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# Determinants of rural-urban differential in asset poverty: Evidence from South Africa



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#### Abstract

Since the advent of democratic governance in 1994, poverty eradication has been a central focus of policy development in South Africa. This objective is in line with the first Sustainable Development Goal, which seeks to eliminate global poverty in all its forms by 2030. This study aims to explore the factors that contribute to asset poverty in South Africa, both urban and rural, an issue that data constraints have largely overlooked. This work utilises principal component analysis to calculate weights and appropriate panel data models to identify essential drivers of asset poverty within distinct geographical areas in South Africa. The findings from the random effect probit model revealed that variables such as land ownership, age of the head of the household, being married, and educational status have a significant mitigating impact on asset poverty. However, the factors contributing to rural asset poverty differ somewhat from those contributing to urban asset poverty. For instance, land ownership appears to be a key factor in explaining poverty in rural areas, relative to their urban areas. Additionally, we found that being married and having all levels of education are key predictors of the rural sample based on the magnitudes of the impact. These findings imply that land remains a fundamental component of different livelihoods for rural dwellers and might encourage rural, emerging agriculturalists to participate in large-scale farming. Thus, the government should continue to redistribute land and further assist rural emerging agriculturalists who want to be involved in large-scale farming.

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Data Availability Statement: Talent Thebe Zwane may provide study data upon reasonable request.

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## 1. Introduction

Since the establishment of democratic governance in 1994, poverty eradication has remained as the driving objective of policy formulation in South Africa. This goal aligns with the first Sustainable Development Goals (SDGs), which aim to eradicate global poverty in all forms by 2030 (Adetoro, Ngidi, & Danso-Abbeam, 2023; Halisçelik & Soytas, 2019). The South African economy has faced prolonged sluggishness, influenced by both domestic and global factors like rising unemployment, inflation, stagnant investment, and policy uncertainty (Mdluli-Maziya, Mncayi, & Sere, 2024; Statistics South Africa, 2019). Stats (2018) reports that the 2014/15 Living Conditions Survey found that 46.6% of African-headed households lived below the upper-bound poverty line, while nearly 32.3% of colored-headed households were also below this threshold. Mdluli-Maziya et al. (2024) cited Stats (2018) and noted that Indian/Asian and White-headed households had the lowest poverty rates, with less than 5% and 1% below all poverty lines, respectively. The 2021 population results indicated that South Africa's population was around 60.14 million, with Africans accounting for approximately 80.9%, colored individuals at 8.8%, whites at 7.8%, and Indians/Asians at 2.6% (Stats, 2021). Most of the population resides in rural areas, where poverty is prevalent, at least for now.

Figures from Stats (2017) reveal that the poverty headcount ratio in rural locations is remarkably higher at 81.3% relative to 40.7% in urban locations. While poverty literature in South Africa has investigated trends in income poverty within these geographic locations and other components, the results from these descriptive assessments are only suggestive. However, while this analysis highlights the higher prevalence of poverty in rural areas, it fails to explain the underlying factors contributing to these disparities. Hence, tackling poverty in the country demands a novel approach that implicitly distinguishes between the requirements of urban and rural dwellers.

Moreover, poverty literature in South Africa, except for Muzindutsi (2018); Biyase, Zwane, and Rooderick (2019); Zwane (2022) and Adetoro et al. (2023) has heavily relied on a uni-dimensional measure such as the money-metric approach (i.e., income and expenditure), while ignoring other alternative measures, like asset poverty measures. In South Africa, we typically measure poverty by comparing "expenditure or income to a money-metric poverty threshold" (Posel & Rogan, 2012). However, A. Sen (1999) has criticized the money-metric poverty threshold for failing to fully capture the experience of the poor. Scholars like McKnight (2011) and (Sherraden, 2014) argue that the poor define their situation more broadly, referring to multiple dimensions of deprivation that are inter-connected and often occur together. Blank (1997) argues that poverty measures are usually static and do not reflect changes in policy and socio-economic conditions such as shifts in the composition of the labour force, like an increase in female participation. Posel and Rogan (2012) state, "In the South African context, state-subsidized housing and access to basic services like electricity and water may not be reflected in income- or expenditure-based poverty rates, but they can influence subjective assessments of economic well-being".

Undoubtedly, the core of the poverty problem is the unequal distribution of resources, which denies a large portion of the world's population access to necessities (Muzindutsi, 2018). As Scott (2002) aptly notes, this disparity in wealth, income, and resource access is defined by socio-economic status (SES). The literature defines socio-economic status as a theoretical construct that encompasses the access of individuals, households, or societies to material resources and services (Scott, 2002). Consequently, socio-economic factors primarily drive human functioning within communities and can identify poverty status (Scott, 2002). This study defines SES as a household's access to specific assets and measures the household's poverty status based on the extent of this access. Assets serve as crucial symbols of SES, and incorporating asset ownership into a poverty measurement ensures the inclusion of a crucial additional dimension of economic well-being. Moreover, it is possible that an asset-based poverty measure can reveal different dimensions of poverty depending on the geographical types.

What factors contribute to driving households into asset poverty in South Africa? Are these factors similar in urban and rural areas? Scholars such as Ashley and Maxwell (2001) have noted that apartheid policies forced many South Africans, particularly Africans, into rural areas, making these questions crucial. As Ashley and Maxwell (2001) stated, "[p]overty is not only widespread in rural areas [where Africans live], but most poverty is rural, at least for now." Additionally, urban and rural areas have distinct characteristics, suggesting that asset poverty and its causes may vary in the different geographical areas. While there are a limited number of studies that have examined the role of assets in poverty reduction in South Africa, these studies have depended on cross-sectional data instead of panel data. This is due to the lack of national representative panel data. However, this study is using the newly available data type.

Therefore, this study makes various contributions to the current poverty literature. First, it delves into the factors that contribute to asset poverty in both urban and rural areas of South Africa, an issue that has received little attention. An improved understanding of the factors contributing to rural and urban asset poverty is key. We can direct interventions towards the most subjectively poor areas with this understanding. Second, we use assets as a suitable measure of poverty in specific geographical areas. The study builds on the seminal work of Sen (1999) who argued: "money or income should not be valued in itself, since it is merely a means to an end, thus money gives us the freedom to choose the kind of lives that we would like to live. A measure of household welfare should encompass not only monetary dimensions but also a household's broad range of capabilities." We create an asset poverty index constructed using the principal component analysis (PCA). Some researchers, like Tabachnick and Fidell (2007) and Hair, Black, Babin, and Anderson (2010) strongly recommend using the PCA model. They say that it produces few uncorrelated components and that each component describes less variation than the one before it. Finally, we applied appropriate panel data estimation techniques to explore the factors influencing asset poverty, using data from the five-wave (2008-2017) National Income Dynamics Study. The significance of this work lies in its call for researchers and policymakers in the country to reconsider poverty measures, placing a greater emphasis on the utilization of households' assets. This paper arranges the remaining sections as follows. Section 2 explains theoretical and empirical literature. Section 3 explains the research techniques used in this paper, while section 4 discusses the empirical results. Section 5 provides some concluding remarks.

#### 2. Literature Survey

#### 2.1. Theoretical Background

Sen (1976) observed that several fundamental causes, not a single factor, determine people's conditions of poverty. In fact, various theories exist to explain the perpetuation of poverty, including the individual deficiencies theory. Specifically, the theory of individual deficiencies proclaims that individuals are to blame for making choices that eventually lead to their deficiencies and/or their own state of poverty (see, for example,

(Addae-Korankye, 2019; Bradshaw, 2006; Mdluli-Maziya et al., 2024)). Addae-Korankye (2019) argued that individual aspects such as people's attitudes, human capital, and welfare participation fuel poverty. Bradshaw (2006) argued that trust in individualism puts more emphasis on individual hard work and accountability to attain basic fundamental necessities like food, housing, and medical services. However, this theory has faced significant criticism from Schwartz (2000) and Sameti, Esfahani, and Haghighi (2012) whose studies revealed that individuals experiencing poverty often emphasize the importance of hard work, express dissatisfaction with the welfare system, and value personal responsibility. These findings challenge the common societal belief that an individual's negative attitude drives poverty.

Conversely, the theory of cultural belief systems suggests that poverty is influenced by a set of beliefs, values, and skills that are cultivated by society and perpetuated through upbringing (see for instance, (Bradshaw, 2006; Sameti et al., 2012)). Consequently, society does not hold poor people accountable for their state of poverty, as flawed culture also affects the vulnerable (Davis & Sanchez-Martinez, 2014). The theory of geographical disparities attempts to conceptualise poverty along the lines of geographical differences leading to the development of a geography of poverty (Bradshaw, 2006). Bradshaw (2006) sees this as a driver of poverty representing rural impoverishment, urban neglect, and other factors that occur distinctly from other theories. A study by Abdulai and Shamshiry (2014) argued that analysing poverty based on regional differences assumes that poverty is concentrated in specific locations, societies, and areas within countries as well as among different regions of the world.

According to structural theorists (Odeh & Okoye, 2014) the composition of the broader socioeconomic system causes poverty. Proponents of this theory point to economic, political, and social orders that constrain possibilities and resources needed for people to earn income and improve their well-being (Bradshaw, 2006; Odeh & Okoye, 2014). Consistent with this view, Sameti et al. (2012) argue that broader economic and social constructs are the main causes of poverty. The literature (see, for instance, (Bradshaw, 2006; Davis & Sanchez-Martinez, 2014; Sameti et al., 2012)) is full of evidence suggesting that the economic structure is set up in a manner that keeps the impoverished at the bottom despite their level of knowledge.

The emergence of these theories has transformed the conceptualization, definition, and measurement of poverty. Some studies have used these theories in their analysis of poverty, but the results have been mixed, inconsistent, and inconclusive.

#### 2.2. Empirical Literature: Determinants of Asset Poverty

Numerous empirical studies have investigated the determinants of asset poverty by examining the characteristics of the household head and household structure across various countries. These studies have employed a range of methodologies, including binary logistic/probit models, pooled ordinary least squares techniques, and micro-level quantile analysis. For a comprehensive overview, refer to Table 1, which summarizes the asset poverty literature. However, the findings from these studies have been mixed and inconclusive.

For example, various researchers such as Daka and Fandamu (2016); Habyarimana, Zewotir, and Ramroop (2015); and Zwane (2022) have explored the uniqueness of education as a determinant of asset poverty. As correctly put by Filmer and Pritchett (2001) asset buildup improves the likelihood of children being in school and improves educational accomplishment in general. Such studies have reported that as the educational status of the household head improves, the likelihood of plugging into asset poverty diminishes. By and large, these studies have shown that education generally improves the stock of human capital, which is a factor in increasing labour productivity and earnings. Contrary to the contribution of the above-mentioned studies, Sadeghi (2001) observed that increased levels of education were not constantly essential in rural regions where merely a few well-educated individuals reside. This implies that the causal nexus between education and asset poverty often differs across various geographical regions. The results of Sadeghi (2001) reinforce those of Sekhampu (2013) who observed that the poverty status of individuals will not diminish regardless of improved levels of education attainment.

Another significant factor influencing asset poverty is the age of the household head. Various empirical studies, including those by Achia, Wangombe, and Khadioli (2010); Tsehay and Bauer (2012); Biyase et al. (2019) and Muzindutsi (2018) have reported an inverse relationship between poverty and the age of the household head. The findings suggest that as the head of the household ages, the likelihood of experiencing asset poverty decreases. Similarly, Garza-Rodriguez, Ayala-Diaz, Coronado-Saucedo, Garza-Garza, and Ovando-Martinez (2021) concluded that as household heads gain more experience, their income tends to increase, thereby reducing poverty levels. However, Majeed and Malik (2015) presented opposing evidence, indicating a positive relationship between poverty and the age of the household head. In terms of employment status, Biyase et al. (2019) found that employment reduces the probability of falling into poverty.

Among the most broadly scrutinized drivers of asset poverty is the ownership of land. In South Africa, landownership poses significant challenges and requires careful handling. The literature describes land ownership as a crucial symbol of an individual's ability to accrue income through their own activities (Grootaert, 1997). A study by Zwane (2022) used panel data estimation techniques to explore the drivers of non-monetary household poverty utilising 5 waves of the NIDS in South Africa. The panel data models revealed that landownership was associated with diminishing poverty levels. Results revealed that landownership was negatively associated with poverty in South Africa. The major limitation of Zwane (2022) study is the fact that

the author failed to disaggregate the panel nature of NIDS into urban and rural regions to establish whether the circumstances are similar. Being able to identify the main determinants of asset poverty within these subsamples could contribute to the formulation of targeted policies to reduce the overall impact of poverty at the most subjectively underprivileged localities, rather than adopting a one-size-fits-all approach.

Most empirical studies have found that household size has a significant positive impact on a household's poverty status. Specifically, larger households are more likely to fall into poverty due to the increased resources required to meet essential needs (see, for example, (Akinbode & Hamzat, 2017; Habyarimana et al., 2015; Mburu, Otterbach, Sousa-Poza, & Mude, 2017)). Akinbode and Hamzat (2017) used a probit model in their study, 'Women Asset Ownership and Household Poverty in Rural Nigeria,' and found a positive correlation between household size and poverty, which aligns with the findings of Habyarimana et al. (2015) for Rwanda. Marital status also plays a critical role in determining asset poverty. For instance, Garza-Rodriguez et al. (2021) found that poverty decreases if the household head is divorced, while Dunga (2024) reported that married household heads are more likely to be poor. Conversely, Dunga (2017) observed that married individuals are less likely to experience poverty, as they can combine their incomes to combat economic hardship.

The literature on the drivers of asset poverty at a national level across countries has expanded with time. However, data constraints have neglected the determining factor of asset poverty in samples divided by location (such as urban and rural areas) in South Africa. Therefore, the purpose of this paper is to investigate the factors that contribute to asset poverty, specifically focusing on the differences between rural and urban areas, a topic that has not received enough attention in South Africa.

Table 1. Summary of asset poverty literature.

Author	Countries	Data	Methodology	Results
Akinbode and Hamzat (2017).	Rural Nigeria	Primary data from 363 households	Principal component analysis and probit model	Education, marital status, and income were key determinants of poverty.
Wang and Li (2024)	African countries	Nighttime light data and world settlement footprint data	Random forest model	Asset wealth is generally low across most African settlements, showing a clear two-tier differentiation on the continent.
Muzindutsi (2018)	Selected South African townships	Primary data from 364 households	Principal component analysis and binary logistic model	The main determinants of asset- based poverty status were the marital status of the household head, household size, and receipt of a social grant.
Koomson, Abdul- Mumuni, Ampah, and Afful (2023).	Ghana	Ghana living standards survey (GLSS7)	Ordinary least squares	Education and entrepreneurship serve as key channels through which asset accumulation impacts healthcare utilization and spending.
Booysen, Van Der Berg, Burger, Von Maltitz, and Du Rand (2007).	Seven Sub- Saharan African countries	Demographic and health surveys	Multidimensional correspondence analysis techniques	Poverty decreased in five out of the seven countries
Daka and Fandamu (2016)	Zambia	Demographic and health surveys	Principal component analysis and logistic model	The results indicate that DHS data can be utilized to identify the correlates of poverty.
Mare, Gecho, and Mada (2022).	Southern Ethiopia	Primary data	Binary logistic model	Education level, livestock ownership, farm size, and distance to the market were significant at the 5% significance level.
Habyariman a et al. (2015)	Rwanda	Rwanda demographic health surveys	Principal component analysis and binary logistic regression	The significant predictors of household poverty in Rwanda included age, education level, gender, place of residence, provincial variables, and household size.

Author	Countries	Data	Methodology	Results
Ullah and	Pakistan	National socio-	Multidimensional	The results showed that the
Chishti		economic registry	correspondence	incidence of asset-based poverty
(2023).		(NSER) data set	analysis techniques	varied between provinces when the
				MCA score was broken down at the
				district level
Anand,	US, UK	Own 2011 Oxwell	Multidimensional	The results of the non-poverty
Jones,	and Italy	survey of working	correspondence	index indicate that the poorest
Donoghue,		adults, which was	analysis techniques	groups are large families and
and Teitler		collected in three		households in rural areas.
(2021)		countries (Italy,		
,		USA, and UK)		

#### 3. Methodology

To assess asset poverty on samples split by localities (urban and rural), we applied numerous methods. We begin our analysis by implementing PCA as presented in section 3.2. Section 3.3: We analyse the main factors influencing asset poverty by implementing the random effect probit model.

#### 3.1. Description of Data Set

The Southern African Labor and Development Research Unit (SALDRU) at the University of Cape Town's School of Economics collected the first five waves of the NIDS dataset, a continuing panel survey, to provide the data used in this study to explore urban-rural disparities in asset poverty (DataFirst., 2021; SALDRU, 2016). The South African government commissioned the survey in 2008 (DataFirst., 2021). Currently, there are five existing waves of the NIDS, conducted between 2008–2017. This dataset is exceptional, as it is the first cross-country panel data covering all South African provinces (SALDRU, 2016). The major advantage of the NIDS dataset is that it contains questions about deprivation items across all nine provinces (Nwosu & Woolard, 2017; SALDRU, 2016). These deprivation items include ownership of households' assets; access to sources of drinking water; access to assets such as wall material; and sanitation facilities (Nwosu & Woolard, 2017; SALDRU, 2016). The NIDS dataset is longitudinal data for people of all ages in South Africa. For a comprehensive analysis of the NIDS dataset, please visit www.nids.uct.ac.za.

#### 3.2. The Principal Component Analysis

In this empirical work, we measured poverty using durable and non-durable assets and applied the PCA to generate an index, following the approach of Vyas and Kumaranayake (2006). The PCA, as described by Tabachnick and Fidell (2007) and Hair et al. (2010) reduces dimensionality by using machine learning techniques to condense a large dataset into a smaller, more manageable set while preserving key patterns and trends. These authors argue that the PCA achieves this by deriving a smaller number of factors that capture most of the variation in the original data. Undoubtedly, the PCA extracts a few uncorrelated components (Tabachnick & Fidell, 2007). Each subsequent component describes additional but less variation than the previous one (Tabachnick & Fidell, 2007). Here's an illustration of the PCA-based weight construction process:

The subscript  $\beta_{pp}$  denotes for the weights for the  $p^{th}$  principal component and the  $p^{th}$  factor. In principal component analysis, these weights are determined by the eigenvectors of the correlation matrix or the covariance matrix (Hair et al., 2010; Tabachnick & Fidell, 2007).

Zwane (2022) referenced Tabachnick and Fidell (2007) to explain how an asset index is calculated using PCA. Tabachnick and Fidell (2007) argue that the calculation of an asset index through PCA involves several steps. The initial step is to check for sufficient correlation among variables (Xhafaj & Nurja, 2015). To assess this, the Kaiser–Meyer–Olkin (KMO) test is used. This test measures the sampling adequacy of variables, indicating the level of correlation among them (Tabachnick & Fidell, 2007). For the application of PCA, the KMO statistics should be at least 0.6 (Hair et al., 2010). Additionally, the Bartlett test of sphericity is employed to test the assumption that variables in the population correlation matrix are uncorrelated, essentially forming an identity matrix (Hair et al., 2010; Tabachnick & Fidell, 2007). If the associated probability is below 0.05, the Bartlett test rejects the hypothesis (Hair et al., 2010), indicating that PCA is suitable for the data set (Fisher & Weber, 2004).

Finding the precise number of components to extract is the second step in applying PCA. We use a variety of techniques for this purpose. Some studies use the correlation matrix instead of the covariance matrix to extract the components (Tabachnick & Fidell, 2007). When determining the exact number of components to be extracted, Tsehay and Bauer (2012) argue that extracting principal components equal to the number of observed variables being analysed is common. However, recent studies have shown that extracting and utilizing the first

few components that account for a significant amount is more effective (Fisher & Weber, 2004; Xhafaj & Nurja,

The literature Xhafaj and Nurja (2015); Khudri and Chowdhury (2013) and Akinbode and Hamzat (2017) is full of evidence indicating that it is important to use the Kaiser's rule, which is associated with the eigenvalue of each principal component. Kaiser's criterion dictates the extraction of only components with eigenvalues equal to 1.0 or greater (Kaiser, 1974). Following the study by Achia et al. (2010) and Habyarimana et al. (2015), we used the 40th percentile as an appropriate poverty line to identify the poor. Scholars like Achia et al. (2010) and Xhafaj and Nurja (2015) have used this poverty line.

#### 3.3. Empirical Model

Following previous literature (see for instance, (Biyase et al., 2019; Habyarimana et al., 2015)) we implemented the novel random effect probit estimator. The novelty of this panel data model is its ability to estimate the likelihood of individuals being asset-poor as the dependent variable against a set of different explanatory variables (Wooldridge, 2001).

Therefore, the random effect probit estimator is a binary choice estimator that assumes the value of one and zero dummy variable used as the dependent variable (Wooldridge, 2001). The random effect estimator can be expressed as follows:

$$Y_{it}^* = \pounds_{it}\beta + \alpha_{it} \tag{4}$$

Hence

$$P_{it} = \begin{cases} Y_{it}^*, if Y_{it}^* > 0\\ 0, otherwise \end{cases}$$
 (5)

 $P_{it} = \begin{cases} Y_{it}^*, if Y_{it}^* > 0 \\ 0, otherwise \end{cases}$ Here *i* denotes each household at time *t*.  $Y_{it}^*$  represents the latent dependent variable indicating asset poverty, while  $Y_{it}$  denote the observed outcome. The vector consists of time-varying and time-invariant  $\mathcal{L}_{it}$ consists of time-varying and time-invariant regressors (see also, Wooldridge (2001)). The subscript  $\beta$ corresponds to the vector of coefficients associated with the  $\mathcal{L}_{it}$  regressors, and  $\alpha_{it}$  is a random error, assumed to be identically distributed.

Equation 5 implicitly defines the observed binary variable. For a detailed explanation logistic regression, refer to Wooldridge (2001). In a panel context, the error term is generally shown as follows:

$$\alpha_{it} = \mathbf{e}_i + \mathbf{\omega}_{it}$$

The subscript  $\mathbf{\epsilon}_i$  indicates household-specific unobservable effects and  $\omega_{it}$  shows the unobservable individual and random effects (Hair et al., 2010) we used the 40th percentile as a poverty line, consistent with the work of earlier studies (see for example, Achia et al. (2010); Habyarimana et al. (2015); Mburu et al. (2017) and Akinbode and Hamzat (2017).

To establish the factors contained in the  $\beta$  vector, we build earlier empirical work that assume the likelihood of being in asset poverty depends on numerous explanatory variables — head of household's education level, age structure, employment status, household size, region, and race.

#### 4. Results

We now present the results obtained by using the techniques discussed in the methodology section. Thus, section 4.1 presents the findings obtained from applying PCA, while section 4.2 discusses the findings from the random effect model.

#### 4.1. Results from PCA

To ensure that PCA was suitable for this study, we calculated KMO scores for all samples, which confirmed PCA's appropriateness. We determined the number of components to extract using Kaiser's rule, the scree plot, and the rotated matrix (Akinbode & Hamzat, 2017).

Appendix Tables A1 and A2 provide detailed eigenvalue breakdowns for the rotated extracted components. Kaiser's rule suggests extracting 19 components with eigenvalues greater than 1.0 (Hair et al., 2010). Similarly, the rural sample recommended extracting 22 components according to Kaiser's rule. To verify the number of components, we also examined the scree plot (Figure 1 and 2) to identify the cut-off point based on the variance of the principal components (Hair et al., 2010).

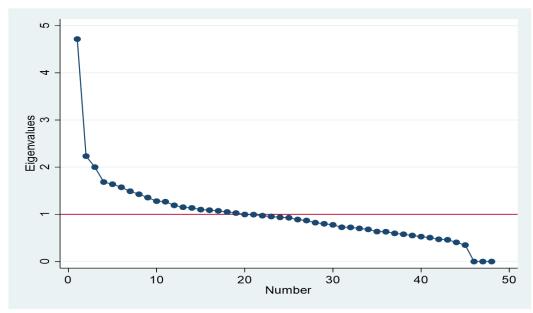


Figure 1. Urban sample scree plot.

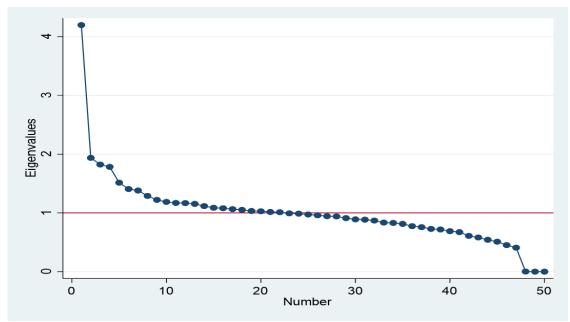


Figure 2. Rural sample scree plot.

Consistent with the work of Bhorat and Van Der Westhuizen (2013) we generated kernel density and compared the outcomes of the index coefficients across these geographical areas (urban and rural samples). The most prominent highlights of the urban sample design are the appearance of two exclusive spots in the density charts. The location of the coefficients in these spots symbolizes an uneven supply of assets in Figure 3. The initial spot reveals that many households have a low asset-poverty index, as seen in the skew to the left. These coefficients reinforce the conclusion made by Bhorat and Van Der Westhuizen (2013). The second curve in Figure 4 reveals another unique segment of individuals who are wealthy and hold higher index value. This shows that these people have assets with higher factor scores, revealing asset wealth (Bhorat & Van Der Westhuizen, 2013). Over time, the findings indicate a diminishing number of individuals with low asset value from wave 1 to wave 5. On the other hand, the number of people with a high asset index has increased significantly. Not surprisingly, the rural residents continue to live in poverty, with many individuals concentrated at the bottom end of the asset-index density plots. Conversely, over time the number of individuals with lower asset-poverty indices has diminished. Interesting, the same trend of individuals with higher asset indices, as seen in Figure 3 and Figure 4, is not as predominant. The results indicate that individuals in rural localities still have low asset-poverty indices.

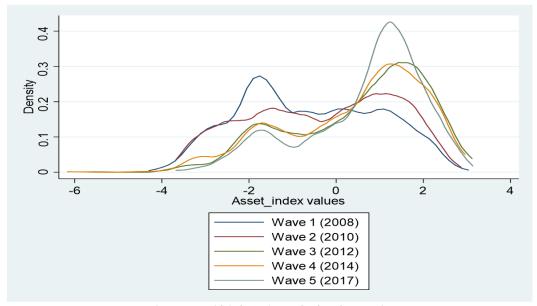


Figure 3. Wealth index estimates for the urban sample.

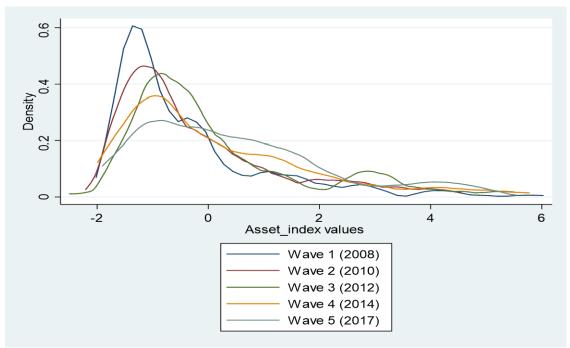


Figure 4. Wealth index estimates for the rural sample.

In this subsection, the aim is to report the factor scores for selected variables based on the first principal component as commonly done in this field (see, for example, (Biyase et al., 2019; Habyarimana et al., 2015; Vyas & Kumaranayake, 2006)). Table 1 illustrates the separate generation of factor scores for individual asset variables in samples from urban and rural areas. The initial column of Table 2 describes the factor scores for the index based on urban locations. Interestingly, positive symbols accompany many factor scores, suggesting a strong correlation between these assets and high socio-economic status (Zwane, 2022). In the urban column, factors with large positive scores indicating high socio-economic status include owning a satellite dish, owning a DVD player, owning a computer, owning a camera, having a gas stove, having a washing machine, possessing a sewing machine, having a private vehicle, and owning a bicycle. On the other hand, factors contributing to increased socio-economic status in rural South Africa include owning a radio, a television set, a satellite dish, a DVD player, a cellular phone, an electric stove, a fridge, a chemical toilet, and bricks. Based on these varying weights and directions of impact, the life of the urban population differs from that of their rural counterparts. The results reveal that policymakers should formulate tailor-made policies that suit a particular geographical area rather than assuming that all areas are uniform.

Table 2. Scoring factors for urban and rural areas.

		Urban sa	ample					
		Std.		Std.				
Variable	Mean	dev.	Factor score	Mean	dev.	Factor score		
Radio	0.674	0.468	0.053	0.626	0.483	0.164		
Television	0.854	0.352	-0.013	0.659	0.473	0.454		
Satellite_dish	0.297	0.456	0.397	0.140	0.347	0.134		
DVD_player	0.468	0.498	0.104	0.258	0.437	0.330		
Computer	0.197	0.398	0.446	0.055	0.229	-0.037		
Camera	0.147	0.354	0.411	0.040	0.196	-0.153		
Cell_phone	0.861	0.345	-0.021	0.826	0.378	0.406		
Electric_stove	0.855	0.351	0.006	0.621	0.484	0.418		
Gas_stove	0.180	0.384	0.222	0.130	0.336	-0.017		
Paraffin stove	0.181	0.385	-0.018	0.253	0.434	-0.074		
Fridge_freezer	0.813	0.389	0.037	0.586	0.492	0.427		
Washing_machine	0.479	0.499	0.272	0.124	0.330	0.056		
Sewing_machine	0.115	0.319	0.111	0.051	0.220	0.049		
Private_car	0.248	0.432	0.335	0.087	0.282	0.037		
Bicycle	0.110	0.313	0.390	0.052	0.222	0.036		
Plough	0.011	0.106	-0.033	0.054	0.226	-0.006		
Tractor	0.005	0.071	0.046	0.017	0.132	0.007		
Grinding_mill	0.009	0.097	0.032	0.016	0.127	-0.012		
Livestock	0.328	0.469	0.025	0.712	0.452	0.063		
Sanitation_facility	1		1		1	T .		
Flush_toilet_with_on-site disposal	0.520	0.499	-0.008	0.096	0.295	-0.015		
Chemical_toilet	0.012	0.110	0.043	0.059	0.237	0.101		
Bucket_toilet	0.022	0.149	-0.045	0.040	0.196	-0.007		
Flush_toilet _with_off-site disposal	0.338	0.473	0.003	0.060	0.239	0.017		
Pit_latrine_with_ventilation pipe	0.035	0.184	0.010	0.256	0.436	-0.017		
Pit_latrine_without ventilation_pipe	0.052	0.222	-0.008	0.404	0.490	-0.019		
Any_other	0.017	0.130	0.028	0.078	0.269	-0.002		
Wall_material	0.000	0.400	0.013	0.400	0.407			
Brick	0.686	0.463	0.012	0.430	0.495	0.104		
Cement_block	0.150	0.357	-0.000	0.213	0.409	0.049		
Corrugated iron/Zinc	0.095	0.293	0.019	0.056	0.231	-0.019		
Wood Cardboard	0.025	0.159	0.027	0.006	0.077	-0.083		
	0.003	0.061	0.025	0.001	0.036	0.037		
Mixture_of_mud _and cement Wattle_and_daub	0.015	0.123	-0.058	0.154	0.360	-0.026		
Tile	0.002	0.049	0.017	0.011	0.106	0.030		
Mudbrick	0.004		0.032	0.002	0.046 0.318	-0.053 -0.130		
Thatching		0.084	0.026	0.114				
Asbestos_cement roof sheeting	0.007	0.027	-0.013	0.001	0.034	-0.105		
Stone_ and_ rock		0.067	-0.007	0.001	0.035	-0.029		
Source_of_drinking_water	0.001	0.039	-0.157	0.006	0.081	0.017		
Water in dwelling	0.633	0.491	0.000	0.182	0.996	0.009		
Piped in yard	0.033	0.481	-0.005	0.182	0.386 0.437	0.009		
Public tape	0.284	0.431	0.006	0.237	0.464	0.006		
Water - carrier/Tank	0.004	0.249	-0.079		0.187	-0.006		
Borehole on site	0.004	0.041	0.007	0.036		-0.006		
Borehole off site	0.001	0.041	-0.057	0.014	0.120	-0.007		
Rainwater tank on site	0.001	0.042	-0.037	0.024	0.133	-0.006		
Flowing water/Stream	0.002	0.032	-0.014	0.013	0.115	-0.007		
Dam/Pool/Stagnant water	0.001	0.043	0.026		0.282	-0.024		
Well	0.000	0.030	-0.026	0.038	0.192	-0.002		
Spring	0.000	0.014	-0.029	0.003	0.062	0.037		
Spring	0.002	0.014	-0.003	0.012	0.112	0.037		

The current discussion indicates that the findings from the PCA are primarily descriptive, lacking an empirical examination that extends beyond the standard explanation of asset poverty. From this perspective, the subsequent section of the study expands on the descriptive analysis of asset poverty, providing an empirical investigation through the use of various models.

### 4.2. Empirical Results

Table 3 presents the empirical findings from the random effect probit technique on the determinants of asset-poverty. Similar to the results in Table 2, the outcomes in Table 3 include both urban and rural samples.

We will first discuss findings from the urban sample in column (1) of Table 3. Interestingly, ownership of land is associated with negative and statistically significant coefficients. This suggests that owning land in South Africa significantly reduces the likelihood of experiencing poverty. Similar results were found by Tsehay and Bauer (2012) in Ethiopia. They concluded that individuals who own more land have the opportunity to cultivate more crops, generate additional income, and potentially escape poverty by either farming the land themselves or leasing it for profit.

These findings align with the importance of land availability in discussions about poverty, as it can serve as a crucial factor in preventing individuals from falling into poverty over time. The government in South Africa has long been concerned about land reforms, as evidenced by the quote from Nelson Mandela (1995) who emphasized the importance of restoring land rights as a way to rectify historical injustices: "With freedom and democracy came the restoration of the right to land." This also presents the chance to confront the consequences of centuries of expropriation and suppression. At last, we can, as a people, look our ancestors in the face and say, your sacrifices were not in vain."

Consistent with the study by Achia et al. (2010) and Daka and Fandamu (2016) we observed that asset-poverty in the urban sample is influenced by the education attainment of the head of the household (primary, secondary, matric, and tertiary). Education enters with negative and statistically significant coefficients. This suggests that schooling in South Africa provides increased opportunities for securing well-paid employment, which, according to Hunter, May, and Padayachee (2003) would lead to increased income and therefore a decrease in poverty.

Thus, advancement in schooling is a fundamental tool for poverty alleviation in South Africa. The results are consistent with Nelson Mandela's philosophy on education, as he emphasised the role of schooling as a chance for people to change their lives for the better. Education provides opportunities for successful careers and the ability to work at any workplace of our choice. The debate on land is a sensitive issue in South Africa, as evidenced by the National Development Plan (NDP), which states that land reform can unlock the potential for a dynamic, growing, and employment-creating agricultural sector.

The results for other control variables are consistent with previous findings on asset poverty correlates. While not statistically significant, married household heads are notably less likely to be poor compared to single individuals. This supports Zenda (2002) assertion, as cited in Adekunle (2013) that household heads with partners are more likely to share household responsibilities. The relationship between age and asset poverty is negative and significant at the 1% level, aligning with findings from Daka and Fandamu (2016) in Zambia and Akinbode and Hamzat (2017) in Nigeria. However, Biyase et al. (2019) in South Africa only analyzed a single wave, which contrasts with our findings. The reliance on cross-sectional data in earlier studies, rather than panel data at a national level, may be the cause of these discrepancies.

Interestingly, the age of the household head has a negative and statistically significant coefficient in the urban sample. This finding aligns with the results of Daka and Fandamu (2016) for Zambia and Akinbode and Hamzat (2017) for Nigeria, but contrasts with the findings of Habyarimana et al. (2015) for Rwanda and Biyase et al. (2019) for South Africa, who based their analysis on a single wave of the NIDS dataset. The variation in results may be attributed to the use of cross-sectional data in earlier studies rather than panel data at a national level (see, for example, (Biyase et al., 2019; Habyarimana et al., 2015)).

Additionally, household size shows a positive and statistically significant coefficient, which is consistent with Imai, Gaiha, and Kang (2011) who reported that larger household sizes increase the risk of falling into poverty in Vietnam.

Are the drivers of asset-poverty similar across urban and rural areas? To answer this question, we will now discuss the findings from the rural sample, which are reported in column (2) of Table 3. Interestingly, the results of these rural samples mirror the same trends as those of the urban sample. As anticipated, land ownership continues to exhibit a negative and significant coefficient. The main difference between the urban and rural samples lies in the magnitude of this impact. These results suggest that the coefficient of land ownership in the rural sample is larger than that of the urban sample, highlighting the importance of land ownership in rural areas.

The rural sample's household size exhibits a similar pattern to the urban samples. Consequently, the conclusions about significance drawn from the urban sample are also applicable to the rural sample. The estimates for the rural sample reaffirm that the age of the household head is a significant predictor of asset poverty, as indicated by a negative and significant coefficient. Moreover, the significant variables identified in the urban sample also hold true for the rural sample.

It is fascinating to observe that marriage plays an important role in determining whether people in the rural sample are able to escape asset poverty or fall into it. The standard of living for urban dwellers is different from their rural counterparts. Education is also of interest, as it suggests that households with highly educated heads are less likely to fall into asset-poverty (Zwane, 2022). Other variables included in the analysis show how similar patterns in terms of the direction of impact and level of significance as those reported earlier.

Table 3. Random-effects probit estimates on the determinants of asset poverty.

	Urban	sample	Rural sample			
Asset poverty	Marginal effects	Standard errors	Marginal effects	Standard errors		
Land holdings	-0.00487***	(0.00056)	-0.02391***	(0.00128)		
Size of the household	0.00069**	(0.00025)	0.00296***	(0.00037)		
Household head characteristics	s:					
Unemployed	0.00348*	(0.00144)	0.021165***	(0.00285)		
Household age	-0.00012*	(0.00005)	-0.00084***	(0.00011)		
Gender	0.00187	(0.00144)	0.00461	(0.00303)		
Married	-0.00062	(0.00050)	-0.00662***	(0.00109)		
Levels of education (No school	ling omitted)					
Primary_schooling	-0.01195***	(0.00171)	-0.00330***	(0.00381)		
Secondary_schooling	-0.01710***	(0.00155)	-0.06094***	(0.00475)		
Matric_schooling	-0.02038***	(0.00284)	-0.06388***	(0.00297)		
Tertiary_schooling	-0.02250***	(0.00165)	-0.06788***	(0.00268)		
Provincial dimensions (Wester	rn cape omitted):					
Eastern Cape	-0.02205***	(0.00238)	-0.05891***	(0.00437)		
Northern Cape	-0.00743*	(0.00324)	0.11725***	(0.01024)		
Free State	-0.01492***	(0.00215)	-0.03295***	(0.00718)		
KwaZulu-Natal	-0.00670*	(0.00342)	0.02494	(0.01771)		
North-West	-0.00019	(0.00475)	0.05741***	(0.00528)		
Gauteng	-0.01492***	(0.00151)	-0.04825***	(0.00449)		
Mpumalanga	-0.01353***	(0.00273)	-0.03518***	(0.0069)		
Limpopo	0.006497	(0.00342)	-0.01878**	(0.00645)		

Note: \*\*\*significant at 1%; \*\*significant at 5%; \*significant at 10%.

#### 5. Conclusion and Implication

#### 5.1. Conclusion

This study utilized PCA to create an asset index that distinguishes the impoverished from the non-poor in both urban and rural regions of the nation. We generated the asset index for both urban and rural samples to address the gap in the literature, given the limited number of studies focused solely on these two distinct geographical locations. The paper used all five current waves of the NIDS longitudinal dataset, commissioned by the South African government in 2008. Likewise, the paper used the random effect probity to investigate the factors influencing asset poverty within these two unique geographical locations.

The findings from the random effect probity model revealed that variables such as land ownership, age of the head of the household, being married, and educational status have a significant mitigating impact on asset poverty. However, the factors contributing to rural asset poverty differ somewhat from those contributing to urban asset poverty. For instance, land ownership appears to be a key factor in explaining poverty in rural areas, relative to their urban areas. Additionally, we found that being married and having all levels of education are key predictors of the rural sample, based on the magnitudes of the impacts. Conversely, some variables, such as unemployment and the size of the household, present a positive impact on asset poverty.

The estimates derived from this study have crucial and broader policy implications. Given that access to land has been found to be one of the main instruments in reducing the probability of being asset poor, the government should continue to redistribute land, especially to the poor, and further assist rural emerging agriculturalists who want to be involved in large-scale farming. Further implications suggest that providing poor individuals with access to land and enhancing their capacity to use it effectively is crucial for reducing poverty and empowering disadvantaged people and communities. Land reforms in South Africa have been a persistent priority for the government, as underscored by Nelson Mandela (1995) who emphasized the importance of restoring land rights to rectify historical injustices: "With freedom and democracy came restoration of the right to land. This also presents a chance to confront the consequences of centuries of expropriation and suppression. At last, we can, as a people, look our ancestors in the face and say, your sacrifices were not in vain." With respect to education, the Nelson Mandela Foundation (2005) cited in Biyase and Zwane (2018) concludes the policy implications response coming from our findings as follows: "A powerful rationale for rural education and a robust political constituency to argue for it are now required. We can provide a rationale that recognizes education's potential to contribute to rural development, complementing and integrating with other social policies that target inequality and poverty. In recent years, a significant body of empirical work has advocated that the growth of agricultural production implicitly addresses poverty and improves asset ownership on the African continent. This could potentially result in increased access to land and education for the poor.

#### 5.2. Limitation and Future Research

While this work makes a significant contribution, it only focuses on assets as an alternative measure of poverty. We recommend future studies to compare the outcomes of an income-based approach and an asset-based approach to poverty analysis, utilizing a comprehensive panel data set in South Africa. This study's short

panel serves as a crucial reservoir of knowledge, not only for South Africa, the study's focus, but also for other former colonies with similar characteristics. Therefore, we recommend focusing future research on comparing the results from South Africa, a former British colony, to Mozambique, a former Portuguese colony. This comparative analysis will allow us to understand potential variations in socio-economic conditions between these two colonial regions and, subsequently, to establish the underlying factors contributing to any disparities observed. Our aim would be to gain a broader perspective on the dynamics of poverty and economic empowerment in different colonial contexts, enriching our overall understanding of these critical issues in Africa.

# References

- Abdulai, A. M., & Shamshiry, M. (2014). Linking sustainable livelihoods to natural resources and governance: The scale of poverty in the muslim world. Singapore Heidelberg New York Dordrecht London: Springer
- Achia, T. N., Wangombe, A., & Khadioli, N. (2010). A logistic regression model to identify key determinants of poverty using demographic and health survey data. *European Journal of Social Sciences*, 13(1), 38–45.
- Addae-Korankye, A. (2019). Theories of poverty: A critical review. *Journal of Poverty, Investment and Development, 48*(1), 55-62. https://doi.org/10.7176/jpid/48-08
- Adekunle, O. O. (2013). An investigation of challenges facing home gardening farmers in South Africa: A case study of three villages in Nkokonbe municipality Eastern Cape Province. *Journal of Agricultural Science*, 6(1), 102-109.
- Adetoro, A., Ngidi, M., & Danso-Abbeam, G. (2023). Towards the global zero poverty agenda: Examining the multidimensional poverty situation in South Africa. SN Social Sciences, 3(9), 148. https://doi.org/10.1007/s43545-023-00735-2
- Akinbode, S., & Hamzat, S. (2017). Women asset ownership and household poverty in rural Nigeria. *Journal of Studies in Social Sciences*, 16(1), 45-64.
- Anand, P., Jones, S., Donoghue, M., & Teitler, J. (2021). Non-monetary poverty and deprivation: A capability approach. Journal of European Social Policy, 31(1), 78-91. https://doi.org/10.1177/0958928720938334
- Ashley, C., & Maxwell, S. (2001). Rethinking rural development. Development Policy Review, 19(4), 395-425. https://doi.org/10.1111/1467-7679.00141
- Bhorat, H., & Van Der Westhuizen, C. (2013). Non-monetary dimensions of well-being in South Africa, 1993–2004: A post-apartheid dividend? *Development Southern Africa*, 30(3), 295-314. https://doi.org/10.1080/0376835x.2013.817308
- Biyase, M., & Zwane, T. (2018). An empirical analysis of the determinants of poverty and household welfare in South Africa. The Journal of Developing Areas, 52(1), 115-130. https://doi.org/10.1353/jda.2018.0008
- Biyase, M., Zwane, T., & Rooderick, S. (2019). Assets and poverty alleviation in south africa: Evidence from the national income dynamics study. *Journal of Economic Cooperation & Development*, 40(1), 55-77. https://doi.org/10.1080/0376835x.2017.1362331
- Blank, R. (1997). It takes a nation: A new agenda for fighting poverty. New York: Russell Sage Foundation.
- Booysen, F. L. R., Van Der Berg, S., Burger, R., Von Maltitz, M., & Du Rand, G. (2007). Trends in poverty and inequality in seven African countries. Retrieved from Poverty Monitoring, Measurement and Analysis (PMMA) Working Paper No. 2007-06. Quebec, Canada: Poverty and Economic Policy Network.
- Bradshaw, T. K. (2006). Theories of poverty and anti-poverty programs in community development. Retrieved from Rural Overty Research Centre (RPRC) Working Series No.06-05 Oregon State University and University of Missouri:
- Daka, L., & Fandamu, H. (2016). Evaluating poverty determinants in Zambia with principle component analysis and logistic regression. *International Journal of Multidisciplinary Research and Development*, 3(2), 320-327.
- DataFirst. (2021). National income dynamics study 2017, Wave 5. Retrieved from https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/712
- Davis, P., & Sanchez-Martinez, M. (2014). A review of the economic theories of poverty. Retrieved from National Institute and Social Research. Discussion Paper, No. 435:
- Dunga, S. H. (2017). A gender and marital status analysis of household income in a low-Income township. *Studia Universitatis Babes Bolyai-Oeconomica*, 62(1), 20-30. https://doi.org/10.1515/subboec-2017-0002
- Dunga, S. H. (2024). An analysis of poverty among the poor using the poverty depth measure. *International Journal of Economics and Financial Issues*, 14(5), 167-176.
- Filmer, D., & Pritchett, L. H. (2001). Estimating wealth effects without expenditure data—or tears: an application to educational enrollments in states of India. *Demography*, 38(1), 115-132. https://doi.org/10.2307/3088292
- Fisher, M., & Weber, B. A. (2004). Does economic vulnerability depend on place of residence? Asset poverty across metropolitan and nonmetropolitan areas. Review of Regional Studies, 34(2), 137-155. https://doi.org/10.52324/001c.8381
- Garza-Rodriguez, J., Ayala-Diaz, G. A., Coronado-Saucedo, G. G., Garza-Garza, E. G., & Ovando-Martinez, O. (2021).

  Determinants of poverty in Mexico: A quantile regression analysis. *Economies*, 9(2), 60. https://doi.org/10.3390/economies9020060
- Grootaert, C. (1997). The determinants of poverty in cote d'Ivoire in the 1980s. *Journal of African Economies*, 6(2), 169-196. https://doi.org/10.1093/oxfordjournals.jae.a020925
- 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), 1472-1482. https://doi.org/10.11564/29-1-700
- Hair, J., Black, W., Babin, R., & Anderson, R. (2010). Multivariate data analysis (7th ed.). New York: Pearson Prentice Hall. Halisçelik, E., & Soytas, M. A. (2019). Sustainable development from millennium 2015 to sustainable development goals 2030. Sustainable Development, 27(4), 545-572. https://doi.org/10.1002/sd.1921
- Hunter, N., May, J., & Padayachee, V. (2003). Lessons for PRSP from poverty reduction strategies in South Africa. Retrieved from Working Paper. No 39.

Imai, K. S., Gaiha, R., & Kang, W. (2011). Poverty, inequality and ethnic minorities in Vietnam. *International Review of Applied Economics*, 25(3), 249-282. https://doi.org/10.1080/02692171.2010.483471

Kaiser, H. F. (1974). An index of factorial simplicity. Psychometrika, 39(1), 31-36. https://doi.org/10.1007/bf02291575

Khudri, M. M., & Chowdhury, F. (2013). Evaluation of socio-economic status of households and identifying key determinants of poverty in Bangladesh. *European Journal of Social Sciences*, 37(3), 377-387.

Koomson, I., Abdul-Mumuni, A., Ampah, D. K., & Afful, A. F. (2023). The link between households' durable asset accumulation and healthcare utilisation and spending. *International Review of Applied Economics*, 37(5), 686-710. https://doi.org/10.1080/02692171.2023.2254246

Majeed, M. T., & Malik, M. N. (2015). Determinants of household poverty: Empirical evidence from Pakistan. *The Pakistan Development Review*, 54(4), 701–717.

Mare, Y., Gecho, Y., & Mada, M. (2022). Determinants of multidimensional rural poverty in Burji and Konso area, Southern Ethiopia. *Cogent Social Sciences*, 8(1), 1-18.

Mburu, S., Otterbach, S., Sousa-Poza, A., & Mude, A. (2017). Income and asset poverty among pastoralists in Northern Kenya. *The Journal of Development Studies*, 53(6), 971-986. https://doi.org/10.1080/00220388.2016.1219346

McKnight, A. (2011). Estimates of the asset-effect: The search for a causal effect of assets on adult health and employment outcomes. Retrieved from LSE STICERD Research Paper No. CASE149.

Mdluli-Maziya, P., Mncayi, P., & Sere, K. (2024). Poverty among youth-headed households in South Africa: Quo vadis. Journal of Poverty, 28(3), 196-210. https://doi.org/10.1080/10875549.2022.2128979

Muzindutsi, P.-F. (2018). A comparative analysis of income-and asset-based poverty measures of households in a township in South Africa. *International Journal of Economics and Finance Studies*, 10(1), 184-202.

Nelson Mandela. (1995). Nelson Mandela inaugural speech 1995. Pretoria.: Government Printer.

Nelson Mandela Foundation. (2005). Emerging voices: A report on education in South African rural communities. Cape Town: HSRC Press.

Nwosu, C. O., & Woolard, I. (2017). The impact of health on labour force participation in South Africa. South African Journal of Economics, 85(4), 481-490. https://doi.org/10.1111/saje.12163

Odeh, M. A., & Okoye, C. O. (2014). Poverty reduction policy and youth unemployment in Nigeria. *Public Policy and Administration Research*, 3(4), 92-103.

Posel, D., & Rogan, M. (2012). Gendered trends in poverty in the post-apartheid period, 1997–2006. Development Southern Africa, 29(1), 97-113. https://doi.org/10.1080/0376835x.2012.645645

Sadeghi, J. M. (2001). Determinants of poverty in rural areas: Case of Savejbolagh farmers in Iran. World Bank Working Papers No. 0112.

SALDRU. (2016). National income dynamics study wave 3 [dataset]. Version 1.3. Cape Town: Southern Africa labour and development research unit. Cape Town: DataFirst.

Sameti, M., Esfahani, R. D., & Haghighi, H. K. (2012). Theories of poverty: A comparative analysis. Arabian Journal of Business and Management Review (Kuwait Chapter), 1(6), 45-56.

Schwartz, B. (2000). Self-determination: The tyranny of freedom. American Psychologist, 55(1), 78-88.

Scott, J. (2002). Social class and stratification in late modernity. Acta Sociological, 45(1), 23-35.

Sekhampu, T. J. (2013). Determinants of poverty in a South African township. Journal of Social Sciences, 34(2), 145-153. https://doi.org/10.1080/09718923.2013.11893126

Sen, A. (1976). Poverty: An ordinal approach to measurement. *Econometrica*, 46, 437–446.

Sen, A. (1999). Development as freedom. Oxford: Oxford University Press.

Sherraden, M. (2014). Asset building research and policy: Pathways, progress, and potential of a social innovation. In: Cramer, R., Shanks, T.R.W. (Eds.), The Assets Perspective. New York: Palgrave Macmillan.

Statistics South Africa. (2019). Overcoming poverty and inequality in South Africa. Overcoming Poverty and Inequality in South Africa. Pretoria: Statistics South Africa.

Stats, S. (2017). Poverty trends in South Africa: An examination of absolute poverty between 2006 and 2015. Retrieved from Report No. 03-10-06. Pretoria. South Africa:

Stats, S. (2018). Findings of the living conditions survey 2014/15. Retrieved from Report No.: 03-10-02 (2014/2015):

Stats, S. (2021). Statistical release P0211 quarterly labour force survey. Pretoria: Quarter 1.

Tabachnick, B., & Fidell, L. S. (2007). Using multivariate statistics (5th ed.). Boston: Allyn & Bacon.

Tsehay, A. S., & Bauer, S. (2012). Poverty and vulnerability dynamics: Empirical evidence from smallholders in northern highlands of Ethiopia. *Quarterly Journal of International Agriculture*, 51(4), 301-332.

Ullah, K., & Chishti, M. Z. (2023). Spatial distribution of poverty in Pakistan: An asset-based approach. Future Business Journal, 9(1), 2-20. https://doi.org/10.1186/s43093-022-00162-4

Vyas, S., & Kumaranayake, L. (2006). Constructing socio-economic status indices: How to use principal components analysis. Health Policy and Planning, 21(6), 459-468. https://doi.org/10.1093/heapol/czl029

Wang, M., & Li, X. (2024). Estimating asset wealth using multidimensional luminous information in areas lacking nighttime light. *International Journal of Digital Earth*, 17(1), 2-19. https://doi.org/10.1080/17538947.2024.2336049

Wooldridge, J. M. (2001). Applications of generalized method of moments estimation. *Journal of Economic Perspectives*, 15(4), 87-100.

Xhafaj, E., & Nurja, I. (2015). The principal components analysis and cluster analysis as tools for the estimation of poverty, an Albanian case study. *International Journal of Science and Research*, 4(1), 1240-1243.

Zenda, M. (2002). A system approach to marketing in less developed agriculture with reference to bululwane irrigation scheme. Unpublished MSc Thesis, Department of Agriculture, University of Fort Hare.

Zwane, T. T. (2022). Socio-economic status of households and the determinants of asset poverty: A case of South Africa. *International Journal of Economics and Financial Issues*, 12(4), 114-122. https://doi.org/10.32479/ijefi.12975

# APPENDIX

Table A1. Results for the extraction of components based on the urban sample.

Initial eigenvalues				Eigenval	ues of extracted	components		Eigenvalue of extracted compon	
Component	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	4.7151	0.0982	0.0982	4.7151	0.0982	0.0982	2.5389	0.0529	0.0529
2	2.2342	0.0465	0.1448	2.2342	0.0465	0.1448	2.0359	0.0424	0.0953
3	2.0008	0.0417	0.1865	2.0008	0.0417	0.1865	1.8800	0.0392	0.1345
4	1.6852	0.0351	0.2216	1.6852	0.0351	0.2216	1.7117	0.0357	0.1701
5	1.6390	0.0341	0.2557	1.6390	0.0341	0.2557	1.7109	0.0356	0.2058
6	1.5743	0.0328	0.2885	1.5743	0.0328	0.2885	1.6657	0.0347	0.2405
7	1.4901	0.0310	0.3196	1.4901	0.0310	0.3196	1.6106	0.0336	0.2740
8	1.4267	0.0297	0.3493	1.4267	0.0297	0.3493	1.5888	0.0331	0.3071
9	1.3558	0.0282	0.3775	1.3558	0.0282	0.3775	1.5217	0.0317	0.3388
10	1.2801	0.0267	0.4042	1.2801	0.0267	0.4042	1.5159	0.0316	0.3704
11	1.2684	0.0264	0.4306	1.2684	0.0264	0.4306	1.4618	0.0305	0.4009
12	1.1916	0.0248	0.4555	1.1916	0.0248	0.4555	1.4117	0.0294	0.4303
13	1.1518	0.0240	0.4795	1.1518	0.0240	0.4795	1.3962	0.0291	0.4594
14	1.1369	0.0237	0.5031	1.1369	0.0237	0.5031	1.3819	0.0288	0.4882
15	1.1011	0.0229	0.5261	1.1011	0.0229	0.5261	1.2633	0.0263	0.5145
16	1.0893	0.0227	0.5488	1.0893	0.0227	0.5488	1.2632	0.0263	0.5408
17	1.0747	0.0224	0.5712	1.0747	0.0224	0.5712	1.2604	0.0263	0.5671
18	1.0509	0.0219	0.5931	1.0509	0.0219	0.5931	1.1696	0.0244	0.5914
19	1.0278	0.0214	0.6145	1.0278	0.0214	0.6145	1.1055	0.0230	0.6145
20	0.9980	0.0208	0.6353						

**Table A2.** Results for the extraction of components based on the rural sample.

								Eigenvalue	of extracted
Initial eigenval	Initial eigenvalues		Cumulative	E	igenvalues of ext	component			
Component	Total	% of variance	%	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	4.1979	0.0840	0.0840	4.1979	0.0840	0.0840	2.7274	0.0545	0.0545
2	1.9370	0.0387	0.1227	1.9370	0.0387	0.1227	2.1052	0.0421	0.0967
3	1.8235	0.0365	0.1992	1.8235	0.0365	0.1992	1.8127	0.0363	0.1329
4	1.7835	0.0357	0.1948	1.7835	0.0357	0.1948	1.6810	0.0336	0.1665
5	1.5144	0.0303	0.2251	1.5144	0.0303	0.2251	1.5754	0.0315	0.1980
6	1.4068	0.0281	0.2251	1.4068	0.0281	0.2251	1.4767	0.0295	0.2276
7	1.3810	0.0276	0.2809	1.3810	0.0276	0.2809	1.4750	0.0295	0.2571
8	1.2890	0.0258	0.3067	1.2890	0.0258	0.3067	1.4424	0.0288	0.2859
9	1.2219	0.0244	0.3311	1.2219	0.0244	0.3311	1.3426	0.0269	0.3128

10	1.1875	0.0238	0.3549	1.1875	0.0238	0.3549	1.3326	0.0267	0.3394
11	1.1698	0.0234	0.3783	1.1698	0.0234	0.3783	1.2687	0.0254	0.3648
12	1.1671	0.0233	0.4016	1.1671	0.0233	0.4016	1.2526	0.0251	0.3899
13	1.1540	0.0231	0.4247	1.1540	0.0231	0.4247	1.2010	0.0240	0.4139
14	1.1163	0.0223	0.4470	1.1163	0.0223	0.4470	1.1957	0.0239	0.4378
15	1.0875	0.0218	0.4688	1.0875	0.0218	0.4688	1.1459	0.0229	0.4607
16	1.0795	0.0216	0.4903	1.0795	0.0216	0.4903	1.1444	0.0229	0.4836
17	1.0644	0.0213	0.5116	1.0644	0.0213	0.5116	1.1441	0.0229	0.5065
18	1.0512	0.0210	0.5327	1.0512	0.0210	0.5327	1.1009	0.0220	0.5285
19	1.0333	0.0207	0.5533	1.0333	0.0207	0.5533	1.0813	0.0216	0.5501
20	1.0279	0.0206	0.5739	1.0279	0.0206	0.5739	1.0800	0.0216	0.5717
21	1.0156	0.0203	0.5942	1.0156	0.0203	0.5942	1.0689	0.0214	0.5931
22	1.0122	0.0202	0.6144	1.0122	0.0202	0.6144	1.0668	0.0213	0.6144
23	0.9930	0.0199	0.6343		•				