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Assets and Poverty Alleviation in South Africa: Evidence from the National Income Dynamics Study (NIDS)

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This paper investigates a number of factors responsible for asset poverty in South Africa. We use data from the first four waves of the National Income Dynamic Study to bring new evidence to bear on the determinants of assets poverty. We use the Principal Component Analysis (PCA) to create the asset index and the logit model to identify the main determinants of asset poverty in South Africa. Results of the logit model show that some factors such as education levels (secondary, matric and tertiary), race dummies and location dummies (farms and urban areas) have a reducing effect on asset poverty in South Africa. However, other factors – employment and household size have no significant effect on asset poverty.

Keywords: asset poverty, logit model, Principal Component Analysis, Kaiser-Meyer-Olkin.

JEL Classifications: I32

1. Introduction

Although poverty has decreased in South Africa in the past years, it remains high compared to other emerging market economies. For instance, the percentage of population living on less than $1.90 a day in 2011 purchasing power parity (PPP) is 16.6% in South Africa compared to only 1.7% in Argentina, 3.7% in Brazil and 0.08% in Russia. Appropriate poverty policy responses in South Africa clearly require more understanding regarding the nature and causes of poverty.

Perhaps unsurprisingly, the issue of poverty has been on the agenda of the South African government for many years. For example, in 2004 the

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Accelerated and Shared Growth Initiative for South Africa (ASGISA) acknowledged the challenges of prolonged poverty and other related problems (unemployment, and low earnings, and the jobless nature of economic growth). The New Growth Path raised similar issues – unemployment and poverty remains extremely high by international standards. The most recent government policy (the National Development Plan) introduced in 2013 as South Africa's long-term socio-economic development roadmap placed even more emphasis on similar issues and was viewed as a policy blueprint for eradicating poverty and reducing inequality in South Africa by 2030 (Biyase and Zwane, 2017). While efforts to alleviate poverty have been somewhat successful, poverty remains very high by international standards.

Despite the fact that levels of poverty are high, there are reasons to believe that poverty headcount and income/consumption inequality indicators may not be the most appropriate measures to use. Sen (1981) has shed some light on why money metric measures may not be appropriate or adequate to use. He argues that pattern of consumption behaviour may not be uniform, so attaining the poverty line level of income does not guarantee a person will meet the minimum needs. Moreover, people may face different prices, reducing the accuracy of the poverty line. As regards income inequality, a most recent paper by Wittenberg and Leibbrandt (2017) find evidence 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 there is a need for a more nuanced understanding of the complex socio-economic pathologies (such as poverty) facing South Africa.

The contribution of this paper is twofold. First, we apply asset index method to the measurement of poverty in South Africa. This asset index is constructed using Principal Component Analysis. An obvious strength of the principal component (see detailed discussion of its advantages in subsection 3.2) 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 (Van der Berg et al., 2003; Bhorat et al., 2014). The second contribution of this study is that we further investigate the determinants of asset poverty using the logit model.

The paper proceeds as follows. In section two we review the existing empirical literature on asset poverty and its determinants. Section three then, describe the dataset and discusses the methods used in this paper. Section four presents the results, and section five concludes.

2. Literature survey

2.1. Problems associated with money-metric poverty measures

Much of the theoretical and empirical work on poverty in general, has focused on money-metric measures of poverty (for example, Serumaga-Zake and Naude, 2002; Van der Walt, 2004; Sekhampu, 2012; Statistics South Africa, 2014). These money-metric measures (such as income or consumption) are considered to be a good proxy of the well-being of households and have been very useful in guiding policy action and raising public concern for poverty (Brandolini et al., 2009; Michelson et al., 2013). Money-metric measures are also useful when comparing differences in poverty between nations or regions.

Recent analysis (Carter and Barrett, 2006; Vandemoortele, 2009; Naschold, 2012; Wietzke, 2015; Brandolini et al., 2010; Filmer and Pritchett, 2001; Wooldridge, 2002; Vyas and Kamaranayake, 2006; Habyarimana et al., 2015) have been critical of money-metric approach as an adequate measures of poverty and its determinants. They contend that in spite of its intuitive appeal and use, these measures cannot sufficiently and convincingly capture the overall amount of resources (real and financial assets) used by households to cope with various shocks. Secondly, it fails to account for the numerous dimensions of human well-being.

A forceful proponent of this view is Sen (1999) who takes the view that while the money- metric measures shed some light on poverty, the existence of ineffective institutions and social arrangements alongside with having no political freedom are extremely important to consider. The needs of the poor are not only made evident on the amount of their income, but also, for instance, on mortality rates, malnutrition, and illiteracy.

Money-metric measures have also been criticized because they ignore aspects of poverty that are related to commodities not typically transacted in the market — education or health outcomes that have intrinsic values beyond their costs while the welfare loss from unemployment is potentially associated not only with the observed income loss but also with a lower perception of the quality of life and human dignity. Health, nutrition, education, physical security, voice, justice, and capacity and opportunity to improve one's life are also essential dimensions of poverty and wellbeing (World Bank, 2010).

Perhaps a common criticism of the money-metric approach relates to measurement errors. First, collecting data on income and expenditure can be time and money consuming (Vyas and Kamaranayake, 2006). Secondly, measurement of consumption and expenditure in low-income countries is fraught with difficulties such as problem of recall and reluctance to divulge information (Akinbode and Hamzat, 2017). Thirdly, prices of goods often differs substantially across times and areas, forcing complex adjustment of the expenditure figures to reflect these price differences (Xhafaj and Nurja, 2013; Habyarimana et al., 2015). Fourthly, consumer price indices in developing countries are unavailable and unreliable, especially when inflation tends to be high or variable (Habyarimana et al., 2015). Other issues has 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 (Xhafaj and Nurja, 2013; Habyarimana et al., 2015; Akinbode and Hamzat, 2017).

In view of the problems associated with money metric measures, attempts have been made to broaden these measures beyond the narrow confines of consumption/income (to be discussed in the subsequent sections). For example, recent analysis (Filmer and Pritchett, 1998; Sahn and Stifel, 2000;Booysen et al., 2005) has used data on ownership of assets and access to services to derive alternative indicators of household socio-economic status.

2.2. Non-money metric measures

As noted in the previous section, attempts have been made in the literature to expand money- metric measures beyond the narrow confines of consumption or income. Recently, most studies have resorted to using asset index to measure the well-being/socio-economic status and determinants of household poverty (see for example, Achia, Wangombe and khadioli, 2010; Filmer and Pritchett, 2001; Sahn and Stifel, 2003, Vyas and Kumaranayake, 2006; Xhafaj and Nurja, 2013; Habyarimana et al., 2015; Booysen, 2002; Farah, 2015).

Although there are different methods used to construct the asset index, the Principal Component Analysis (discussed in more detail in the next section) remains the most popular technique used in this field. For example, using the Demographic health Survey dataset and the principal component analysis Habyarimana et al. (2015) constructed an asset index for Rwanda. They found that flush toilet, cement, electricity, piped water to the yard had high and positive factors scores. While other variables such as sand floor material, borehole and river/dam as source of drinking water and latrine as toilet facility had a negative factor scores.

Filmer and Pritchett (2001) used a similar method to construct an asset index and use the index to investigate the relationship between household wealth and children school enrolment in India. Their results suggest that owning a watch, radio and television, flushing toilet, light electricity and dwelling in a high quality material was associated with positive SES for the households in India. In contrast, drinking water from open pump and dwelling in low quality materials were associated with negative SES. Booysen (2002) found that electricity for cooking, flush toilet, piped water in a dwelling and public had a high SES. Other assets such as using paraffin, wood and dung for cooking as well as number of members per sleeping room had a negative SES.

A study by Vyas and Kumaranayake (2006) used the Principal Component Analysis to construct a separate asset index for urban and rural areas in Brazil and Ethiopia. Using the factors scores from the first principal component they found that in the urban areas of Brazil, pipe drinking water to residence, sanitation facility, finished floor and the number of rooms for sleeping were associated with high social-economic status (SES) of households. Similar results were obtained for rural Brazil except for the fact that it comprised any sanitation facility and a well in the residence. In urban Ethiopia, drinking water pipe to the compound achieved high SES. Whereas in rural Ethiopia access to infrastructure facilities and ownership of any assets was associated with high SES of the households.

Similarly, Xhafaj and Nurja (2013) used the Principal Component Analysis to construct a separate index for urban and rural areas in Albania. They found that computer, mobile phone, and owning a car were associated with high SES of households both in rural and urban areas. The other assets such as gas/electric stove, washing machine and color television were also associated with positive SES of households, although their magnitude were relatively lower. They also found that a household with a wood stove were ranked lower in terms of SES than a household that does not own a wood stove.

Other studies performed a Principal Components Analysis first and then apply a logistic regression of the socio-economic status (SES) as response variable and the demographic characteristics of the household as explanatory variables. For example, a study by Habyarimana et al. (2015) used a logistic regression model to assess the determinants of asset poverty in Rwanda. They used asset index as dependent variable and number of household's demographics as explanatory variables. Their finding suggest that age of household head, education level and gender of household head are important determinants of asset poverty in Rwanda.

In another study, Achia et al. (2010) also used logistic regression treating the asset index as a dependent variable. They found that religion, age of household head, region and ethnicity of a household head were significant predictor of asset poverty in Kenya. In this paper we follow a similar approach of firstly constructing the asset index using Principal Component technique. We then apply the logistic regression model to assess the determinants of asset poverty in South Africa.

3. Methodology

This section looks at the methodology used to examine an asset based approach to poverty analysis in South Africa. To analyse assets poverty we use a variety of methods. We start with the Principal Component Analysis (section 3.2). In the next step we investigate the determinants of asset poverty using the logit model.

3.1. Data Source

The National Income Dynamics Study (NIDS) used in this paper to analyse asset poverty is an ongoing longitudinal survey conducted by the

Southern African Labour and Development Research Unit (SALDRU), based at the University of Cape Town's School of Economics. The NIDS started in 2008 with over 28 000 individuals in 7 300 households across the country. The subsequent waves of the NIDS were implemented in 2010, 2012 and 2014, and re-surveyed original NIDS wave1 households.

The reasons for using the NIDS dataset is that it comprise comprehensive set of questions on various types assets (both public and private), which are important for our paper. At the time of performing the analyses data from four waves were available. However the first three waves did not have as much information on assets compared to wave 4. Therefore we limit the analyses to wave 4 of the NIDS data. Wave 4 comprise a wide range of assets: ownership of a radio, television, satellite, DVD player, computer, camera, cell phone, electric/gas/paraffin stove, microwave, fridge, washing machine, sewing/knitting machine, lounge suite, private or commercial vehicle, motorcycle, bicycle, boat, cart and various kinds of agricultural equipment and so forth (Yu, 2012). In this wave participants are further asked to provide in-depth information about their access to services such as sanitation facilities, source of drinking water, housing material and so forth.

3.2. Statistical technique for computing a poverty index

Earlier studies have relied heavily on equal weighting approach when dealing with asset ownership. Equal weighting approach involves according equal weights to all assets that a household owns (Bhorat et al., 2014). However, the use of this approach has been criticized since it does not have much to recommend it, except ease of use. McKenzie, 2005 cited in Bhorat et al. (2014) notes that equal weighting makes it more difficult to include measures of quality, for assets or services, when there are more than two quality options. Reaching a similar conclusion, Wittenberg (2009) writes "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".

Recent studies recognising this problem have attempted to avoid it by making use of either the Principal Component Analysis, Factor Analysis, Multiple Correspondence Analysis and a Livelihood Regression (see for example, Filmer and Pritchett, 2001; McKenzie, 2005; Naschold, 2006; Sahn and Stifel, 2003; Xhafaj and Nurja, 2013; Habyarimana et al., 2015;

Vandenberg et al.,, 2008; Adato et al., 2006; Naschold, 2009). These methods weight assets differently, letting the correlation structure between the assets determine which assets should count for more. Notwithstanding the availability of these numerous techniques, the Principal Component Analysis has proved to be an intriguing technique for use in any poverty studies. There are several reasons to prefer a Principal Component Analysis over other methods. First, it is relatively intuitive as a way of regrouping variables into a limited set of clusters based on shared variance. As Filmer and Pritchett (2001: 116) put it, "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".

Secondly, 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 (Van der Berg et al., 2003; Bhorat et al., 2014). For example, if ownership of one type of asset is highly indicative of ownership of other assets for a given population, these assets will receive a positive weight and vice versa (Habyarimana et al., 2015). Moreover, assets that are more unequally distributed across households are accorded greater weight in a Principal Component Analysis (see Van der Berg et al., 2003; Bhorat et al., 2014; Habyarimana et al., 2015 for more illustrative examples) Finally, PCA can provide insight into which variables have greater influence on the dimension(s) of SES. Generally, a variable with a positive factor score is associated with higher SES. While a variable with a negative factor score is associated with lower SES (Habyarimana et al., 2015).

Following many important scholars in this field, (Van der Berg et al.,2003; Schiel, 2012; Schroeder et al.,, 1992; Pollitt et al.,, 1993) we employ the Principal Components Analysis to construct the weights of asset index.

The Principal Components Analysis takes the following form:

$$PC_1 = \forall_1 X_1 + \forall_2 X_2 + \forall_3 X_3 \dots \dots + \forall_n X_n$$

$$PC_m = \forall_{m1} X_1 + \forall_{m2} X_2 + \forall_{m3} X_3 \dots \dots + \forall_{mn} X_n \quad (1)$$

Where the subscript $\forall_{mn}$ denotes the weights for the m^{th} principal component and variableX_n.

Generally the components are ordered in such a way that the first principal component has the largest variance (i.e. captures the largest variation in the original dataset), the second principal component, which is uncorrelated with the first component comprise the second largest variance, and the subsequent components comprise additional but less variance than the first component.

Following many scholars in this field we adopt a three-step estimation procedure in implementing the PCA. First an attempt is made to verify whether there is enough correlation between the variables (Habyarimana et al., 2015). This is often achieved by applying the Kaiser-Meyer-Olkin (KMO), which is called a measure of sampling adequacy (Henry et al., 2003). The KMO computes the degree of intercorrelations among the variables in the dataset (Córdova, 2008). KMO values less than 50% are considered inadequate and unacceptable, while values above 60% are acceptable and recommended.

The second step is to decide on the number of components to be extracted. In this case, we used the Kaiser's criterion which recommends retaining the components that have an eigenvalue greater or equal to one (Xhafaj and Nurja, 2013). We complemented the Kaiser criterion with the scree plot showing the proportion of variance explained by each principal component. The last step involves the rotation of the data set. After extracting the components, the factor loading of each variable is calculated (Tsehay and Bauer, 2012). The main objective of rotation according to (Vyas and Kumaranayake, 2006) is to minimise the variables that have a higher loading on certain components. Appendix Table 1.1 shows the rotation of the component using varimax rotation.

An in-depth analysis of poverty should go beyond a routine description of poverty profiles (which is only suggestive of the correlations between variables) if we are to adequately deal with the factors underlying poverty. Thus, this section will place more emphasis on the determinants of poverty. Specifically, we applied a logistic regression analysis of the socio-economic status (SES) as response variable and the demographic characteristics of the household as explanatory variables.

3.3 Logistical regression Model

To identify the determinants of poverty in this study, a logit regression model was adopted. The logit (or binary choice model) is a model with a zero-one dummy variable being the dependent variable. The logit model is expressed as follows:

$$Y^* = \alpha_0 + \beta X + \mu \qquad (2)$$

Y is household poverty and the 40th percentile was used as the poverty line (Achia, Wangombe and Khadioli, 2010; Vyas and Kamaranayake, 2006; Booysen, 2002). We classified the social economic status as poor if the household poverty index is below the 40th percentile, otherwise it was classified as not poor. The α and β are coefficients to be estimated, μ is a stochastic error term. In determining the variables contained in the X vector, we followed existing studies which suggest that the probability of being poor depends on various explanatory variables such as education of the head of the household, the age of the head of the household, employment status of the head of household, household size (represented by number of household members in the household), location, and race of the head of household.

4. Results

This section reports the results obtained by using the methods outlined in the previous sections. Section 3.1 reports the results obtained by using the Principal Component Analysis, while section 3.2 reports the results using logit method.

4.1 Results from the Principal Components Analysis

To assess the appropriateness of our data set for implementing the Principal component analysis, we computed the KMO score. We found the data to be supportive of the analysis in question: the KMO score was 0.70 suggesting that the data is suitable for the implementation of the Principal Component Analysis. To determine the number of factors to be extracted, we applied the basic rule of Kaiser's criterion complemented with the scree plot and the rotated component matrix. Table 1.1 below present the results of the extracted components. There are three columns depicted in Table 1.1. The first column present the original eigenvalues, while the second column depicts the results of the extracted components. The number of components extracted based on the Kaiser rule is equal to 11. The extracted 11 components contains 59% of the variation of the observed 31 original variables. Basically, component 1 describes 15% of the variation, component 2 explains 7% and the last component 11 explains 3%, etc.

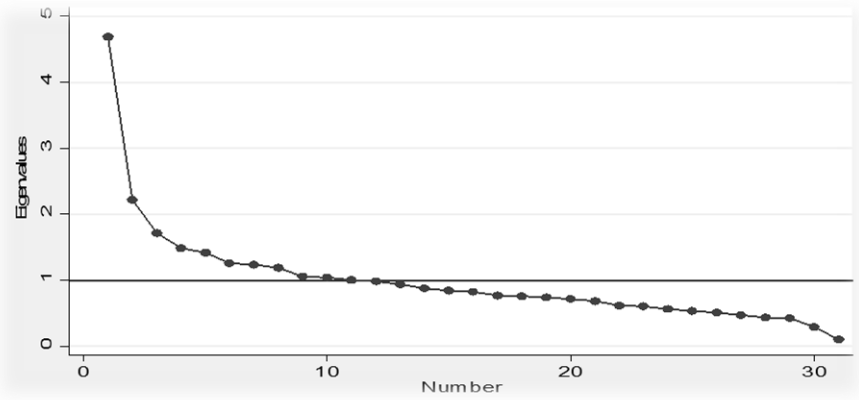
To validate the number of components extracted we used the scree plot showing the cut-off point of the precise number of components extracted based on the magnitude of the variance of the principal component. These results are shown in Figure 1.1 below.

Table 1.1: Extracted components for the analysis of poverty using Principal Component Analysis

Components	First eigenvalues			Eigenvalues of extracted components		
	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1	4.68978	0.1513	0.1513	4.68978	0.1513	0.1513
2	2.22162	0.0717	0.2229	2.22162	0.0717	0.2229
3	1.71388	0.0553	0.2782	1.71388	0.0553	0.2782
4	1.48766	0.048	0.3262	1.48766	0.048	0.3262
5	1.41648	0.0457	0.3719	1.41648	0.0457	0.3719
6	1.25716	0.0406	0.4125	1.25716	0.0406	0.4125
7	1.23623	0.0399	0.4523	1.23623	0.0399	0.4523
8	1.1888	0.0384	0.4907	1.1888	0.0384	0.4907
9	1.05478	0.034	0.5247	1.05478	0.034	0.5247
10	1.03928	0.0355	0.5582	1.03928	0.0355	0.5582
11	1.00175	0.0323	0.5905	1.00175	0.0323	0.5905

Source: Own calculations using NIDS data

Figure 1: The scree plot graphing the percentage of variation explained by each component.



Lastly, we affirmed the number of components extracted by means of rotated component matrix. Thus an orthogonal rotated solution was implemented as a tool of choice meant to attain the highest factor loadings of indicators on each component using varimax rotation technique. For a complete analysis of the eigenvalues of rotated extracted component results, see appendix Table A1.1.

We now turn to key results from the Principal Component Analysis. Table 1.2 below reports the scoring factors or weights for the index based on the PCA (the first principal component). Many weights entered with its predicted signs, with positive signs indicating that the ownership of assets is associated with higher SES. Relatively large positive weights were derived for the following assets: television; satellite dish; DVD/player; computer; electricity stove; fridge/freezer; washing machine; private car) and piped drinking water to dwellings etc.

Although other assets such as ownership of a camera, cell phone, gas stove, sewing machine, and having access to flush toilet on site have lower magnitude based on their factors scores, they still contribute positively to household socio-economic status. In contrast, relatively large negative weights were derived for the following assets: ownership of mixture of mud and cement, livestock, having access to drinking water from a public tap, mud bricks etc. Only the factor scores of the first principal components were used in the computation of a poverty index following studies such as those of Farah (2015) and Habyarimana et al. (2015).

Table 1.2: Factor scores and ssummary statistics of the variables used in the computation of a poverty index

Variables	Mean	Std. dev.	Factor score	Min	Max	Variables	Mean	Std. dev.	Factor score	Min	Max
Radio	0.667	0.471	0.091	0	1	Tractor	0.062	0.241	0.045	0	1
Television	0.783	0.412	0.27	0	1	Grinding mill	0.03	0.171	0.037	0	1
Satillite dish	0.271	0.444	0.266	0	1	Livestock	0.594	0.491	-0.102	0	1
DVD/player	0.345	0.475	0.218	0	1	Flush toilet onsite	0.134	0.34	0.187	0	1
Computer	0.125	0.331	0.228	0	1	Chemical toilet	0.008	0.093	-0.009	0	1
Camera	0.044	0.206	0.182	0	1	Bucket toilet	0.041	0.198	-0.03	0	1
Cell phone	0.919	0.272	0.14	0	1	Bricks	0.579	0.493	0.264	0	1
Electric stove	0.767	0.422	0.274	0	1	Cement block/concrete	0.777	0.416	0.287	0	1
Gas stove	0.193	0.394	0.118	0	1	Mixt. of mud/cement	0.082	0.275	-0.205	0	1
Paraffin stove	0.211	0.408	-0.058	0	1	Mud bricks	0.079	0.27	-0.18	0	1
Fridge/freezer	0.768	0.421	0.281	0	1	Iron/zinc	0.802	0.398	-0.105	0	1
Washing Machine	0.248	0.431	0.281	0	1	Asbestos	0.01	0.103	0.064	0	1
sewing machine	0.096	0.096	0.135	0	1	Piped water in dwelling	0.222	0.415	0.211	0	1
Private car	0.211	0.408	0.224	0	1	Piped water to yard	0.325	0.468	0.065	0	1
Bicycle	0.092	0.289	0.135	0	1	Public tap water	0.219	0.413	-0.121	0	1
Plough	0.062	0.241	0.012	0	1						
Source: Own calculations using NIDS data											

Table 1.3 : Logit estimates of the determinants of assets poverty, 2014

Asset poverty	Coefficients	Robust Std. Err.
HH_size	0.0020865	(0.0010811)
Primary education	-0.0174809	(0.0113477)
Secondary education	-0.0432344***	(0.0110238)
Matric education	-0.0589375***	(0.0113444)
Tertiary education	-0.0600557***	(0.0107489)
HHH_age	0.0006642***	(0.0001897)
HHH_empl	-0.0080079	(0.0050213)
Coloured	-0.0372193***	(0.0076092)
Indian	-0.0409316***	(0.0083023)
White	-0.0372002***	(0.0075267)
Farms	-0.0435521***	(0.0124253)
Urban	-0.0345608***	(0.010273)
Eastern Cape	0.0337868***	(0.0091272)
Northern Cape	-0.0121904	(0.0112192)
Free State	0.0524215***	(0.0093509)
KwaZulu-Natal	0.0106365	(0.0101205)
North West	0.0675567***	(0.0105076)
Gauteng	0.0201411**	(0.0087474)
Mpumalanga	0.0108493	(0.0121262)
Limpopo	0.0117658	(0.0141377)
Cons	0.0296899	(0.0206059)
Number of obs	9235	
Notes: Clustered standard errors are reported in parentheses with ***, **, and *, denoting significance at the 1%, 5%, and 10% levels, respectively.		

4.2 Result from logistic regression

Table 1.3 present the estimation results from the logit model. As it is evident from the results presented with the exception of household size, head of household employment status, primary education and some provinces (Limpopo, Mpumalanga, KZN etc), all the specified socio-economic characteristics, demographic characteristics and location variables are statistically significant at 10 percent or lower level. As expected, education significantly decreases the likelihood of falling into poverty. The higher the level of education attained by the household head the lesser the likelihood of falling into poverty. For example, the completion of secondary education by the household head reduces the likelihood of the household being poor by 4.3%, of matric by 5.8% and tertiary education by 6.0%. These findings are consistent with our expectation and are similar to those found in other international studies (see Achia et al., 2010)

With regards to the geographical variables, the results suggest that the location of the household influences the likelihood of falling into poverty. Specifically, households in urban and farm areas are less likely to be poor than households in traditional rural areas. The coefficient estimates on urban and farm areas are all negative and significant at the 1% level of significance. Moreover, we find that households in provinces of North West, Free State, Gauteng and Eastern Cape are more likely to be poor than households in Western Cape province (reference category). It is interesting to note that households in the Eastern Cape Province which contain a higher percentage of traditional areas are more likely to be a poor than Western Cape Province.

Perhaps unsurprisingly, probabilities of being in poverty also differ by race, with Africans significantly more likely than White, Indians and Coloureds to be in poverty. The results also show that the household size are positively associated with the incidence of poverty, although insignificant. These findings are largely consistent with the work of Imai et al., (2011) who found that household size increase with the risk of falling into poverty in Vietnam.

5. Conclusion

This paper employs the Principal Component Analysis to create the asset index. This paper also attempts to extend the existing South African studies that focus on asset based approaches, which have mostly provided a descriptive analysis of the household welfare computation. Specifically, this paper applies the logit model to identify the main determinants of asset poverty in South Africa. Results of the logit model show that some factors such as education levels (secondary, matric and tertiary), race dummies and location dummies (farms and urban areas) have a reducing effect on asset poverty in South Africa. Unsurprisingly, education significantly decreases the likelihood of falling into poverty. The higher the level of education attained by the household head the lesser the likelihood of falling into poverty. For example, the completion of secondary education by the household head reduces the likelihood of the household being poor by 4.3%, of matric by 5.8% and tertiary education by 6.0%. These findings are consistent with our expectation and are similar to those found in other international studies (see Achia et al., 2010; Daka and Fandamu, 2016; Akinbode and Hamzat, 2017).

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These results have important policy implications for design and implementation of poverty reduction policies for South Africa. For instance, education was found to significantly decrease the likelihood of falling into poverty in South Africa. This suggests the need to prioritize education and training of labour force as key priority area in the struggle against poverty which can help in the way of enhancing the skills and productivity among poor households. In South Africa, the government should increase it’s funding through the National Student Financial Aid Scheme (NSFAS) to avoid high dropout rates in institutions of higher learning. This will help broaden the country’s skills development base amongst the youth, while producing graduates who are able to contribute to the growth of our economy.

Given that the rural household residing in Limpopo, Eastern Cape, Kwazulu natal and other province are more likely to be poor compared to other households from Western Cape province (reference variable), policy makers should formulate targeted provincial/rural interventions. Thus policies that would improve the provision of infrastructure, quality service delivery and further promote investment and employment creation.

The results further indicate that poverty increases with increased in household size, suggesting that policies should be drawn that priorities the use of family planning initiatives. Awareness creation on family planning would go a long way in reducing the household size especially in rural areas of South Africa where the majority of the poor lives. Basically, policy makers should formulate policies that enables women to make their own choices about their fertility thereby empowering and offering better economic and social opportunities. Thus, public education should be geared towards influencing sexual behavioural change to the South Africans.

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Appendix A

Table A1.1: Eigenvalues of rotated extracted component

	Eigenvalues of rotated extracted component		
Components	**Total**	**% of variance**	**% cumulative**
1	2.49044	0.0803	0.0803
2	2.36269	0.0762	0.1566
3	2.18991	0.0706	0.2272
4	1.95808	0.0632	0.2904
5	1.55316	0.0501	0.3405
6	1.45537	0.0469	0.3874
7	1.43571	0.0463	0.4337
8	1.40297	0.0453	0.479
9	1.20987	0.039	0.518
10	1.18702	0.0383	0.5563
11	1.0614	0.0342	0.5905