farming activity was heavily dependent on nature. Some local cultural practices are still practiced among rural subsistence farmers today, and indigenous knowledge on how to distinguish seasons and time is still evolving among many people in the villages.

According to Christian & Obi (2018), the main characteristics of subsistence household production systems include simple, outdated systems, labour intensity, large seasonal variability, and women playing an important part in farming. Subsistence households produce primarily for survival and, to a lesser degree, for marketable surpluses (Christian & Obi, 2018). According to Christian & Obi (2018), subsistence farming accounts for a larger share of certain rural households' overall income livelihoods. Given this perspective, farming in subsistence households serves primarily to meet the necessities of the household. Indeed, it is because of such low production levels that policymakers are encouraging subsistence farmers to produce above subsistence levels in meeting the national food security and poverty-reduction goals.

Subsistence farming in South Africa is characterized by the intensive use of labour, the majority of which is provided by the household members. Subsistence farmers perform the farming operations on their own, with the assistance of members of the family. Some members of the family, such as siblings or grown-up children, are occasionally compensated to assist in farming activities. External inputs such as machines and fertilizers are used minimally in this circumstance. The use of labour in subsistence farming is sometimes a kind of self-exploitation because most people are poor and cannot afford external agricultural inputs and labour costs, therefore they must rely on family labour.

Subsistence farming in South Africa is characterized by primitive production systems (Department of Agriculture, 2008). According to Christian & Obi (2018), subsistence farming in Southern Africa mostly utilizes traditional farming practices, and productivity levels are frequently poor. Considering this setting, subsistence farming frequently has a limited output base. Farming is the primary source of food for rural populations as well as an income-generating activity in many developing nations' rural areas. This suggests that farming is crucially important in reducing hunger and poverty, particularly in rural areas (Christian & Obi, 2018).

The level of rural households' asset endowment can also have implications on the long-term food security of the entire household. Consequently, during the off-season or in the event of crop failure as a result of climate change, the households' financial resources needed to meet basic needs such as food could utterly depend on the sales of the households' assets.

2.3 Household welfare

While the international community recognizes poverty as the principal problem, the conceptual understanding of what poverty is, how to quantify it, and how to track its reduction progress remains ambiguous (Niyimbanira, 2016). This emphasizes the fact that poverty is a multifaceted phenomenon with several expressions. A more significant topic is whether income deprivation is the best approach to assess poverty or whether other measures should be used in addition. According to the World Bank (2005), poverty is a complicated issue that is resistant to simple solutions. Poverty attitudes have shifted dramatically, with a greater knowledge of the varied nature of poverty and the need of defining the depth and severity of poverty (Niyimbanira, 2016). Given the importance of the "poverty" term in defining the indicators for measurement, as well as the significance of measurement in identifying the poor, policymakers are faced with establishing well-targeted anti-poverty programs.

Poverty, being a multifaceted notion, is defined in a variety of ways, and definitions differ from nation to nation . Several definitions of poverty include preconceived notions of welfare; the selection of a "poverty line" separates the population into those who have an appropriate amount of welfare and those who do not. Measuring an individual's or a household's economic well-being can be a complicated process, but it can be simplified by limiting the term to material well-being. This leaves out several immaterial elements that influence poverty. Poverty has always been considered a distinguishing quality.

Given a certain measure of well-being, a line or standard is drawn, and a household or an individual falls on one side or the other, resulting in analysis at two distinct levels. To define poverty, divide the population into two groups: the poor and the non-poor. Measuring poverty attempts to condense the "amount" of poverty into a single metric. While asset accumulation is a positive consequence of a household's ownership over such assets, asset poverty is defined as one's deprivation or a lack of ownership over the market and/or non-market goods and services.

It should be highlighted that wealth is distinct from income in that it is common for a person or household to have a high salary yet have a low total wealth owing to credit-dependent lifestyles (Augustine, 2015). Although income and wealth are interconnected terms, they are not the same and have different meanings. Income may be thought of as one aspect of wealth (Howe et al, 2009). The flow of capital resources such as profits, salaries, wages, or government payments is characterized as income. On the other hand, wealth is defined as the ownership of both marketable (mostly acquired via either savings or investments) and non-marketable assets by households or individuals (Howe et al, 2009).

Unlike income, wealth is a stock variable that reflects an individual's or household's net financial position at a specific point in time (Musundwa et al., 2014). While income and consumption are major predictors of present well-being, assets are an essential predictor of long-term consumption. Wealth is defined as the total value of all valuable assets possessed by a person, household, community, or country. Although literature frequently refers to wealth in tangible forms such as natural, physical, and financial capital, other types of wealth are less obvious, such as human and social capital. Wealth can be in the form of money, shares in corporations, debt instruments, land, buildings, intellectual property such as patents and copyrights, and treasures such as works of art (Howe et al., 2009).

Wealth is a broad and dynamic concept that refers to an abundance of monetary and/or non-monetary assets. Non-monetary wealth is related to appropriate access to public goods or services, whereas monetary wealth is associated private assets and with sufficient money to purchase private goods or services.

To arrive at a complete measurement of the wealth of an economic unit, a wide range of assets need to be accounted for. Second, measuring wealth necessitates accurate appraisals of all assets and liabilities, the majority of which are difficult to get. For example, the price of assets such as jewellery or stock prices may change significantly over time, and in certain circumstances, the value of the asset may only be assessed upon its sale (Augustine, 2015).

Given the importance of wealth as a driver of the consumer's consumption possibilities, a major part of the research has been focused on income rather than wealth (Augustine, 2015). The emphasis on income is due in part to the fact that it is easier to measure and is assessed more regularly in most nations. Furthermore, due to its social sensitivity, wealth data is not as widely available as income data.

Property and assets may also be held under trusts, complicating measurement even further. Finally, another difficulty with quantifying wealth is that the sorts of assets that are representative of wealth differ among places and countries, as well as across time. This is because numerous variables influence asset ownership, such as affordability, choice, availability, and culture; for example, cattle ownership may be more prevalent in rural regions than in cities (Howe et al., 2009).

The traditional and modern definitions of household wealth are not always mutually exclusive. This difference is mostly defined by the market and symbolic worth of the asset (Joubert & Van der Merwe, 2021; and Garenne, 2015). In traditional or pre-modern societies where agriculture is the major economic activity, household wealth relates to prestige, power, and social standing in addition to the holding of assets (Bowles, Smith & Mulder, 2010). The majority of assets/goods are gained via household effort rather than monetary trade (Bowles, Smith & Mulder, 2010; and Garenne, 2015).

In pre-modern societies, there are three indicators of household wealth. The size of the house is the first indicator since it determines the quantity of family labour (manpower) available to generate goods and services (Bowles, Smith & Mulder, 2010). The second indicator is agricultural land (Garenne, 2015). Finally, cattle ownership serves as a source of food, transportation, agricultural labour (ploughing fields), and a social status signal (Joubert & Van der Merwe, 2021). Agricultural products, home equipment, and jewellery are further examples of household wealth (Bowles, Smith & Mulder, 2010 ; and Garenne, 2015).

In contrast, to traditional pre-modern society, trading marketplaces characterize contemporary society. Modern prosperity is built on manufactured commodities and modern services (Garenne, 2015). Today, quality housing and comfort are essential signs of prosperity (Joubert & Van der Merwe (2021). The second form of wealth indicator includes household amenities such as running water, sanitation, power, furniture, and other electronic equipment (radio, television, telephone, computers, etc.) (Bowles, Smith & Mulder, 2010). Modern forms of transportation, such as airplanes, vehicles, bicycles, and motorbikes, as well as modern agricultural instruments, comprise a third category (tractor, plow, and planter) (Garenne, 2015). Bank accounts and internet connection are the remaining two categories (Joubert & Van der Merwe, 2021). Modern wealth is largely earned via the exchange of money (Bowles, Smith & Mulder, 2010).

2.4 Asset ownership and accumulation

According to Meng (2007), the distribution of asset ownership exhibits greater inequality than income distribution. Several theories have been formulated to explain the patterns of asset ownership distribution, including the Lifetime Saving (Accumulation) Theory and the Intergenerational Connections (Inheritance) Theory (Skopek et al., 2014; and Augustine, 2015). Inheritance plays a substantial role in shaping asset ownership distribution, leading to significant disparities in asset ownership levels and serving as a primary channel for the transmission of assets between generations. An important characteristic of household asset ownership and distribution is the way inheritance takes place. When the older generation possesses minimal or low levels of assets, the subsequent generation inherits fewer assets than their predecessors (Meng, 2007).

Asset accumulation tends to follow a life cycle pattern for many middle-income households, with lower levels during youth that increase through middle age, peak just before retirement, and then decline during the post-retirement years (Augustine, 2015). The Lifecycle Hypothesis (LCH) model represents an intragenerational accumulation model, where households accumulate savings over their lifetime through labour-force participation and draw upon those resources in retirement. Consumers benefit from a consumption stream throughout their lives, and their choices are constrained by their lifetime budget (Augustine, 2015). The mode's key assumptions include forward-thinking consumers, preferences over present and future consumption, an expected retirement period at the end of no's life, no uncertainty, a consistent rate of return for all consumers, uniform lifespan (T), and no inheritance.

2.5 Urban-rural asset distribution

Asset indices are typically constructed using the same set of assets across different populations, often without considering geographical variations such as urban and rural areas. Additionally, the weighting of asset items is usually uniform across different locations, assuming that all included assets have the same significance across diverse regions and that their relationship with economic well-being is consistent (Howe et al., 2009). However, this assumption has a limitation because specific asset items tend to be concentrated geographic areas. For instance, technology assets like internet access are more prevalent in urban areas, whereas assets like livestock are more common in rural regions. Urban-centric assets significantly influence the weighting of asset items (Martel et al., 2021). Assets primarily found in rural settings, such as land ownership and domestic animals, tend to be undervalued (Martel et al., 2021).

Differences between urban and rural lifestyles in developing countries add complexity to the design and use of asset indices. There are disparities in tastes, costs, product and service availability, employment opportunities, and educational access between urban and rural settings (Howe et al., 2009). Since most asset items used in index construction have an urban bias, there is concern that an asset index might overestimate the economic well-being of urban households while underestimating that of rural households (Howe, 2009; and Poirier et al., 2019). Many assets included in the construction of asset indices are more likely to be owned by urban households than rural ones. This overestimation of urban household welfare and underestimation of rural households can lead to misclassification, as urban households equivalent in wealth to certain rural households may be incorrectly classified as wealthier (Booysen et al., 2008; and Howe et al., 2009).

To address these issues and apply location-specific weights, Poirier et al. (2019) suggest that one can split the sample into two groups and independently calculate rural and urban indices, thereby mitigating urban-rural biases. However, this approach has its limitation as agricultural assets receive positive weights for rural households but negative weights for urban households (Ward, 2014). Research in Zimbabwe comparing a rural-only sample asset index to one calculated for the entire sample revealed a strong relationship with a Spearman rank correlation coefficient of 0.862, indicating a strong association (Poirier et al., 2019). There is an ongoing debate about whether to develop an asset index for the entire population or conduct separate analyses for rural and urban areas.

2.6 Measuring of household welfare

An economic welfare measure is a gauge that consolidates comprehensive data concerning the target population (Niyimbanira, 2016). Household economic well-being measures are commonly employed to track socioeconomic conditions and establish benchmarks for evaluating success or failure (Niyimbanira, 2016). The determinants of household economic well-being have been a subject of extensive research and study for many years, both in developed and developing nations. Two methods have been used to model the determinants of household economic well-being. The first method employs the unidimensional indicator, often referred to as the money metric, which relies on per capita income or consumption expenditure measurements.

The second approach involves the use of the asset index. Filmer & Pritchett (2001) and Sahn & Stifel (2000) introduced asset indexes as an alternative measure to address the challenges associated with accurately measuring income and expenditure. Advocates of the asset index argue that households find it considerably easier to provide accurate responses to questions about asset ownership, such as whether they possess items like radios, televisions, or piped water. These data are further supported by direct observations of these assets. Nonetheless, empirical findings suggest that asset index measures tend to align with consumption measures (Biyase & Zwane, 2017).

In comparison to alternative indicators, asset index-based methods offer several advantages, including a strong correlation with expenditure data across a wide range of situations. Howe et al. (2009) explored whether asset indexes could serve as a suitable proxy for consumption expenditure and found a moderate association between the two measures, with a correlation coefficient of 0.54 and a Kappa value of 0.11. When comparing log expenditure per capita, Kolenikov & Angeles (2005) found a modest but positive correlation coefficient of 0.3510. The researchers employed polychoric PCA to generate index scores. Recent research on asset index methodologies and alternatives revealed a moderate correlation between asset indices and money-metric measures, with average Spearman's rho values of 0.42 and 0.55 for income and expenditure, respectively (Poirier et al. 2019). Additionally, vast datasets on asset ownership have been available for many countries and years (Karigi, 2014). Finally, the asset index is believed to better reflect long-term poverty and living standards compared to short-term income and consumption.

2.6.1 Monetary measurements

Income and/or consumption are widely recognized as suitable indicators for measuring only one aspect of economic well-being. Monetary measurements have proven particularly valuable in assessing household'' short- to medium-term living standards and have been effective indicators of poverty in various regions and countries (Biyase et al., 2019).

Income poverty can be objectively quantified using either absolute or relative methods (Jansen et al., 2015). Absolute income poverty is determined by calculating the minimum income required for survival. For instance, the World Bank's US$1 per day absolute poverty threshold is frequently used for cross-country comparisons (Jansen et al., 2015). In contrast, relative income poverty entails identifying the lowest 20% or 40% of the population using a relative poverty threshold (Jansen et al., 2015; and Woolard & Leibbrandt, 2006).

The assumption underlying the use of monetary measures is that income levels or proxy expenditures can accurately determine whether households can meet essential needs such as nutrition, clothing, and housing (Niyimbanira, 2016). Employing monetary measures often implies that these measures (income/expenditure) adequately represent multidimensional well-being and that those classified as income poor are nearly identical to those experiencing malnutrition, lack of education, insufficient productive assets, or disempowerment.

Expenditure is the most used measure, as it is believed to better reflect a person's consistent income (Niyimbanira, 2016). However, concerns have been raised about the accuracy and reliability of income and expenditure data, particularly in low- and middle-income countries. Habyarimana et al. (2015) and Biyase et al. (2019) highlighted several issues associated with monetary measures:

i. Collecting income and expenditure data in impoverished communities is often costly and challenging, with data quality issues.
ii. Households may be reluctant to disclose sensitive income and expenditure information, leading to recall bias and sampling bias (Biyase et al. 2019).
iii. Determining prices of goods, nominal interest rates, and depreciation rates for durable goods can be problematic when constructing consumption aggregates. (Habyarimana et al2015).
iv. Prices can substantially vary across time and regions, necessitating complex adjustments to reflect these differences in expenditure figures (Habyarimana et al., 2015; and Biyase et.al 2019).

v. Seasonal income fluctuations, particularly in rural areas where agriculture plays a significant role, pose challenges in data collection (Howe, 2009).

vi. Estimating household income often relies on questioning a single household member, who may not have complete knowledge of all income sources.

Several studies, such as Gounder (2012); Biyase & Zwane (2017); Quartey (2006); and Akerele & Adewuyi (2011), have supported the use of monetary measurements. For example, Gounder (2012) employed the natural logarithm of total per capita household consumption as a proxy for household welfare to analyse the determinants of household consumption and poverty. Multivariate analysis was conducted to identify household factors associated with welfare. Biyase & Zwane (2017) utilized income per capita to examine the relationship between household welfare and demographic characteristics.

2.6.2 Composite asset index measurement

Studies by Filmer & Pritchett (2001), Sahn & Stifel (2000), and Sahn & Stifel (2003) introduced the concept of composite asset indexes, utilizing data on asset ownership and access to services. Subsequently, economists and social scientists have shown keen interest in using asset indexes to measure welfare, poverty, and disparities (Achia et al., 2010; Booysen et al., 2000; McKenzie, 2005; Vyas & Kumaranayake, 2006; Gachanja & Kinyanjui, 2016; Kolenikov & Angeles, 2004; and Booysen et al., 2008).

The composite asset index approach for measuring welfare has gained popularity due to its comprehensive evaluation of various aspects of household economic well-being (Mosasane & Oyekale, 2021). This method utilizes data on the ownership of various durable assets (e.g., TV, Radio, Cell phone, Laptop), housing characteristics (e.g., cooking fuel, dwelling floor, roof material), and access to essential services (e.g., electricity, sanitation, water source). These indicators provide extensive information for poverty measurement to develop a composite asset index that quantifies household economic status. Because this technique relies on high-quality, nationally representative, and globally comparable survey data, asset index measures are considered more reliable than monetary metrics (Howe, 2009).

Another notable difference between asset indices and monetary measures is that asset indices cannot be expressed in per capita units, as they are typically based on household assets rather than individual assets. Asset indices are more strongly associated with the theory of household economies of scale than per capita consumption, highlighting that they measure a distinct yet equally relevant aspect of household well-being (Filmer & Scott, 2012; and Poirier et al., 2019).

Furthermore, it is argued that asset indices are not necessarily inferior to monetary measures, as intrahousehold income distribution is often highly unequal, and expenditure is not evenly distributed among household members (Poirier et al., 2019).

While asset-based measures are gaining popularity, there is still considerable debate about their interpretation. One challenge is that asset indexes often lack information about prices and asset values, making it difficult to assess the quality and age of owned assets (Karigi, 2014). For instance, data on television ownership does not distinguish between a household with a modern smart TV and one with an old black and white TV. Supporters of asset indexes often contend that they should be viewed as long-term, stable economic measures, while income and consumption expenditure are typically seen as short-term economic measures (Howe et al., 2009).

Additionally, it is argued that in many countries, short-term income and expenditure fluctuations do not significantly affect a household's overall welfare picture (Poirier et al., 2019). Howe et al. (2009) assert that household asset holdings tend to grow gradually over time and are unlikely to change rapidly even during periods of income volatility or short-term shifts in consumption patterns. According to Poirier et al. (2019), an asset index represents relative, rather than absolute, economic status and can be used to determine economic status rankings within a population hierarchy. In contrast, monetary measures represent the 'absolute' value of economic well-being.

Achia et al. (2010) employed the asset index methodology to explore the determinants of asset poverty in Kenya. Their study revealed significant positive associations between the household head's religion, geography, ethnicity, and asset poverty. In a similar study, Gachanja and Kinyanjui (2016) investigated the impact of the household head's years of schooling, household size, and region of residence on household welfare status. Employing Principal Component Analysis, they constructed a comprehensive wealth index. Furthermore, they used both the binary and ordered multinomial logit models, their study to examine the determinants of household welfare status.

Their findings highlight the key role of the household head's years of education, marital status, household size, and region of residence (province) in determining household welfare status (Gachanja and Kinyanjui, 2016). This significance was consistently observed across both binary and ordered logistic models. Notably, the results highlighted that married households were more likely to attain higher levels of welfare status.

The choice of whether to assess household welfare using monetary indicators (income or consumption) or the asset index remains a subject of debate, considering the merits and drawbacks of each. This study follows the asset index approach, as advocated by Booysen et al. (2008), rather than relying on income or consumption measures. Two factors influenced the selection of an asset index-based measure of welfare in this study. First, income is often irregular, especially in rural areas where farmers and subsistence households receive income seasonally.

2.6.3 Methods used to construct asset index

In the current body of research, the most frequently employed method for constructing asset indexes is Principal Components Analysis (PCA). Filmer & Pritchett (2000, 2001) proposed PCA as a technique for assigning weights to various assets in the Demographic and Health Survey (DHS) Dataset. This approach involves standardizing input variables before calculating factor loadings for each asset. These loadings are then applied to the asset variables, and their sum yields the household's index value. Typically, only the first component generated by this process is utilized to represent the asset index. The outcomes are standardized scores with a mean of zero and a standard deviation of one (Karigi, 2014).

PCA is a data reduction method commonly used in poverty and economic research. It involves replacing a set of correlated variables with uncorrelated principal components that represent latent population characteristics. These principal components are linear combinations of the original variables, determined by the data's correlation or covariance matrix. Standardization is necessary when the indicator scales significantly differ, as PCA tends to select variables with the greatest variance as sources of variation. The first principal component typically accounts for the most variance, with subsequent components explaining less. If the initial components capture a substantial portion of the total variance, they can represent the original items, reducing the number of variables needed in models.

The first principal component, derived from PCA, is chosen to represent the asset index. It assigns more weight to assets that exhibit greater inequality across the sample. The weights allocated to each item in this first principal component are used to calculate a household's score, with higher weights indicating greater economic well-being. The relative ranking of households based on this score serves as a measure of their relative welfare or economic status.

However, there are limitations to using PCA for asset index construction. First, PCA is primarily designed for continuous variables and assumes normal distribution, making it less suitable for categorical asset indicators. Second, the first principal component often explains a small proportion of overall variance, typically less than 20%. Third, using binary variables for categorical assets can lead to spurious correlations between them.

While PCA is widely adopted for asset indexes, there are alternative methods. The equal weighting approach allocates equal weights to all household assets, but it has limitations when dealing with assets of varying quality or performance. Additionally, some assets may be “inferior goods” leading to misleading wealth assessments (Poirier et al., 2019).

The inverse proportion of identical weights is another approach, using pricing data to assign weights based on the fraction of the population owning an item. However, this method has been criticized for not considering factors like asset scarcity. Factor analysis, like PCA, is used to reduce variables into a smaller number of factors.

Multiple Correspondence Analysis (MCA) is an alternative to PCA, particularly suitable for categorical data. MCA does not assume normal distribution and can handle categorical variables without ordinal structures. Multiple Correspondence Analysis (MCA) has emerged as a valuable tool in social science research, particularly for investigating complex relationships between categorical variables. One noteworthy application of MCA is found in the work of Booysen et al. (2008), where the authors employ the method to analyse changes in poverty across seven African countries.

Booysen et al. (2008) build upon the foundation laid by Sahn & Stifel (2000), utilizing an asset index to explore the intricacies of poverty dynamics. The study leverages comparable, nationally representative surveys to assess changes in poverty over time. This index helped them see if people were getting richer or poorer in the selected African nations.

An aspect illustrated by Booysen et al. (2008) work is the role of MCA in capturing shifts in wealth and well-being. The asset index, a central component of their analysis, serves as a proxy for economic status, revealing trends in the accumulation of private assets and access to public service.

However, the study acknowledges the methodological shortcomings of MCA. Booysen et al. (2008) highlight the slow-changing and discrete nature of assets, emphasizing potential limitations in accurately capturing changes in well-being. The method’s poor discrimination ability at the lower end of the scale raises questions about its suitability for studying ultrapoverty. This critique contributes to the ongoing discourse on refining methodologies for poverty assessment.

In tandem with Booysen et al. (2008) exploration of poverty dynamics in African countries, Fomum & Jesse (2017) contribute significantly to the discourse on poverty alleviation, specifically in the context of South Africa. Their study investigates the feasibility of implementing asset-building social welfare programs, a subject of paramount importance in the realm of poverty eradication.

Fomum and Jesse leverage the consumer survey dataset and employ the quantile regression technique to examine the relationship between financial inclusion and asset ownership, particularly focusing on individuals situated at the lower strata of the asset distribution.

By incorporating Multiple Correspondence Analyses (MCA) to construct a composite assets index, the study presents a nuanced understanding of asset ownership. Their analysis explores how financial inclusion, measured through monthly savings and insurance, influences asset ownership across different quantiles of the asset distribution.

The findings revealed through mean and quantile regressions that there is a positive and statistically significant relationship between financial inclusion and asset ownership. Notably, this association is strongest at the lower tail quantile (1^{0t}h), indicating a substantial impact on the most economically vulnerable individuals. Surprisingly, the impact decreases at the median quantile (5^{0t}h) but resurfaces and deepens at the upper tail from the 6^{0t}h quantile. This analysis suggests that while the working class might experience less pronounced benefits, the poor and low-income households, some venturing into formal financial access for the first time, derive substantial gains. While recognizing the inherent limitations of cross-sectional data analysis, the study provides evidence for the viability of asset-building social welfare programs.

2.7 Determinants of household asset accumulation

The most extensively researched determinants of household asset accumulation include the age, gender, education level of the head of household, marital status, employment status (permanent employment, self-employment), household characteristics: household size, dependency ratio, and geographical factors: rural, urban, and provincial dummies. In terms of asset accumulation, the following factors are likely to have a positive association with an increased asset ownership: age, education, income, and marital status. However, if many of the household members are dependents (particularly youngsters and the elderly) and hence do not produce income may reduce the stock of assets owned, household size may result in decreased asset accumulation.

Most of the empirical research indicates that household size has a considerable negative influence on household asset ownership. Particularly, the larger the household size, the greater the probability of falling into poverty, because more resources are necessary to cover the household's necessities (Sekhampu, 2013; Gounder, 2013; and Lekobane & Seleka, 2017). Achia et al. (2010) demonstrate that larger households are much more likely to be poor than small households using the asset index as an indicator of asset poverty. Similarly, there is substantial evidence that bigger household size is inversely connected with the household living standards when assessed by consumption and income per capita (Gounder, 2012; Biyase and Zwane, 2017).

Age is another important determinants of asset accumulation. For example, Augustine (2015), Gounder (2012); Biyase & Zwane (2017); Booysen et al. (2008); Habyarimana et al. (2015); Gachanja & Kinyanjui (2016); and Biyase et al. (2019) have discovered that elderly household heads had greater assets than younger household heads. The gender variable accounts for the general assumption that a female-headed household is more vulnerable to asset poverty. The literature on the predictors of asset poverty has documented three potential explanations for this, which are generally referred to as the "triple burden" which comprise the inequalities faced by women in the job market, added house chores and parental care duties, and a higher dependency ratio on being a single income earner (Gounder, 2012).

Mbewe & Woolard (2016) observe that ethnic disparities in asset ownership exist in South Africa, hence the ethnicity of the head of the household is an important household asset ownership factor. The economic inequality literature provides some evidence of the relationship between race and economic disparity. South Africa, on the other hand, is a distinctive instance due to its history of racial tyranny against the Black population during the Apartheid era. During this time, Black South Africans were denied equal economic opportunities, perpetuating a cycle of disproportionate assets and income distributions not just between Black and White South Africans, but also among Black South. Research shows that this pattern continues in the post-apartheid era, with most Black households still having little or no wealth or income when compared to their White counterparts (Mbewe & Woolard 2016).

Mbewe & Woolard (2016) show significant rural and urban poverty disparities. The area variable thus proxies for remoteness and is expected to capture if people in rural areas are more vulnerable to asset poverty. Furthermore, rural households face fewer equitable opportunities than their urban counterparts, have lower education levels, and are more likely to be unemployed (Jin & Xie, 2017). Evidence presented by Biyase & Zwane (2017); and Bila & Biyase (2022) shows that households living in urban areas are less likely to be poor than those living in homelands.

2.8 Chapter Summary

The Chapter showed that there are some conceptual definitions and approaches to the measurement of asset poverty. In this regard, the traditional monetary approach, and the more broad-based multidimensional approaches are viewed as critical. The measures of wealth and/or assets include the monetary (such as income and/or consumption) and the nonmonetary metrics (such as private and public assets or access to basic services). The determinants and factors affecting asset accumulation include the gender of the household head, age of the household head, household size, number of economically active person, primary source of income, and household engagement in subsistence farming.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapters articulates the methodologies used in gathering and analysing secondary data from Stats SA (2018) the General Household Survey (GHS) of South Africa. The chapter explains method, data gathering and tool, and sampling method that was utilized to gather the quantitative data set that is utilized for this research. It also outlines the research approach and regression technique that is used to determine the factors affecting household assets attainment in rural residents of South Africa.

3.2 Data

This study will make use of secondary data obtained in the 2018 General Household Survey (GHS) steered by Statistics South Africa in South Africa (Stats SA, 2019). The survey sample was designed to be nationally representative, encompassing the entire population. Statistics South Africa (Stats SA) conducted the survey in January 2018, covering various domains such as education, healthcare, social development, housing, service access and facilities, food security, and agriculture (Stats SA, 2019). It is important to note that the available data is of a cross-sectional nature, and this study focuses specifically on a sub-sample of rural residents.

3.2.1 Survey scope

The target demography for the study includes all rural households in South Africa's nine provinces. Other communal staying in quarters like student hostel, old-age residents, hospitals,' prisons,' and army camps are excluded from the poll, thus it only reflects non-institutionalized and, non-military citizens or families of South Africa (Stats SA, 2019).

3.2.2 Sample design

This survey used a stratified sampling with probability relative to the size selection of principal sample unit at the first phase and systematic sample of residence groups in the subsequent phase (see Stats SA, 2019). Using census information of 2011, the sampling was additionally stratified by location (primary stratification) and demographic characteristics after allocation to provinces (secondary stratification). Stats SA survey workers visited each of the nine provinces sampled dwelling units. The initial stage of the survey, sampled housing were paid a visit and educated on the forthcoming survey as part of the marketing campaign. The survey undertook four weeks afterward. A sum of 21 908 homes (plus complex houses) were productively physically surveyed.

3.2.3 Weighting

The sample weights for the data gathered from samples were designed so that the replies could be appropriately broadened to reflect South Africa's overall civilian population. The design weights, which are the province's inverted sample rate (ISR), are given to each home in the province. These were changed for four factors: informal primary sampling units (PSU), growth PSUs, sample stabilization, and non-responding units. The Demographic Analysis (DA) division's mid-year population estimates were utilized for benchmarking.

The final survey weights were calibrated to national population estimations cross-categorised by 5-year age classes, gender, and race, as well as province population estimates by broad age categories, using regression estimation. The age groupings are as follows: 0 to 4, 5 to 9, 10 to 14, 55 to 59, 60 to 64; and 65 and older. Age groupings at the provincial level are 0 to 14, 15 to 34, 35 to 64, and 65 and older. The standardized loads were designed so that all members of a family would have the same ultimate weight. For the cells specified by age cross-classification by gender and race, national and provincial population controls were employed. Records with item non-response due to age, population group, or gender could not be weighted and were thus omitted from the dataset. To keep these records, no imputation was performed.

3.3 Study Variables

3.3.1 Dependent variable: household welfare

The research focuses on asset accumulation as the dependent variable. This measure is approximated using a composite household asset-index. To construct this wealth/asset-index, the study employs the Multiple Correspondence Analysis (MCA) method. The selected indicator variables used in this index are all binary in nature, denoting the presence (1) or absence (0) of assets within households. The study encompasses three distinct categories of asset ownership indicators, which are as follows:1) Domestic Assets: These include items such as refrigerators, stoves, and washing machines. 2) Communication Assets: This category involves assets related to communication and entertainment, such as televisions, cell phones, radios, telephones, computers, and internet connections.3) Transportation Assets: Here, the focus is on ownership of vehicles. This approach to measuring asset accumulation is drawn from the work of Mushongera et al. (2017).

3.3.2 Independent variables

Among the household characteristics available in the dataset, we carefully selected potential predictors of asset accumulation. Our choices were guided by factors expected to have a substantial impact on household asset holdings. In determining these determinants of asset accumulation, we adhered to a methodology akin to that employed by Gounder, 2012 for the selection of explanatory variables.

These potential explanatory variables encompassed several factors, including the continuous variable of the age of the household head, gender (categorized as male or female), the household's geographical location (represented as province dummies), and household size. Notably, variables such as education level, marital status, ethnicity, and access to electricity were excluded from consideration in our analysis. For a comprehensive understanding of the variables and their definitions, please refer to Table 1.

Table 1. Variable description

Variables	Description	Hypothesised relationship
Household head age	Age in years	Positive
Household size	number of people in the household	Positive
Household size squared	Square of the number of people in the household	negative
Household head gender	1 if a Household head is a male, 0 otherwise	Positive
Economically active members	number of people economically in the household	Positive
Province	Province Dummy	
Subsistence farming	1 if Household practices subsistence farming, 0 otherwise	Positive
Income group	Income dummy	
Source of income	Source of income dummy	

3.4 Method of data analysis

The following procedure was implemented to analyse the asset accumulation behaviour among the rural households:

i. We conducted descriptive analysis by looking at the variable of interest.

ii. We conducted multiple correspondence analysis on household asset variables to obtain weights for each asset item and subsequently the asset-index of a household.

iii. Linear regression was estimated to analyse the relationship between dependent and explanatory variables.

iv. The asset-index was stratified into five quantiles, to classify households according to their socio-economic status as "poorest", "poor", "middle", "rich" and "wealthiest". In addition, an ordered logit model is estimated to examine the relationship between asset accumulation and explanatory variables.

3.4.1 Multiple Correspondence Analysis

MCA, like principal component analysis, it aims to reduce the dimensionality of a data matrix and represent it in a low-dimensional subspace, typically two or three dimensions. MCA extends from PCA in that it is used for discrete/category variables, which means that the data of interest is generally in a multi-way table, with each row representing an observation/case and each column representing a variable (categorical). MCA is typically used to evaluate survey data. Questionnaires frequently produce responses to many questions with a limited set of response options. The answers to these p questions, coded in a disjunctive form, result in "p" different ways of classifying all the individuals in the sample. Let $X = [x_1] \ldots [X_p]$ represent the indicator matrix of p categorical variables observed on the same set of n individuals, with $J = \sum_{k=1}^{p} j_k$ representing the total number of categories, which is the number of columns in matrix X. Let X_k be the indicator matrix of the k^{th} variable, with marginals $x_{j_k} = \sum_{i=1}^{n} x_{ij_k}$. Let D also be a diagonal matrix of size J x J, the generic diagonal elements of which are supplied by the diagonal elements of the k distinct matrices $D_k = x_{j_k}$. MCA can be employed as an indicator (disjunctive) or a Burt matrix.

i. Correspondence analysis on the n x J indicator matrix **X.**

ii. Correspondence analysis on the J x J Burt matrix **B.**

In the first approach to MCA, we perform a singular value decomposition (SVD) of matrix $\frac{1}{p\sqrt{n}} X D^{-1/2}$, written as:

$$SVD\left(\frac{1}{p\sqrt{n}} X D^{-\frac{1}{2}}\right) = \Phi \Lambda \Upsilon' \tag{3.1}$$

Where $\Lambda = \{\lambda_m\}, m = 1, \ldots, min\,(n, J - p)$, which represents the singular values in decreasing order, and Φ and Υ denote the corresponding left and right singular vectors, respectively, subject to the constraint, $\Phi'\Phi = I$ and $\Upsilon' D \Upsilon = I$

A variable is regarded as a set of category points in multiple correspondence analysis. The proximity of the categories of distinct variables in a graphical representation represents the relationship between them (refer to Lombardo & Meulman, 2010). We may define the set of column profile (variables) coordinates based on the matrix X as:

$$G = \Lambda\Upsilon' = \left(\frac{1}{p\sqrt{n}} X'\Phi D^{-\frac{1}{2}}\right) \tag{3.2}$$

One can also determine the relative proximity of the individuals in the study. Coordinates for the individuals can be defined as:

$$F = \Lambda\Phi = \left(\frac{1}{p\sqrt{n}} X\Upsilon D^{-\frac{1}{2}}\right) \tag{3.3}$$

Using both sets of coordinates, the total inertia of the data can therefore be expressed as:

$$trace(G'DG) = trace(F'F) = trace(\Lambda^2)$$

The Burt matrix B is a matrix composed of diagonal blocks with univariate marginals on the main diagonal and a collection of all tables with bivariate marginals in off-diagonal blocks. The Burt matrix can also be written as B = X'X. Correspondence analysis on the Burt matrix is the second strategy to MCA, yields an eigenvalue decomposition of $\frac{1}{p\sqrt{n}} BD^{-\frac{1}{2}}$, written as:

$$EVD\left(\frac{1}{p\sqrt{n}} XB\right) = \Upsilon\Lambda^2\Upsilon'$$

Where, Λ^2contains the eigenvalues λ_m^2on its diagonal (m=1,…, J–- p), with Υ representing the corresponding eigenvectors $\{v_m\}$.

3.4.2 Construction of asset-index

This research utilized the statistical method known as Multiple Correspondence Analysis (MCA) to derive weights for constructing a household welfare of several distinct asset indicators. MCA is a powerful technique for analysing discrete data, serving as a development of Simple Correspondence Analysis (CA) to handle supplementary than two variables. While CA explores relationships between two discrete variables, MCA extends this to evaluate multivariate relationships among multiple discrete or categorical variables. MCA resembles Principal Component Analysis (PCA), but it is tailored for categorical data rather than continuous data. Unlike CA, which focuses on relationships between two variable sets, MCA delves into relationships within a single set of variables.

In the context of MCA, principal components are arranged in such a way that the 1st principal component captures most variance in the primary data, followed by the second component (uncorrelated with the 1st), and so on. This order reflects the decreasing amount of variance explained by each subsequent component. Consequently, the first principal component, in all residents, exhibits an average of zero and a variance of σ, which matches to the greatest eigenvalue in the correlation matrix. The primary component of MCA generates an index which allocates greater weights to asset exhibiting the highest variability across residents, while asset present in all household receive a weight of zero.

The study adopted the non-monetary, asset index approach following Zwane (2022); and Booysen et al., (2008). Asset index was derived using a statistical technique known as Multiple Correspondence Analysis (MCA), which aimed at combining asset variables (i.e. private assets and public services). Set below is a standard formula to create index scores on the first component extracted by employing the MCA:

$$y_i^{*} = Xi1W1 + Xi2W2 + \ldots + XijWj \qquad (3.4)$$

Y – Asset index scores for household i

X – Binary variable (1 if household i owns asset j)

W – Weights

We computed these weights for asset indicators using the "mjca" command in the R software, following the approach detailed in Nenadić & Greenacre (2007). Other studies that have used MCA for constructing asset-indexes, including Booysen et al. (2008); McKenzie (2005); Jansen et al. (2015); Akotey (2015); Howe et al. (2009); and Fomum & Jesse (2017).

The limitation of the MCA index is that the principal factor may yield negative values at the lower end of the index, which can pose interpretation challenges. To address this issue, Booysen et al. (2008) recommends an addition of a value equal to the highest negative factor to every value of the index, effectively transforming the smallest value into zero.

Using asset indices as a marginal indicator of economic welfare status offers several advantages. Firstly, it simplifies data collection, as individuals find it easier to report on asset ownership compared to recalling precise expenditure amounts on various items. Secondly, asset ownership information is less susceptible to seasonal variations, unlike income data, which can fluctuate significantly in informal and agricultural sectors due to economic conditions (Fomum & Jesse, 2017).

3.4.3 Ordinary Least Square regression

We employ the Ordinary Least Squares (OLS) regression technique to estimate a linear regression model, aiming to examine the association amongst asset accumulation as captured by the asset index and several explanatory variables. Extensive literature has identified key factors that affect asset building including house head sex , number of years, number if people in living In the house , earned-income, and main sources of earnings (Vyas & Kamaranayake, 2006; Fomum & Jesse, 2017; Augustine, 2017; Biyase et al., 2019; and Shaukat et al., 2019). We estimated the following model:

$$y^* = \beta_0 + \beta_1 X + \beta_2 X + \cdots + \mathcal{E} \qquad (3.5)$$

y – Asset index

X – Explanatory variables

– Estimated coefficients

Ɛ – Error term

3.4.4 Ordered logit regression.

To assess the reliability and of the outcomes derived from the OLS regression, an ordered logit regression was utilized. The continuous asset index variable was transformed to a polychotomous categorical outcome variable with asset index quantiles (1 = poorest, 2 = poor, 3 = middle, 4 = rich, 5 = wealthiest) (following Gachanja and Kinyanjui, 2016). The terms asset index and wealth index are used interchangeably in this study to refer to the same thing, the index generated in this study.

We estimated a multinomial ordered logit (Maximum likelihood procedure) with the asset index quintiles as an outcome variable. Assuming Y is in a class of cumulative link regression, model specification is as follows:

$$Pr\,\{y^* \leq j\} = \alpha_j + f(X, \beta) + \varepsilon \qquad (3.6)$$

y – ordinal Asset index variable

X – Explanatory variables

$\boldsymbol{\alpha}$ – estimated intercept coefficients

$\boldsymbol{\beta}$ – Estimated coefficients

Ɛ – Error term

In the ordered logit model, the categorical outcome can take on values from 1 to 5, corresponding to the quantiles. We assume that the ordinal variable Y falls within a class of cumulative link regression models, with parameters βj to be estimated. We further assume that the error-term ε_i follows a logarithmic distribution. The estimation of intercept parameters is done concurrently with the β_j values using the max likelihood procedure to derive likelihood estimates for the model.

Utilizing the ordered logit model for identifying determinants of asset accumulation has been applied in various contexts, including research by Gachanja & Kinyanjui (2016) on asset poverty in Kenya. Other scholars have also utilized independent variables for example household head age, household size, and household location to assess socioeconomic status (Booysen et al., 2008; Habyarimana et al., 2015; Gachanja & Kinyanjui, 2016; and Biyase et al., 2019).

3.5 Chapter Summary

The chapters highlighted the methodologies used in gathering and analysing secondary data from Stats SA (2018) the General Household Survey (GHS) of South Africa. The study adopts and implements the Multiple Correspondence Analysis (MCA) approach. The two multivariate approaches adopted in this study include Ordinary Least Squares (OLS) regression and multinomial regression, aimed at identifying factors influencing asset accumulation in rural South African households. The subsequent chapter will focus on presenting and discussing the analysis results.

CHAPTER 4: CHARACTERISTICS OF THE RURAL HOUSEHOLDS

4.1 Introduction

This chapter describes the attributes of participants in the South African General Household Survey (2018) dataset according to the responses of the household heads from rural areas. Firstly, it presents the descriptive statistics household asset ownership. Secondly, it presents the results obtained from the Multiple Correspondence Analysis and the characteristics of the asset index that was generated. Furthermore, the chapter presents the descriptive analysis of household characteristics including the demographic and socio-economic attributes of rural households. Lastly, the household characteristics are decomposed by the wealth quantiles.

4.2 Demographic and socio-economic characteristics

Table 2 provides a summary of demographic and socioeconomic characteristics of a sample population with a total of 6347 households. There is roughly an equal distribution between males (49%) and females (51%) among household heads that reside in rural areas. Typical household is in the middle age of just above 51 years. A typical household has about four members. The median household size is 3, ranging from 1 to 21 members. Nearly half (46%) of households in the rural areas of South Africa have no economically active persons. Most households (51%) have 1 to 2 economically active persons, while only a small percentage have 3 to 4 (2%), 5 to 6 (1%), or 7 or more (1%).

Table 2. Descriptive Statistics of household's demographic characteristics.

	Total (N = 6347)
Gender	
Male	3110 (49%)
Female	3237 (51%)
Age (years)	
Mean (SD)	50.87 (17.08)
Median [Min, Max]	50 [16, 108]
Household Size	
Mean	3.78
Median [Min, Max]	3 [1, 21]
Number of economically active person	
Zero	2944 (46%)
1 to 2	3262 (51%)
3 to 4	134 (2%)
5 to 6	1 (1%)
7 or more	6 (1%)

Source: Authors' calculations using GHS data from Stats SA (2018).

According to Table 3, the main sources of primary income are social grants (39%) and salaries/wages (35%), followed by remittances (13%), business income (6%), and other sources such as farming income and pensions. Most individuals belong to the low-income group (79%), followed by middle-income (14%) and high-income (7%) groups. 42% of respondents engage in subsistence farming, while 58% do not.

Table 3. Descriptive Statistics of household's socio-economic characteristics.

	Total (N = 6347)
Source of primary income	
Business income	412 (6%)
Social grants	2488 (39%)
Salary and wages	2216 (35%)
Farming income	13 (1%)
Pension	82 (2%)
Remittances	862 (13%)
Other	28 (4%)
Income groups	
Low	4990 (79%)
Middle	899 (14%)
High	458 (7%)
Subsistence farming engagement	
Yes	2666 (42%)
No	(3681) 58%

Source: Authors' calculations using GHS data from Stats SA (2018).

4.3 Descriptive statistics of household assets

This section discusses the descriptive statistics of household assets. According to the data presented Appendix 1, less than 7% of rural households had no access to electricity in 2018. This shows considerable progress made by the country to ensure that everyone has access to electricity. The percentage of people without computers and internet were 92% and 98.35, respectively. A demonstration that the country is falling behind in terms of improving access to Information, Communication and Technology (ICT). There is more wide access to mobile cell phones (94,8%).

The skewness values (refer to Appendix 2) highlight strong concentration of ownership towards assets like cell phones, electricity, TV, and electric stove. For example, the positive skewness (4.15) indicates that cell phone ownership is widespread, with only a small number of households not having it. While other assets like vehicles and solar panels, solar geyser are not common. The highly negative skewness value of -12.32, and -11,37 for solar panels and solar geyser indicates that the ownership of these assets is not as universal as some other assets.

4.4 Validity and Reliability

Validity in the context of socially constructed knowledge regarding an issue encompasses two essential characteristics: accuracy and trustworthiness, as highlighted by Sibisi (2015). There are two types of validity in quantitative research: internal and external validity, each encompassing various subtypes (Sibisi, 2015). In this study, we have used internal consistency, a facet of internal validity, to validate the data related to household asset characteristics (refer to Appendix 2).

The computed Cronbach's alpha value of 0.823 suggests that the selected asset variables exhibit relatively high homogeneity. This finding indicates that the assets indicators of the first principal component collectively measure the same underlying construct.

4.5 Asset-index

Regarding the asset-index, we conducted a Multiple Correspondence Analysis (MCA) on chosen asset item variables. The mapping of household asset items onto the first two dimensions is visually represented in Figure 1. The 1st principal component, along the horizontal axis, explains 57.2% of the total variance, while the second principal component captures 12.3%.

Upon examining the eigenvalues of the first principal component, we observed that positive coefficients are related with assets items of higher asset accumulation, such as ownership or access to a computer, DSTV, vehicles, telephones, or the internet, among others. Conversely, negative coefficients are linked to items displaying lower living standards or asset poverty (e.g., lacking indoor plumbing, electricity, cell phones, televisions, etc.). This signifies that asset items aligned with improved living standards attributes positively to the household asset-index, while indicators reflecting lower living standards contribute negatively. In simpler terms, owning certain assets or having access to specific amenities raises a household's asset-index score, indicating a higher level of welfare, while the absence of these assets lowers the score, signifying a lower standard of living.

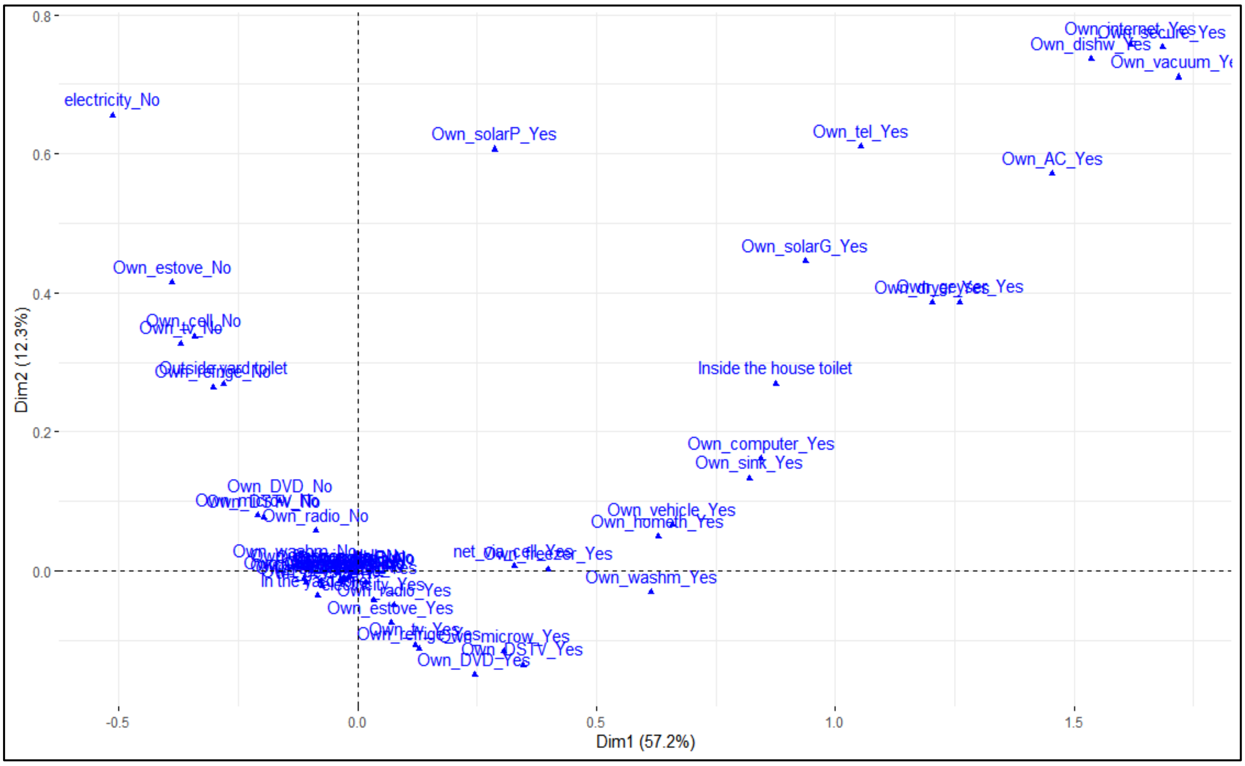

Figure 1. A two-dimension MCA solution showing variable representation on the first two factorial axes.

Source: Authors' calculations using GHS data from Stats SA (2018).

Appendix 3 provides the assigned weights for each modality. These results present asset weights for the 1st factorial axis based upon 27 categories, accounting for 57.17% of the inertia (eigenvalue). The study employed the formula (3.4) to compute the asset-index for each household resulting in the formation of the asset-index. This composite index serves as an indicator of welfare index.

Dealing with negative values can complicate the analysis, especially in assessing living standards. To rectify this, we added a value equal to the minimum value to all household asset-score values, effectively setting the smallest observed values to zero (resulting in a non-negative numbers). This transformation, is also used by other studies such as Asselin (2002); Sahn & Stifel (2003); and Booysen et al. (2008). In our case, this transformation involved adding the number 0.6630 in the asset index for each household.

Figure 2 display the MCA scree plot for the principal components discussed in Chapter 3. Notably, the curve begins to level off after the third principal component. This observation implies that the primary shared variation among asset variables is predominantly captured by the first two principal components, while the remaining eight principal components are considered "noise." The eigenvalue of the first principal component amounts to 57.2%, with the second principal component contributing 12.3%. Collectively, these top two principal components elucidate 70% of the entire variance or total information, justifying the utilization of the first principal component as a measure of asset ownership in our analysis.

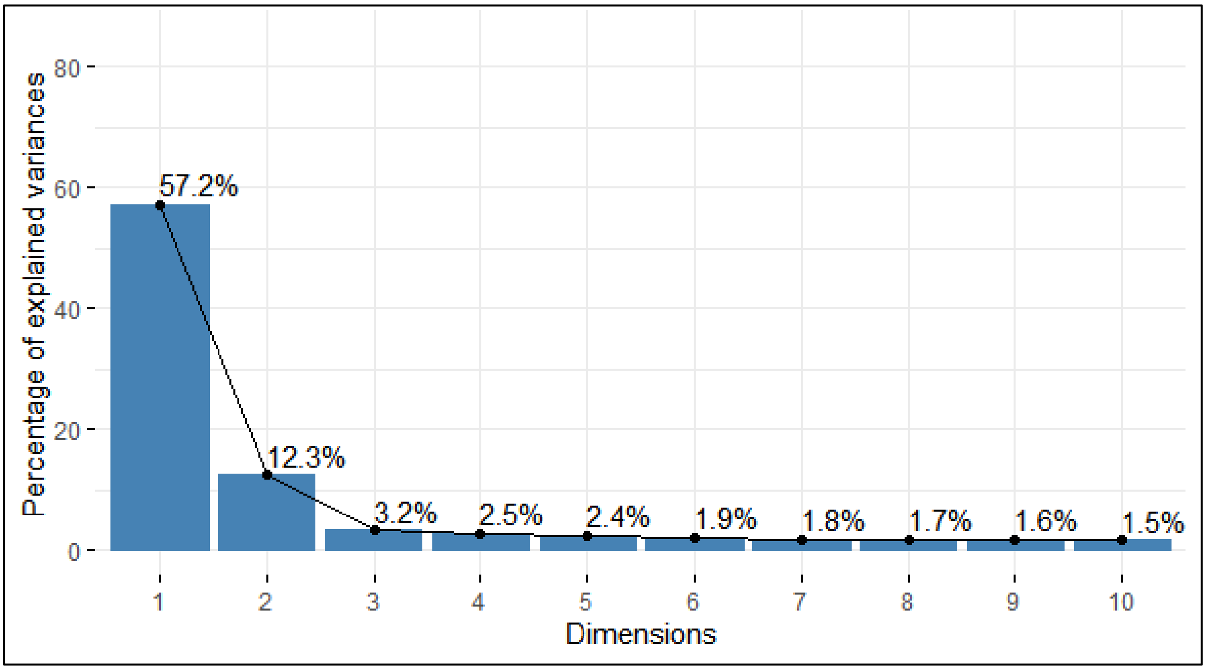

Figure 2. Scree plot from MCA showing the percentage of variance explained by each of the ten principal components.

Source: Authors' calculations using GHS data from Stats SA (2018).

4.6 Asset-index distribution

The density distribution of the continuous asset-index is presented in Figure 3. The density reveals that asset accumulation is to the left, indicating that just a few people have a lot of overall asset ownership in rural areas. It signifies that families at the tail possess almost all the asset items required to calculate the index.

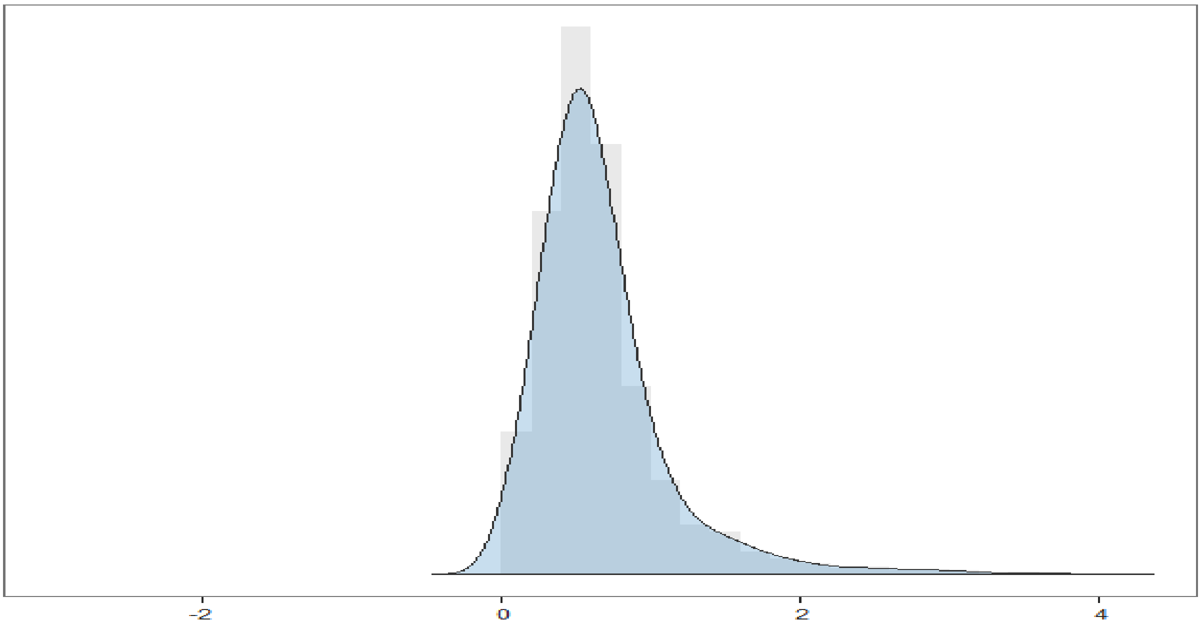

Figure 3. Density distribution of the continuous asset-index.

Source: Authors' calculations using GHS data from Stats SA (2018).

4.7 Wealth decomposition by household characteristics

Asset index quantiles were used for categorization of household into five distinct groups: poorest, poor, middle, rich, and richest. The quantiles served as cutoffs for the raking and categorization of the household by the asset index. The asset-index played an important role in generating a polychotomous variable which will later be used in our ordered logit model.

Notably, among the 6,347 households analyzed, 321 were classified as the poorest while majority of households fell into the poor category, amounting to 51.6 percent (Table 4). This highlights that, despite the country's efforts to combat poverty, a significant portion of households still grapples with economic challenges, lacking access to essential assets and public services. Additionally, 37% of households in rural areas of South Africa are categorized as middle class.

Table 4. Distribution of households by wealth quantiles.

	Poorest	Poor	Middle	Rich	Richest	Total
Frequencies	321	3278	2342	331	75	6347
Percentage	5,1%	51,6%	36,9%	5,2%	1,2%	100%

Source: Authors' calculations using GHS data from Stats SA (2018).

4.7.1 Descriptive analysis of the wealth quantile by gender

The data indicates a prevailing trend in rural areas where many households are headed by women (Figure 4). On average, the rural population comprises 51% female household heads and 49% male household heads. This gender distribution stems from historical practices where women were traditionally marginalized to stay home in rural areas, fulfilling caregiving roles for their families, while men were expected to work in cities to provide for their families. This historical pattern persists today for many families. However, contrasting with the rural scenario, national statistics from Stats SA in 2021 reveal a different picture. At the national level, only 42.1% of households across the country are led by females, while 57.9% are headed by males. Figure 4 provides an overview of the gender distribution among household heads in rural South Africa.

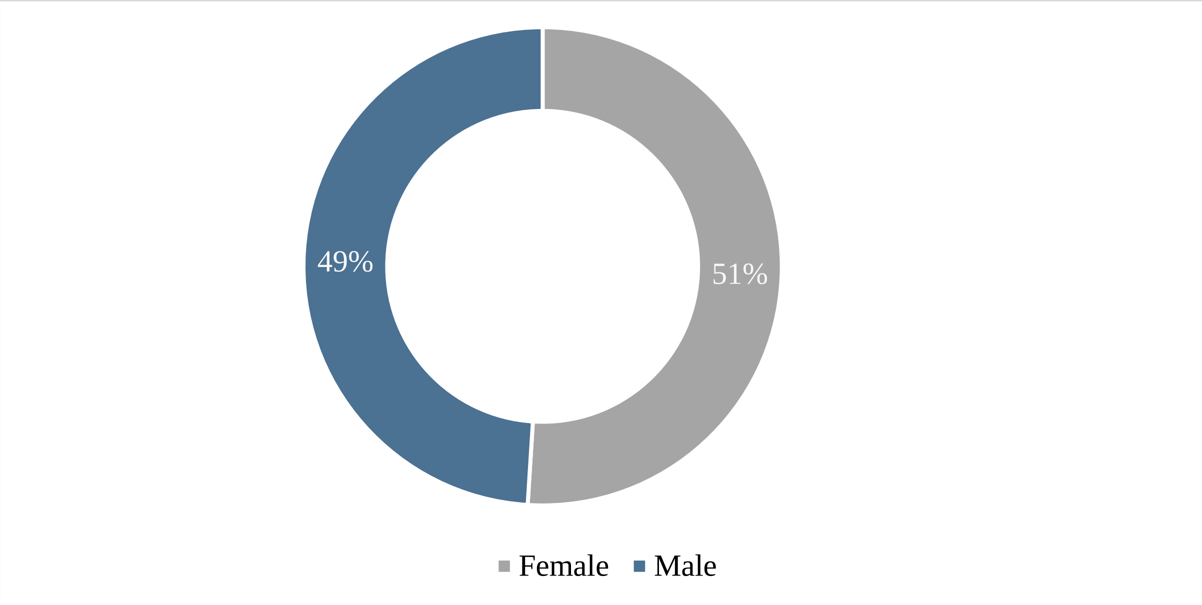

Figure 4. Gender composition of household head in the rural areas of South Africa.

Source: Authors' calculations using GHS data from Stats SA (2018).

Figure 5 shows that female-headed households demonstrate a higher percentage in the poor category (54%) compared to their male counterparts (49%). Conversely, male-headed households display higher percentages in the rich (7%) and richest (2%) categories, in contrast to female-headed households, with percentages of (4%) and (0%) respectively.

The elevated prevalence of female-headed households in the poorest category suggests a higher incidence of poverty among women in rural areas. In contrast, the intensified representation of male-headed households in the rich and richest categories may indicate an existing disparity between men and women concerning asset ownership and economic opportunities. This underlines the need for targeted interventions to address gender-based economic disparities in rural communities, promoting more equitable access to resources and opportunities.

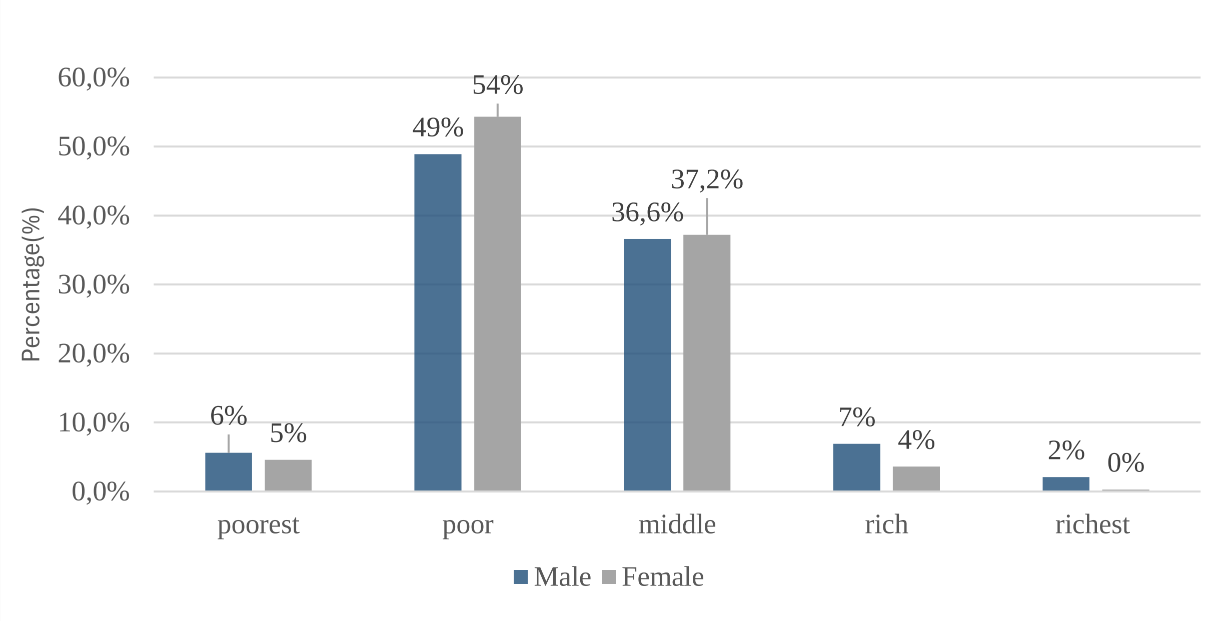

Figure 5. Wealth quantile decomposed by gender.

Source: Authors' calculations using GHS data from Stats SA (2018).

4.7.2 Descriptive analysis of the wealth quantile by household size

According to Table 5, approximately 78% of households have a size ranging from 1 to 5 members, indicating a prevalent pattern of smaller family units. Only 21% of households fall within the 6-to-10-member range. Households with sizes exceeding ten members are very rare, with negligible occurrences.

Table 5. Frequency table of the household size.

Household size	Number	Percentage
1 to 5	4932	78%
6 to 10	1307	21%
11 to 15	96	2%
16 to 20	11	0,17%
Over 20	1	0%

Source: Authors' calculations using GHS data from Stats SA (2018).

Table 6 reveals an interesting pattern concerning household size and wealth distribution. Larger households, specifically those with more than 11 members, exhibit no occurrences in the rich and richest wealth categories. This observation highlights the scarcity of large households achieving classification as rich or richest. It suggests that as the number of household members increases, living expenses rise, potentially constraining these households from accumulating significant assets.

Table 6. Contingency table of wealth quantile by household size.

Household size	Poorest	Poor	Middle	Rich	Richest	Total
1 to 5	270(5,5%)	2588(52,5%)	1721(34,9%)	285(5,8%)	68(1,4%)	4932(100%)
6 to 10	50(3,8%)	633(48,4%)	571(43,7%)	46(3,5%)	7(0,5%)	1307(100%)
11 to 15	1(1%)	49(51%)	46(47,9%)	0(0%)	0(0%)	96(100%)
16 to 20	0(0%)	8(72,7%)	3(27,3%)	0(0%)	0(0%)	11(100%)
Over 20	0(0%)	0(0%)	1(100%)	0(0%)	0(0%)	1(100%)
Total	321(5,1%)	3278(51,6%)	2342(36,9%)	331(5,2%)	75(1,2%)	6347(100%)

Source: Authors' calculations using GHS data from Stats SA (2018).

4.7.3 Descriptive analysis of the wealth quantile by the number of economically active members

In the context of this study, the term "economically active" refers to individuals who are employed and/or self-employed, as defined by Statistics South Africa (Stats SA, 2012). The data highlights a concerning trend in rural households, where a sizeable portion of households lacks any economically active member(s). Specifically, 46% of surveyed households reported having zero economically active family member (Figure 6).

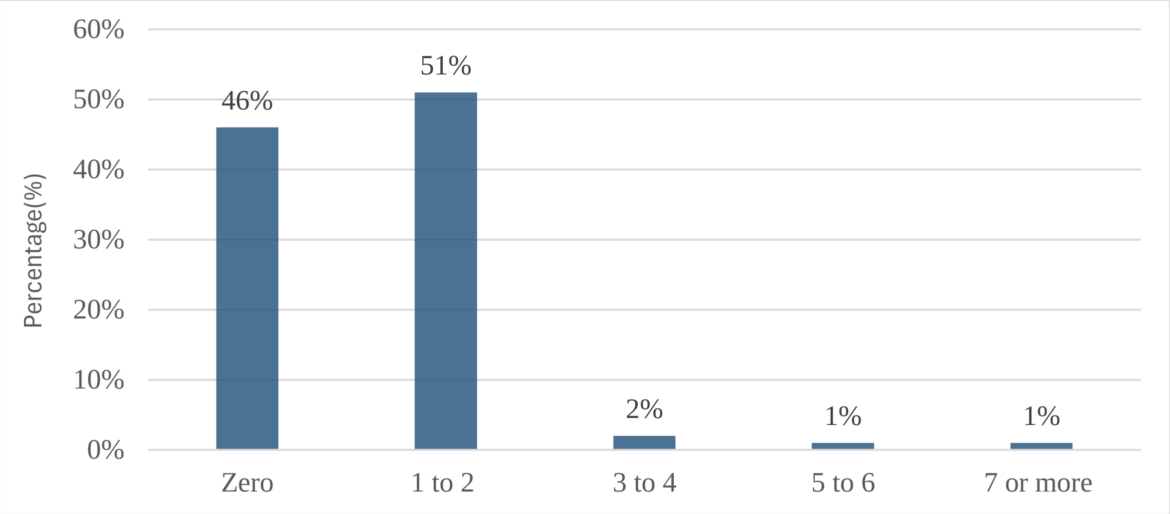

Figure 6. Proportion of economically active person.

Source: Authors' calculations using GHS data from Stats SA (2018).

Notably, it is very rare to encounter households with more than three household members that are economically active, precisely less than 2 percent. These findings highlight the prevalent challenges in rural areas, which include a high unemployment rate, less economic activities, and the lack of opportunities. Figure 6 presents the statistics of economically active persons in the rural areas.

The provided contingency table (Table 7) outlines the relationship between the number of economically active family members and their distribution across different wealth quantiles. Families with "zero" economically active members are primarily situated in the poor category (59.3%), followed by the middle class (32.3%). Notably, there is only a marginal representation in the richest category (0.3%). Conversely, households with one or two economically active members are predominantly found in the poor and middle categories, with a noticeable presence in the rich category (7.7%). Similarly, households with three to four members are concentrated in the middle and rich categories, with minimal presence in the poorest category (2%).

Table 7. Contingency table of wealth quantile by economically active family member(s).

Economically active family member(s)	Poorest	Poor	Middle	Rich	Richest	Total
Zero	178(6%)	1747(59,3%)	951(32,3%)	59(2%)	9(0,3%)	2944(100%)
1 to 2	139(4,3%)	1492(45,7%)	1320(40,5%)	250(7,7%)	61(1,9%)	3262(100%)
3 to 4	4(2%)	37(27,6%)	67(50%)	21(15,7%)	5(3,7%)	134(100%)
5 to 6	0(0%)	0(0%)	1(100%)	0(0%)	0(0%)	1(100%)
7 and more	0(0%)	2(33,3%)	3(50%)	1(16,7%)	0(0%)	6(100%)
Total	321(5,1%)	3278(51,6%)	2342(36,9%)	331(5,2%)	75(1,2%)	6347(100%)

Source: Authors' calculations using GHS data from Stats SA (2018).

Furthermore, a visible trend reveals a decline in the percentage of households in the poorest category as the number of economically active members increases. This pattern is similarly observed in the poor category, where the percentage decreases from 59.3% for zero economically active households to 45.7% for one to two economically active households, and further to 27.6% for three to four economically active households. Conversely, an opposite trend is noted for the middle and rich categories. For instance, in the rich category, the percentage for zero economically active households is 2%, increasing to 7.7% for one to two family members, and further improving to 15.7% for three to four active household members. These trends are consistent with other results that the more households are economically active they are less likely to be in the poor and poorest category.

4.7.4 Descriptive analysis of the wealth quantile by province

The data (Figure 7) reveals that the highest concentration of rural residents is observed in Limpopo (26%), Kwa-Zulu Natal (22%), and the Eastern Cape (19%), with Western Cape and Gauteng accounting for a lower proportion at 2 percent each. The historical context of South Africa, particularly the Land Disposition Act, contributes significantly to the prevalence of rural areas in Limpopo, Kwa-Zulu Natal, and the Eastern Cape. Moreover, Gauteng and Western Cape exhibit greater development relative to other provinces, offering enhanced economic opportunities.

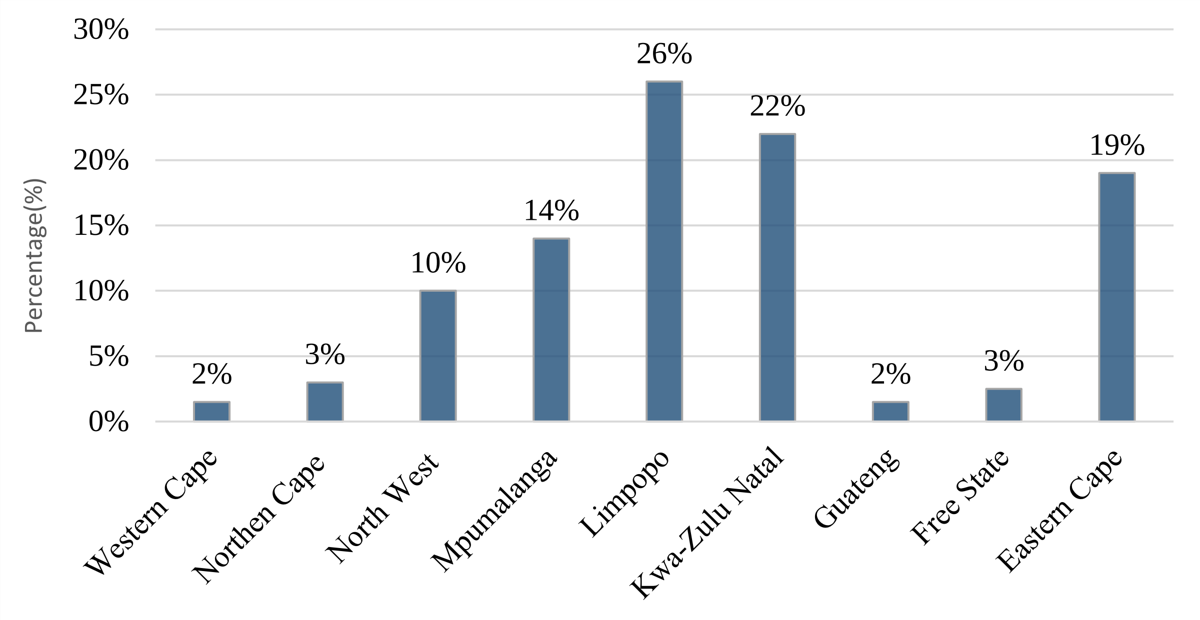

Figure 7. Distribution of the households by province.

Source: Authors' calculations using GHS data from Stats SA (2018).

According to Table 8, KwaZulu-Natal, Eastern Cape, and Limpopo stands out with the highest percentage of households classified as poor at 62.5%, 60.1% and 52,3% respectively, emphasizing the prevalence of economic challenges in these provinces. Provinces like Western Cape (25.7%), Northen Cape (11.5%) and Gauteng (10.8%) exhibit higher percentages of households in the rich category, reflecting a more favourable economic status for residents. Western Cape, Gauteng, and Free State are identified as the provinces with the highest percentages of households in the richest category, indicating a concentration of affluent residents in these regions.

A clear regional divide is evident, with provinces such as Western Cape, Gauteng, and Free State displaying higher percentages of households in wealthier categories, while Eastern Cape, KwaZulu-Natal, and Limpopo are characterized by a higher prevalence of poorer households. The observed trend suggests that provinces with higher percentages of households in the poorest category tend to have lower percentages in wealthier categories, and vice versa. This emphasizes the economic disparities across regions in South Africa. Provinces with major urban centres, such as Gauteng, reveal a more balanced distribution across wealth categories, reflecting the economic opportunities associated with urbanization. Rural provinces, such as Eastern Cape and Limpopo, show a higher concentration of poorer households, underscoring the challenges faced in rural economic development.

Table 8. Contingency table of wealth quantile by province.

Provinces	Poorest	Poor	Middle	Rich	Richest	Total
Western Cape	3(3%)	25(24,8%)	33(32,7%)	26(25,7)	14(13,9)	101(100%)
Eastern Cape	104(8,8%	709(60,1%)	339(28,8%)	21(1,8%)	6(0,5%)	1179(100)
Northern Cape	2(0,9%)	82(34,9%)	118(50,2%)	27(11,5)	6(2,6%)	235(100%)
Free State	8(4,4%)	74(40,47%)	83(45,6%)	10(5,5%)	7(3,8%)	182(100%)
Kwa-Zulu Natal	91(6,5%)	879(62,5%)	390(27,7%)	35(2,5%)	12(0,9)	1407(100)
North West	24(3,6%)	310(46%)	285(42,3%)	50(7,4%)	5(0,7%)	674(100%)
Gauteng	23(17,7)	44(33,8%)	40(30,8%)	14(10,8%)	9(6,69%)	130(100%)
Mpumalan ga	26(3%)	326(38,2%)	419(49,1%)	75(8,8%)	8(0,9%)	854(100%)
Limpopo	40(2,5%)	829(52,3%)	635(40,1%)	73(4,6%)	8(0,5%)	1585(10%)
Total	321(5,1)	3278(51,6)	2342(36,9)	331(5,2%)	75(1,2%)	6347(10%)

Source: Authors' calculations using GHS data from Stats SA (2018).

4.7.5 Descriptive analysis of the wealth quantile by the primary source of income

Figure 8 illustrates that the predominant sources of income for rural households in South Africa were social transfers (39%), followed by salaries and wages (35%). Only a limited number of rural households derive income from farming and business activities. Revenue from a farming and business accounted for 1% and 6% respectively. These results highlight that most households in South Africa's rural areas primarily depend on government assistance as their main source of income.

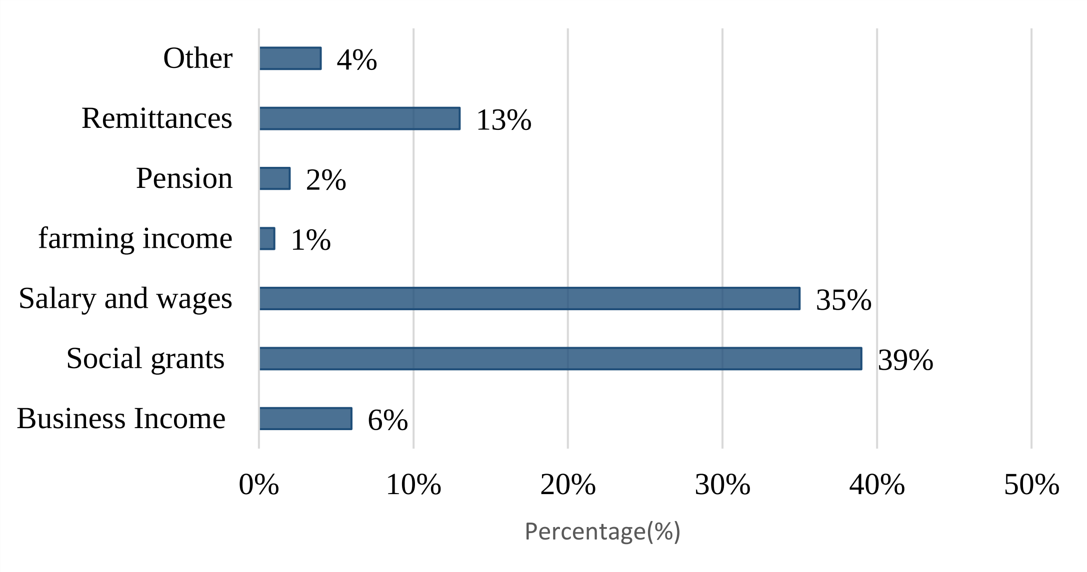

Figure 8. Distribution of the households by primary source of income.

Source: Authors' calculations using GHS data from Stats SA (2018).

Table 9 illustrates that the primary income sources with the highest percentages for households classified as middle class are pensions (62.2%), business (43%), and salary/sages (41.3%). Conversely, farming (7.7%), grants (5.6%), and remittances (5%) exhibit high percentages for households categorized as the poorest. Social transfers, such as grants and remittances, are crucial income sources for lower wealth categories. While, entrepreneurial activities (business income) and income from farming gain prominence in wealthier categories.

Table 9. Contingency table of the wealth quantile by primary source of income.

Primary source of income	**Poorest**	**Poor**	**Middle**	**Rich**	**Richest**	**TOTAL**
Salary	101(4,6%)	965(43,5%)	915(41,3%	199(9%)	36(1,6%)	2216(100%)
Business	12(2,9%)	156(156%)	177(43%)	40(9,7%)	27(6,6%)	412(100%)
Remittances	43(5%)	446(51,7%)	349(40,5%)	23(2,7%)	1(0,1%)	862(100%)
Pensions	0(0%)	10(12,2%)	51(62,2%)	17(20,7%)	4(4,9%)	82(100%)
Grants	139(5,6%)	1534(61,7%)	779(31,3%)	35(1,4%)	1(0%)	2488(100%)
Farming	1(7,7%)	6(46,2%)	1(7,7%)	3(23,1%)	2(15,4%)	13(100%)
Other income	3(10,7%)	16(57,1%)	5(17,9%)	2(7,1%)	2(7,1%)	28(100%)
Total	299(4,9%)	3133(51,4%)	2277(37,3%)	319(5,2%)	73(1,2%)	6101(100%)

Source: Authors' calculations using GHS data from Stats SA (2018).

4.7.6 Descriptive analysis of the wealth quantile by income groups

The continuous income variables were categorized into three groups: a low category for households with income less than R5000 per month, a middle category for households earning more than R5000 and less than R15 000 per month, and a high category for households earning more than R15 000. Figure 10 illustrates that approximately 79% of households fall into the low-income category, earning less than R5000. The middle-class comprises 14%, and the high-income class accounts for 7% in rural areas.

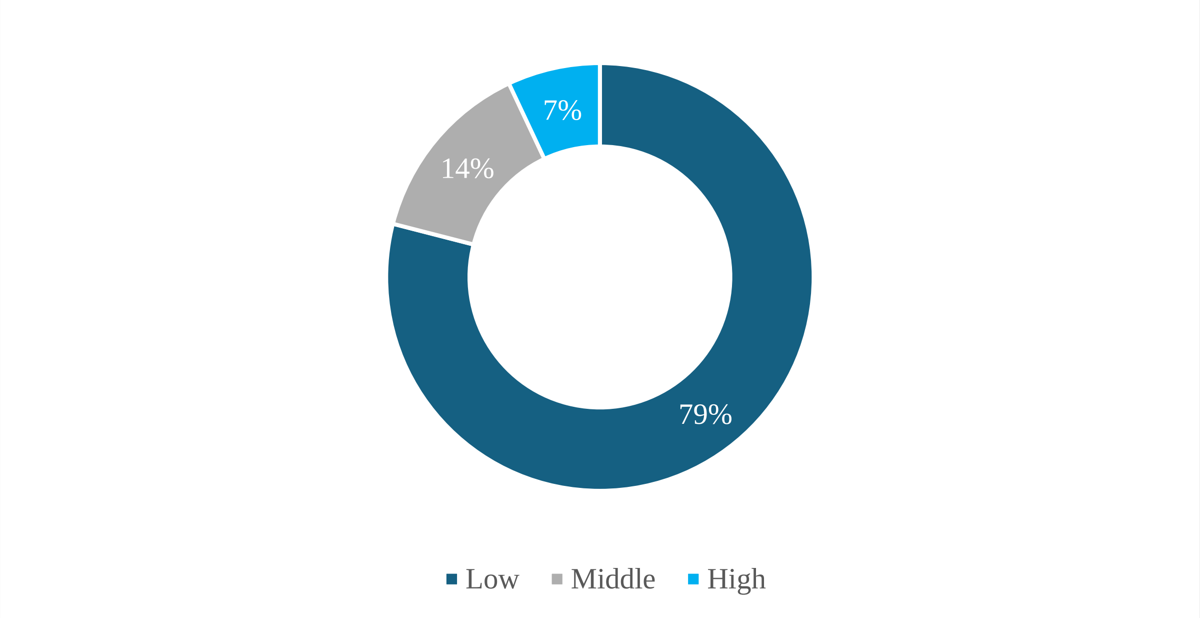

Figure 9. Distribution of the households by income groups.

Source: Authors' calculations using GHS data from Stats SA (2018).

Low-income households are primarily ranked in the poor (57,6%) and middle (33,8%) categories, with a minimal presence in the rich, and richest categories (Table 10). In the same way, the low-income household constitute the highest percentage in the poorest category. This suggests a concentration of economic vulnerability in the lower wealth strata. While, High-income households are distributed across the middle, rich and richest categories, with a considerable proportion in the middle category (41.6%), followed by rich (26.6%).

Table 10. Contingency table of wealth quantiles by income group.

Income group	Poorest	Poor	Middle	Rich	Richest	Total
Low	289(5,8%)	2876(57,6%)	1685(33,8%)	114(2,3%)	26(0,5%)	4990(100%)
Middle	26(2,9%)	328(36,5%)	446(49,6%)	95(10,6%)	4(0,4%)	899(100%)
High	6(1,3%)	74(16,2%)	211(46,1%)	122(26,6%)	45(9,8%)	458(100%)
Total	321(5,1%)	3278(51,6%)	2342(36,9%)	331(5,2%)	75(1,2%)	6347(100%)

Source: Authors' calculations using GHS data from Stats SA (2018).

4.7.7 Descriptive analysis of the wealth quantile by subsistence farming

Figure 10 illustrates the percentage of rural households engaged in subsistence farming. The data depicted in the figure indicates that over 42% of rural households rely on self-produced food. Notably, this percentage significantly surpasses the 36% reported by Stats SA (2021), indicating a recent decline in the number of individuals involved in producing their own food.

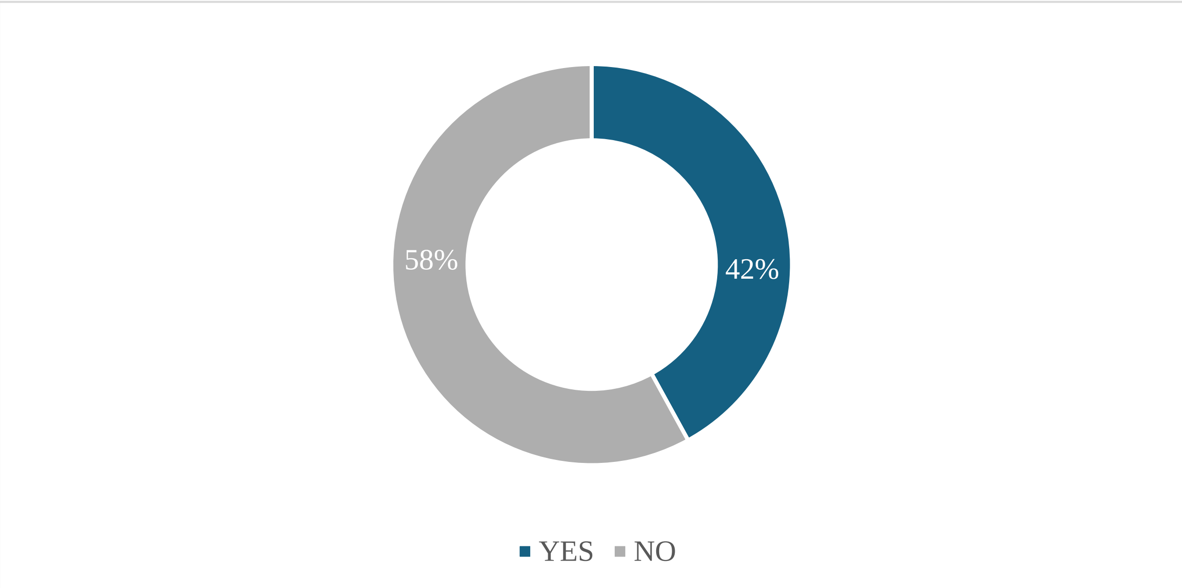

Figure 10. Proprtion of rural households involved in subsistence farming.

Source: Authors' calculations using GHS data from Stats SA (2018).

Figure 11 shows that households engaged in subsistence farming have a lower percentage in the poorest category (4%) compared to those that are not engaged (6%). Conversely, households practicing subsistence farming exhibit higher percentages in the middle (39%) and richest (1.3%) categories, in contrast to those not engaged, with percentages of (36%) and (1.1%) respectively. The lower prevalence in the poorest category for subsistence farming households suggests a potential economic impact, while the higher representation in the middle and richest categories may indicate varying economic conditions and resource access.

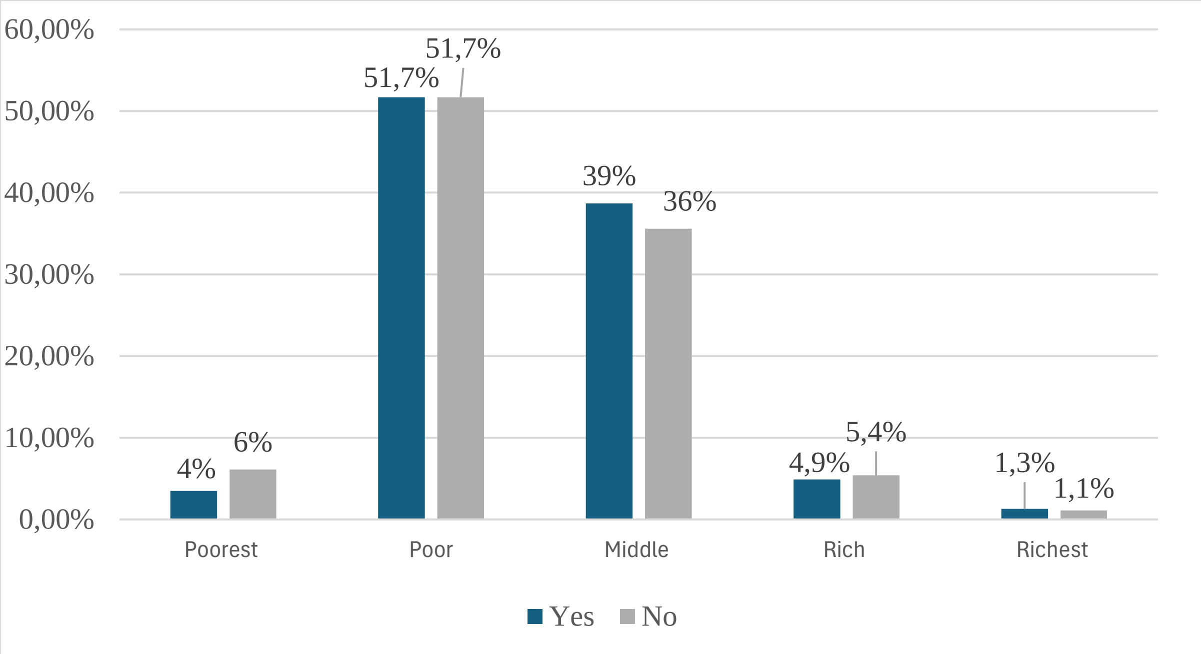

Figure 11. Wealth quantile decomposed by participation in subsistence farming.

Source: Authors' calculations using GHS data from Stats SA (2018).

4.8 Chapter Summary

This chapter presented the results from the Multiple Correspondence Analysis. It also discussed the finding of the asset-index as well as the meaning of its results. In addition, the chapter also covered the univariate and bivariate descriptive analysis of the demographic, socio-economic and regional factors. The following chapter will cover empirical results from the multivariate analysis that was conducted.

CHAPTER 5: EMPIRICAL ANALYSIS AND DISCUSSION OF RESULTS

5.1 Introduction

This chapter examines and explains the multivariate analysis that was conducted. The chapter presents an examination of results in relative to the examination of the other scholars. Section 5.1 report the results obtained by using the OLS regression method and discusses the findings, while section 5.2 presents the findings using the ordered logit approach. Furthermore, a comparison is made from the results obtained using the two approaches.

5.2 Multiple linear regression model

The OLS regression model results, presented in Table 11, reveals that the chosen independent variables collectively account for 30% of the change in the interest variable, the asset-index. This R-squared value of 30% suggests that there are likely other significant factors influencing asset accumulation that were not-included in the model due to dataset constraints, such as education, the unemployment status of the house leader, and marriage status.

The p-test statistics indicate that several variables are statistically significant at the 1% level. As anticipated, the age of the house leader shows a positive association with wealth, indicating that an increase in the age of the head of the household is linked to increased affluence. This relationship is statistically significant ($\beta = 0.003$, $p<0.001$), implying that for one additional year of the household head's age, asset wealth accumulates by 0.003. This finding aligns with previous studies emphasizing the positive correlation between age and wealth.

The finding highlights the significance of household size in asset accumulation. The regression coefficient for household size indicates a positive association with welfare measures, and this relationship is statistically significant at the 1% level ($\beta = 0.052$, p-value < 0.001). This suggests that larger households tend to have higher asset endowments, likely because they benefit from the increased number of earning members supporting the house. The findings are in line with Shaukat et al. (2019), who found that house with seven or additional people are not likely to live in poverty in comparison with to smaller house. However, it's worth noting that the literature presents mixed results on the association between welfare indicator and household size, with some studies suggesting a negative association.

In particular, the square of family size variable exhibits a negative and significant coefficient, this variable depicts the non-linear influence of family size on household welfare, which indicates the effect of one more person on asset accumulation reaches a point of diminishing returns. These results contradict the findings of Gounder (2012), who reported a positive relationship between the squared family size and household welfare.

Table 11. Multiple linear regression model estimates of factors influencing asset accumulation

Dependent variable:	**Household Welfare Measure(asset-index)**	**Std. Err**
Head age	0.006***	0.002
Household size	0.051***	0.005
Household size squared	-0.004***	0.0004
Economically active members	0.007	0.009
Subsistence farming [Yes]	0.037***	0.011
Province [Eastern Cape]	-0.629***	0.040
Province [Northern Cape]	-0.359***	0.046
Province [Free State]	-0.367***	0.048
Province [KwaZulu-Natal]	-0.617***	0.040
Province [North West]	-0.447***	0.041
Province [Gauteng]	-0.350***	0.051
Province [Mpumalanga]	-0.427***	0.041
Province [Limpopo]	-0.518***	0.040
Household head gender [Female]	-0.026**	0.010
Income group [low]	-0.616***	0.021
Income group [Middle]	-0.458***	0.022
Income source [Farming]	0.127	0.108
Income source [Pension]	0.252***	0.047
Income source [Remittances]	-0.098***	0.025
Income source [Salary/wages]	-0.178***	0.021
Income source [Social grants]	-0.277***	0.023
Constant	1.565***	0.063
Observations	6,347	
R2	0.298	
Adjusted R2	0.295	
Residual Std. Error	0.382 (df = 6323)	
F Statistic	116.529*** (df = 23; 6323)	
Note: Significance levels	*p<0.1; **p<0.05; ***p<0.01	

Subsistence farming emerges as a positive and significant factor ($\beta = 0.03$, $p < 0.001$), suggesting that households engaged in subsistence farming tend to have greater asset wealth. This finding indicates the potential advantages of small-scale farming in supporting wealth accumulation. Such households benefit from consuming their own produce, which allows them to save and allocate resources to other expenditure items, ultimately contributing to increased asset accumulation. These results align with research indicating that subsistence farming can reduce rural poverty and food insecurity (Gounder, 2012).

The variable related to subsistence farming exhibits a noteworthy and positive coefficient ($\beta = 0.03$, $p < 0.001$), signifying that households engaged in subsistence farming tend to possess greater wealth in terms of assets. This observation highlights the advantageous position of households reliant on small-scale farming practices. One plausible explanation for this phenomenon is rooted in the substantial consumption of homegrown produce within these households, enabling them to save. Additionally, it is of great significance to highlight that a sizeable portion of the income and expenses incurred by subsistence households is derived from their own agricultural yields. As they consume their self-produced goods, they can accumulate savings and reallocate these funds toward other essential household expenditures, such as electronic devices, refrigerators, televisions, and more, consequently bolstering their overall wealth.

These findings highlight the inherent benefits associated with being a subsistence household. Indeed, research conducted in countries like Kenya has demonstrated that subsistence farming possesses the potential to mitigate rural poverty, alleviate food insecurity, and reduce rural-to-urban migration by fostering a thriving agricultural sector (Gounder, 2012).

Geographically, the study reveals that the location of the house effects its economic welfare. Households in provinces such as Eastern Cape, Northern Cape, Free State, Kwa-Zulu Natal, North West, Gauteng, Mpumalanga, and Limpopo are most likely to be poor in comparison to households in the WC. This discrepancy can be attributed to varying economic opportunities in these regions, with Western Cape offering more formal and informal employment prospects. These findings are consistent with another research (Mosasane & Oyekale, 2021).

Regarding gender, the findings show that female-lead house reveal a negative association with asset accumulation. This observation aligns with the broader trend of women typically earning less than men, highlighting gender-based disparities in asset accumulation. These findings are consistent with previous studies (Mosasane & Oyekale, 2021; and Gounder, 2012) emphasizing the on the susceptibility of female-lead house to poverty.

The analysis of income sources reveals that high income is positively related with better welfare when compared to middle-income. The findings are consistent with research results by

Fomum & Jesse (2017), suggesting that lower income is negatively correlated with asset ownership, while middle and high-income levels exhibit a positive relationship.

Moreover, the main source of earning significantly impacts asset accumulation. Households reliant on business income demonstrate more house welfare comparing to those dependent on salaries/wages, social grants, remittances, and other income sources. Additionally, households relying on pensions also exhibit higher asset accumulation. However, households depending on farm product sales or services as the primary income source do not appear to accumulate more wealth. This suggests that income diversification plays a vital role in wealth accumulation.

5.3 Ordered logit model.

The findings from the logit regression, shown in Appendix 4, largely support the findings obtained from the OLS model analysis. The age variable remains positively associated with wealth, as does household size. Subsistence farming, provinces, and gender also maintain their significance and direction of impact. These findings provide robust support for the conclusions drawn in the previous sections.

5.4 Chapter Summary

This chapter presented the empirical results of multiple linear regression and ordered logit model. The significance factors included the number of years of household leader, household size, gender of the house head, subsistence farming engagement, and the main source of earning, in determining asset accumulation and living standards among rural households in South Africa. These findings provide valuable insights into the complex interplay of factors shaping household wealth and asset ownership in the rural areas of South Africa.

CHAPTER 6: SUMMARY AND RECOMMENDATIONS

6.1 Introduction

This chapter serves as a comprehensive summary of the study's primary findings, outlines pertinent policy recommendations derived from empirical insights, and provides guidance for prospective research endeavours. The chapter is structured into three distinct sections. Section 6.2 encapsulates the study's essence, offering conclusions that emanate from its core findings. Section 6.3 furnishes policy recommendations, while Section 6.4 propounds suggestions for further research. Lastly, Section 6.5 delves into the study's limitations.

6.2 Summary and conclusions

The primary focus of this study was to elucidate the determinants of asset accumulation within rural South African households and explore the contributory role of subsistence farming in this context. Leveraging data from Stats SA's 2018 GHS dataset, the study scrutinized the demographic and socio-economic factors influencing asset accrual. A composite asset-index was established through Multiple Correspondence Analysis (MCA) methodology, acting as a gauge for rural household asset endowment. The study's multivariate analysis revealed significant associations between household size, gender of the household head, age of the household head, and asset accumulation.

The study's initial objective was achieved by constructing a composite asset-index for rural households and gauging the distribution of asset accumulation. Subsequently, households were categorized into distinct asset wealth quantiles, representing socio-economic positions as "poorest," "poor," "middle," "rich," and "wealthiest" based on their asset-index scores. The relationship between wealth quantiles and demographic and socio-economic factors was scrutinized. The study employed an OLS regression model to discern the factors impacting asset accumulation among South Africa's rural households. Additionally, the study validated the OLS regression results by employing an alternative approach, the multinomial ordered logit regression model, which yielded concordant outcomes.

The empirical analysis, encompassing both OLS and Ordered logit regressions, divulged several critical insights. Firstly, it established that the age of the household head positively and significantly correlates with asset ownership, validated at a 1% significance level. Secondly, the study uncovered a robust positive association between household size and asset accumulation, signifying that a greater number of earning members fosters augmented household savings. Additionally, the research illuminated the pivotal role played by livelihood strategies (primary income sources) in asset accumulation. Households relying on pensions, business income, and, though not statistically significant, farming income, exhibited enhanced asset ownership compared to those dependent on salary income, remittances, and social grants.

The study highlighted the advantageous impact of subsistence farming on asset accumulation among rural residents. Households actively engaged in small-scale subsistence farming demonstrated superior asset endowments. This phenomenon is underpinned by these households' consumption of self-produced goods, allowing for savings and the reallocation of resources to other expenditure categories, thereby enhancing asset accumulation. Importantly, the study validated these findings through two distinct estimation techniques, highlighting the robustness of the results.

6.3 Recommendations

The results stemming from both OLS and ordered logit regression models unequivocally highlight the salutary effect of subsistence farming on asset ownership among rural households. Notably, participation in subsistence farming augments the likelihood of belonging to the wealthiest category by an average of 1.27 percent. This underlines the pivotal role of subsistence farming in bolstering household asset ownership and mitigating asset poverty. Consequently, it is imperative to formulate policies and strategies that enhance rural farmers' access to input and output markets, as well as land markets, thus facilitating increased asset ownership, both non-farm and farm, in South Africa's rural regions.

In tackling issues surrounding market access, the government and private sector should prioritize substantial investments in infrastructure development and market accessibility for subsistence farmers. The creation of Small and Medium-sized Enterprises (SMEs) in rural areas could serve as an effective strategy for establishing marketplaces for smallholder farmers' produce. These SMEs can subsequently facilitate the marketing of these products to lucrative markets, thereby ameliorating the financial circumstances of rural households.

The study's findings highlight the prevalence of asset poverty among households relying on social grants compared to those dependent on pensions, farming, and business income. This the necessity of intertwining social assistance programs with economic activities such as farming, with a view to eradicating asset poverty and advancing the government's rural development objectives.

Moreover, the research highlights the pronounced gender disparity in asset accumulation, with asset poverty being more prevalent in female-headed households than in male-headed ones.

This emphasizes the urgency of supporting policies aimed at empowering women in rural South Africa, aimed at addressing this gender-based asset inequity.

Given that asset poverty disproportionately affects younger household heads in rural South Africa, interventions targeted at rural youth or those thrust into household headship due to parental loss are warranted. Strategies to address this demographic segment's unique needs must be devised.

Lastly, the study unveiled an inverted U-shaped relationship between household size and asset accumulation, as evidenced by the negative coefficient of squared household size. Consequently, policies aimed at optimizing household size to align with available resources are imperative. This may necessitate initiatives promoting birth control in rural South Africa, underpinned by accessible clinical interventions and tailored media programs.

6.4 Recommendation for further research

Several avenues for further research are discernible from this study:

- This study cast a wide net by focusing on all South African provinces. Future research could delve into more granular analyses by concentrating on each province individually.
- In constructing asset indices, future studies may consider incorporating a broader array of publicly provided goods and other financial assets, such as savings, investment accounts, and more.
- The influence of additional informal activities, such as Stokvels, on asset accumulation merits exploration in future research endeavours.
- Investigating the role of marital status and the educational level of rural households in shaping asset accumulation could yield valuable insights for future research.

6.5 Limitations of the Study

Two key limitations warrant mention: The asset-index developed in this study primarily encompasses private household assets, with limited inclusion of public assets, such as electricity and bathroom facilities. Furthermore, it excludes other financial assets like retirement packages, investment portfolios, savings, pensions, real estate, and bonds. Consequently, the study's findings should be interpreted with caution, particularly concerning their applicability.

REFERENCES

Achia, T. N. O., Wangombe, A., & Khadioli N. (2010). A Logistic Model to Identify Key Determinants of Poverty Using Demographic and Health survey Data. European Journal of Social Sciences, 13(1), pp. 38-45.

Akerele, D., & Adewuyi, A. (2011). Analysis of poverty profiles and socioeconomic determinants of welfare among urban households of Ekiti State, Nigeria. Current Research Journal of Social Sciences, 3(1), pp. 1–7.

Fomum, A. T., & Jesse, M. A. (2017). Exploring the relationship between financial inclusion and assets accumulation in South Africa. International Journal of Social Economics, 44(12), pp. 2157-2172.

Augustine, T. (2013). Determinants of Wealth in South Africa. University of Cape Town. Masters' thesis.

Awotide, B.A., Alene D.A., Abdoulaye T., & Manyong, V.M. (2015). Impact of agricultural technology adoption on asset ownership: the case of improved cassava varieties in Nigeria. Agricultural Economics, 46(3), pp. 305-314.

Barrett, C. B., & Swallow, B. M. (2006). Fractal poverty traps. World Development, 34(1), pp. 1–15.

Bila, S., & Biyase, M. (2022). Determinants of subjective poverty in rural and urban areas of South Africa. EDWRG Working Paper Number 02-2022.

Biyase, M., & Zwane, T. (2017). An empirical analysis of the determinants of poverty and household welfare in South Africa. Munich Personal RePEc Archive (MPRA).

Biyase, M., Zwane, T., & Rooderick, S. (2019). Assets and Poverty Alleviation in South Africa: Evidence from the National Income Dynamics Study (NIDS), Journal of Economic Cooperation and Development, pp. 55-78.

Booysen, F. L. R (2002). Using demographic and health survey to measure poverty-an application to South Africa. Journal for studies in Economics and Econometrics, 26(3), pp. 53-70.

Booysen, F., van der Berg, S., Burger, R., Maltitz, M., & Rand, G Du. (2008). Using an asset-index to assess trends in poverty in seven Sub-Saharan African countries. World Development, 36, pp. 1113–1130. https://doi.org/10.1016/j.worlddev.2007.10.008.

Bowles, S., Smith, E. A., & Mulder, M. (2010). The Emergence and Persistence of Inequality in Premodern Societies: Introduction to the Special Section. Current Anthropology, 51(1), pp. 7–17. https://doi.org/10.1086/649206

Carter, M. R., & Barrett, C. B. (2006). The economics of poverty traps and persistent poverty: an asset-based approach. Journal of Development Studies, 42(2), pp. 179–199.

Christian, M & Obi, A. (2018). Impact of irrigation adoption on rural farmer's welfare in Eastern Cape Province of South Africa: A propensity score matching approach. African Journal of Agricultural Research. 13(46), pp. 2641-2650. DOI: 10.5897/AJAR2018.13086

Daniels R. C., Finn A., & Musundwa S. (2014). Wealth data quality in the National Income Dynamics Study Wave 2. Development Southern Africa, 31(1), pp. 31-50.

Department of Agriculture (2008). Land and Agrarian Reform Project – The Concept Document.

Department for International Development (2000). Sustainable Livelihoods Guidance Sheets..

Filmer, D., & Pritchett, L. H. (2001). Estimating wealth effects without expenditure data—or tears: An application to educational enrolment in states of India. Demography, 38, pp. 115–132. https://doi.Org/10.1353/dem.2001.0003.

Filmer, D., & Scott, K. (2012). Assessing asset indices. Demography, 49, pp. 359–392. https://doi.org/10.1007/ s13524-011-0077-5.

Gachanja, P.M., & Kinyanjui, G.K (2016). Household Poverty Determinants in Kenya: A Demographic and Health Survey Wealth Index Approach. Africology: The Journal of Pan African Studies, 9(3).

Gachanja, P.M., & Kinyanjui, G. K. (2016). Household Poverty Determinants in Kenya: A Demographic and Health Survey Asset-index Approach, Africology: The Journal of Pan African Studies, 9(3).

Garenne M. (2015). Traditional Wealth, Modern Goods, and Demographic Behaviour in Rural Senegal" World Development, 72, pp. 267–276

Gounder, N. (2012). The Determinants of Household Consumption and Poverty in Fiji, Griffith Business School. pp. 2012-05,

Greenacre, M., & Jorg, B. 2006. Multiple Correspondence Analysis and Related Methods.

Habyarimana, F., Zewotir, T., & Ramroop, S. (2015). Analysis of demographic and health survey to measure poverty of household in Rwanda. African Population Studies, 29(1), pp. 1472-1482.

Hackman, J., Hruschka D. & Vizireanu M. 2021. An Agricultural Asset-index for Multidimensional Wealth Assessments. Population and Development Review 47(1), pp. 237-254.

Howe, L. D., Galobardes, B., Matijasevich, A., Gordon, D., Johnston, D., & Onwujeke, O., et al. (2012). Measuring socio-economic position for epidemiological studies in low- and Middle-income countries: A methods of measurement in epidemiology paper. International Journal of Epidemiology, 41, pp. 871–886. https://doi.org/10.1093/ije/dys037.

Howe, L. D., Hargreaves, J. R., Gabrysch, S., & Huttly, S. R. (2009). Is the asset-index a proxy for consumption expenditure? A systematic review. Journal of Epidemiology and Community Health, 63, pp. 871–877. https://doi.org/10.1136/jech.2009.088021

Jansen, A., Moses, M., Mujuta, S., & Yu, D. (2015) Measurements and determinants of multifaceted poverty in South Africa, Development Southern Africa, 32(2), pp. 151-169. DOI: 10.1080/0376835X.2014.984377

Jin, Y., & Xie, Y. (2017). Social determinants of household wealth and income in urban China. Chinese Journal of Sociology, 3(2), pp. 169-192. https://doi.org/10.1177/2057150X17695689

Joubert, F., & Van der Merwe, T. (2021). Household saving and wealth in South Africa. South African Journal of Economic and Management Sciences 24(1).

Karigi A.M. (2014) Construction of household asset-based asset-index for Eastern region, Kenya. Master of Science (MSc) in Social Statistics.

Kolenikov, S., & Angeles, G. (2005). The Use of Discrete Data in Principal Component Analysis for Socio-Economic Status Evaluation

Lekobane, R., & Seleka, B. (2017). Determinants of Household Welfare and Poverty in Botswana, 2002/2003 and 2009/2010, Journal of Poverty, 21(1), pp. 42-60.

Lombardo R., & Meulman, J.J. (2010). Multiple Correspondence Analysis via Polynomial Transformations of Ordered Categorical Variables, Journal of Classification 27, pp. 191-210, DOI: 10.1007/s00357-010-9056-6

Martel, P., Mbofana, F., & Cousens, S. (2021). The polychoric dual-component asset-index as an alternative to the DHS index: Addressing the urban bias. J Glob Health.

McKenzie, D. J., (2005). Measuring inequality with asset indicators. Journal of Population Economics, 18, pp. 229–260. https://doi.org/10.1007/s00148-005-0224-7.

Meng, X. (2007). Wealth Accumulation and Distribution in Urban China. Economic Development and Cultural Change. 55(4), pp. 761-791.

Mosasane, B.C., & Oyekale, A.S. (2021). Multidimensional Poverty Indicator and Its Determinants in Rural South Africa. Euro Economica. Business Administration and Business Economics. Issue 2(40)/2021.

Mushongera, D., Zikhali, P., & Ngwenya, P. (2017). A multidimensional poverty index for Gauteng province, South Africa: evidence from Quality-of-Life Survey data. Social Indicators Research, 130(1), pp. 277-303.

Nenadi´c, O., & Greenacre, M.J. (2007). Correspondence Analysis in R, with Two- and Three-dimensional Graphics: The ca Package. Journal of Statistical Software. 20(3).

Perry, A. (2012). Rural homestead design and permaculture, South Africa. Sustainable Settlements Articles. pp. 6.

Poirier, M.J. P., Grépin, K.A., & Grignon, M(2020), Approaches and Alternatives to the Asset-index to Measure Socioeconomic Status Using Survey Data: A Critical Interpretive Synthesis, Social Indicators Research, 148, pp. 1–46 https://doi.org/10.1007/s11205-019-02187-9

Quartey, P., & Blankson, T. (2004). Do Migrant Remittances Minimize the Impact of MacroVolatility on the Poor in Ghana? Final report submitted to the Global Development Network (GDN).

Sahn, D. E., & Stifel, D. (2003). Exploring alternative measures of welfare in the absence of expenditure data. Review of Income and Wealth, 49, pp. 463–489. https://doi.org/10.1111/j.0034-6586.2003.00100.x.

Sahn, D.E., & Stifel, D.C. (2000). Poverty comparisons over time and across countries in Africa. World Development 28(12), pp. 2123-2155.

Sahn, D.E., & Stifel, D.C. (2003). Urban-rural inequality in living standards in Africa. Journal of African Economies 12, pp. 564-597.

Sahn, D.E., & Stifel, D. (2000). Poverty comparison over time and cross countries in Africa", World development, 28(12), pp. 2123-2155.

Sekhampu, T. S., (2013). Determinants of poverty in South African township. Journal of Social Sciences, 34(2), pp. 145–153.

Shaukat B., Javed, S.A., & Imran, W. (2019). Asset-index as Substitute to Income and Consumption: Assessment of Household Poverty Determinants Using Demographic and Health Survey Data, Journal of Poverty, DOI: 10.1080/10875549.2019.1678550

Sibisi, B.N. (2015). Agricultural extension and post-settlement support of land reform beneficiaries in South Africa: The case of Ixopo in the province of Kwazulu-Natal. University of KwaZulu-Natal, Agricultural Extension and Rural Resource Management, School of Agriculture, Earth and Environmental Sciences, College of Agriculture, Engineering and Science. Master of Agriculture.

Skopek, N., Buchholz, S., & Blossfeld, H. (2014). National patterns of income and wealth inequality. International Journal of Comparative Sociology. 55(6). pp. 463–488.

Statistics South Africa. (2017). Poverty trends in South Africa: an examination of absolute poverty between 2006 and 2015. Report No. 03-10-06. Pretoria. South Africa

Statistics South Africa. (2014). Poverty Trends in South Africa: an examination of absolute poverty between 2006 and 2011. Report No. 03- 10-06. Pretoria. South Africa.

Statistics South Africa. (2015). Information and Communication Technologies (ICT) In-depth analysis of the General Household Survey data 2002–2013. Report 03-18-05, pp. 130, Pretoria. South Africa.

Statistics South Africa. (2018). General Household Survey. Pretoria: Statistics SA. Cape Town: DataFirst. Version 1.

Vyass, S., and Kumaranayake, L. (2006). Constructing socioeconomic status indexes: How to use principal component analysis. Health Policy and Planning, 21(6), pp. 459- 468.

Ward, P. (2014). Measuring the level and inequality of wealth: An application to China. Review of Income and Wealth, 60, pp. 613–635. https://doi.org/10.1111/roiw.12063.

Xhafaj, E., & Nurja, I. (2013). The Principal Components Analysis and Cluster Analysis as Tools for the Estimation of Poverty, an Albanian Case Study. International Journal of Science and Research, 6 (14): pp. 1240- 1243.

APPENDICES

Appendix 1. Descriptive statistics of asset modalities

Assets	Yes	No
Electricity	93.21 %	6.79 %
Own telephone	1.53 %	98.47 %
Own cell phone	94.85 %	5.15 %
Own internet	1.65 %	98.35 %
Has internet via cell phone	4.20 %	95.80 %
Own radio	52.92 %	47.08 %
Own tv	74.24 %	25.76 %
Own DVD	39.20 %	60.80 %
Own DSTV	35.26 %	64.74 %
Own AC	1.83 %	98.17 %
Own computer	8.21 %	91.79 %
Own vacuum	2.08 %	97.92 %
Own dish washing machine	1.28 %	98.72 %
Own wash machine	16.99 %	83.01 %
Own dryer	2.82 %	97.18 %
Own Deep freezer	19.22 %	80.78 %
Own refrigerator	68.79 %	31.21 %
Own electric stove	83.39 %	16.61 %
Own micro-wave	39.69 %	60.31 %
Own sink	11.38 %	88.62 %
Has home security	1.51 %	98.49 %
Own home theatre	5.94 %	94.06 %
Own geyser	5.44 %	94.56 %
Own solar geyser	0.73 %	99.27 %
Own solar power	0.64 %	99.36 %
Own vehicle	14.34 %	85.66 %

Appendix 2. Internal consistency validity of the asset variables from Principal Component 1.

Asset variables	Missing	Mean	SD	Skew	Item Difficulty	Item Discrimination	α if deleted
Electricity	0.00 %	1.06	0.24	3.67	0.53	0.31	0.82
Telephone	0.00 %	1.98	0.12	-7.95	0.99	0.18	0.82
Mobile cell	0.00 %	1.05	0.22	4.15	0.52	0.18	0.82
Internet	0.00 %	1.98	0.13	-7.47	0.99	0.31	0.82
Internet via mobile cell	0.00 %	1.96	0.2	-4.52	0.98	0.12	0.82
Radio	0.00 %	1.47	0.5	0.14	0.73	0.18	0.83
TV	0.00 %	1.25	0.43	1.18	0.62	0.51	0.81
DVD	0.00 %	1.6	0.49	-0.41	0.80	0.44	0.81
DSTV	0.00 %	1.64	0.48	-0.58	0.82	0.55	0.81
Air Conditioner	0.00 %	1.98	0.14	-7.07	0.99	0.31	0.82
Computer	0.00 %	1.92	0.28	-2.99	0.96	0.43	0.81
Vacuum	0.00 %	1.98	0.14	-6.61	0.99	0.39	0.82
Dish wash	0.00 %	1.99	0.11	-8.52	0.99	0.26	0.82
Wash machine	0.00 %	1.83	0.38	-1.72	0.91	0.53	0.81
Dryer	0.00 %	1.97	0.17	-5.65	0.99	0.32	0.82
Freezer	0.00 %	1.81	0.4	-1.54	0.90	0.35	0.82
Refrigerator	0.00 %	1.3	0.46	0.87	0.65	0.46	0.81
Electric stove	0.00 %	1.15	0.36	1.92	0.58	0.39	0.81
Micro wave	0.00 %	1.59	0.49	-0.39	0.80	0.53	0.81
Sink	0.00 %	1.88	0.32	-2.39	0.94	0.51	0.81
Home secure	0.00 %	1.98	0.12	-7.82	0.99	0.31	0.82
Home theatre	0.00 %	1.94	0.24	-3.66	0.97	0.27	0.82
Geyser	0.00 %	1.94	0.23	-3.87	0.97	0.50	0.81

Solar geyser	0.00 %	1.99	0.09	-11.37	1.00	0.13	0.82
Solar panel	0.00 %	1.99	0.08	-12.32	1.00	0.02	0.82
Vehicle	0.00 %	1.85	0.35	-2.01	0.93	0.48	0.81
Toilet facility	0.00 %	1.93	0.34	-1.14	0.64	0.43	0.81
Mean inter-item-correlation=0.153 · Cronbach's α=0.823							

Appendix 3. Asset variables and variable weights from the MCA.

Modalities	Weights
Electricity [Yes]	0.03
Electricity [No]	-0.51
Own telephone [Yes]	1.05
Own telephone [No]	-0.02
Own cell [Yes]	0.02
Own cell [No]	-0.34
Own internet [Yes]	1.62
Own internet [No]	-0.03
Internet via cell [Yes]	0.33
Internet via cell [No]	-0.01
Own radio [Yes]	0.08
Own radio [No]	-0.09
Own tv [Yes]	0.12
Own tv [No]	-0.37
Own DVD [Yes]	0.24
Own DVD [No]	-0.16
Own DSTV [Yes]	0.35
Own DSTV [No]	-0.2
Own AC [Yes]	1.45
Own AC [No]	-0.03
Own computer [Yes]	0.84
Own computer [No]	-0.08
Own vacuum [Yes]	1.72
Own vacuum [No]	-0.04
Own dishwash [Yes]	1.54
Own dishwash [No]	-0.02
Own wash machine [Yes]	0.61
Own wash machine [No]	-0.13
Own dryer [Yes]	1.2
Own dryer [No]	-0.04
Own freezer [Yes]	0.4
Own freezer [No]	-0.1
Own refrigerator [Yes]	0.13
Own refrigerator [No]	-0.3
Own electric stove [Yes]	0.07
Own electric stove [No]	-0.39
Own microwave [Yes]	0.31
Own microwave [No]	-0.21
Own sink [Yes]	0.82
Own sink [No]	-0.11
Own secure [Yes]	1.69
Own secure [No]	-0.03
Own home theatre [Yes]	0.63
Own home theatre [No]	-0.04
Own geyser [Yes]	1.26

Own geyser [No]	-0.07
Own solar Geyser [Yes]	0.94
Own solar Geyser [No]	-0.01
Own solar Panels [Yes]	0.29
Own solar Panels [No]	0,00
Own vehicle [Yes]	0.66
Own vehicle [No]	-0.11
Inside the house toilet	0.88
In the yard toilet	-0.08
Outside yard toilet	-0.28

Appendix 4. Ordered multinomial logit model estimates of determinants of household asset accumulation.

Asset index quantiles (1 = poorest, 2 = poor, 3 = middle, 4 = rich, 5 = wealthiest)	**Estimate**	**std. Error**	**Odds Ratio**	**p**
poorest| poor	-1.796	0.292	0.17	**<0.001**
poor| middle	0.603	0.289	1.83	**0.037**
middle| rich	1.990	0.296	7.32	**<0.001**
rich| wealthy	3.486	0.343	32.66	**<0.001**
head age	0.023	0.002	1.02	**<0.001**
Household size	0.266	0.038	1.31	**<0.001**
Household size^2	-0.018	0.003	0.98	**<0.001**
Economic active household members	0.019	0.056	1.02	0.735
Subsistence farming [Yes]	0.157	0.072	1.17	**0.030**
Province [Eastern Cape]	-2.803	0.228	0.06	**<0.001**
Province [Northern Cape]	-1.070	0.242	0.34	**<0.001**
Province [Free State]	-1.229	0.257	0.29	**<0.001**
Province [KwaZulu-Natal]	-2.757	0.221	0.06	**<0.001**
Province [North West]	-1.401	0.219	0.25	**<0.001**
Province [Gauteng]	-1.106	0.277	0.33	**<0.001**
Province [Mpumalanga]	-1.345	0.216	0.26	**<0.001**
Province [Limpopo]	-1.880	0.214	0.15	**<0.001**
Household head gender [Female]	-0.211	0.068	0.81	**0.002**

Income group [low]	-2.320	0.119	0.10	**<0.001**
Income group [Middle]	-1.388	0.119	0.25	<0.001
Income source [Farming]	0.360	0.613	1.43	0.557
Income source [Other]	-0.755	0.202	0.47	**<0.001**
Income source [Pension]	1.180	0.245	3.25	**<0.001**
Income source [Remittances]	-0.200	0.150	0.82	0.182
Income source [Salary/wages]	-0.619	0.118	0.54	**<0.001**
Income source [Social grants]	-1.461	0.141	0.23	**<0.001**
Observations	6,347			
R2 Nagelkerke	0.298			