DEVELOPING A RESILIENCE INDICATOR FOR FOOD SECURITY MONITORING AND EVALUATION: INDEX CONSTRUCTION AND HOUSEHOLD CLASSIFICATION FOR SIX AFRICAN COUNTRIES

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ABSTRACT

The objective of the study was to develop an indicator of household resilience as a measure of progress towards achieving the first of four elements identified in the Framework for African Food Security. A review of the literature provided support for the use of assets owned by a household as an indicator of household resilience. Several methods of constructing household asset indices emerged from the literature reviewed. The application of four of these methods to Demographic and Health Survey data from six African countries is presented in this paper. The resulting indices were used to estimate individual socio-economic status scores for all households. All four methods performed similarly across the assessment characteristics, but yielded different results when the households were grouped into quintiles based on the estimated socio-economic status scores. As suggested by the literature, quintiles were used to classify the study households into categories of socio-economic status based on the estimated socio-economic status scores. However, socio-economic status was not evenly distributed across the study households making the use of a quintile approach inappropriate for grouping the households. Cluster analysis was applied as an alternative to the quintile classification to group the study households. Cluster analysis appeared to be a more effective approach to grouping households, both in that it does not assume an even distribution of socio-economic status across households - as the quintile approach does - and it provides a useful indication of changes in the per cent of households falling into different socio-economic status groups over time.

Keywords: CAADP, resilience, asset index, PCA, cluster analysis, food security

JEL Classification: Q18

1 INTRODUCTION

The 2008 global food crisis and, more recently, the Horn of Africa crisis, have renewed focus on the need to build household resilience with regard to food security. Evidence suggests that the inability to cope with risk and vulnerability plays a role in perpetuating poverty (Collier and Gunning, 1999; Dercon *et al*., 2005; Dercon, 2005; Dercon, 2006) and several continental and international frameworks for food security indicate the importance of building, protecting and promoting resilience. The Comprehensive African Agricultural Development Programme's (CAADP) Framework for African Food Security or FAFS (NEPAD, 2009a) recognise the need for national governments to institute public programmes that focus on ensuring households are able to withstand and recover from shocks that threaten or reduce food insecurity. However, resilience is inherently difficult to measure (FAO and the WFP, 2013). Attempts to develop multiple-indicator resilience indexes for food security assessments (Alinovi *et al*. 2008, 2010) have shown that the indexes themselves do not add diagnostic value to programming food security interventions, but the individual indicators do have value.

The CAADP sets out Africa's plan of action to attain food security, improve agricultural productivity, develop dynamic regional and sub-regional agricultural markets, integrate farmers into a market economy and to achieve a more equitable distribution of wealth (NEPAD, 2009a). The plan for achieving these three priorities is set out in four complementary CAADP frameworks[1]. The FAFS sets out an analysis of the causes of food insecurity in Africa and presents a suite of programmes recommended to overcome these challenges (Hendriks *et al*., 2009). The FAFS aims to ensure that agricultural growth simultaneously stimulates economic growth and reduces hunger and poverty to meet the first Millennium Development Goal (MDG). The framework identifies four elements key to addressing food insecurity in Africa (NEPAD, 2009a), namely:

- Reducing risk and improving the resilience at all levels (household to national as well as systems for early warning and monitoring food insecurity and hunger)
- Increasing the supply of affordable food to improve the availability and access to food
- Increasing incomes of the poor through pro-poor growth and development opportunities across the agriculture and food system
- Improving diet quality and nutrition of individuals across the life cycle.

The CAADP Mutual Accountability Framework (NPCA, 2011) was established in 2011 and sets out a list of just over 30 core indicators to track progress towards national, regional and continental targets. Rather than estimating a complex index, CAADP identifies strategic indicators that can be uniformly monitored across multiple countries. Currently, the only impact indicators tracked in relation to FAFS relate to the first Millennium Development

[1] The CAADP Pillar 1 Framework on Sustainable Land and Water Management (NEPAD, 2009b), the Framework for Improving Rural Infrastructure and Trade Related Capacities for Market Access (FIMA) (NEPAD, 2009c), The Framework for African Food Security (FAFS) (NEPAD, 2009a), and the Framework for African Agricultural Productivity (FAAP) (NEPAD, 2006).

Goal of halving extreme poverty and hunger. This is done using poverty head counts and the Global Hunger Index[2] (Omilola, 2010).

The FAFS recognizes the significance of resilience and risk management in reducing household poverty and has, as its first priority, the improvement of household risk management (or resilience). This study formed part of an attempt to develop a FAFS Scorecard to measure the status quo and track performance on the four CAADP Pillar III elements listed above to improve and strengthen the CAADP Mutual Accountability Framework indicator set. While many indicators exist for measuring the supply of affordable food at national and household levels, income and dietary quality and nutrition, the same cannot be said for indicators of risk and resilience. It was therefore necessary to investigate an appropriate measure of resilience to complete the set of indicators for developing a comprehensive score card. The indicator data would need to be widely available across countries and collected at regular intervals to be used in the score card.

The paper is organised as follows. The first section presents a brief overview of the related literature followed by a description of the data and methodology in section 2. The results are discussed in sections 3 and 4: estimation of socio-economic scores by application of the four asset indices, and the cluster analysis of the estimated socio-economic status scores, respectively. Conclusions and recommendations are presented at the end.

2 LITERATURE REVIEW

2.1 Household assets and resilience

Following Sen (1981), vulnerability (to famine) is a function of relative poverty and relative poverty is a function of a household's ownership of tangible assets and the rate at which these can be exchanged for food. Swift (2006) explains that a reduction in assets increases vulnerability to poverty and hunger, and concludes that a low asset status could indicate vulnerability. Chambers (2006) lends support to Swift's suggestion that a low asset level would be a useful indicator of food insecurity. Similarly, Maxwell and Smith (1992) suggest that asset holdings could be used as an indicator of food insecurity, while Moser and Holland (1997), and Moser (1998) agree that assets and entitlements provide liquidity during times of stress. In their discussion of the measurement of vulnerability, Lovendal and Knowles (2005) postulate that asset values could be used as a proxy of the ability of a household to cope with shocks. They explain that assets are an important part of risk management as they can be used to smooth consumption, and access to assets influences the ability to prevent, mitigate and cope with shocks.

From the literature it is clear that assets play a role in a household’s ability to cope with risk; hence, measuring asset ownership could provide an indication of a household’s level of resilience. Asset-based indices have been applied in several studies (e.g. Filmer and Pritchett, 1994, 1999, 2001; Rutstein and Johnson, 2004; McKenzie, 2005; Gwatkin *et al*., 2007a), giving an indication of the wealth of assets owned by a particular household. This, in turn,

[2] The Global Hunger Index combines three equally weighted indicators, namely: undernourishment as share of the population with insufficient energy intake, child underweight as the proportion of children younger than age five who are underweight, and under-five child mortality (IFPRI, 2013).

could be used as a relative indication of household resilience. Based on the premise that the level of asset ownership is an indication of a household's ability to cope with risk, an asset-based index could be used to estimate a socio-economic status score as an indicator of the relative resilience of the particular household.

2.2 Household asset indices

There is no set methodology for the development of asset-based indices (Montgomery *et al*., 1999). Their construction differs mainly in the choice of asset and service variables for inclusion in the index, and the approach used to assign weights to the individual indicator variables. A review of the literature related to asset-based indices revealed four common methods of constructing household asset indices specifically with respect to generating the weights of the variables included in the index, and showed no single method to be widely accepted as superior to the others. Consequently, in this study, all four methods were applied and compared:

a) The application of *linear principal component analysis (PCA)* to *dichotomous variables* (Filmer and Pritchett, 2001);
b) The application of *linear PCA* to *categorical variables* ranked in order of socio-economic status (Kolenikov and Angeles, 2009);
c) The application of *non-linear or categorical PCA* (Linting *et al*., 2007); and
d) A simple *sum of assets* technique.

3 RESEARCH METHODOLOGY

3.1 Data description

The data used in the study were taken from the household component of the Demographic and Health Surveys (DHS) for six African countries. The countries were chosen using poverty ranking estimates based on the proportion of the population living below U.S. $1.25 per day, from the 2009 Human Development Report (UNDP, 2009). The African countries appearing in the report were grouped into three categories – 'rich', 'middle' and 'poor' - based on their poverty ranking. Two countries from each category with a DHS version V – the most recent round of surveys - were selected for analysis. The six surveys chosen were: Liberia 2007 and Tanzania 2007/08 (from the 'poor' category), Mali 2006 and Uganda 2006 (from the 'middle' category) and Egypt 2008 and Kenya 2008/9 (from the 'rich' category). Details of the six datasets used in the study are given in Table 1.

Table 1: Details of the datasets used in the study

Country	Year	Sample size (*N*)	Number of variables
Tanzania	2007/08	8497	15
Liberia	2007	6824	21
Uganda	2006	8870	21
Mali	2006	12998	16
Kenya	2008/09	9057	16
Egypt	2008	18968	27

Source: Macro International Inc. (2010)

The variables included in the asset indices were selected based on those used in the studies by Filmer and Pritchett (2001) and Kolenikov and Angeles (2009), and available in the DHS datasets. These variables included items such as ‘owns a car’, ‘owns a phone’ and ‘owns a television’ for the asset ownership variables, and ‘type of toilet facility’, ‘source of drinking water’ and ‘has electricity’ for the household characteristics variables. The indices did not include identical variables for each country due to limitations in the data.

The descriptive statistics from the Tanzania DHS data for 2007/08 are given in Table 2. The last column of Table 2 reports the expected sign of the component loading for the first principal component of each of the variables generated by PCA of the variables. From the literature reviewed, it was expected that all the component loadings of the first PC would be positive. All the variables should be positively correlated with a household’s level of socio-economic status (SES), as access to better sanitation, ownership of assets and good quality housing materials should all increase a household’s wealth. However, a negative sign on the component loading for the variable *has bicycle* has been reported in past studies (McKenzie, 2005; Gwatkin, 2007b). A negative component loading for this variable could be expected since bicycle ownership increases with increasing wealth only up to a point, after which bicycle ownership decreases as households substitute motorized vehicles for bicycles.

Table 2: Descriptive statistics for the Tanzanian DHS, 2007/8 (N=8497)

Variable	Missing values	Categories	Mean	Standard deviation	Expected sign
Source of drinking water	3	20	n/a	n/a	+
Type of toilet facility	11	4	n/a	n/a	+
Main floor material	3	6	n/a	n/a	+
Main wall material	6	8	n/a	n/a	+
Main roof material	6	5	n/a	n/a	+
Type of cooking fuel	0	8	n/a	n/a	+
Has electricity	6	2	0.12	0.329	+
Has radio	2	2	0.6	0.489	+
Has television	5	2	0.1	0.295	+
Has refrigerator	7	2	0.06	0.23	+
Has bicycle	10	2	0.43	0.495	+/-
Has motorcycle/scooter	11	2	0.02	0.154	+
Has car/truck	11	2	0.01	0.113	+
Has telephone	10	2	0.01	0.094	+
Has a watch	9	2	0.4	0.49	+

Source: Macro International Inc. (2010)

3.2 Index construction

The principal theory of an asset-based index is that wealth is an underlying unobserved variable that can be determined through indicator variables that are associated with a household’s relative wealth position (Rutstein and Johnson, 2004). It is expected that ownership of various assets would be correlated across households; therefore a single summary measure should account for a reasonable proportion of the variation in wealth or socio-economic status across households (McKenzie, 2005). The four methods of generating the weights of the variables included in the asset indices are discussed below.

3.2.1 Linear principal component analysis following Filmer and Pritchett (2001)

The first method of generating the weights for the asset index followed that of Filmer and Pritchett (1994, 1999, 2001). The categorical variables (to be included in the index) were transformed into dichotomous variables by creating a dummy variable for each category of the categorical variable. For example, the variable *type of toilet facility* would be recoded from one variable with four categories, to four dummy variables. Linear principal component analysis was applied to the transformed variables using the PCA function in the Statistical Package for the Social Sciences (SPSS) version 15.0 for Windows. This procedure was repeated for each of the six chosen countries.

3.2.2 Linear principal component analysis following Kolenikov and Angeles (2009)

The second method of index construction was taken from Kolenikov and Angeles (2009) who contend that one of the assumptions underlying PCA is that the input variables are multivariate normal; thus, when the data are discrete this assumption is violated. From the recommendations of Kolenikov and Angeles (2009), the ordinal PCA procedure was adopted as the second approach to constructing an asset index. The categorical variables as well as the dichotomous variables were recoded to start at one, with an interval of one between each category, with the higher number linked to a greater level of socio-economic status. Consequently, an order of socio-economic status is forced onto the categorical variables. The dichotomous variables were treated in this way as they can be viewed as a special type of ordinal data with only two categories (Kolenikov and Angeles, 2009). For example, the variable *type of toilet facility* would keep its four categories, but be recoded as: one for *no facility/bush/ field*, two for *traditional pit latrine,* three for *ventilated improved pit latrine* and four for *flush toilet*. Linear (standard) PCA was then applied to the transformed ordinal data as if they were continuous data, using SPSS version 15.0 for Windows.

3.2.3 Non-linear principal component analysis following Linting et al. (2007)

Several of the variables included in the indices were categorical in nature. It has been suggested that linear PCA applied to categorical data may be inappropriate and nonlinear PCA has been suggested as an alternative (Meulman *et al*., 2004a; Meulman *et al*., 2004b; Linting, 2007; Linting *et al*., 2007; Costantini *et al*., 2009; Mair and de Leeuw, 2010; Manisera *et al*., 2010). A detailed discussion of the mathematics of nonlinear PCA is given by Gifi (1990), Meulman *et al*. (2004b) and Linting (2007). In this approach, the index weights were estimated using Categorical Principal Component Analysis (CATPCA), a non-linear principal component analysis technique available in SPSS Categories 10 onwards (Meulman *et al*., 2004a; Meulman *et al*., 2004b).

3.2.4 Simple sum of assets

As an alternative to a statistical means of generating weights for an index of SES, a simple count of household possessions could be used to generate a score of socio-economic status (Hatloy *et al*., 2000; Montgomery *et al*., 1999; Garenne and Hohmann-Garenne, 2003). A list of household possessions was selected from those available in the DHS data surveys for the chosen countries and recoded as dummy variables with a value of one assigned to the category linked to a higher level of socio-economic status and zero otherwise. Consequently, the final index score was simply a sum of all the dummy variables. This method does not differentiate between assets in terms of their value. Owning a television or owning a large, expensive fridge would simply add a one to the count of assets, without reflecting the difference in value of the assets. This is potentially problematic when using the estimated score as an indicator of resilience, as two households with the same score could not necessarily trade their assets for the same monetary value and, therefore, would not actually have the same level of resilience. The method is included in this study as a comparison to determine whether the choice of weighting method affects the ensuing household classification results.

3.3 Score estimation and household classification

Once the indicator weights had been estimated using the first three methods, the three indices were applied (separately) to the individual household data and scores for each household were calculated using Equation (1).

$$A_j = f_1 \text{ x } (a_{j1} - a_1) / (s_1) + ... + f_N \text{ x } (a_{jN} - a_N) / (s_N) \quad (1)$$

where A_j is the socio-economic status score for household j, f_1 is the component loading generated by the respective method for the first variable, a_{j1} is the j^{th} household's value for the first variable, and a_1 and s_1 are the mean and standard deviation, respectively, of the first variable over all the households. The scores calculated from the sum of assets method were simply a count of household assets owned by the study households. Once the individual household scores had been estimated (using all four methods), for each country dataset, the households were classified into quintiles based on the estimated scores. Each quintile represented a 'level' of household resilience, with quintile one comprising the relatively poorest 20 per cent of the population and quintile five containing the relatively richest 20 per cent.

4 METHOD RESULTS

The results of the construction and application of each of the four indices to the DHS data from the six African countries were compared across several characteristics. The results are summarised below for each assessment criterion, where:

- 'Dichot. PCA' refers to the linear PCA method put forward by Filmer and Pritchett (2001);
- 'Ordinal PCA' indicates that the linear PCA method proposed by Kolenikov and Angeles (2009) was used;
- 'CATPCA' refers to the non-linear PCA method suggested by Linting *et al*. (2007); and
- 'Simple sum' indicates that the sum of assets method was used.

4.1 Principal component analysis (PCA) results

The application of PCA to generate the weights of an asset index is based on the underlying assumption that household long-run wealth explains the maximum variance and covariance in the selected set of variables. To this end, the first principal component (PC) is of most interest in this study. The Eigenvalue and proportion of variance accounted for (PVAF) by the first PC were compared for the three PCA based methods. The Eigenvalue is an indication of the proportion of variation in the total data explained by that principal component (Vyas and Kumaranayake, 2006). The PVAF is a measure of the internal validity of the method; the higher the PVAF the greater the amount of variance in the total data that is explained by the estimated principal component (Kolenikov and Angeles, 2009). Table 3 is a summary of results from the PCA of the chosen variables for the three PCA based methods across all six countries.

Table 3: Principal component analysis results of the first principal component, across the six countries studied

Component	Method	Country					
		Tanzania 2007/08	**Liberia 2007**	**Uganda 2006**	**Mali 2006**	**Kenya 2008/09**	**Egypt 2008**
No. Vars†	Dichot. PCA	61	77	78	41	84	53
	Ordinal PCA	15	21	21	16	16	27
	CATPCA	15	21	21	16	16	27
Eigenvalue	Dichot. PCA	1.06	1.67	1.3	0.73	1.18	1.08
	Ordinal PCA	4.6	6.36	6.4	5.20	6.37	5.49
	CATPCA	5.36	6.50	7.34	5.46	6.88	5.51
PVAF♠ (%)	Dichot. PCA	24.20	31.89	22.28	20.34	20.42	25.16
	Ordinal PCA	30.66	30.28	30.46	32.48	39.8	20.34
	CATPCA	35.76	30.94	34.93	34.15	43.01	20.79

Notes:
† represents the number of variables included in the respective index
♠ represents the proportion (as a percentage) of variance accounted for by the first principal component for the particular index.
Source: Authors' calculations

Considering the Eigenvalue of the first PC generated by the three PCA methods across the six countries, the categorical principal component analysis (CATPCA) method consistently generated the highest Eigenvalue. However, the CATPCA method only had the highest PVAF for four of the six applications (countries), while the dichotomous PCA method had the highest PVAF values for the Liberia and Egypt applications.

4.2 Stability of the Principal Component Analysis Solutions

A stability analysis was performed for all three of the PCA-based methods by running PCA on 10 subsets of size $0.75N$ drawn from the total sample. The position of the estimated component loadings in relation to a reference line on a graph of the first versus the second principal component was used as an indication of stability. If the solution is stable, the 10 estimated component loadings for the same variable should all be above or below the reference line (Manisera *et al*., 2010). A stable solution should produce a small spread of the estimated component loadings for each variable of the index. The stability results for the three methods across the six country applications are summarized in Table 4. The CATPCA method performed the best with regards to method stability. The linear PCA method applied to dichotomous variables produced a consistently unstable solution, most likely caused by the coding of each one of the categories, for all the categorical variables, into a separate variable. This resulted in a significant increase in the number of variables in the analysis, many of which were poorly populated variables, which causes instability.

Table 4: Stability analysis results for each method, by country

Method	Country					
	Tanzania 2007/08	Liberia 2007	Uganda 2006	Mali 2006	Kenya 2008/09	Egypt 2008
Dichot. PCA	Unstable	Unstable	Unstable	Unstable	Unstable	Unstable
Ordinal PCA	1 unstable variable	2 unstable variables	1 unstable variable	Stable	Stable	2 unstable variables
CATPCA	Stable	1 unstable variable	Stable	Stable	2 unstable variables	Stable

Source: Authors' calculations

4.3 Score estimation and household classification

Socio-economic status scores were calculated for each household of the six datasets using each of the four methods. For the simple sum method, the score was simply a count of the number of assets owned by the household. The households were classified into quintiles based on the estimated scores where the first quintile contained the 20 per cent of households with the lowest scores while the fifth quintile contained the 20 per cent of households with the highest scores. The estimated household scores for the first and last quintiles for each of the six countries are given in Table 5. The scores are not directly comparable across countries as the variables used in the construction of the indices differed slightly across the countries. However, the scores are comparable across methods within the individual countries. From Table 5, it is evident that the four methods generated scores that differed from one another.

Table 5: Mean household scores for quintile 1 (Q1) and quintile 5 (Q5) for all methods across the six country applications

	Method	Country					
		Tanzania 2007/8	Liberia 2007	Uganda 2006	Mali 2006	Kenya 2008/9	Egypt 2008
Mean SES across Q1	Dichot. PCA	-6.318	-9.532	-8.55	-4.495	-8.756	-7.835
	Ordinal PCA	-3.904	-6.731	-6.06	-3.749	-7.052	-7.29
	CATPCA	-4.440	-6.837	-6.69	-3.933	-7.372	-7.237
	Simple sum	0	0.106	0.37	0.164	0.168	7.22
Mean SES across Q5	Dichot. PCA	11.081	13.119	13.73	5.102	11.539	9.131
	Ordinal PCA	7.542	10.234	10.53	8.512	10.317	8.076
	CATPCA	8.878	7.929	12.15	8.906	10.883	8.389
	Simple sum	4.022	7.426	8.61	5.514	6.069	15.175

Source: Authors' calculations

For each of the four methods the lowest mean score across quintile one was allocated to a different country. For example, Liberia had the lowest mean score for quintile one by the dichotomous PCA method (-9.5), but did not have the lowest mean score by any of the other methods. The results across the four methods were more similar for the fifth quintile. Uganda had the highest mean score by all the methods except the simple sum method. The results suggest that the three PCA based methods perform more similarly to one another at higher levels of socio-economic status.

The composition of the quintiles was compared between the four methods by setting one of the indices as the base method and determining, for each quintile of the base method, into which quintiles the same households were classified by the other methods. The process was repeated with each of the four indices as the base method and for each country. For example, the classification differences for quintile one between the CATPCA index (base method) and the other three indices for the Liberian data are given in Table 6. Of the households classified into quintile one by the base method, 93.3 per cent were also classified into quintile one and 6.7 per cent into quintile two by the ordinal PCA method. None of the households allocated to quintile one by the CATPCA index were classified into either quintile four or five by any of the other methods.

Table 6: Household classification comparisons (percentages) between the CATPCA index and the three alternate indices, for quintile one, Liberia 2007 (N=6824)

Quintile 1	Base method	PCA - ordinal	PCA - dichotomous	Simple sum
Q1	100.0	93.3	86.7	73.2
Q2	0.0	6.7	13.2	24.6
Q3	0.0	0.0	0.1	2.3
Q4	0.0	0.0	0.0	0.0
Q5	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0

Source: Authors' calculations

Overall, the three PCA-based indices classified households relatively similarly to each other, especially for the first and last quintiles. Classification similarities were the poorest for the simple sum index: the highest classification similarity being 83 per cent (for quintile five with the ordinal PCA index, Liberia) and the lowest 21.5 per cent (for quintile two with the ordinal PCA index, Mali).

4.4 Method reliability

The reliability of the various asset indices applied in this study was investigated using two methods of evaluating reliability put forward by Filmer and Pritchett (2001).

4.4.1 Internal coherence

Internal coherence can be established if there is a difference in the average ownership of a particular asset (variable) between groups (Filmer and Pritchett, 2001). Internal coherence could not be concluded for all or even the majority of variables for any of the methods across all the country applications using the quintile classification. In almost all instances, quintile five was distinct from the other quintiles, but there was frequently little distinction in the ownership of variables between quintiles one to four. The simple sum method appeared to be the best at separating households into five distinct quintiles as at least three of the variables included in the simple sum method showed internal coherence across the five quintiles for all the countries.

4.4.2 Robustness

A second means of assessing the reliability of an asset index, as suggested by Filmer and Pritchett (2001), is to consider how robust the index is to the choice of variables. The robustness of the asset indices applied in this study was assessed through comparisons of household classifications using all the variables to classifications based on three subsets of variables. In total four different sets of variables were compared for each method:

- The base index - all the variables;
- Index A - all variables except those relating to drinking water and toilet facilities;
- Index B - only asset ownership variables; and
- Index C - only categorical variables (variables with multiple categories).

As an example of an individual robustness assessment, results from the Kenyan household analysis using the CATPCA method are presented and discussed. Table 7 is a summary of the Eigenvalues and percentage of variance accounted for (PVAF) obtained from the application of CATPCA to the four sets of variables. The PVAF by the first principal component of the categorical variables only index (Index C) was the highest of the three indices. As pointed out by Houweling *et al*. (2003), reducing the number of variables included in the index tends to increase the proportion of variance accounted for by the first principal component, which explains why the first principal component for the categorical variables index had the highest PVAF – the categorical variables index contained the fewest variables.

Table 7: Eigenvalue and PVAF (per cent) results for the first principal component of CATPCA of all the variables and each of the subsets of variables, Kenya 2008/9 (N=9057)

	All Vars	**Index A**	**Index B**	**Index C**
Eigenvalue	6.881	5.700	3.486	3.744
No. Vars†	16	14	10	6
PVAF♠	43.008	40.713	34.855	62.405

Notes:
† represents the number of variables included in the respective index
♠ represents the proportion (as a percentage) of variance accounted for by the first principal component for the particular index.
Source: Authors' calculations

Table 8 shows the comparison of household classifications for the first quintile between the base index (all the variables) and the three subsets of variables indices for the Kenyan households using the CATPCA method of index construction. The index including all the variables except the variables *source of drinking water* and *type of toilet facility* (Index A) most similarly classified the households to the base index – 88 per cent of households classified into quintile one by the base index appeared in quintile one by Index A. This was expected as these two indices only differed by two variables.

Table 8: Household classification similarities (per cent) between the base method and the subsets of variables indices for quintile (Q) one, using the CATPCA method of index construction, Kenya 2008/9 (N=9057)

Quintile	Base method: All Vars	Index A	Index B	Index C
Q1	100.0	88.0	66.9	61.2
Q2	0.0	12.0	27.0	26.8
Q3	0.0	0.0	5.9	12.0
Q4	0.0	0.0	0.2	0.0
Q5	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0

Source: Authors' calculations

The classifications by index B and C were less similar: 66.9 per cent and 61.2 per cent, respectively. However, none of the households classified by the base index into the first quintile appeared in the fifth quintile by any of the subset variables indices and only 0.2 per cent of the variables in quintile one by the base index appeared in quintile four by the asset variables only index and none in quintile four by the other indices. Following the Filmer and Pritchett (2001) interpretation of these results, it can be concluded that the CATPCA method of index construction was robust to the inclusion of variables in the index as none of the households classified into the 'poorest' group by the base index were classified into the 'rich' group by any of the other indices. The classification similarities observed for the first quintile deteriorated for the second and third quintiles; however the similarities improved for quintile four and were even higher across all the subset variables indices for quintile five (a minimum classification similarity of 83 per cent). The results showed that the index constructed using the CATPCA method, for Kenyan households in 2008/9, was more robust to the choice of variables for the first and fifth quintiles with classification similarities declining across the middle quintiles. Reducing the number of classification groups could improve the robustness of the index.

Overall, across all the countries and index construction methods, classification similarities and hence the robustness of the indices declined for the middle quintiles. The results imply that an asset index using a quintile classification method was somewhat able to distinguish between the 'poorer' and the relatively 'richer', but was not able to separate out the households in-between with the same clarity.

A frequency histogram of the estimated scores by each method was constructed for each country application. A frequency histogram of the household scores provides an indication of the distribution of the scores across the country. Figure 1 is the frequency histogram of the estimated scores generated using the Filmer and Pritchett (2001) PCA method across the Malian households for 2006. The figure shows a lack of uniformity in the estimated scores across households. Many more households had relatively low scores and only a few households had relatively high scores – the distribution of scores is skewed. Similar frequency histograms were obtained for all four of the construction methods across the six countries: the distribution of the estimated scores was uneven for all the countries by all four construction methods.

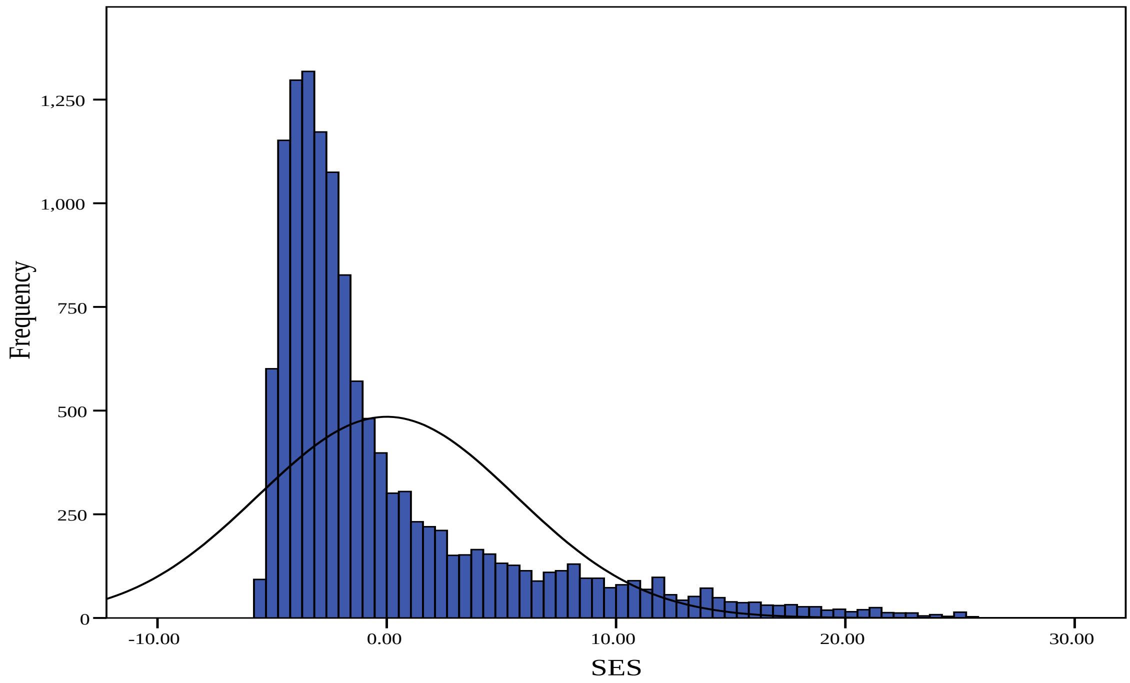

Figure 1: Frequency histogram of socio-economic status scores, Mali 2006 (*N*=12998)

Note: SES refers to the estimated scores
Source: Authors' calculations

It became clear from the frequency histograms of the estimated scores and the robustness results, that the distribution of socio-economic status across households was not uniform by any of the methods. Therefore, the use of quintiles as group cut-off points is not appropriate as the assumption of uniformity made when using quintiles is violated. Applying a quintile split did not reflect the clustered nature of the household data.

5 CLUSTER ANALYSIS RESULTS

In response to the non-uniform distribution of socio-economic status across households it was decided to investigate the use of cluster analysis as an alternative means of grouping households into groups of similar socio-economic status. Cluster analysis is a procedure that aims to identify homogenous groups or clusters of cases in datasets (Norusis, 2008:359), cases are grouped based on the values of selected variables so that 'similar' cases fall into the same group or cluster (Manly, 1994:128). K-means cluster analysis was applied to the previously estimated socio-economic status scores as dataset sizes exceeded 1000 cases: k-means cluster analysis is appropriate when *N* exceeds 1000 (Garson, 2010).

5.1 K-means cluster analysis with five clusters

In order to compare household classifications by cluster analysis to the original quintiles the five cluster option of the k-means procedure was chosen. The households from each of the six countries were clustered into five groups based on the estimated scores by the CATPCA method using the k-means cluster analysis option in the Statistical Package for the Social Sciences (SPSS) version 15.0 for Windows.

K-means cluster analysis did not result in five clusters of equal size (quintiles) for any of the six countries. The country results are given in Table 9 where the percentage of households allocated to each of the five clusters is shown. The results are presented in order of the 2009 Human Development Report (UNDP, 2009) poverty rankings – 'poorest' to 'richest'. In the discussion, 'poor' refers to countries with relatively greater levels of poverty by the Human Development Report and 'rich' to those with relatively lower levels of poverty. The clusters are arranged in order of increasing socio-economic status.

Table 9: Cluster sizes (per cent of total sample) for each of the six countries of analysis, using the k-means cluster analysis with five clusters

Country	*N*	Cluster (%)					
		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Total
Tanzania	8498	58.0	24.9	9.0	6.4	1.7	100.0
Liberia	6824	41.0	29.2	18.5	8.2	3.1	100.0
Uganda	8870	45.3	31.9	12.7	6.9	3.2	100.0
Mali	12998	65.8	19.3	8.9	4.0	2.0	100.0
Kenya	9057	30.3	32.6	19.9	12.2	5.0	100.0
Egypt	18968	10.4	31.6	30.9	19.4	7.7	100.0

Source: Authors' calculations

For the five-cluster solution, a larger proportion of the households in each country sample were allocated to the group of lowest socio-economic status for the four 'poorest' countries of the study, and to the second level of socio-economic status for the two relatively better off countries of the study (Kenya and Egypt). The highest socio-economic status level (cluster 5) contained the lowest per cent of households for all six countries. Of the proportion of households allocated to cluster 5 (the relatively more resilient cluster), the lowest per cent occurred for Tanzania (1.7 per cent) – the 'poorest' country in the study – and the largest per cent for Egypt (7.7 per cent) – the 'richest' country of study.

The results showed that a greater proportion of households fell into clusters of relatively lower levels of socio-economic status. This is in contrast to the assumption of uniformity of socio-economic status made when using the quintile cut-off approach. Cluster analysis better reflected the clustered nature of the household data compared to the quintile cut-off method. Additionally, the cluster sizes seem to reflect the 2009 Human Development Report (UNDP, 2009) poverty rankings: Tanzania (the 'poorest' country by the report) had the lowest proportion of more wealthy households (cluster 5) and Egypt (the 'richest' country by the report) had the largest proportion of cluster 5 households.

Garson (2010) defines several criteria to assess the validity of the cluster analysis solution. The first is cluster size: each cluster should contain enough cases to be meaningful (Garson, 2010). One or more relatively small clusters in the solution may indicate that too many clusters have been requested and a single dominant cluster may indicate too few clusters. For the k-means five-cluster solution the fifth cluster of each of the six country solutions tended to be relatively small, with a maximum of 7.7 per cent of households allocated to the fifth cluster (Egypt) and a minimum of 1.7 per cent (Tanzania). This result suggested that five clusters were too many in classifying households into groups of differing socio-economic levels for the six countries analysed.

The second validity criterion is that of cluster meaningfulness (Garson, 2010). The meaning of each of the clusters should be easily interpreted from the variables used to generate the clusters. In this study, only the household socio-economic status score was used to cluster the households, therefore, differing levels of household socio-economic status should be discernable between the five clusters. The meaningfulness of the solution was improved by using cluster analysis rather than classification by quintiles. However, not all of the variables (used to estimate the socio-economic scores) showed internal coherence across all five clusters.

5.2 K-means cluster analysis with two and three clusters

In an attempt to improve the internal coherence of the household classifications, the two- and three-cluster solutions were investigated. K-means cluster analysis with two clusters was applied to the estimated scores - using the CATPCA method - from each of the six countries of study. The proportion of households (in per cent of the total sample size) allocated to each of the clusters for the six countries is shown in Table 10.

Table 10: Cluster sizes (per cent of total sample) for each of the six countries of analysis, using the k-means cluster analysis with two clusters

Country	*N*	Cluster (%)		
		Cluster 1	Cluster 2	Total
Tanzania	8498	85.0	15.0	100.0
Liberia	6824	69.8	30.2	100.0
Uganda	8870	81.8	18.2	100.0
Mali	12998	85.8	14.2	100.0
Kenya	9057	72.7	27.3	100.0
Egypt	18968	61.6	38.4	100.0

Source: Authors' calculations

For all the countries, the larger proportion of households was allocated to the first cluster - the cluster representing the lowest level of socio-economic status. For three of the six countries, over 80 per cent of the households were allocated to the first cluster. Considering Garson's (2010) criteria of cluster validity, the cluster solution for each country appeared to be dominated by a single large cluster, suggesting that too few clusters were requested for the cluster analysis procedure. It was decided to run the k-means cluster analysis with three clusters since the five cluster solution showed some evidence of too many clusters and the two cluster solution too few clusters. The results of the k-means three-cluster country analyses are shown in Table 11.

Table 11: Cluster sizes (per cent of total sample) for each of the six countries of analysis, using the k-means cluster analysis with three clusters

Country	*N*	Cluster (%)			
		Cluster 1	Cluster 2	Cluster 3	Total
Tanzania	8498	68.6	21.9	9.5	100.0
Liberia	6824	56.7	31.7	11.6	100.0
Uganda	8870	67.1	23.6	9.3	100.0
Mali	12998	77.8	16.7	5.5	100.0
Kenya	9057	56.0	33.2	10.8	100.0
Egypt	18968	29.0	50.0	21.0	100.0

Source: Authors' calculations

For five of the six countries of analysis, the first cluster contained the greatest per cent of households; only for Egypt, the 'richest' country, was this not the case. The greatest per cent of households was allocated to the second cluster for Egypt. For Tanzania, Liberia and Uganda there was some improvement in the internal coherence between the clusters for the three-cluster solution for a number of variables, especially the asset variables. However, the improvement in internal coherence came at the expense of information regarding the structure of the households. Mali, Kenya and Egypt showed little improvement in internal coherence except for the asset variables. The size of the third cluster was relatively small (less than 15 per cent) for all of the countries except Egypt.

Comparing the two-, three- and five-cluster solutions; the two-cluster solution was not useful in that the majority of the households were allocated to one broad cluster. Both the three-cluster and five-cluster solutions were more useful: the three-cluster solution resulted in slightly improved cluster sizes, but the five-cluster solution offered a more detailed separation of households into socio-economic status groups. The five-cluster solution also provided a more even distribution of households with the differences in the mean score between clusters being more similar to one another than for the three-cluster solution.

6 SYNOPSIS OF RESULTS

The CATPCA index generated a first principal component (PC) that explained a greater proportion of the variance in the variables than the first PCs of the other PCA-based methods. The CATPCA method produced a stable solution for all the countries of analysis across almost all of the variables. The linear PCA method applied to dichotomous variables produced a consistently unstable solution, due most likely to the inclusion of a number of poorly populated categories. The household scores estimated using each of the four indices differed from one another in terms of the mean score for each quintile and the difference between the minimum and maximum scores for each method. The distribution of scores was uneven for all four methods across all six countries, although only mildly so for Egypt where the frequency histograms showed a less-skewed distribution. For each country, the socio-economic distribution was less skewed and the differences between the mean score for each quintile were more equal for the simple sum method than for the others. The classification of households into quintiles was not internally coherent for all, or even the majority of variables for any of the methods.

However, the simple sum method appeared to perform slightly better, in terms of internal coherence, at separating households into five quintiles. The PCA-based indices were generally robust to changes in the variables included in the index for the first and fifth quintiles. However, the similarities in household classifications between subsets of variables declined across the middle quintiles. Lastly, the differences in the classification of the households into quintiles based on the estimated scores between the four methods showed the three PCA-based methods to classify households relatively similarly, especially for the first and fifth quintiles. The household classifications by the simple sum method were the most different from the classifications by the other methods. Classification similarities between the methods declined across the middle quintiles for all countries.

7 CONCLUSIONS

From these observations, it can be concluded that no single method stands out as being 'better' than the others for all the assessment characteristics. The CATPCA method performed better in terms of the proportion of variance explained by the first principal component and the stability of the initial CATPCA solution. To this end, the choice of weighting method would depend on the objective of the researcher in terms of which of the assessment characteristics was deemed most important. The time period available for analysis and the type of data to be analysed would be further considerations. For example, as in the case of Demographic and Health Survey data, as used in this study, a number of variables for inclusion in the asset index were categorical and, therefore, if the dichotomous PCA method was chosen, these variables would require recoding to transform each category of the variable into a variable of its own. This is time-consuming. Of the four methods investigated here, the simple sum method was the quickest to apply as it made use of only the asset (dichotomous) variables.

The application of cluster analysis as a means of classifying a set of households into groups representing a certain level of socio-economic status appeared to be more useful than the quintile split: both in that it did not assume an even distribution of socio-economic status across households – as the use of quintiles did - and, if measured over time, it could provide a clear indication of changes in the per cent of households falling into the different clusters of socio-economic status. Cluster analysis of the estimated household scores could give a general indication of adjustments in household resilience - perhaps as a result of policy developments or interventions – by allowing the observation of changes in the per cent of households allocated to the different clusters over time. Additionally, tracking the movement of a single household from one cluster to another over time could show the effect of such interventions on a particular household's livelihood.

The resilience score developed in the study, along with k-means cluster analysis, has the potential to be a measure of the relative resilience of rural households in developing areas as well as a means of measuring progress towards improved household resilience. The resilience score alone (based on a PCA weighting method) cannot be used to identify absolute levels of resilience, but rather it is a comparative tool allowing a population to be broken into groups representing increasing levels of resilience. If, however, detailed, context specific research regarding the nature of asset ownership is conducted for the study population, it could be used along with the resilience score to identify actual levels of resilience. The resilience measure is of use in tracking changes in household resilience over time and could be used to monitor progress towards improved household resilience. The resilience measure, along with detailed asset ownership information, could be valuable to policy-makers for identifying vulnerable households and monitoring the impacts of new policies on such households. However, much research is still required. Further studies regarding the construction of the asset index are necessary

- to determine the most appropriate set of variables – related to household resilience - to use in the construction of the index - this is likely to be context specific;
- to decide on the most suitable and reliable method of weighting the variables in the index; and
- to validate the measure.

The reliability of the asset index and the resulting resilience score depends heavily on the quality of data used in the analysis. Asset data is relatively quick to collect and it avoids the problems of recall bias and seasonality associated with income and expenditure data. However, further studies are required to determine the reliability of such data.

REFERENCES

Alinovi, L., Mane, E. and Romano, D. 2008. Towards the Measurement of Household Resilience to Food Insecurity: Applying a Model to Palestinian Household Data. In Sibrian, R., (ed.). *Deriving Food Security Information From National Household Budget Surveys. Experiences, Achievement, Challenges*. FAO. Rome: 137–52. Available at: ftp://ftp.fao.org/docrep/fao/011/i0430e/i0430e.pdf. Accessed 3 May 2013.

Alinovi, L., D'Errico, M., Mane, E. and Romano, D. 2010. Livelihoods strategies and household resilience to food insecurity: an empirical analysis to Kenya. Paper prepared for the Conference on "Promoting Resilience through Social Protection in Sub-Saharan Africa", organised by the European Report of Development in Dakar, Senegal, 28–30 June, 2010.

Chambers, R. 2006. Vulnerability, coping and policy (editorial introduction). *IDS Bulletin* 37(4):33–40.

Collier, P. and Gunning, J.W. 1999. Explaining African economic performance. *Journal of Economic Literature* 37(1):64–111.

Costantini, P., Linting, M. and Prozio, G.C. 2010. Mining performance data through nonlinear PCA with optimal scaling. *Applied Stochastic Models in Business and Industry* 26(1):85–101.

Dercon, S. 2005. Risk, poverty and vulnerability in Africa. *Journal of African Economies* 14 (4):483–488.

Dercon, S., Hoddinott, J. and Woldehanna, T. 2005. Vulnerability and Shocks in 15 Ethiopian Villages, 1999-2004. *BASIS Collaborative Research Support Program*. University of Wisconsin-Madison. Madison.

Dercon, S. 2006. Vulnerability: A micro perspective. *QEH Working Paper*, 149. Department on International Development, University of Oxford. Oxford.

Filmer, D. and Pritchett, L.H. 1994. Estimating wealth effects without expenditure data – or tears: With an application to educational enrolments in states of India. *World Bank Policy Research Working Paper*. Washington, D.C.

Filmer, D. and Pritchett, L.H. 1999. The effect of household wealth on educational attainment: evidence from 35 Countries. *Population and Development Review* 25(1):85–120.

Filmer, D. and Pritchett, L.H. 2001. Estimating wealth effects without expenditure data – or tears: An application to educational enrolments in states of India. *Demography* 38 (1):115–132.

Food and Agriculture Organisation (FAO) and the World Food Programme (WFP). 2013. Summary of the Expert Consultaion on Resilience Measurement for Food Security.

Available at http://agrilinks.org/library/summary-expert-consultation-resilience-measurement-food-security. Accessed 3 May 2013.

Garenne, M. and Hohmann-Garenne, S. 2003. A wealth index to screen high-risk families: Application to Morocco. *Journal of Health, Population and Nutrition* 21(3):235–242.

Garson, G.D. 2010. *Cluster Analysis*. *Statnotes: Topics in Multivariate Analysis*. North Carolina State University. Available at http://faculty.chass.ncsu/garson/pa765/statnote.htm (Accessed 27 October 2010).

Gifi, A. 1990. *Nonlinear Multivariate Analysis*. Chichester: Wiley.

Gwatkin, D.R., Rutstein, S., Johnson, K., Suliman, E., Wagstaff, A. and Amouzou, A. 2007a. Socio-economic differences in heath, nutrition and population within developing countries: An overview. Country reports on HNP (Health Nutrition and Population) and Poverty. World Bank, Washington, D.C.

Gwatkin, D.R., Rutstein, S., Johnson, K., Suliman, E., Wagstaff, A. and Amouzou, A. 2007b. Socio-economic differences in heath, nutrition and population within developing countries: Kenya. Country reports on HNP (Health Nutrition and Population) and Poverty. World Bank. Washington, D.C.

Hatloy, A. Hallund, J., Diarra, M.M. and Oshaug, A. 2000. Food variety, socio-economic status and nutritional status in urban and rural areas of Koutiala (Mali). *Public Health Nutrition* 3(1):57–65.

Hendriks, S.L, Kiamba, J. and Ngidi, M. 2009. Country responses to high food prices: Challenges and opportunities for Africa. Paper prepared for the April 2009 Agriculture, livestock and Lands African Ministers' Conference and the June/July 2009 AU Heads of State Government Summit. Addis Ababa.

Houweling, T.A.J., Kunst, A.E. and Mackenback, P.J. 2003. Measuring health inequality among children in developing countries: Does the choice of the indicator of economic status matter? *International Journal for Equity in Health* 2:8 published on line http://www.ncbi.nlm.nih.gov/pmc/articles/PMC272937/pdf/1475-9276-2-8.pdf (Accessed 16 February 2010).

IFPRI (International Food Policy Research Institute). 2013. The Concept of the Global Hunger Index. Available at www.ifpri.org/ghi/2013/concept-global-hunger-index (Accessed 29 March 2013).

Kolenikov, S. and Angeles, G. 2009. Socioeconomic status measurement with discrete proxy variables: Is Principal Component Analysis a reliable answer? *Review of Income and Wealth* 55(1):128–165.

Linting, M. 2007. Nonparametric Inference in Nonlinear Principal Components Analysis: Exploration and Beyond. Dissertation, Leiden University. The Netherlands. Available at www.openaccess.leidenuniv.nl.dspace/handle/1887/1238 (Accessed 16 February 2010).

Linting, M., Meulman, J.J., Groenen, P.J.F. and van der Kooij, A.J. 2007. Nonlinear Principal Components Analysis: Introduction and application. *Psychological Methods* 12(3):336–358.

Lovendal, C.R. and Knowles, M. 2005. Tomorrow's Hunger: A framework for analyzing vulnerability to food insecurity. *ESA Working Paper*, 05-07. Food and Agriculture Organization of the United Nations. Rome.

Macro International Inc. 2010. Demographic and Health Survey Data (various countries and years). Available at www.measuredhs.com (Accessed 5 July 2010).

Mair, P. and de Leeuw, J. 2010. A General framework for multivariate analysis with optimal scaling: The R package aspect. *Journal of Statistical Software* 32(9):1–23.

Manisera, M., Dusseldorp, E. and van der Kooij, A.J. 2010. Identifying the component structure of satisfaction scales by Nonlinear Principal Components Analysis. *Quality Technology and Quantitative Management* 7(2):97–115.
Manly, B.F.J. 1994. *Multivariate Statistical Methods: A Primer*, 2nd edition. London: Chapman and Hall.
Maxwell, S. and Smith, M. 1992. Household Food Security: A Conceptual Review. In Maxwell, M. and Frankenberger, T.R. (Eds), *Household Food Security: Concepts, Indicators and Measurements. A Technical Review*. UNICEF/ IFAD, 1–7. New York and Rome.
McKenzie, D.J. 2005. Measuring inequality with asset indicators. *Journal of Population Economics* 18:229–260.
Meulman, J.J., Heiser, W.J. and SPSS Inc. 2004a. *SPSS Categories 13.0*. Chicago: SPSS Inc.
Meulman, J.J., van der Kooij, A.J. and Heiser, W.J. 2004b. Principal Components Analysis with Nonlinear Optimal Scaling Transformations for Ordinal and Nominal Data. In Kaplan, D. (Ed), *The Sage Handbook of Quantitative Methodology for the Social Sciences*. California: Sage Publications Inc.
Montgomery, M.R., Gragnolati, M., Burke, K. and Paredes, E. 1999. Measuring living standards with proxy variables. *Demography* 37(2):155–174.
Moser, C. and Holland, J. 1997. Household Response to Poverty and Vulnerability. Volume 4: Confronting Crisis in Carvana, Lusaka, Zambia. *Urban Management Programme Report*, 24. Washington, D.C: World Bank.
Moser, C. 1998. The asset vulnerability framework: Reassessing urban poverty reduction strategies. *World Development* 26(1):1–19.
NEPAD (The New Partnership for Africa's Development). 2009a. *Comprehensive African Agriculture Development Programme (CAADP) Pillar 3, Framework for African Food Security (FAFS)*. Midrand: NEPAD.
NEPAD (The New Partnership for Africa's Development). 2009b. CAADP Pillar 1 Framework on Sustainable Land and Water Management. Available at www.caadp.net/pdf/CAADP%20Pillar%201%20Framework.pdf (Accessed 30 March 2013).
NEPAD (The New Partnership for Africa's Development). 2009c. Framework for Improving Rural Infrastructure and Trade Related Capacities for Market Access (FIMA). Available at www.caadp.net/pdf/CAADP%20Pillar%20II%20FIMA%20Full%20Document.pdf (Accessed 30 March 2013).
NEPAD (The New Partnership for Africa's Development). 2006. Framework for African Agricultural Productivity (FAAP). Available at www.caadp.net/pdf/FAAP_English_13Oct06.pdf (Accessed 30 March 2013).
Norusis, M.J. 2008. *SPSS 16.0 Statistical Procedures Companion*. New Jersey: Prentice Hall Inc.
NPCA (African Union/New Partnership for Africa's Development Planning and Coordination Agency). 2011. Mutual Accountability Framework for the Comprehensive Africa Agriculture Development Programme. Available at www.nepad.org/system/files/CAADP%20MAF%20Final%20Draft%20Report%20%20March%202011.pdf (Accessed 30 March 2013).
Omiliola, B. 2010. Monitoring and Evaluation System for CAADP Implementation. Presentation at the Partnership to Cut Hunger and Poverty in Africa Annual Forum, Washington Court Hotel, Washington DC., February 25 – 26, 2010. Available at

partnership-africa.org/sites/default/files/3-F%20Omilola%20Presentation.pdf (Accessed 30 March 2013).

Rutstein, S.O. and Johnson, K. 2004. The DHS (Demographic and Health Survey) Wealth Index. *DHS Comparative Reports*, No. 6. OCR Macro. Calverton, Maryland.

Sen, A. 1981. *Poverty and Famines: An Essay on Entitlement and Deprivation*. Oxford: Clarendon Press.

Swift, J. 2006. Why are rural people vulnerable to famine? *IDS Bulletin* 37(4):41–49.

UNDP (United Nations Development Programme). 2009. *Human Development Report, 2009, Overcoming Barriers: Human Mobility and Development*. Hampshire and New York: Palgrave Macmillan.

Vyas, S. and Kumaranayake, L. 2006. Constructing socio-economic status indices: How to use Principal Component Analysis. *Health Policy and Planning* 21(6):459–468.