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Socio-Economic Status of Households and the Determinants of Asset Poverty: A Case of South Africa

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ABSTRACT

When measuring poverty in South Africa, much of the theoretical and empirical work has focused on money-metric measures of poverty. The conventional approach has been the use of a poverty line sufficient to meet primary human needs, often derived from consumption, expenditure or income levels. This narrow perspective has tended to divert the attention of development economists towards the pursuit of income growth, which has been associated with development and a necessary condition for poverty reduction. However, with a changing emphasis on development, the model, analytical methods, and related frameworks have been subjected to critical scrutiny by populists and neoliberals alike. The purpose of this study is to contributes to the existing literature by using an alternative approach ─ a non-monetary approach to the measurement of poverty in South Africa. To the best of our knowledge, this is the first study in South Africa to compute an asset poverty index using principal component analysis in a panel setting and use appropriate panel data models to investigate the key determinants of asset poverty. We used data drawn from the existing five waves of the National Income Dynamic Study. Using the random effect probit model, we found that some factors, such as levels of education of the head of household (primary, secondary, matric and tertiary) and land ownership, have a reducing influence on asset poverty. Factors The results also revealed that household size and unemployed people are more prone in South Africa.

Keywords: Asset Poverty, Random Effect Probit, Principal Component Analysis, South Africa
JEL Classifications: 132; 138

1. INTRODUCTION

While South Africa is classified as an upper middle income economy (also considered as Africa's biggest economy), the incidence of poverty remains obstinately high by historical and international standards. Using a baseline poverty line of R450 per capita per month, Tregenna (2012) found a poverty incidence of 52.45% (using expenditure) and 49.56% (using income) in 2006. The government's economic policies are focusing on the dual objective of fast-tracking growth and fighting poverty and unequal access to opportunities with stronger emphasis than before (Stats SA, 2017). Post-apartheid examples of economic policies designed for this under the rubric of the New Growth Path (NGP) policy announced by President Zuma in 2010 indicated that inequality, unemployment and poverty in South Africa are high by international standards (Stats SA, 2017). Similarly, the National Development Plan (NDP), adopted by both Cabinet and Parliament some years ago as the country's policy blueprint for poverty eradication and elimination of inequality by 2030 also raised similar issues of the vulnerability of households as a result of prolonged poverty (Stats SA, 2017).

Generally, as is common practice in South Africa, when measuring poverty, much of the theoretical and empirical work have focused on the monetary dimension as measures of poverty (see for example, Sekhampu, 2013; Tregenna, 2012; Gumede, 2008; Leibbbrandt and Woolard, 2006; Leibbrandt et al., 2005; Finn, 2013; Stats SA, 2017). For years' monetary dimensions, income and consumption have provided a remarkable and stable framework for measuring poverty at the level of the individual and households, and have for some time stabilised policymaking in the face of a highly complex and uncertain economic and development environment in the developing world. The conventional approach has been the use of a poverty line – often derived from consumption, expenditure or income levels – sufficient to meet primary human needs (Tsehay and Bauer, 2012). This narrow perspective has tended to divert the attention of development economists towards the pursuit of income growth, which has been associated with development and a necessary condition for poverty reduction. However, with a changing emphasis on development, populists and neoliberals alike have subjected the model, analytical methods, and related frameworks to critical scrutiny.

Although poverty may be high in South Africa, as shown by the numbers above, there are good reasons to suggest that the money-metric measures (such as income or consumption) may not be appropriate measures of poverty in the country. For instance, Sen (1999) sheds some light on the reasons why the income poverty line may not be a good measure to use in developing countries, South Africa included. In his seminal paper, Sen (1999: 18) wrote: "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 include other dimensions rather than simply relying on monetary dimensions, and would include a household's broad set of capabilities."

Recent analysis (see for instance, Bhorat et al., 2014; Farah, 2015; Daka and Fandamu, 2016; Akinbode and Hamzat, 2017) have argued that the patterns of households' consumption behaviour may not be the same: hence, reaching an income poverty line may not give an assurance that a household will meet the minimum needs. With regards to income inequality, Wittenberg and Leibbrandt (2017) find evidence that seem to suggest that "the money-metric approach to inequality measurement in South Africa may have obscured the real progress in large portions of the population and in important dimensions of inequality". Given these challenges, appropriate anti-poverty strategies in South Africa clearly should be based on a thorough understanding of the nature and causes of poverty.

The aim of this study is to contributes and improves upon the existing literature by using an alternative approach ─ a non-monetary approach to the measurement of poverty. The novelty of this study is that we all five waves of the NIDS data to create an asset-poverty index in a panel setting using the PCA to identify the poor. Compared to other alternative statistical techniques (refer to section 3.1 for a comprehensive analysis of its strength), PCA is computationally easier, can use the type of data that can be more easily collected in household surveys, and uses all of the variables in reducing the dimensionality of the data (Vyas and Kamaranayake, 2006; Habyarimana et al., 2015). To the best of our knowledge, this is the first study that used panel data models, such as a random effect probit model, to investigate the main determinants of asset poverty in South Africa. Being able to identify the key determinants of asset poverty could contribute to the formulation of specific policies to reduce the overall impact of poverty on the South Africa population. With South Africa quickly emerging as a fast-growing economic hub, it is important to understand the underlying welfare dynamics that determine people's escape from asset poverty or, alternatively, their plunge into asset poverty over time. The rest of this study is arranged as follows: Section 2 presents a brief review of the existing empirical literature. Section 3 offers a broader overview of the methodology used. Section 4 describes the data source, while Section 5 discusses the results. Section 5 concludes.

2. LITERATURE REVIEW

The empirical and theoretical literature on the determinants of poverty is well established (see for example, Geda et al., 2005; Datt and Jolliffe, 2005; Mok et al., 2007; Julie et al., 2008; Litchfield and McGregor, 2008; Akerele and Adewuyi, 2011; Gounder, 2012; Edoumiekumo et al., 2013; Sekhampu, 2013; Edoumiekumo et al., 2014; Lekobane and Seleka, 2017). On the empirical front, the results have repeatedly spawned arguments among researchers, with no clear empirical answer about the main determinants of poverty. Arguments, particularly with reference to the inconclusive results, can be largely due to scholars adopting various poverty measurement approaches (Akinbode and Hamzat, 2017).

For instance, there is a strand of literature that have endorsed the use of money-metric approach ─ such as income or consumption as measures of household welfare (see for example, Sekhampu, 2013; Tregenna, 2012; Finn, 2013; Hoogeveen and Ozler, 2006; Gyekye et al., 2001; May et al., 1995; Whiteford et al., 1995; Finn, 2013). The income-insufficient approach as a measure of poverty has been very efficient in shaping policy action directed towards poverty reduction in developing countries (Nolan and Whelan, 2010). Monetary dimensions, income and consumption as measures of poverty have been very useful when comparing differences in poverty between countries (Naschold, 2012).

However, most recent studies (see, for example, Naschold, 2012; Brandolini et al., 2010; Filmer and Pritchett, 2001; Vyas and Kamaranayake, 2006; Habyarimana et al., 2015) have been skeptical of using monetary dimension indicators, arguing that, despite their intuitive appeal and use, money-metric measures cannot adequately and credibly capture all the resources used by households to cope with various shocks. Reaching a similar conclusion, Akinbode and Hamzat (2017) argued that the measurement of consumption and expenditure in low-income countries may be fraught with difficulties, such as the problem of recall and a reluctance to divulge information. Perhaps a common criticism of the monetary dimension indicators refers to the reliability of income or expenditure data. For example, Yu (2009) found that numerous households in South Africa reported zero or unspecified income in censuses, yet excluding these households would have led to a biased sample, thereby resulting in unreliable poverty estimates.

Vyas and Kumaranayake (2006) echoed the same sentiment on the inadequacies of the money-metric approach, arguing that the collection of data on income and expenditure can be time- and money-consuming. In developing countries (see, for example, Deaton and Zaidi, 1999; Sahn and Stifel, 2003; Vyas and

Kumaranayake, 2006), prices often differ substantially across times and areas, demanding a complex adjustment of the expenditure figures to reflect these price differences. Other concerns have also been raised in the literature, such as problems of sampling bias, under-reporting of income and difficulties of converting household products into money terms (see also Farah, 2015; Daka and Fandamu, 2016; Akinbode and Hamzat, 2017).

But given the challenges of deploying the conventional frameworks associated with the money-metric approach, recent studies have embraced a non-monetary approach – computing an asset index which gives socio-economic status of each household in the sample (see for example, Sen, 1999; Xhafaj and Nurja, 2013; Bhorat et al., 2014; Farah, 2015; Daka and Fandamu, 2016; Akinbode and Hamzat, 2017). These studies considered it to be a feasible practice to focus on households' ownership of assets and access to services, arguing that assets symbolise a household's capabilities and thus multi-dimensional welfare. Measures that embrace a household's command over assets, including different forms of capital, would explicitly be more representative of the underlying achievement of a household (Sahn and Stifel, 2003), given that the underlying functioning of assets is indicative of the household's capabilities (Sen, 1999), and can presumably present a fair picture of a household's wellbeing and allow for a richer analysis of policy impacts (Daka and Fandamu, 2016). Generally, the vulnerability of a household is influenced by the nature of its poverty in assets rather than income poverty since it is asset poverty that mainly contributes to income poverty (Daka and Fandamu, 2016).

Amidst the multi-dimensional approaches to the measurement of poverty, the asset index approach applied to Demographic and Health Survey data (DHS) has gained increasing popularity since the last couple of years (Wittenberg and Leibbrandt, 2017). Recently, Wittenberg and Leibbrandt (2017) argued that the DHS are among the richest, most reliable and representative series of data for health and demographic analysis in developing nations. In their paper, Wittenberg and Leibbrandt (2017) observed that a Google scholar search (April 18, 2014) came up with 13 900 "hits" on the "DHS wealth index", 2434 citations of the work of Filmer and Pritchett (2001), and 591 citations of the article by Rutstein and Johnson (2004), detailing the computation of the DHS index using household assets. Data of household's assets, such as durable and semi-durable goods, are used to depict household socio-economic status by this method (Wittenberg and Leibbrandt, 2017). In contrast, an asset index requires data that are easily and quickly collectable and less intensive, which feasibly result in smaller measurement errors (Khudri and Chowdhury, 2013).

In the absence of income or expenditure data and on account of the widespread availability of the DHS for many developing nations, the asset index method is often utilised for this type of dataset to measure the wellbeing/socio-economic status and determinants of household poverty (see for instance, Filmer and Pritchett, 2001; Booysen, 2002; Sahn and Stifel, 2000, 2003; Vyas and Kumaranayake, 2006; Achia et al., 2010; Habyarimana et al., 2015; Akinbode and Hamzat, 2017).

Regarding household wellbeing/socio-economic status, Vyas and Kumaranayake (2006) utilised PCA to compute a separate asset index for urban and rural regions of Brazil and Ethiopia using the DHS dataset. Using factors scores from the first PCA, Vyas and Kumaranayake (2006) reported that, in the urban regions of Brazil, piped drinking water to residence, sanitation facility, finished floor and the number of rooms for sleeping were related to high socio-economic status of households. Similar results were observed for rural Brazil except for the fact that it comprised any sanitation facility and a well in the residence (Vyas and Kumaranayake, 2006). In urban Ethiopia, drinking water piped to the compound was indicative of high social-economic status of households (Vyas and Kumaranayake, 2006). Whereas in rural Ethiopia access to infrastructure facilities and ownership of any assets was associated with high socio-economic status of households (Vyas and Kumaranayake, 2006).

Habyarimana et al. (2015) used the DHS dataset and PCA to compute an asset index for Rwanda. They reported that flush toilet, cement, electricity, and piped water to the yard had larger and positive factors scores. On the other hand, assets like sand floor material, a borehole and river/dam as sources of drinking water and a latrine as toilet facility had a negative factor scores (Habyarimana et al., 2015). In their study, Booysen (2002) measured differences in socio-economic status of South African households based on 19 variables from DHS survey data. The results revealed that electricity for cooking, flush toilet, piped water in a dwelling and public had a high socio-economic status (Booysen, 2002). In contrast, assets such as using paraffin, wood and dung for cooking, as well as the number of members per sleeping room had a negative socio-economic status (Booysen, 2002). Filmer and Pritchett (2001) used DHS data to compute an asset index and use the constructed index to examine the association that exists between household wealth and children's school enrolment in India. The findings revealed that owning a watch, radio and television, flushing toilet, light electricity and dwelling in a high-quality material was associated with positive socio-economic status of households in India. In contrast, drinking water from open pumps and dwelling in low-quality materials were associated with negative socio-economic status of households (Filmer and Pritchett, 2001).

There is emerging strand of literature that have measured the wellbeing/socio-economic status of households using PCA first and then utilised logistic regression to investigate the determinants of household poverty using DHS dataset. For instance, Achia et al. (2010) investigated the determinants of poverty in Kenya. They constructed an asset index using PCA from asset-ownership variables from the Kenyan DHS of 2003. A logistical regression to identify the key determinants of poverty in Kenya showed that a rural family has a high probability of being poor when compared to an urban family. According to their study, demographic variables that increased the probability of being poor included the age of the head of household, religion and ethnicity (Achia et al., 2010).

Another study by Akinbode and Hamzat (2017) used PCA to compute an asset index using data from the Zambia DHS conducted between 2013 and 2014. Using logistical regression, they found that the education level of the head of household and the marital status and income earnings from the heads of households were significant determinants of poverty status in rural Nigeria. Habyarimana et al. (2015), who also applied PCA to create an asset index using the Rwanda Demographic Health Survey of 2010, also found similar results.

Consistent with previous studies, Habyarimana et al. (2015) affirmed that the educational status of the household head, age of the household head, gender of the household head, place of residence, the location of the household and the size of the household were significant predictors of the poverty of a household in Rwanda. In this empirical work, we follow a related approach of firstly creating an asset-index applying PCA and the use the random probit model to investigate the main determinants of asset poverty in South Africa.

3. RESEARCH METHODS AND DATA

This section presents the methodology applied in this study to assess an asset-based approach to poverty analysis in South Africa. To investigate asset poverty, we implemented various methods. We began with PCA (Section 3.1), while Section 3.2 investigates the determinants of asset poverty using a random effect probit model.

3.1. Computation of an Asset-poverty Index

Contrary to most existing studies in this field, which have a money-metric approach to poverty analysis, we used an alternative approach — an asset-based index approach. A wide range of possible aggregation methods can be used to create an asset index. There are studies that have adopted the equal-weighting approach (Montgomery et al., 2000). Bhorat et al. (2014) described equal weight as an approach that gives the same weighting to the total assets controlled by the households. However, various scholars have criticised the equal-weighting technique, arguing it has nothing special except its ease of use. Arriving at a similar conclusion, McKenzie (2005) argued that this approach makes it more challenging if scholars wish to incorporate measures of quality for goods or services, once there are more than two quality options. In summarising the criticism of the equal-weighting approach, Wittenberg (2009. p. 24) wrote: "it can also have paradoxical effects when certain assets are inferior goods, so that their ownership makes households look more affluent when in reality it might signal less affluence."

In recent years, poverty scholars have eluded the criticisms of equal weighting by adopting PCA (Khudri and Chowdhury, 2013; Daka and Fandamu, 2016; Akinbode and Hamzat, 2017), while other scholars have used factor analysis (FA) (Sahn and Stifel, 2003; Naschold, 2006).

Despite the availability of multiple techniques in the computation of an asset index, the PCA – a technique that is closely linked to FA – has proven to be an appealing technique for use in poverty analysis. The reasons for its popularity are many and here we provide the key ones. A noticeable strength of the principal component is that it is computationally easier and the weights assigned to each component in the analysis are not difficult to interpret, since the weight assigned to any variable relates to the extent of the information provided about the other variables (Filmer and Pritchett, 2001; Bhorat et al., 2014). First, as a technique to extract shared information from a set of interrelated variables, it is often seen as relatively intuitive (Naschold, 2006). Filmer and Pritchett (2001: 116) wrote, "the first principal component of a set of variables is the linear index of all the variables that captures the largest amount of information that is common to all the variables. Second, the weights that are given to individual components in regression are fairly simple to explain because the weight that is given to each factor relates to the extent of the information provided about the other variables (Vyas and Kumaranayake, 2006). Thirdly, assets that are more unequally distributed across households are accorded greater weight in a PCA (see for example, Bhorat et al., 2014; Habyarimana et al., 2015). Lastly, in terms of interpretation, a variable with a positive weight is associated with higher socio-economic status, and conversely a variable with a negative weight is associated with lower socio-economic status (Vyas and Kumaranayake, 2006; Xhafaj and Nurja, 2013).

Therefore, our decision to use the PCA is based on the merits outlined above, apart from the fact that this method has been popularised as an analysis tool, both globally and locally. For South Africa, the main proponents include Booysen (2002) and Van der Berg et al. (2003), while the global studies include Vyas and Kumaranayake (2006), Tsehay and Bauer (2012), Habyarimana et al. (2015), and Akinbode and Hamzat (2017). The main objective of applying the PCA in a poverty analysis is to extract the poverty component that can be used to derive a poverty index for each household (Akinbode and Hamzat, 2017). Set out below is a standard formula to create scores on the first component extracted by employing the PCA:

$$\begin{aligned} PC_1 &= \Phi_{11}A_1 + \Phi_{12}A_2 + \cdots + \Phi_{1P}A_P \\ PC_2 &= \Phi_{21}A_1 + \Phi_{22}A_2 + \cdots + \Phi_{2P}A_P \\ \cdots &\quad \cdots \quad \cdots \quad \cdots \quad \cdots, \\ PC_p &= \Phi_{p1}A_1 + \Phi_{p2}A_2 + \ldots + \Phi_{pp}A_P \end{aligned} \tag{1}$$

Where φ_{pp} denotes the weights for the p^{th} principal component and the A_p variable. In principle, the components are ordered such that the first principal component contains the biggest variation in the original dataset, while the second principal component, which is uncorrelated with the first component contains the second-biggest variance, and the successive components contain additional but less variance than the first component (see also, Vyas and Kumaranayake, 2006; Xhafaj and Nurja, 2013; Akinbode and Hamzat, 2017).

We follow many prominent researchers in this field and implement a three-step estimation procedure in implementing the PCA (see for example, Vyas and Kumaranayake, 2006; Akinbode and Hamzat, 2017). The first step involves verifying whether there is adequate correlation between the variables (Akinbode and Hamzat, 2017). To achieve this objective, the Kaiser–Meyer–Olkin (KMO) test is applied. KMO values less than 50% are considered inadequate and unacceptable, while values above 60% are acceptable (Tabachnick and Hair et al., 2010). The second step, involving the information criteria used to determine the number of common factors to keep, is from Kaiser (1974). The recommendation is to retain factors with an eigenvalue greater or equal to one (Tabachnick and Hair et al., 2010). The Kaiser's rule is often complemented with the use of the scree plot. This distinct break is referred to as the "elbow" and it is generally recommended that all factors above this break should be retained (Hair et al., 2010), as they contribute most to the explanation of the variance in the dataset (Tabachnick and Fidell, 2007). The third step involves the rotation solution (Hair et al., 2010). After extracting the components, the factor loading of each variable is calculated (Xhafaj and Nurja, 2013). Following many scholars in this field, we also used a varimax rotation solution (Habyarimana et al., 2015; Akinbode and Hamzat, 2017).

A comprehensive analysis of poverty should go beyond a routine description of poverty trends, if we are to effectively account for factors underlying poverty. Thus, the following section will pay more attention to the determinants of asset poverty. Precisely, we used an asset-poverty index as the dependent variable in the regression model and applied a random effect probit estimator.

3.2. Statistical Analysis

To investigate the key determinants of asset poverty in South Africa, a random effect probit model was used. The random effect probit model estimates the probability of people being asset-poor as the dependent variable against a combination of independent variables ─ the age of the head of the household, employment status of the head of household, household size, location, landholding, saving by the head of the household, province dummies, gender of the household head and marital status of the household head. The novelty of the random effect probit model, unlike in the fixed-effect logit, is that the model is able to capture variables that are time-invariable. This technique has been used in many previous studies in this field (for example, Ghazouani and Goaied, 2001; Fisher and Weber, 2004). Given the dichotomous nature of the outcome variable, we assigned a value of 1 if the household is poor and 0 if not. The estimation procedure is expressed as follows:

$$AssP_i t^* = \forall_{it}\beta + v_{it} \tag{2}$$

Hence

$$AssP_{it} = \begin{cases} P_{it}^*, if\ P_{it}^* > 0 \\ 0, otherwise \end{cases} \tag{3}$$

Where i represents each household at time period t ($t = 5$), $AssP_{it}^*$ denotes the latent dependent variable for being in asset poverty, while $AssP_{it}$ shows the observed outcome, and $\forall_{it}$ represents a vector of time-varying and time-invariant regressors. The subscript β shows the vector of coefficients linked to the $\forall_{it}$ regressors, while v_{it} is a random error which is assumed to be identically distributed. Whereas equation (3) implicitly indicates the observed binary outcome variable, for a detailed description of logistic regression refer to Wooldridge (2001). In a panel context, the error term is generally shown as follows:

$$v_{it} = \lambda_i + \mu_{it}$$

where λ_i denotes household-specific unobservable effects, while $\propto_{it}$ indicates the unobservable individual and random effects (for example, Guilkey and Murphy, 1993; Ghazouani and Goaied, 2001). As the estimated coefficients of the probit model are not directly interpretable, in this study the marginal effects were computed to facilitate ease of interpretation.

In deciding on the appropriate poverty line, we followed others in this field (Booysen, 2002; Achia et al. 2010; Farah, 2015; Habyarimana et al., 2015; Mburu et al., 2016; Akinbode and Hamzat, 2017) and used the 40th percentile as an appropriate poverty line and to classify households according to their poverty status. As observed by Achia et al. (2010) and Habyarimana et al. (2015), the use of a 40th percentile as a poverty line is standard and consistent with what is frequently recommended by the World Bank in poverty analysis. In selecting this poverty line, households were classified as poor if the asset index was less than the 40th percentile; otherwise, households were classified as not poor (Habyarimana et al., 2015).

4. DATA SOURCE

The data used in this paper come from the newly available panel dataset, the NIDS observed over the period 2008-2017. The NIDS dataset was conducted by the Southern African Labour and Development Research Unit (SALDRU), based at the University of Cape Town's School of Economics (see, for example, SALDRU, 2016). The NIDS began in 2008 with over 28 000 individuals in 7300 households across South Africa (Finn and Leibbrandt, 2017). The initial respondents are tracked over the years (Finn and Leibbrandt, 2017). After that, individuals who were interviewed in the initial sample, including their spouses and children, are re-interviewed, in biennial waves. In wave two, conducted in 2010/2011, the survey successfully interviewed 6787 households, with a total of 28 551 individuals successfully completing the interviews (Nwosu and Woolard, 2017). In wave three, a total of 8040 households were successfully interviewed, with an overall total of 32 633 individuals successfully completing the interviews (Finn and Leibbrandt, 2017). Wave four of the NIDS data was collected between 2014 and 2015 and 37 396 individuals were successfully interviewed (SALDRU, 2016). The most recent wave, wave five, was conducted in 2017. The survey successfully interviewed 10 800 households, with 39 400 individuals completing the interviews. See www.nids.uct.ac.za for a comprehensive description of the NIDS dataset.

5. RESULTS

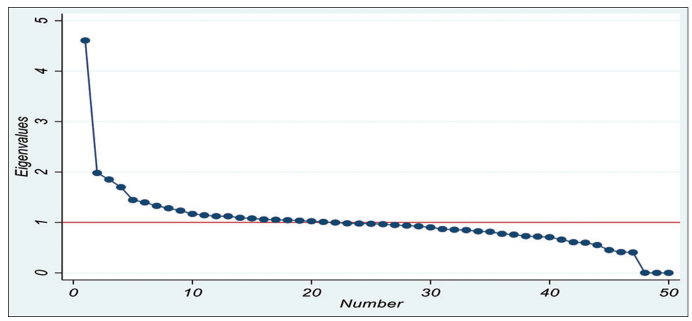
This section presents the results obtained from implementing the methods outlined earlier. Thus, the first section presents the PCA results, while the second section discusses the results obtained using the panel random effect probit estimator.

5.1. Results from Principal Component Analysis

To assess the suitability of using the PCA in the NIDS dataset, the KMO scores were computed across regions and the results show that the NIDS is appropriate for the use of PCA. In an attempt to determine the precise number of components to be extracted, we relied on the Kaiser's rule supplemented by the scree plot and the rotated matrix. For a comprehensive analysis of the eigenvalues of extracted component results, refer to Appendix Table 1. The results of Kaiser's rule indicate that the extracted 21 components explain 59% of the variation observed in the original dataset. Thus, component 1 explain 9% of the variation, and each component excluding the first one describes a diminishing proportion of variance afterwards. To validate the number of components extracted, we used the scree plot (Figure 1) showing the cut-off point of the precise number of components extracted based on the magnitude of the variance of the principal component (Habyarimana et al., 2015).

Following other studies in this field (see for example, Bhorat and Van der Westhuizen, 2013; Naschold, 2006), we estimated a kernel density. The most striking features of Figure 2 are the existence of two peaks in the density plots; thus, where the values are concentrated is an indication of an unequal distribution of assets in South Africa. The first peak shows that many households have a relatively low asset-poverty index. This is displayed by the distribution, which is skewed towards the left. These estimates support those found by Bhorat and Van der Westhuizen (2013). The second peak of Figure 2 indicates a second lump of households who are relatively prosperous and have a higher index. The implication is that this group of people controls assets that have higher factor scores, a sign of asset wealth (see, for example, Bhorat and Van der Westhuizen, 2013). Over time, from wave 1 to wave 5, the number of households that are asset-poor (low asset index) has decreased, whereas the number of households that are asset rich (high asset index) increased. This is an indication of the success of interventions to decrease asset poverty.Lastly, we present the factor scores for each specific variable, based on the first principal component consistent with other studies in this field (for example, Vyas and Kumaranayake, 2006; Habyarimana et al., 2015). The first column of Table 1 presents the factor scores for the index based on the full sample. As can be observed in this column, many factor scores entered with their predicted signs ─ positive signs showing that the ownership of assets is associated with high socio-economic status. Fairly large and positive factor scores are derived from the following assets variables: ownership of radio (0.222); television (0.455); satellite dish (0.114); DVD/player (0.281); cellphone (0.399); electricity stove (0.395); and fridge/freezer (0.431). In addition, some variables in this group are still factors linked to the households' improved socio-economic status, since they contain positive values. Although small in magnitude, these

Figure 1: Scree plot for component analysis computed for the full sample



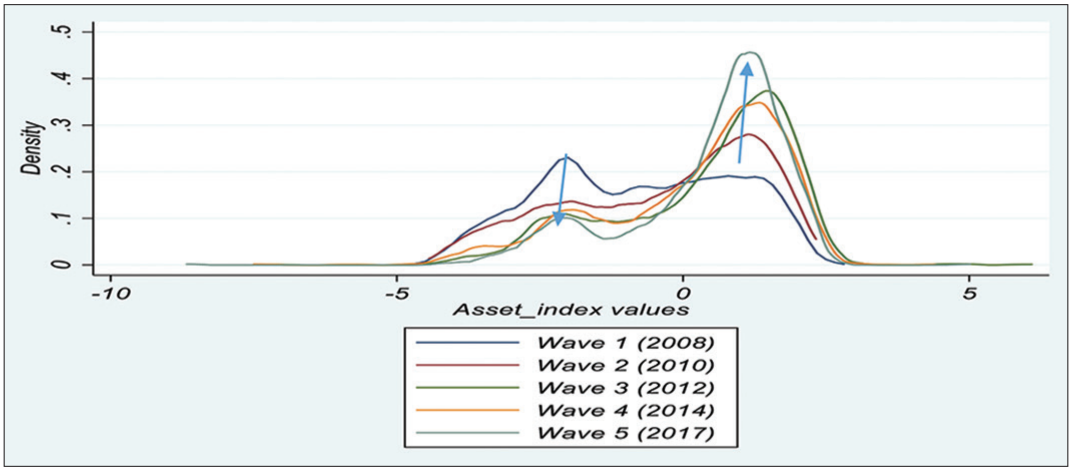
Source: Author's calculations based on NIDS data 2008-2017

Table 1: Scoring factors and summary statistics for an asset index for South Africa

Variables	Mean	SD	Factor scores	Variables	Mean	SD	Factor scores
Radio	0.643	0.479	0.222	Wall material			
Television	0.768	0.421	0.455	Brick	0.544	0.498	0.098
Satellite dish	0.244	0.429	0.114	Cement block	0.197	0.397	0.067
DVD player	0.360	0.480	0.281	Corrugated iron/zinc	0.077	0.267	−0.130
Computer	0.132	0.339	−0.021	Wood	0.014	0.117	−0.060
Camera	0.088	0.283	−0.106	Cardboard	0.002	0.048	0.112
Cell phone	0.862	0.345	0.399	Mixture of mud and cement	0.086	0.287	−0.025
Electric stove	0.750	0.432	0.395	Wattle and daub	0.007	0.086	0.011
Gas stove	0.156	0.363	−0.004	Tile	0.003	0.053	−0.033
Paraffin stove	0.213	0.409	−0.079	Mudbrick	0.061	0.239	−0.120
Fridge/freezer	0.716	0.451	0.431	Thatching	0.001	0.035	0.160
Washing machine	0.299	0.458	0.049	Asbestos/cement roof sheeting	0.003	0.053	0.082
Sewing machine	0.078	0.268	0.074	Stone and rock	0.004	0.062	0.002
Private car	0.169	0.375	0.025	Source of drinking water			
Bicycle	0.083	0.276	0.015	Water in dwelling	0.385	0.486	0.019
Plough	0.031	0.173	0.029	Piped in yard	0.271	0.444	0.019
Tractor	0.012	0.106	−0.005	Public tape	0.199	0.399	−0.007
Grinding mill	0.014	0.118	−0.026	Water - carrier/tank	0.024	0.153	−0.002
Livestock	0.664	0.472	0.064	Borehole on site	0.009	0.097	0.040
Sanitation facility				Borehole off site	0.015	0.122	−0.013
Flush toilet with on-site disposal	0.285	0.451	−0.006	Rainwater tank on site	0.008	0.089	−0.029
Chemical toilet	0.037	0.189	0.089	Flowing water/stream	0.049	0.217	−0.012
Bucket toilet	0.031	0.173	0.006	Dam/pool/stagnant water	0.020	0.141	−0.035
Flush toilet with off-site disposal	0.187	0.389	−0.018	Well	0.002	0.047	0.038
Pit latrine with ventilation pipe	0.163	0.369	0.002	Spring	0.005	0.077	0.046
Pit latrine without ventilation pipe	0.248	0.431	0.006	Others	0.008	0.092	−0.015
Any other	0.047	0.210	−0.059				

Source: Author's calculation based on NIDS 2008-2017

Figure 2: Distribution of households according to asset index values for the full sample



Source: Authors' calculations based on NIDS data 2008-2017

variables still approve their meaning in influencing household socio-economic status. In sharp contrast, variables that are linked to fairly large negative aspects of socio-economic status are derived from the following variable assets: ownership of camera (0.106); corrugated iron/zinc (-0.130); mud bricks (-0.120); and thatching (-0.160). This suggests, all things being equal, that a household which controls these forms of assets will be ranked lower in terms of socio-economic status relative to a household that does not own them (Xhafaj and Nurja, 2013).

From the discussion set out above, it is evident that the results from the PCA are more descriptive in nature and lack precisely an empirical enquiry that goes beyond the routine description of poverty. For this reason, the next section extends the descriptive analysis of poverty in South Africa by presenting an empirical enquiry by means of regression analysis.

5.2. Results from Random Effect Probit Regression

Table 2 present the empirical estimates from the random effect probit technique. The marginal effects and standard errors for the full sample are reported in Table 2. The results indicate that households' land matter in explaining asset poverty in South Africa – enters negatively and significantly in the random effect probit estimator. The results show that landholding in South Africa significantly reduces the probability of being asset poor. The results suggest that individuals with more land would have more room to grow crops or alternatively lease out the land for money (see also, Tsehay and Bauer, 2012). The results of this study concur with previous studies (for instance, Tsehay and Bauer, 2012; Bruck, 2001; Shete, 2010; Dartanto and Nurkholis, 2013), that also confirmed the positive role of landholding size in improving household's wellbeing. These results, of course, resonate with the rationale for a poverty discourse that emphasises the accessibility of land, as it plays a major role in avoiding the economic destruction caused by unintended economic shocks (McKerrnan et al., 2011). By and large, the results indicate that land is a key pillar in understanding the underlying welfare dynamics that determine people's escape from asset poverty or, alternatively, their plunge into asset poverty over time.

Table 2: Random-effects probit estimates on the determinants of asset poverty

Asset poverty	Marginal Eff	SE
Land	−0.01267***	(0.00053)
Household size	0.00105**	(0.00015)
Unemployed	0.01169***	(0.00120)
Household age	−0.00034***	(0.00005)
Gender	0.06824	(0.05907)
Married	−0.00235***	(0.00043)
Primary	−0.01389***	(0.00161)
Secondary	−0.02585***	(0.00205)
Matric	−0.02912***	(0.00135)
Tertiary	−0.03190***	(0.00133)
Urban	−0.02950***	(0.00184)
Farms	−0.00694**	(0.00213)
Eastern Cape	−0.02024***	(0.00245)
Northern Cape	0.05684***	(0.00049)
Free State	−0.00299	(0.00344)
KwaZulu-Natal	0.03007***	(0.00613)
North West	0.03558***	(0.00301)
Gauteng	−0.02230***	(0.00174)
Mpumalanga	0.00728	(0.00420)
Limpopo	0.004603	(0.00335)

Source: Own calculation from NIDS data, 2008-2017. ***Significant at 1%; **Significant at 5%; *Significant at 10%

The results for other control variables are similar to those obtained in other analyses of asset poverty correlates. For example, levels of education (that is, primary, secondary, matric and tertiary) have a reducing impact on asset poverty in South Africa. Thus, the higher the level of education attained by the household head, the less the likelihood of falling into poverty. These results compare favourably with those found in other international studies (Achia et al., 2010; Daka and Fandamu, 2016; Akinbode and Hamzat, 2017). The results suggest that, in South Africa, education presents greater opportunities for finding well-paid jobs, which, according to Hunter et al. (2003), would result in higher income and a subsequent reduction in poverty. Thus, improvement in education in South Africa is one of the most effective ways of alleviating the poverty curse. These results support a direct quote from Nelson Mandela Foundation, (2005:139) cited in Zwane (2020) who argued that: "A powerful rationale for rural education and a robust political constituency to argue for it are now required. Such a rationale can be provided: it is one that sees education as being able to play a role in rural development alongside and integrated with other social policies aimed at addressing inequality and poverty".

The results further indicate that heads of households who are married are significantly less likely to be poor than people who are single. These results reinforce those of Zenda (2002), cited in Adekunle (2013), who argued that heads of households who are living together with their partners stand a better chance of sharing household duties.

The relationship between age and asset poverty is negative and significant at the 1% probability level. These results concur with those of Daka and Fandamu (2016) for Zambia, as well as Akinbode and Hamzat (2017) for Nigeria, but contradict those of Habyarimana et al. (2015) for Rwanda. The differences in the direction of the impact might be because previous studies used cross-sectional data not panel data at a national level. The marginal effects of urban and rural are negative and significant at the 1% level. Factors such as gender has no significant effect on asset poverty in South Africa. The results further indicate that household size is positively related to asset poverty and significant at the 5% probability level. These results are largely in line with the work of Imai et al. (2011), who found that household size increases with the risk of falling into poverty in Vietnam. We also found that households residing in provinces of KwaZulu-Natal, North West and Gauteng are more likely to fall into asset poverty relative to households in the Western Cape province (reference category). It is remarkable to observe that households in KwaZulu-Natal, which encompasses a higher percentage of traditional areas, are more likely to be a poor than the Western Cape.

6. CONCLUSION

In this study, we examined the determinants and effects of non-monetary household asset poverty in South Africa, using all the existing five waves of the NIDS panel dataset. This paper attempts to contribute and improve upon the existing sparse literature on asset poverty in South Africa that has mostly presented a descriptive analysis of the socio-economic status of the household. Two estimation techniques were employed in this paper: the PCA to compute an asset in an attempt to identify the poor and the random effect probit model to examine the key determinants of asset poverty. The asset poverty index was computed for different geographical regions (full sample, urban and rural sample) and drew comparisons across each of these unique geographical regions. The results of the random effect probit model identified numerous factors such as savings by the head of household, landholding, levels of education of the household head (secondary, matric and tertiary), some province/regional dummies, and marital status of the household head, reduced the probability of being asset poor in both samples. Predictably, landholding lowers the probability of falling into poverty. By-and-large the results indicate that land is a key pillar in understanding the underlying welfare dynamics that determine people's escape from asset poverty or, alternatively, their plunge into asset poverty over time.

Education by the head of household and landholding have appeared as key determinants of household asset poverty. Therefore, these results have profound policy implications for the design and execution of poverty-reduction strategies. The results suggest that education and training of the labour force ought to be an important priority area in the fight against asset poverty in South Africa. The results thus support attempts to improve the provision of quality education and dropping teacher-student ratios, mainly in primary and secondary schools.

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APPENDIX

Appendix Table 1: Results for the extraction of components based on the full sample

Initial eigenvalues		% of variance	Cumulative %	Eigenvalues of extracted components			Total	Eigenvalue of extracted component	
Component	Total			Total	% of variance	Cumulative %		% of variance	Cumulative %
1	4.6091	0.0922	0.0922	4.6091	0.0922	0.0922	2.7068	0.0541	0.0541
2	1.9811	0.0396	0.1318	1.9811	0.0396	0.1318	2.3166	0.0463	0.1005
3	1.8519	0.0370	0.1688	1.8519	0.0370	0.1688	2.1301	0.0426	0.1431
4	1.6998	0.0340	0.2028	1.6998	0.0340	0.2028	1.5803	0.0316	0.1747
5	1.4448	0.0289	0.2317	1.4448	0.0289	0.2317	1.5496	0.0310	0.2057
6	1.3975	0.0280	0.2597	1.3975	0.0280	0.2597	1.5088	0.0302	0.2358
7	1.3288	0.0266	0.2863	1.3288	0.0266	0.2863	1.4587	0.0292	0.2650
8	1.2821	0.0256	0.3119	1.2821	0.0256	0.3119	1.383	0.0277	0.2927
9	1.2345	0.0247	0.3366	1.2345	0.0247	0.3366	1.3287	0.0266	0.3193
10	1.1690	0.0234	0.3600	1.1690	0.0234	0.3600	1.3069	0.0261	0.3454
11	1.1430	0.0229	0.3828	1.1430	0.0229	0.3828	1.2731	0.0255	0.3709
12	1.1247	0.0225	0.4053	1.1247	0.0225	0.4053	1.2269	0.0245	0.3954
13	1.1229	0.0225	0.4278	1.1229	0.0225	0.4278	1.1993	0.0240	0.4194
14	1.0923	0.0218	0.4496	1.0923	0.0218	0.4496	1.1869	0.0237	0.4431
15	1.0923	0.0218	0.4496	1.0923	0.0218	0.4496	1.1188	0.0224	0.4655
16	1.0797	0.0216	0.4712	1.0797	0.0216	0.4712	1.1116	0.0222	0.4877
17	1.0593	0.0212	0.4924	1.0593	0.0212	0.4924	1.0927	0.0219	0.5096
18	1.0451	0.0209	0.5344	1.0451	0.0209	0.5344	1.0890	0.0218	0.5314
19	1.0355	0.0207	0.5551	1.0355	0.0207	0.5551	1.0809	0.0216	0.5530
20	1.0245	0.0205	0.5756	1.0245	0.0205	0.5756	1.0801	0.0216	0.5746
21	1.0105	0.0202	0.5958	1.0105	0.0202	0.5958	1.0616	0.0212	0.5958
22	0.9982	0.0200	0.6158						

Source: Author's calculations based on NIDS data 2008-2017