MEASURING HOUSEHOLD RESILIENCE IN DEVELOPING COUNTRIES: EVIDENCE FROM SIX AFRICAN COUNTRIES

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ABSTRACT

In this study, a household resilience score was developed as a measure of rural household resilience to identify households with low resilience and to measure progress towards improved household resilience. Resilience is the ability of households to cope with risk. The motivation for the study originated from the first objective of the Framework of African Food Security (FAFS) of improved household risk management, and the indicator of progress towards this objective – proposed by the FAFS - a resilience score. A review of the literature indicated that the assets owned by a household could be used as a proxy for resilience.

The household component of the Demographic and Health Surveys for six African countries was used to develop and apply the resilience score. The score was estimated using an index of assets owned by the household and information regarding household access to certain services and characteristics of the dwelling. There is disagreement in the literature concerning the best method of constructing an asset index in terms of how to weight the variables included in the index. As a result, four methods of constructing an index of socio-economic status (SES) were selected for comparison in this study: two linear principal component analysis (PCA) techniques; a non-linear or categorical principal component analysis (CATPCA) method; and a simple sum of assets technique. The results from the application of each of the four indices to the country data and the resulting classification of households into quintiles of SES were compared across several assessment criteria. No single method out-performed the others across all the assessment criteria. However, the CATPCA method performed better in terms of the proportion of variance explained by the first principal component and the stability of the solution.

The results showed that for all methods, SES was not evenly distributed across the sample populations for the countries analysed. This violates the assumption of uniformity implied when using quintiles as classification cut-off points. As an alternate to the quintile split cluster analysis was applied to the SES scores derived for each country. The classification of households into SES groups was repeated using k-means cluster analysis of the household SES scores estimated by the CATPCA method for each country. The results showed that a greater proportion of households fell into relatively lower levels of SES, which is in contrast to the assumption of uniformity of SES made when using the quintile cut-off approach.

Cluster analysis better reflected the clustered nature of the household data analysed in this study, compared to the quintile cut-off method.

In a final analysis, the index of SES along with k-means cluster analysis was applied to household data from two different time periods for five African countries to determine whether the resilience measure was able to detect changes in household SES between the two periods and, therefore, whether the tool could be used to monitor changes in household resilience over time. The results showed evidence of adjustments in SES over time: there were differences in the per cent of households allocated to the clusters of SES between the two periods. Using the CATPCA index and k-means cluster analysis, Egypt, Uganda and Mali showed an increase in the per cent of 'poor' households, while for Kenya and Tanzania there was a reduction in the per cent of households allocated to the first cluster between time periods: the decrease for Kenya from 2003 to 2008 was as much as 13 percentage points. The observed changes in SES were then compared to changes in national poverty estimates reported in the literature.

The resilience score developed in the study displayed an ability to track changes in household SES over time and could be used as a measure of progress towards improved household resilience. As such, the resilience measure could be valuable to policy-makers for monitoring the impacts of policies aimed at improving household resilience. Future research is recommended before the reliability of the resilience measure developed here can be fully ascertained.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Sustained growth in agriculture is required to decrease hunger and poverty in Africa (NEPAD, 2009). In response to this requirement, The Comprehensive Africa Agriculture Development Programme (CAADP) has been established to stimulate agricultural growth in Africa. The programme 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 (Hendriks *et al*., 2009, citing AU/NEPAD, 2003). The Framework for African Food Security (FAFS) is the third pillar of the CAADP. The FAFS aims to ensure that the agricultural growth agenda addresses the chronically poor and vulnerable directly so to insure that the CAADP agenda is aligned with the first Millennium Development Goal (MDG).

Risk is an important factor contributing to poverty in the developing world (Kinsey *et al*., 1998; Dercon, 2006). Evidence suggests that the inability to cope with risk and vulnerability plays a role in perpetuating poverty (Collier & Gunning, 1999; Dercon *et al*., 2005; Dercon, 2005; Dercon, 2006). An improvement in household resilience - the ability to cope with risk - could reduce vulnerability and food insecurity. The FAFS recognizes the importance of resilience and risk management in reducing household poverty. In response to the high levels of food insecurity in Africa, the strain on governments and foreign aid organizations in supporting the poor and food insecure, and the role of risk in perpetuating poverty, the FAFS provides recommendations to reduce food insecurity and poverty by increasing the resilience of vulnerable households in Africa. Within the FAFS there are four objectives towards this aim and four indicators of progress towards achieving the objectives, brought together in the FAFS score card (NEPAD, 2009). The first objective of the FAFS is to improve household risk management, and the indicator proposed as a measure of progress towards this goal is a household resilience score. This score is not developed in the FAFS score card; research is expected and needed to further expand the concept of a resilience score as an indicator of household risk management. It is the goal of this study to elaborate on and apply such a household resilience score.

The use of assets as a risk management tool and the importance of assets in determining the ability of a household or individual to cope with hardship are well documented in the literature (Sen, 1981; Maxwell & Smith, 1992; Morduch, 1995; Moser & Holland, 1997;

Moser, 1998; Dercon, 2001; Carter *et al*., 2004; Lovendal & Knowles, 2005; Chambers, 2006; Doocy & Burnham, 2006; Swift, 2006; WFP, 2009). When a shock occurs, the household could sell assets and use the resulting income to support it through the shock. The ownership of assets by a household could, therefore, be used as a proxy for resilience. An asset-based index could estimate household wealth or SES, which could then be used as an indicator of the relative resilience of the particular household, based on the premise that the level of asset ownership is an indication of a household's ability to cope with risk, provided that the assets could be exchanged for income or some other form of support.

The aim of the study is to develop a household resilience score, as a measure of resilience, for rural households in developing countries as a means of identifying households with low resilience and measuring progress towards improved household risk management. It was proposed that a household resilience score, based on household asset ownership and access to certain facilities, could be used to quantify the ability of households to manage risk so as not to become food insecure. Within this aim are two objectives: (1) to develop an asset-based index for use in the estimation of household socio-economic status (SES) scores as an indication of household resilience by comparing several methods of asset-based index construction; and (2) to apply the index to data, from two different time periods for several African countries, to evaluate the ability of the resilience indicator to measure progress towards improved household resilience.

There are several methods of constructing indices of SES: a popular method is the application of linear principal component analysis (PCA) to the chosen variables. However, no single method has been widely accepted as being superior to the rest in estimating household SES. Although the use of linear PCA to estimate the weights of the chosen variables within the asset-based index is used regularly, a number of studies indicate that the application of linear PCA to non-continuous data is unreliable and even inappropriate (Mayer, 1971; Kim & Mueller, 1994:141-143; Linting, 2007; Chandola *et al*., 2009; Kolenikov & Angeles, 2009). Often, the variables chosen for an index of SES are in binary or categorical form. For this reason, four methods of constructing an index of SES were selected for comparison in this study: two linear PCA techniques, applied to the same data but in different forms; a non-linear or categorical principal component analysis (CATPCA) method; and a simple sum of assets technique.

The first chapter of the study discusses food security, its definition and attempted measurement and reports levels of hunger and poverty in the world. The CAADP is introduced along with its third pillar, the FAFS. The objectives of the FAFS are discussed, specifically the first objective – to improve household risk management – the stimulus for this study. An argument is made of the role of risk in perpetuating poverty and food insecurity and the concepts of risk, resilience and vulnerability are explained. The chapter ends by suggesting that the level of asset ownership by households could be used as an indication of resilience. Chapter two elaborates on the importance of assets in household responses to shocks, discusses household coping strategies and presents support from the literature for asset ownership as an indicator of resilience. The last section of the chapter is a review of the literature on asset-based indices. The third chapter outlines the research methodology and describes the data used in the study. Chapter four presents the results of the application of the four types of asset indices to the data and the classification of households into quintiles based on the estimated SES scores. Chapter five introduces cluster analysis as an alternate method of household classification to the use of quintiles. The results of the application of cluster analysis to the estimated SES scores by the CATPCA method from chapter four are then presented and discussed. The final chapter of the thesis is a comparison of household SES over time based on the results from the application of both the CATPCA index and the simple sum index to country data for two different time periods.

CHAPTER 1: FOOD SECURITY AND HOUSEHOLD RESILIENCE

Food insecurity remains a challenge in Africa. The Comprehensive African Agriculture Development Programme (CAADP) has been developed to stimulate agricultural growth in Africa in an attempt to decrease hunger and poverty. The third pillar of the programme is the Framework for African Food Security (FAFS), which specifically focuses on food security in Africa and reducing hunger in line with the first Millennium Development Goal (MDG). The FAFS acknowledges the role of risk in perpetuating household poverty and hunger and aims to increase resilience - the ability of households to manage risk.

The chapter opens with an introduction to food security: its definitions and an overview of food security measurement tools. Section 1.2 reports levels of poverty and hunger in the world and discusses progress towards the first MDG. The following three sections discuss the CAADP and the FAFS and outline the concepts of risk, resilience and vulnerability. The chapter closes with an introduction to the FAFS objectives, indicators and score card and the aim of the study, namely to develop the first FAFS indicator – a resilience score.

1.1 Food Security

Before household food security can be assessed and those that are food insecure or vulnerable identified, it is necessary to clarify what is meant by food security. The definition has undergone many shifts over time, following developments in the understanding of food security (Maxwell, 1996). By 1992 nearly 200 definitions of food security existed, as shown by Smith *et al*. (1992) in their bibliography of food security concepts and definitions.

1.1.1 Definition of Food Security

The term ‘food security’ originated from the World Food Conference of 1974 and was first defined in terms of food supply (Clay, 2002). Focus was given to assuring the availability of basic foodstuffs at the international and national level: “… *availability at all times of adequate world food supplies*” (UN, 1975:8). This definition led to a concern over national self-sufficiency, with a focus on how much food a country produces (Pinstrup-Anderson, 2009), and attention was given to world and national food stocks (Maxwell, 1996). However, widespread hunger continued even in the presence of an adequate food supply (Maxwell, 1996) leading to a shift in focus from food supply to food demand (Maxwell & Slater, 2003). Sen’s (1981) seminal work played a role in shifting the attention from food availability to food access through his emphasis on food security with food entitlements. Over time it was generally agreed that sufficient food availability did not translate directly into reduced food insecurity (Maxwell & Slater, 2003; Webb *et al*., 2006).

The shift in focus from food availability to food access is apparent in the 1983 FAO (Food and Agriculture Organization of the United Nations) definition of food security: "*Ensuring that all people at all times have both physical and economic access to the basic food that they need*" (Clay 2002:27, citing FAO, 1983). This revised definition altered the focus from national level availability to household and individual access to food. The definition of food security was revisited by the World Bank in 1986 when the 'need for food' was extended to: "*access of all people at all times to enough food for an active, healthy life*" (World Bank, 1986:1). The United States Agency for International Development's (USAID) definition of food security is: "*When all people at all times have both physical and economic access to sufficient food to meet their dietary needs for a productive and healthy life*" (USAID, 1992:2). Their definition points to three distinct components that are essential to the attainment of food security: food availability, food access and food utilization (USAID, 1992). In 1996 the World Food Summit adopted a still more complex definition: "*Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life*." (World Food Summit, 1996:6).

Once again the three aspects are distinct in this definition: food availability, food access and food utilization. Food availability implies that sufficient quantities of appropriate, necessary foods are available through domestic production, imports or donors (USAID, 1992). Food access entails having both physical access to a place where food is available (Staatz *et al*., 2009) as well as having economic access to food through adequate incomes or resources to obtain food (USAID, 1992). Access to food refers to whether individuals and households are able to acquire sufficient food (Maxwell & Smith, 1992). Food utilization stems from having access to 'sufficient, safe and nutritious food for an active and healthy life', and refers to the individual's biological capacity (health) to make use of food for a productive life (Bilinsky & Swindale, 2007). Utilization in the context of food security refers to the ability of the body, at the cellular level, to extract and use the nutrients in the food. Thus, food preparation, sanitation and the health of the individual affect food security (Staatz *et al*., 2009).

Food insecurity is the lack of food security, which, in the extreme, results in hunger (Hendriks, 2005). At household level, a household is food insecure if it does not have sufficient food to maintain an active and healthy lifestyle for all its members (Dutta *et al*., 2006); the household has lost, or is at risk of losing, availability and access to food or the ability to use it (Chung *et al*., 1997). The ability to use food is linked to health and whether the individual is physically able to eat enough and to process the food consumed. The concept of food security also entails an element of time. Chronic food insecurity is a persistent inability to attain access to food over the long-run, while acute or transitory food insecurity is characterized by sudden reductions in access to food over a relatively short period of time (Chung *et al*., 1997). Acute food insecurity is often associated with seasonality (Hoddinott, 1999).

1.1.2 Overview of Food Security Indicators

The measurement of food security is subject to debate and controversy. There is no method for measuring food security in its entirety (Jacobs, 2009). A number of indicators are required in order to capture the multidimensional character of food security (Wolfe & Frongillo, 2001). Often, household food security measures are a mix of indicators representing different aspects of food security (Hendriks, 2005). The choice of approach to assessing food security depends on the availability of data, access to resources, including funds, and the purpose of the analysis (Riley, 2000).

In an attempt to map food security indicators, Jacobs (2009) sets out three groups of indicators: (1) food availability indicators (also known as process indicators) - these generally focus on national or household agro-food output or supply; (2) food access indicators (also known as outcome indicators); and (3) composite food security indicators that attempt to simultaneously capture each dimension of food security in a single index. Figure 1.4 depicts this categorization of food security indicators and lists the different measures under each group. A number of these indicators are briefly discussed in the following paragraphs. Appendix A provides a summary of various food security indicators with reference to authors for further details.

1.1.2.1 Food Supply/Availability Indicators

Food supply indicators provide useful information on the availability of food in a particular region (Frankenberger, 1992:86). Data on agricultural production and food balance sheets are often used as national indicators of food security (Frankenberger, 1992:86), but these indicators measure only the aggregate availability of food and not household or individual access to food. These aggregate measures of food availability can be adapted by compiling household or per capita food balance sheets as done by the FAO to calculate the daily per capita dietary energy supplies for countries (Perez-Escamilla & Segall-Correa, 2008; Gentilini & Webb, 2008). Meteorological data (such as rainfall), the availability of natural resources, pest management practices, the presence of markets and institutional structures and regional conflict information all give an indication of food supply and availability in a particular region (Frankenberger, 1992:88-89). Authors such as Haddad *et al*. (1997), Hoddinott (1999), Wolfe and Frongillo (2001), Webb and Thorne-Lyman (2006) and Perez-Escamilla and Segall-Correa (2008) discuss food supply indicators in more detail.

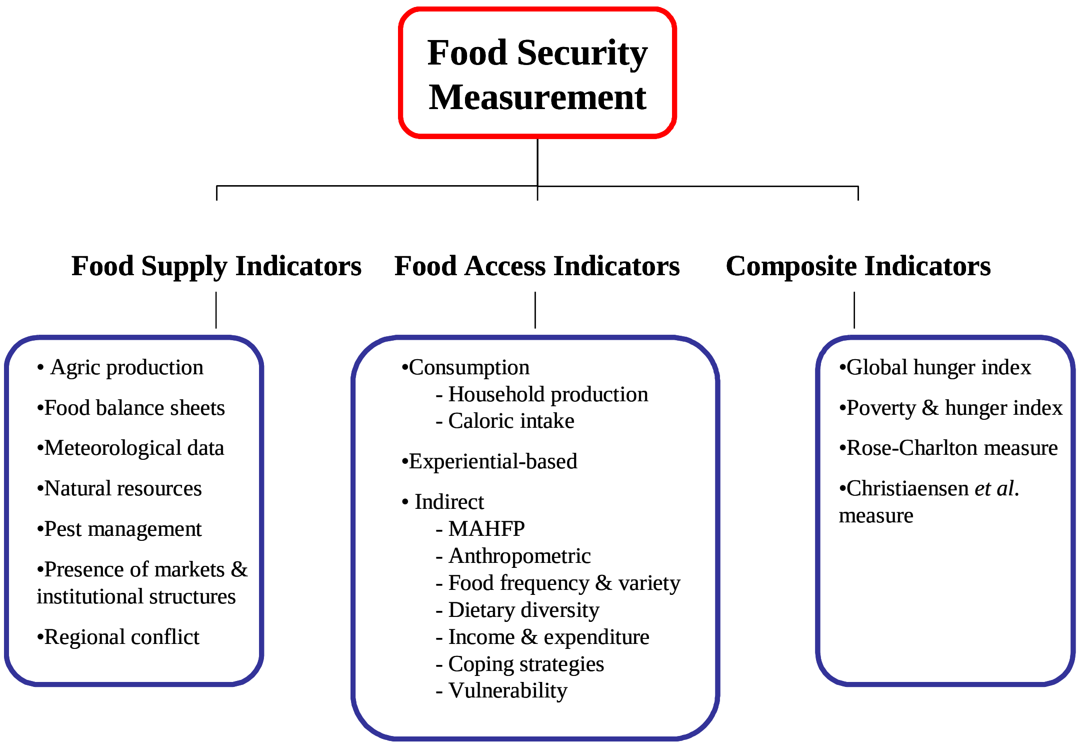

Figure 1.1: Food security indicators
Note: 'MAHFP' refers to the months of adequate household food provisioning indicator
Source: Adapted from Jacobs (2009) and the literature reviewed in section 1.1.2

Food supply indicators do not capture elements of limited household or individual access to food and, therefore, are not fully indicative of the overall food security situation (Perez-Escamilla & Segall-Correa, 2008). These measures also do not consider dietary diversity and assume a caloric consumption above a certain level to be indicative of food security. However, the use of cut-off levels for calorie requirements is conceptually weak. In reality, calorie requirements are a function of many factors such as activity levels, age and gender and thus differ between individuals (Perez-Escamilla & Segall-Correa, 2008).

1.1.2.2 Food Access Indicators

Access to food has become a focal point in the understanding of food security since the 1980s under the influence of Sen (1981), who emphasized consumption and access to food and focused on the entitlements of individuals and households (Clay, 2002). The access to food component of food security has no one accepted measure (Webb *et al*., 2006) and a low-cost method of data collection still has to be developed (Jacobs, 2009). Frankenberger (1992:96) classifies food access measures as either direct or indirect indicators of food security. Direct measures are those that are closest to actual food consumption and measure the experience of food insecurity, while indirect measures are generally related to market information and/or the health status of household members from which the level of food security or vulnerability to food insecurity may be inferred (Frankenberger, 1992:96; Tarasuk, 2001). Direct indicators include food consumption measures and experiential-based measures. Experiential-based measures make use of a household's own perception of its food insecurity as an indication of its food security status. Indirect measures include the months of adequate household food provisioning (MAHFP) indicator, anthropometry (body dimensions) indicators, the food variety score (Hatloy *et al*., 2000), the food consumption score, income and expenditure measures, coping strategy approaches and vulnerability indicators. A summary of these indicators including reference to authors providing more detail on the measures can be found in Appendix A.

1.1.2.3 Composite Food Security Indicators

Due to the multi-dimensional character of food security (Wolfe & Frongillo, 2001), different types of food security indicators exist and these tend to measure specific dimensions of food security. So far there is no single method that measures all aspects of food security simultaneously, but such an indicator is desirable as it would allow for a more comprehensive measurement of food security and a more flexible approach to monitoring overall targets and policy interventions (Jacobs, 2009). There have been attempts to formulate such a composite food security indicator. The International Food Policy Research Institute's (IFPRI) Global Hunger Index (GHI) evaluates hunger beyond dietary energy availability by including indicators of child and maternal health (von Braun, 2007). It can be argued, however, that this index is a health indicator rather than a measure of food security. Gentilini and Webb (2008) developed the Poverty and Hunger Index (PHI) as a composite indicator with the objective of measuring countries' progress towards achieving the first MDG of halving poverty and hunger by 2015. Rose and Charlton (2002) constructed a composite food security measure based on two components, food expenditure and nutrient intake. Christiaensen and Boisvert (2000) and Christiaensen *et al*. (2000) combined different dimensions of food security into a forward-looking measure that accounts for both current dietary inadequacy and vulnerability to dietary inadequacy in the future. Table 1.1 compares the indicators in terms of their associated data collection costs, analysis time required, the capability of the method to measure food security, the level of skill required by users, the susceptibility of the indicators to measurement error and, lastly, whether the indicators can be used for cross-country comparisons.

From this section it is clear that there are a number of indicators of food security, each with their own advantages and disadvantages. However, no single measure exists that captures all the dimensions of food security and no one measure has all the advantages of being cost effective, relatively quick and simple to conduct, accurate and comparable across regions. In conclusion, it can be said that due to the complex nature of food security, as seen from its number of definitions, food security cannot be meansured as a single concept. Secondly, many of the indicators discussed in this section are static measures of past states; yet, the concept of food security is dynamic and includes the future. Indicators of food security should consider households and individuals that are food insecure now and those that are vulnerable to becoming food insecure in the future.

Table 1.1: Comparison of food security indicators

	Cost	Time required for analysis	Ability to indicate food security	Skill level required	Susceptability to misreporting	Comparability
Food supply	Low	Low	Low	Low	High	Moderate
Individual caloric intake	High	High	High	High	Low	High
Household caloric intake	High	Moderate	High	Moderate	Moderate	High
Experiential-based	Moderate - high	Moderate	Moderate	Low	Moderate	Low
MAHFP	Low	Low	Moderate	Low	Moderate	Low
Anthropometry	Low	Moderate	Moderate	Low	Low	High
Food frequency	Low	Low	Low	Low	High	Low
Food variety	Low	Low	Moderate	Low	High	Moderate
Dietary diversity	Low	Low	Moderate - high	Low	Low	High
Income / expenditure	High	High	Low	High	High	Low
Coping strategies	Moderate	Low	Moderate - high	Low	Low	Low
Composite measures	Low	Moderate	Moderate - high	High	Moderate	High

Source: Author’s review of related literature

1.2 Poverty and Hunger in Developing Regions

The 2010 Millennium Development Goals Report (UN, 2010) presents several positive findings with regards to progress towards the first MDG. It reports that despite the global economic crisis of 2008 the world is on track to meet the target of halving poverty between 1990 and 2015. The number of people in developing regions living on less than one U.S. dollar a day fell from 1.8 billion in 1990 to 1.4 billion in 2005 and the poverty rate declined by 19 percentage points as a result of strong economic growth in the first half of the decade (UN, 2010). Even with a slowdown in economic growth as a result of the 2008 economic crisis, overall poverty is expected to decline to 15 per cent by 2015 or 920 million people living below the international poverty line (UN, 2010). This is half the number in 1990 and indicates that the MDG poverty target can be met globally. However, there are several developing regions, namely sub-Saharan Africa, Western Asia and parts of Eastern Europe, that are not currently (based on 2005 data) on track to meet the 2015 poverty target (UN, 2010).

Additionally, some progress has been made towards the first MDG target of halving the proportion of people who suffer from hunger between 1990 and 2005. The 2010 MDGs Report indicates a four percentage point decrease in the share of undernourished populations from 1990-1992 to 2005-2007 (UN, 2010). Undernourishment exists when caloric intake is lower than the minimum dietary energy requirement (FAO, 2009). However, the fall in the share of undernourished populations was not enough to reduce the number of people undernourished over the same period. Between 1990-1992 and 2005-2007 the number of undernourished people increased from 817 million to 830 million. Figure 1.2 shows the proportion of undernourished people (per cent) and the number of undernourished people (millions) between 1990-1992 and 2005-2007. The Food and Agriculture Organization of the United Nations estimates that the number of undernourished people in the world rose to 915 million people in 2008, and rose again in 2009 to 1.02 billion people (FAO, 2009).

Gentilini and Webb (2008) used a Poverty Hunger Index (PHI) to measure country progress towards the first MDG. They concluded that a majority of developing countries, such as Senegal and Kenya, had in fact made progress towards MDG 1 of halving poverty and hunger by 2015. However, some countries including Lesotho, Uganda and Nigeria were still behind target.

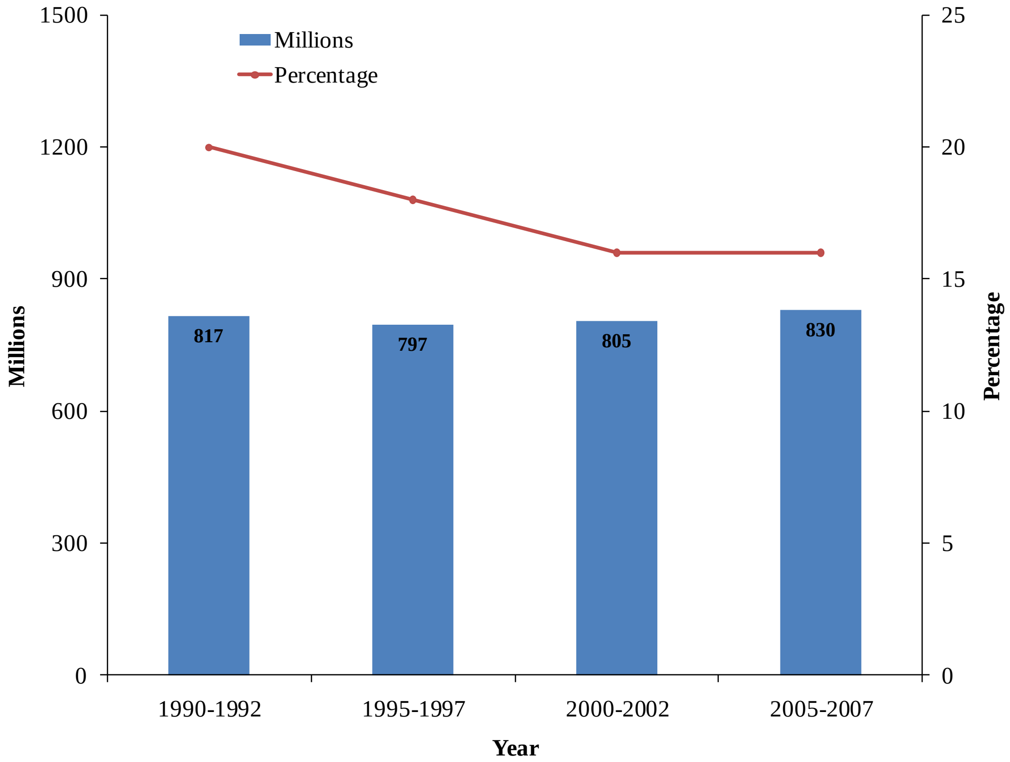

Figure 1.2: The proportion of undernourished people (per cent) and the number of undernourished people (millions), 1990-1992, 1995-1997, 2000-2002 and 2005-2007
Source: UN, 2010

The Global Hunger Index (GHI) is a tool developed by the International Food Policy Research Institute (IFPRI) for tracking global hunger and malnutrition. The most recent GHI index (2010) reflects data from 2003 to 2008. The index ranks countries on a 100-point scale: theoretically zero is the best score and 100 the worst, although neither of these scores is achieved in practice (von Grebmer *et al*., 2010). In accordance with the MDGs, which are benchmarked against the year 1990, the GHI tracks changes from 1990. The 2010 world GHI shows some improvement over the 1990 world GHI – a fall in the world GHI of almost one quarter – however, the level of hunger indicated by the 2010 world index remains serious (von Grebmer *et al*., 2010). Sub-Saharan Africa has one of the highest regional GHI scores (21.7), which is only a 14 per cent decline from the 1990 GHI score of 25.3. Decreases in South Asia and the Near East and North Africa were greater, approximately 25 per cent and 33 per cent, respectively (von Grebmer *et al*., 2010). Of the countries in which the GHI rose, all are in sub-Saharan Africa except for North Korea.

Poverty and hunger are closely related. Poverty causes under-nutrition and food insecurity by limiting people's economic access to food (von Grebmer *et al*., 2010). In 2007, extreme poverty was measured by the $1 a day threshold defined by the international community. Ahmed *et al*. (2007) estimated over a billion people to live below this threshold. In order to more closely examine this group of people, the population of people living below the $1 a day threshold was divided into three categories: (1) the subjacent poor, living on between $0.75 and $1 a day; (2) the medial poor, living on $0.50 to $0.75 a day; and (3) the ultra poor, living on less than a $0.50 a day (Ahmed *et al*., 2007). It was found that 162 million people fall into the third category with more than three-quarters of the world's ultra poor living in sub-Saharan Africa (Ahmed *et al*., 2007). The majority of Asia's poor live just below the $1 a day threshold with decreases in the number of the ultra poor between 1990 and 2004. In contrast there were increases in the number of the poor in each category for Sub-Saharan Africa during the same period (Ahmed *et al*., 2007). Africa has the highest proportion of people suffering from chronic hunger, with the number of undernourished people increasing from 169 million to 206 million over the period 1990-92 to 2001-03 (NEPAD, 2009). These results show that while progress towards reducing the problems of poverty and hunger has been made, they still remain a severe problem in Africa.

1.3 The Comprehensive African Agriculture Development Programme

Sustained growth in agriculture is required to decrease hunger and poverty in Africa (NEPAD, 2009). In response to this requirement, Heads of States and Governments signed the Maputo Declaration that sets out the CAADP to stimulate agricultural growth in Africa. The programme 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 achieve a more equitable distribution of wealth (Hendriks *et al*., 2009, citing AU/NEPAD, 2003). The CAADP is a framework for the restoration of agriculture growth, food security and rural development in Africa (NEPAD Secretariat, 2005) with the specific goal of obtaining an average annual agricultural growth rate of six per cent and achieving the first MDG by 2015 (NEPAD, 2009). Within the CAADP framework are four reinforcing and interlinked pillars:

- Pillar I focuses on extending the area under sustainable land management and reliable water control systems;
- Pillar II aims to assist in improving rural infrastructure and trade-related capacities for market access;

- Pillar III has the objective of increasing food supply, reducing hunger and improving responses to food emergency crises; and
- Pillar IV seeks to aid in improving agricultural research and technology dissemination and adoption (NEPAD, 2009).

Pillar Ш is guided by the Framework for African Food Security (FAFS) and is an attempt to ensure that the agricultural growth agenda directly addresses the chronically poor and vulnerable directly. The FAFS focus is on the chronically food insecure and those vulnerable to falling into food insecurity to ensure that the CAADP agenda is aligned with the first MDG of reducing poverty and hunger by half by 2015. The FAFS acknowledges that risk is a central part of livelihoods in developing countries, thus the ability to respond to, and manage risk - resilience - is a crucial concern in reducing poverty and hunger in Africa. Specifically, the framework seeks to increase the resilience of vulnerable populations in Africa by reducing risks of food insecurity, and through the creation of linkages for participation in agricultural growth (NEPAD, 2009). Resilience is defined as "*the ability of households, communities and countries to anticipate and mitigate risk by providing buffers and insurances to draw on, and having action plans to respond efficiently and quickly to shocks and crises in order to ensure rapid recovery post-shock or crises*" (NEPAD, 2009:11).

Typically, households in developing countries are unprepared to cope with large shocks (Dercon & Christiaensen, 2008). Formal insurance schemes in these areas are generally absent and informal risk-sharing schemes only provide partial consumption smoothing (Morduch, 1995; Townsend, 1995). In response to the threat of such shocks, households frequently opt for lower risk technologies and portfolios in order to reduce future negative outcomes (Dercon & Christiaensen, 2008). However, these lower risk portfolios generally result in lower average returns (Rosenzweig & Binswanger, 1993; Dercon *et al.*, 2005; Dercon, 2006), suggesting that decisions made in response to risk may affect the welfare of households and individuals (Dercon, 2004). The presence of risk may, therefore, induce poverty traps, whereby those with the means to insure their income against shocks are more able to take advantage of profitable opportunities and possibly grow out of poverty, while others are trapped into poverty by low risk, low return activities (Dercon & Christiaensen, 2008).

Thus, if household ability to cope with risk could be improved, household vulnerability and food insecurity could be reduced. This has important implications for governments and food aid organisations that are, most often, responsible for supporting vulnerable and food insecure households. Improvements in household resilience and natural coping strategies would reduce the financial burden on governments and international aid to support these households.

1.4 Household Risk

Risk is an important factor contributing to poverty and deprivation in the developing world (Kinsey *et al*., 1998; Dercon, 2006). Understanding risk and vulnerability, in the context of developing countries, is of increasing importance. There is a growing body of evidence suggesting that the inability to cope with risk and vulnerability plays a role in perpetuating poverty (Collier & Gunning, 1999; Dercon *et al*., 2005; Dercon, 2005; Dercon, 2006). Collier and Gunning (1999) argue, using micro-economic evidence from Africa, that the responses of households or individuals to risk explain, in part, Africa's poor growth and performance. Specifically, it is uninsured shocks and the threat of such shocks that are a cause of poverty (Dercon *et al*., 2005). Uninsured shocks are defined as: "*adverse events that are costly to individuals and households in terms of lost income, reduced consumption, or the sale or destruction of assets*" (Dercon *et al*., 2005:1). The presence of risk affects household behaviour and the decisions households make to reduce the impact of risk have implications for poverty (Dercon, 2006). Those households less able to cope with risk may adopt strategies that provide more certain outcomes, but at the cost of reduced incomes (Rosenzweig & Binswanger, 1993; Dercon *et al*., 2005; Dercon, 2006). Thus, households may fail to take advantage of suitably profitable, yet risky activities, becoming permanently trapped in poverty (Dercon, 2006). In this way, risk is a constraint to broad-based growth in living standards in many developing countries (Dercon, 2006).

Numerous authors have shown that the presence of risk is a typical characteristic of farming activities (Schurle & Erven, 1979; Kaiser & Boehlje, 1980; Hazell, 1982). Walker and Ryan (1990: 253) showed that the average coefficient of variation of household income was in the order of 40 per cent for farmers in a set of villages in South India. Using data from the same set of villages, Rosenzweig and Binswanger (1993) found the average coefficient of variation in total farm profits to be 127 per cent for the sample. In their study of households in Burkina Faso, Reardon *et al*. (1992) estimated coefficients of variation in crop income of 67 per cent and 52 per cent for the Sahelian zone and Sudanian zone, respectively. These studies indicate the relatively high level of variability in income to which farmers are exposed.

In developing countries, farmers face great risk (Collier & Gunning, 1999). Risk stems from a number of sources such as the production risks of drought and pests, health risks, risks from political strife and conflict and commodity price shocks amongst many others (Kaiser & Boehlje, 1980; Morduch, 1995; Dercon, 2006). Dissimilar groups of vulnerable households and their members are affected by a range of risks and in a number of different ways (von Braun *et al*., 1992). Table 1.2 is a summary of livelihood risks faced by vulnerable groups. Market risk would be another source of risk for the rural poor. In an attempt to gauge the welfare effects of such risks, Morduch (1995) calculated the per cent of income households would be willing to pay to eliminate income variability using the coefficient of variation of 40 per cent estimated by Walker and Ryan (1990). He found that households would be willing to give up approximately 16 per cent of their income to achieve a stable income.

Table 1.2: Livelihood risks affecting the rural poor

Nature of risk	People at risk
Crop production risks	Smallholders with little income diversification & limited access to improved technology Landless farm labourers
Agricultural trade risks	Smallholders who specialise in an export crop Small-scale pastoralists Poor households that depend on imported food
Food price risks	Poor, net food-purchasing households, including deficit food producers in rural areas
Employment risks	Wage-earning households & informal sector employees
Health risks	Entire communities, but especially households that cannot afford preventative or curative care, & vulnerable members of these households
Political & policy failure risks	Households in war zones & areas of civil unrest Households in low-potential areas not connected to growth centres via infrastructure
Demographic risks	Women, especially those without education Female-headed households Children at weaning age The aged

Source: von Braun *et al*. (1992:17)

As a result of exposure to risk, households draw on complex strategies to manage or reduce risk ex-ante, as well as strategies to cope with the consequences of shocks, ex-post (Dercon, 2004; Dercon, 2005). Risk management, thus, occurs at two stages. The first is to smooth income, which is achieved by making conservative production or employment decisions and by diversifying economic activities (Morduch, 1995). In this way, households attempt to protect themselves from adverse income shocks before they occur (Morduch, 1995). The second is to smooth consumption, and includes borrowing and saving money, depleting and accumulating non-financial assets, adjusting labour supply, and making use of formal and informal insurance arrangements (Morduch, 1995). These activities are a post-shock response and are intended to insulate consumption against income variability (Collier & Gunning, 1999; Morduch, 1995).

A number of studies have investigated the uses and outcomes of income smoothing activities. Morduch (1990) showed that asset-poor households in India allocate a greater share of land to the production of the safer traditional crops of rice and castor, than to riskier high-value crops (Dercon *et al*., 2005). Similarly, Dercon (1996), in a study of Tanzanian households, found that households having a lower level of assets allocated a larger proportion of land to the production of sweet potatoes; a low-return low-risk crop. Additionally, Dercon (1996) found that the crop portfolio of the poorest quintile yielded a 25 per cent lower return per adult than that of the richest quintile (Dercon, 1996). Studies by Reardon *et al*. (1992) and Tschirley and Weber (1994) give evidence that households in Burkina Faso and Mozambique, respectively, allocate part of their labour to the non-farm sector in an attempt to diversify incomes. By diversifying, as a means of coping with shocks, the household forgoes the gains of specialization in favour of spreading risk across a number of activities (Collier & Gunning, 1999).

Rosenzweig and Binswanger (1993) considered the impact of risk (as measured largely by the timing of rainfall) on input choice in a study of rural India. In order to quantify the impact, they measured the effect on farm profits of increasing the coefficient of variation of rainfall timing by one standard deviation. Their results showed that for a household with median wealth levels, farm profit would be reduced by 15 per cent; for the bottom wealth quintile income smoothing would reduce farm profits by 35 per cent. Additionally, households in the top wealth quintile were found to have adequate means of coping with risk, thus their farm profits would be little affected by an increase in risk (Rosenzweig & Binswanger, 1993). In their sample, 54 per cent of wealth was held by the top 20 per cent of households, clearly showing that the inability to cope with risk can worsen inequalities between the poor and wealthy. Elbers *et al*. (2003) calibrated a growth model accounting for risk and risk responses using panel data from Zimbabwe. Their results showed that risk substantially reduced growth; the mean capital stock was 46 per cent lower than in the absence of risk. They also showed that approximately two-thirds of the impact of risk could be attributed to the behavioural response to risk (ex ante). Dercon and Christiaensen (2008) investigated whether the possibility of poor consumption outcomes affected the adoption of modern inputs in Ethiopia and found fertilizer application rates to increase significantly if some insurance was offered against downside consumption risk. The use of fertilizer is a high risk activity in Ethiopia with moderately higher returns in comparison to not using fertilizer (Dercon & Christiaensen, 2008).

Additional studies suggesting that household strategies to limit risk may come at the cost of reduced incomes are summarized in Dercon (2002) and Morduch (1995). To this end, households may, in a sense, choose to be relatively poor in order to avoid more serious hardship induced by shocks (Dercon, 2006). Those with less access to insurance opportunities select a low-risk, low-return portfolio, while those with better access to insurance take on riskier, higher return activities (Dercon, 2006). In this way, risk, itself, can be considered as a cause of poverty and an improvement in the ability to cope with risk, a means of escaping poverty.

In sum, rural households are exposed to high risk (Collier & Gunning, 1999). A growing body of evidence suggests that uninsured risk increases poverty through reactions by households that affect activities, assets and technology choices. These reactions include self-insurance through diversification, both between agricultural activities and non-agricultural activities and within agricultural activities, and the accumulation of assets for consumption smoothing. However, both responses are likely to reduce growth; income smoothing by lowering mean income and thereby savings, and consumption smoothing by holding assets in liquid form. It is clear that risk is central to livelihood considerations in developing countries and that its exclusion from policy analysis and research will affect the ability to advise sensibly on solutions to poverty and food insecurity (Dercon, 2005). A household's ability to cope with risk - resilience - is crucial to its welfare as it allows the household to allocate resources to more profitable activities that were previously avoided for being too risky in nature

(Morduch, 1995). Building household resilience should, therefore, be part of the focus of poverty reduction efforts (Dercon, 2006).

There is a complex interaction between exogenous threats and the internal capacity of a household or individual to withstand or respond to the threat, and an understanding of both is required in order to understand livelihood sustainability (du Toit & Ziervogel, 2004). Specifically, there is a need to understand both the risks a household or individual faces and the resilience of the unit. As explained by Lovendal *et al*. (2004), risks are those events that create instability, which may negatively affect the system and resilience is the ability of the system to manage the risk. The more resilient a household is, the greater its ability to manage risk.

1.5 Resilience and Vulnerability

The concept of resilience originates from, and is well-known in ecological literature (Adger, 2000; Folke, 2006), where it is defined as the ability of a system to experience change and disturbance and still to persist (Holling, 1973). A system that has lost resilience is no longer capable of absorbing the stresses and shocks imposed on it without undergoing a change, resulting in loss of function and/or productivity (Levin *et al*., 1998). A resilience framework differs from an early warning system in that it does not attempt to predict future crises but rather aims to assess the current state of a system, and consequently its capacity to withstand shocks or disasters (Lau *et al*., 2003; Alinovi *et al*., 2008). The theory of resilience has been used in many contexts, for example in the field of ecology (Holling, 1973; Gunderson, 2000; Peterson, 2000), in social-ecology (Adger, 2000; Folke *et al*., 2002; Folke, 2006), in terms of the economy (Lau *et al*., 2003), and in food security (Hemrich & Alinovi, 2004; Pingali *et al*., 2005; Alinovi *et al*., 2008; Lokosang, 2009). Pingali *et al*. (2005) suggest that resilience in the context of a food system is the ability of the system to remain stable or to adapt to a new situation without experiencing irreversible changes in its basic functioning. At the household level the household would be the system (Alinovi *et al*., 2008) and its resilience would be its capacity to withstand or adapt to exposure to shocks or disasters without becoming food insecure. Lokosang (2009) describes resilience as the immune system that protects the household (as it does the body) from suffering the severe effects of risk, such as starvation, malnutrition, household disintegration or even death. Lokosang (2009) focuses on resilience as a determinant of food insecurity and explains that when household resilience is low, vulnerability to risks is high and the household is rendered food insecure.

It has been shown that risk is an important factor contributing to poverty in the developing world (Kinsey *et al*., 1998; Dercon, 2006). There is a growing body of evidence suggesting that the inability to cope with risk is an impediment to growth (Rosenzweig & Binswanger, 1993; Elbers *et al*., 2003; Dercon *et al*., 2005; Dercon, 2005; Dercon, 2006; Dercon & Christiaensen, 2008) and that household or individual response to risk has played a part in Africa's poor economic performance (Collier & Gunning, 1999). Hence, if the ability to cope with risk – resilience - can be improved for vulnerable households, they will be better able to allocate resources to more profitable enterprises, will be less reliant on welfare support and have a better chance of escaping poverty. This has important implications for governments and providers of welfare support as there are potentially significant benefits to interventions that reduce the exposure of vulnerable households to risk. Protecting vulnerable households against shocks could have a high return in reducing long-term poverty (Dercon *et al*., 2005). The Framework for African Food Security acknowledges the importance of risk to vulnerable households and recognizes that an understanding of the resilience households possess is necessary in order to protect, provide and promote resilience at all levels (Hendriks, 2010). The framework seeks to promote the resilience of vulnerable populations in Africa (NEPAD, 2009).

Vulnerability refers to the relationship between poverty, risk and risk management (Alwang *et al*., 2001) and, therefore, requires discussion. The concept of vulnerability is becoming increasingly important in welfare literature and vulnerability reduction is recognised as necessary for improving human well-being (O'Brien *et al*., 2009). Vulnerability distorts resource allocation behaviour by households and individuals - not only for those who are currently poor, but also for the group of people vulnerable to becoming poor (Carter & Barrett, 2007). As a result of these distortions, vulnerability is economically costly and contributes to the perpetuation of poverty (Carter & Barrett, 2007).

Risk and vulnerability are related, but not synonymous. According to the World Development Report 2000/01, risk "*refers to uncertain events that damage well-being" and vulnerability "measures the resilience against a shock*" (World Bank, 2001:139). Vulnerability is the opposite of resilience – a loss of resilience increases vulnerability. The concept of vulnerability is multi-dimensional (Pritchett *et al*., 2000; World Bank, 2001) and has been used in a number of ways with different implications (Alwang *et al*., 2001; Prowse, 2003). There is no universally accepted single definition of vulnerability (du Toit &

Ziervogel, 2004). Work by Alwang *et al*. (2001), Ellis (2003), Prowse (2003) and du Toit and Ziervogel (2004) offer detailed reviews of the many definitions of, and approaches to, vulnerability.

Alwang *et al*. (2001) review the meaning and approach to vulnerability taken by a number of different disciplines such as economics (including food security), sociology, disaster management, environmental management and health and conclude that the definition of vulnerability differs across disciplines. However, there are a number of general principles related to vulnerability (Alwang *et al*., 2001):

- vulnerability is a forward-looking concept and is related to the probability of experiencing loss in the future;
- a household or individual can be vulnerable to a future loss of welfare, and the loss is a result of uncertain events;
- the degree of vulnerability is a function of the characteristics of the risk and the household's ability to respond to the risk;
- vulnerability and the response to risk depends on the time horizon; and
- the poor and near-poor tend to be vulnerable because of their limited access to assets and, therefore, their limited ability to respond to risk.

In the food security literature vulnerability is defined as the combined effects of risk and the ability of households and individuals to cope with risk and to recover from a shock (Maxwell *et al*., 2000). This definition draws on arguments made by Chambers (2006). Maxwell *et al*. (2000) suggest that vulnerability and the ability to recover from shocks is related to the assets that the household or individual possesses, and that the greater the level of assets held, the less vulnerable the household or individual.

Chambers (2006:1) defined vulnerability as "*the exposure to contingencies and stress, and difficulty in coping with them*". This definition points to two dimensions of vulnerability: exposure to risk and resilience to, or capacity to cope with, risk (Moser & Holland, 1997; Riley, 2000; Dilley & Bordreau, 2001; Lovendal *et al*., 2004; Chambers, 2006). Pritchett *et al*. (2000) define vulnerability as the probability that a household will experience at least one occurrence of poverty in the near future. Similarly, Calvo and Dercon (2005) suggest that vulnerability is the threat of poverty and emphasize the importance of downside risk. Kirby

(2006:11, 13) lends support to these definitions in describing vulnerability as a concept that captures the dynamic character of risk and the variable ability to cope with risk and change.

Lovendal and Knowles (2005) highlight four important reasons why vulnerability should be measured rather than just the current level of poverty and food security. The first reason is that people move in and out of poverty (and other vulnerabilities), and often the share of the population being 'sometimes' poor is much greater than that being 'always' poor and this group of vulnerable people should not be neglected. Vulnerability is a dynamic concept, recognizing and capturing change (Moser, 1998). Secondly, there are differences within food insecure and vulnerable groups such as chronic or transitory food insecurity. These differences have different causes and thus should be addressed with different policies and interventions. The third reason given is that the presence of risk influences livelihood choices which may lead to the selection of income-earning activities with low variability but also low returns. Identifying this risk and reducing it could result in households choosing more productivity-enhancing investments. The last reason in support of vulnerability analysis is that it allows problems to be addressed before they occur rather than just coping with the negative outcomes. Moser and Holland (1997) argue that because households or individuals move in and out of poverty, vulnerability gives a better indication of change than static poverty measures.

This is a brief introduction to the concept of vulnerability. However the important points that emerge from the literature are: vulnerability is a complex concept with a number of definitions and applications across various disciplines; vulnerability plays an important role in human welfare and should be more widely recognized as being a cause, symptom and constituent of poverty (Prowse, 2003); and there is an increased emphasis on assets and entitlements in understanding vulnerability as opposed to the severity of shocks (Moser, 1998). Vulnerability is a forward-looking concept that attempts to explain the ability of households or individuals to cope with uncertain events (Ellis, 2003). It considers not only the threats households or individuals face, but their resilience in resisting or recovering from shocks (Moser & Holland, 2007).

1.6 The Framework for African Food Security's Score Card

Section 1.1 provides a brief overview of past attempts to measure food insecurity and shows that the existing measures are limited by the complexity and multidimensionality of the concept of food security. The concept of food security includes the future - both those groups that are currently food insecure and those that are vulnerable to becoming food insecure need to be considered. Many of the food security measurement tools are static and fail to capture the dynamic nature of food security. From section 1.1 it can be concluded that it is impossible to measure food security in its entirety. Section 1.2 shows that, while progress towards reducing world poverty and hunger has been made, these problems are still of serious concern. Section 1.3 argues that the risks faced by vulnerable households play a role in perpetuating poverty and that an improvement in household risk management and the ability to cope with risk (resilience) can reduce vulnerability and food insecurity. The FAFS recognizes the importance of resilience and risk management as they ‘protect’ the household from vulnerability to food insecurity. If the resilience of households can be understood and gauged, it is then possible to provide, protect and promote resilience at all levels.

The FAFS seeks to reduce food insecurity and poverty by increasing the resilience of vulnerable populations in Africa. The FAFS sets out four key objectives that contribute to the goal of improving the resilience of vulnerable populations and reducing poverty and food insecurity in Africa (NEPAD, 2009). The objectives are: (1) improved risk management, (2) increased supply of affordable commodities through increased production and improved market linkages, (3) increased economic opportunities for the vulnerable and (4) improved quality of diets through diversification of food among the target groups.

Considering the limitations of existing food security measurement methods, the FAFS identifies four indicators, rather than a measure, as a means of tracking progress towards improved household resilience and reduced food insecurity. The FAFS objectives and indicators are brought together in the FAFS score card as shown in Figure 1.3. The first row of the figure shows the FAFS first element of improving risk management and resilience. The indicator of progress towards this goal is shown as a resilience score. The aim is to track changes in the four indicators to show improvement or otherwise in household resilience and food insecurity through country programmes and interventions (Hendriks, 2010). The FAFS score card focuses on tracking progress towards food security goals rather than trying to develop an ineffective composite measure of food security.

FAFS element	Indicator	Critical level	Now: DD/MM/YY Percentage of population below critical level	Progress towards goal -10	0	+10
Improving risk management and resilience	Resilience score (based on assets)	Needs to be country-specific	______%			
Increasing the supply of affordable food	Consumption + production – gifts, donations and transfers	Spend > 60% of total household budget expenditure on food	______%			
Increasing economic opportunities for the vulnerable	Per capita income	$1.25 per person per day	______%			
Improving dietary diversity	Dietary diversity score	Needs to be country-specific	______%			
Main source of food	Food comes from own production or purchases	Apart from gifts, food comes from own production or purchases	______%			
Malnutrition rates	Number of stunted children < 5 years	Z-score for the ratio of weight-for-age is ≤ -2 std deviations	______%			
	Number of wasted children < 5 years	Z-score for the ratio of weight-for-height is ≤ -2 std deviations	______%			

Figure 1.3: The FAFS score card
Source: NPCA (2011)

This study focuses on the first objective of the FAFS which is improved risk management. At the household, community and national levels, improved household risk management will help to strengthen national, regional and community responses to climatic and economic shocks. The indicator identified, by the FAFS, as a measure of progress towards this objective is a resilience score. This score is not, as yet, presented in more detail in the FAFS score card and it is the goal of this research to add to the FAFS score card by elaborating on this indicator. The study aims to develop a resilience score and in doing so to contribute to the overall CAADP goals and objectives. Specifically, this investigation seeks to refine and apply an asset index to a number of African countries as an indicator of a household's resilience and its ability to manage risk and respond efficiently and quickly to shocks and crises to ensure rapid recovery. The measure could be valuable to policy-makers for identifying vulnerable households and to assess the impacts of new policies on such households.

The use of assets as a risk management tool is documented by, amongst others, Dercon (2001) where he discusses the importance of assets in determining the ability of a household or individual to cope with hardship. He concludes that asset ownership can be used as an indication of the ability of a household or individual to cope with shocks. Similarly, Lovendal and Knowles (2005) explain that asset management is used to stabilize purchasing power or consumption ability. Asset ownership can be used as a proxy for the ability of a household or individual to withstand shocks; the level of access to, or ownership of, assets influences the ability to prevent or cope with shocks (Lovendal & Knowles, 2005). Tracking changes in household asset ownership over time would indicate trends in household resilience and vulnerability and show progress towards food security goals.

The first objective of the study is to construct and apply an asset-based index of household SES using household data collected through the Demographic and Health Surveys (DHS) for a number of African countries to identify households with low resilience. This involves the selection of relevant variables for inclusion in the index, appropriate weighting of the chosen variables and application of the index to household data so as to calculate a resilience score for each of the sample households. The households can then be classified into groups (quintiles) based on the value of the resilience score. From a review of literature it was shown that asset indices, as a measure of household wealth or SES, are widely applied (see Chapter 2) and that the use of linear PCA in the construction of such asset-based indices is well established. However, there is some uncertainty in the literature regarding the reliability of linear PCA for such purposes. For this reason, it was decided to compare four methods of constructing asset-based indices in an attempt to develop the index most appropriate for estimating a household’s SES score as an indicator of its resilience. The second objective of the study is to apply the new index to household data from several African countries over two different time periods to determine whether the measure could be used to monitor progress towards improved household risk management.

CHAPTER 2: HOUSEHOLD ASSETS AND RESILIENCE

In Chapter one, the importance of household resilience in alleviating poverty in Africa was discussed. The more resilient a household is, the greater its ability to cope with shocks, the more able it is to make more risky, but more productive decisions and the better chance it will have to remain food secure. The Framework for African Food Security (FAFS) was introduced and its goals, objectives and indicators of progress towards these objectives clarified. This study sets out to develop the first indicator of the FAFS score card – a resilience score. It is proposed that household possession of assets, in terms of an assets index, can be used as an indication of household resilience and used to estimate a household's resilience score.

The chapter outlines how households respond to food shocks and the role assets play in coping with and recovering from shocks. The chapter presents empirical support for the use of assets as an indication of household resilience and wealth. The last section of the chapter is a review of the literature on asset indices in an attempt to ascertain the most appropriate means of constructing such an index.

2.1 Household Coping Strategies

When faced with declining food availability in abnormal seasons, households can respond in a number of ways. It is these responses that are known as coping strategies (Davies, 1993). There are a number of coping strategies available to households (Corbett, 1988; Devereux, 1993) and the choice of strategy varies according to the events leading to the food shortage, the economic environment, the source of livelihood of the household and the comparative resource endowment at the beginning of the food shortage (Corbett, 1988). Table 2.1 is a list of commonly observed coping responses summarised by Corbett (1988) from her review of evidence on coping strategies. Households may make changes in their livelihood activities regarding when, how and what they plant and in the management of their livestock. They may also adapt their consumption in the face of food shortages to include wild foods and fewer, smaller meals. Activities such as borrowing food from family or friends, loaning money from moneylenders and leaving home in search of work are other household responses to food deficits.

Table 2.1: Commonly observed household coping strategies

Coping strategy
Dispersed grazing
Changes in cropping & planting practices
Migration to towns in search of urban employment
Collection of wild foods
Use of inter-household transfers & loans
Use of credit from merchants & moneylenders
Migration to other rural areas in search of employment
Rationing of current food consumption
Sale of productive household assets
Consumption of food distributed in relief programs
Sale of possessions
Break-up of the household
Increased petty commodity production & trading
Distress migration

Source: Corbett (1988: 1100)

Watts (1983:435) argues that coping strategies follow a progression that reflects increasing 'irreversibility' and 'commitment of domestic resources'. Households will respond initially with strategies that involve the smallest commitment of domestic resources and the greatest degree of reversibility (Watts, 1983:435). The progression of response is depicted in Figure 2.1. The first few strategies adopted are those of adjustment such as a change of diet to relatively cheaper foods or the incorporation of wild foods into the diet or borrowing grain from others. These strategies are easily reversible and entail a minimal commitment of domestic resources. Households are moderately vulnerable to famine at this point. The next group of strategies are less reversible and include a commitment of domestic resources, such as the sale of small animals or taking a loan. The household's vulnerability to famine is high at this point and donor assistance is required to mitigate further risk. Once households reach the point of selling off productive assets, they become extremely vulnerable to destitution and require direct donor relief.

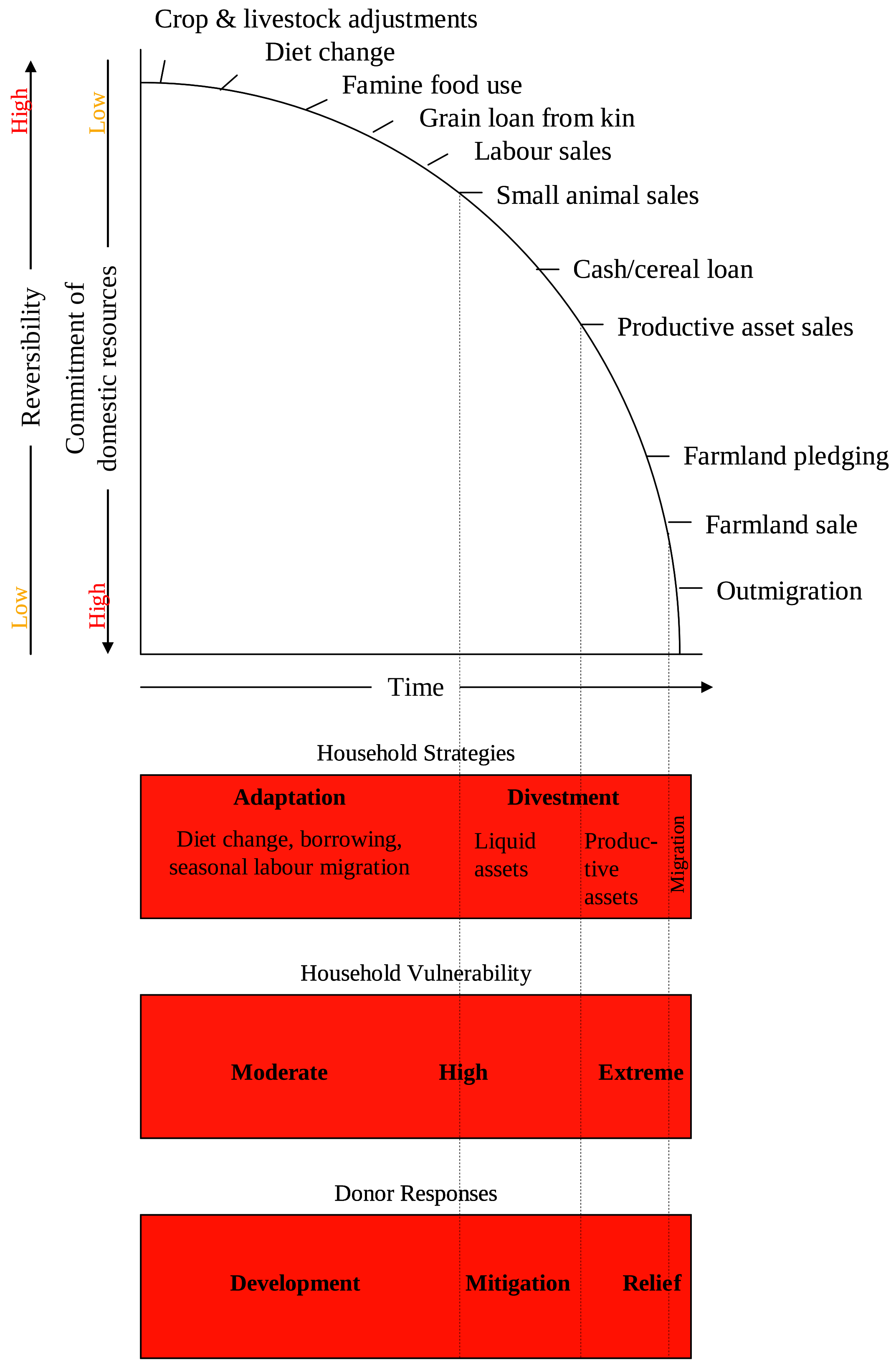

Figure 2.1: Responses to household food shortages
Source: Adapted from Watts (1983:436) and Frankenberger (1992: 95)

In reviewing the study by Watts (1983) and a number of similar investigations, Corbett (1988) proposes that there is a three-stage sequence to household coping strategies. The first stage is one of insurance: households adopt strategies to cope with predictable and non-severe risks. These responses include changes in cropping and planting practices, the sale of small stock, diet adjustments, inter-household transfers and the sale of non-productive assets such as jewellery. Stage one activities have relatively low costs in terms of long-term livelihood of the household. Stage two is one of productive asset disposal and may put the future economic welfare of the household at risk. Activities include the sale of livestock (large animals and breeding stock) and agricultural tools, the sale or mortgaging of land, loans from money lenders and a reduction in consumption levels. The third or last stage is destitution and includes distress migration in search of relief. At this point a household's ability to generate current or future income is severely reduced.

Devereux (1993) argues that the first response of households to a food deficit is not to protect their food consumption, but rather to protect their long-term viability. This view is supported by evidence from de Waal's study of the famine in Sudan in 1987 (de Waal, 2005). There is a trade-off between competing sets of objectives. Devereux (1993) categorizes coping responses into two behavioural groups each with different objectives. The first group includes strategies that attempt to protect consumption and the second contains responses that modify consumption. The two groups along with their associated activities are given in Table 2.2. For example, a food deficit household may have the choice of selling assets for food or going hungry – each choice has a different objective. Selling assets for food is a means of protecting consumption; rationing protects the long-term viability of assets (Devereux, 1993). Devereux (1993) further explains that the (mild) rationing of food is easily reversible and costs relatively little in terms of long-term effects. Therefore, households will avoid selling assets or borrowing money until the perceived costs of doing so exceed the perceived costs of additional rationing.

What does become clear from the literature on household coping strategies is that assets play an important role in risk management and the future viability of the household. The quantity and type of assets a household possesses determines its current and future income (Corbett, 1988). Households that consume assets and income, especially those involved in agriculture, become increasingly vulnerable to future food deficits (Devereux, 1993).

Table 2.2: Categories of household coping responses

Trigger Event	Behavioural Category	Strategy (generic)	Response (specific)
Grain production deficit	Protect consumption	Purchase grain - market exchanges	- sell non-food crops - use off-farm income - sell assets (animals) - borrow cash - postpone debt repayment - reduce non-food spending
		Receive grain - non-market transfers	- remittance - charity - begging - food aid
	Modify consumption	Reduce consumption - ration	- smaller portions - fewer meals per day - fewer snack foods
		Diversify consumption - change diet	- less preferred varieties - wild foods - less nutritious foods
		Reduce consumers - change household size	- wife returns to father - children sent to relatives - male temporary migration - betroth daughter

Source: Devereux (1993: 53)

2.2 Household Assets and Resilience

Drawing on entitlement theory by 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) questions whether low asset status and poverty are synonymous but explains that a reduction in assets makes households and communities more vulnerable and the analysis of household assets would add to the understanding of vulnerability. He concludes that a low asset status would be a good indicator of vulnerability. Swift (2006) further explains that assets create a buffer between production, exchange and consumption. During times of surplus, production and exchange activities create assets and during times of stress, assets can be transformed back into production inputs and consumption (Swift, 2006). Hence, asset ownership contributes towards household resilience or the ability of households to cope with shocks and stresses. Doocy and Burnham (2006) discuss the contribution of assets to household coping capacity during the beginning stages of food insecurity and then the sale of assets in later stages of crises to enable the purchase of food.

In their review of household food security, Maxwell and Smith (1992) conclude that the most vulnerable households are those facing the greatest probability of entitlement failure with the least assets. If these households were faced with shocks they would have to bear the costs in the form of reduced dietary intake either in the current time period or in the future (Maxwell & Smith, 1992). They suggest that asset holdings could be used as an indicator of vulnerability to food insecurity. Moser (1998) developed an Asset Vulnerability Framework as a means of informing interventions with respect to the poor. Once again it was clearly set out that vulnerability is a result of threats and a lack of resilience, or an inability to resist or recover from negative shocks. The means of resistance (or resilience) are the assets and entitlements that can be mobilized during times of stress (Moser & Holland, 1997; Moser, 1998). Therefore, vulnerability is linked to asset ownership; the greater the erosion of assets, the higher the vulnerability (Moser, 1998). From the application of the Asset Vulnerability Framework to regions in Zambia, Ecuador, the Philippines and Hungary, Moser (1998) showed that asset management affects household poverty and vulnerability.

Lovendal and Knowles (2005) developed a framework for analysing vulnerability to food insecurity that brought in the aspect of risk and the ability to manage risk at different levels. In their discussion of the measurement of vulnerability, Lovendal and Knowles (2005) suggest 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. Importantly, they point out the characteristics of assets that contribute to their effectiveness in managing risk: the security of access and use, the rate and volatility of returns, the ability to maintain value during a crisis, the ease with which they can be traded or liquidated, and the ability to fulfil consumption needs.

In his editorial introduction, Chambers (2006) gives support to Swift's suggestion that a low asset level would be a good indicator of vulnerability and proposes that research is needed to ascertain whether it is feasible to monitor household assets so that action can be taken early enough to prevent or reduce damage during times of stress. He concludes that indicators of vulnerability must be developed and tested and suggests one such indicator to be household net assets and future research is needed on "*assessing and comparing vulnerability and assets within households, between groups of people, and between regions and continents, and how these change over time*…" (Chambers, 2006:39).

Dercon (2001) discusses the measurement of vulnerability using assets. He explains that assets are used to generate income and income provides access to dimensions of well-being such as consumption, nutrition and health. Asset ownership could, therefore, be used as a proxy of vulnerability as, without assets, access to consumption, nutrition and health are constrained (Dercon, 2001). The ownership of assets is likely to assist the ability of a household or individual to cope with risk (Dercon, 2001). This conceptual framework is illustrated in Figure 2.2. Dercon (2001) further points out that the sale of assets is a means of coping with risk; the more assets to sell the better the ability to cope. In response to risk, if the household or individual is lacking assets it may resort to reduced food consumption as a mechanism of managing risk (Dercon, 2001).

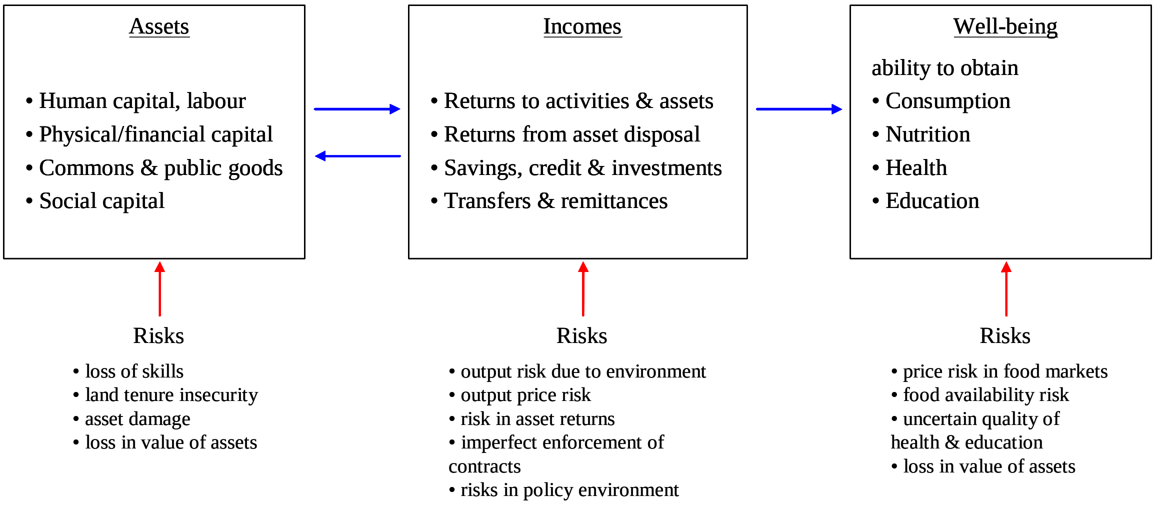

Figure 2.2: The conceptual link between assets and vulnerability
Source: Adapted from Dercon (2001: 17)

Carter *et al*. (2004) discuss resilience in their analysis of the impacts of environmental disaster on assets in Ethiopia and Honduras. They use a diagram, Figure 2.3, to show the importance of household resilience and how asset levels play a role during periods of stress, coping and recovery. The example pertains to a short environmental shock (such as a hurricane). The X axis measures time and the Y axis measures asset stocks and income shocks. A_b is the pre-shock asset trajectory. A_s is the post-shock asset level: asset loss occurs directly as a result of the shock. A''_r is the asset trajectory had the shock not occurred.

A second direct impact of the shock is the possible reduction in disposable income, as a result of crop failure or increased medical expenses due to the shock. During the coping period households may draw on financial markets to obtain additional funds, or increase their work time (Carter *et al*., 2004). Other coping strategies could include informal loans, insurance and disaster assistance (Carter *et al*., 2004). However, for households without access to such coping strategies assets may be further depleted (Carter *et al*., 2004). A_c in the figure represents the added reduction in assets. Households that lack these assets or options or households that are reluctant to further erode their asset base may cope by reducing consumption (Carter *et al*., 2004). The recovery period is the time of asset base rebuilding. Households with access to labour markets and financial services will be better able to accumulate assets, shown by the movement from A_c to A'_r in the figure (Carter *et al*., 2004). Households without access to such markets and services may become trapped at the low asset level (poverty trap), shown by A_r in the diagram.

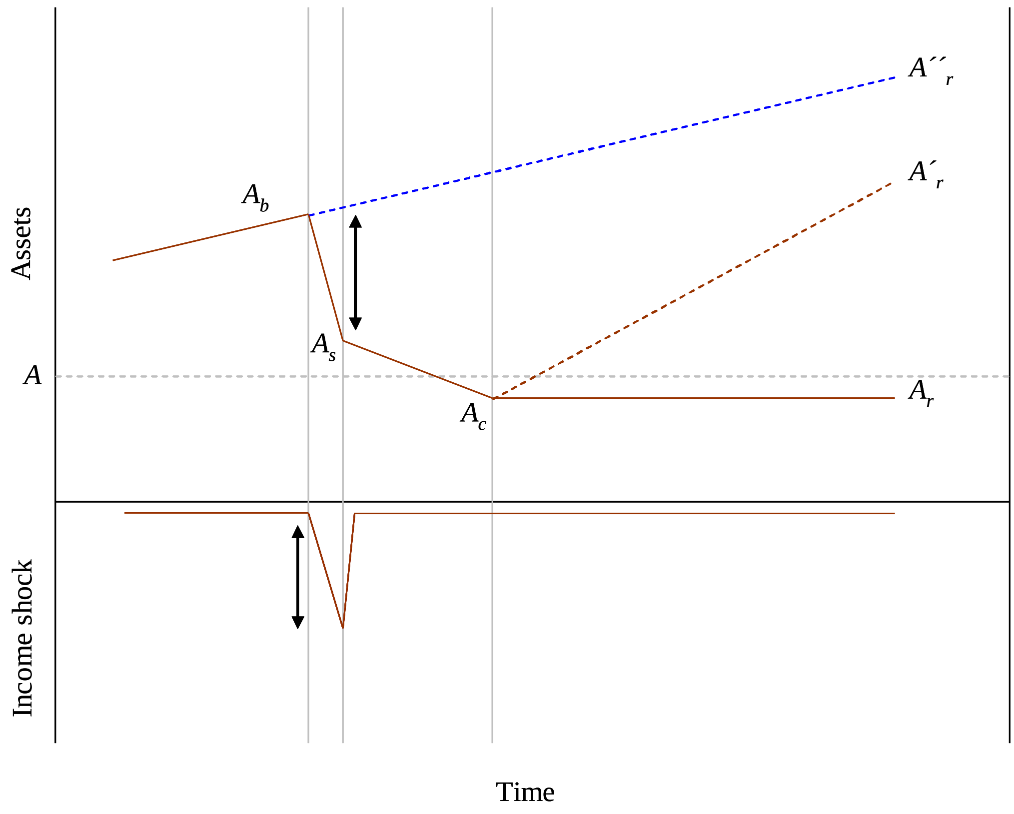

Figure 2.3: Effects of an environmental shock on households
Source: Adapted from Carter *et al*. (2004: 4)

Clearly, the initial level of asset ownership will influence the ability of a household to cope and recover from a shock; those households that exit a shock with low asset levels are likely to experience difficulties in rebuilding their asset base. By identifying low asset households before a shock event, it would be possible to target such households with social safety nets and other interventions to prevent asset loss, consumption reduction and poverty traps (Carter *et al*., 2004). From their analysis Carter *et al*. (2004) show that wealthier households in Ethiopia and the Honduras are better able to protect their assets after a shock, while poorer households suffer further asset losses and become trapped at low asset levels.

The World Food Programme (WFP) (2009) describes assets as representing the ability or inability of households to engage in specific activities that allow them to secure food and other basic needs. Household assets can be used to buffer the household against future shocks and those households with greater asset holdings have greater purchasing power (WFP, 2009). The WFP (2009) suggests that asset ownership can be used as a proxy of household wealth and is, therefore, related to household food security. While the number of assets owned is partly indicative of household wealth, not all assets are equal in terms of their utility (WFP, 2009) and weighting assets becomes an important consideration when using asset ownership as a proxy measure. Morduch (1995) discusses the role of assets in consumption smoothing and explains that households can sell off assets as a means of smoothing consumption during periods of shock and post-shock.

Household asset ownership could, therefore, give an indication of the resilience of a household at the time of measurement. Asset ownership and wealth are stock concepts and reflect a household's position at a particular point *in* time and not *over* time, as a measure of income would. Household income may better reflect the welfare status of a household; however, from the evidence presented in this section, asset ownership is certainly connected to household vulnerability and has the potential to be a useful measure of household resilience. Income data is often relatively difficult to obtain and may be unreliable, as discussed in section 2.3, whereas asset data is often more readily available, such as that contained in the DHSs.

2.3 Asset-Based Measures

From the literature presented in Section 2.1, the level and nature of assets owned by a household can be used as a proxy of the household's resilience to food insecurity. This section discusses asset-based measures of household wealth or socioeconomic status (SES) in an attempt to ascertain the best method of measuring household asset ownership so as to proxy a household's resilience to food insecurity.

Quantifying the welfare of individuals has attracted much attention, mainly in response to difficulties in using the more traditional measures of wealth: consumption, income and expenditure (Falkingham & Namazi, 2002). Data on consumption, income and expenditure are often difficult to come by, expensive and time-consuming to measure and contain errors in measurement (Montgomery *et al*., 1999; Morris *et al*., 2000; Sahn & Stifel, 2000; Falkingham & Namazi, 2002; Azzarri *et al*., 2005). Key problems include measurement error, such as underreporting and recall bias, difficulties in putting a cash value to home production and in deriving the use value of goods and services (Falkingham & Namazi, 2002). For example, incomes are often underreported and expenditures over-reported in household surveys.

Given these difficulties in measuring consumption, income and expenditure it has become of increasing concern to identify an alternate measure of household wealth that is robust, but less data intensive and subject to a smaller measurement error (Falkingham & Namazi, 2002). An alternate indicator of household wealth is also useful in the situation where household data exist but do not include information on consumption, incomes or expenditures. For example, health surveys, such as the Demographic and Health Surveys project funded by the U.S. Agency for International Development, do not collect information on household consumption, incomes or expenditures but contain a wealth of other household information. It would be useful to be able to extract an indicator of wealth from these available data. In many of the studies discussed below, the Demographic and Health Survey (DHS) data have been used as a basis for analysis (Filmer & Pritchett, 1994; Filmer & Pritchett, 1999; Filmer & Pritchett, 2001; Larrea & Freire, 2002; Rutstein & Johnson, 2004; Hong & Mishra, 2006; Hong *et al*., 2006; Rutstein, 2008; Uthman, 2008).

The theory underlying 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 & Johnson, 2004). For example, Figure 2.4 shows the assumed distribution of some of the assets and household services collected in the DHS. The proportion of households owning a TV and a fridge increases with increasing wealth, while the proportion of households relying on surface water as a source of drinking water declines with increasing wealth. The proportion of households owning a motorbike rises with increasing wealth to a point, at which motorbike ownership decreases with rising wealth as households substitute motor vehicles for motorbikes. In this way, ownership of assets and access to services, such as clean drinking water and toilet facilities, can be used to ascertain the relative wealth position of a particular household. It is expected that ownership of different 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 (SES) across households (McKenzie, 2005).

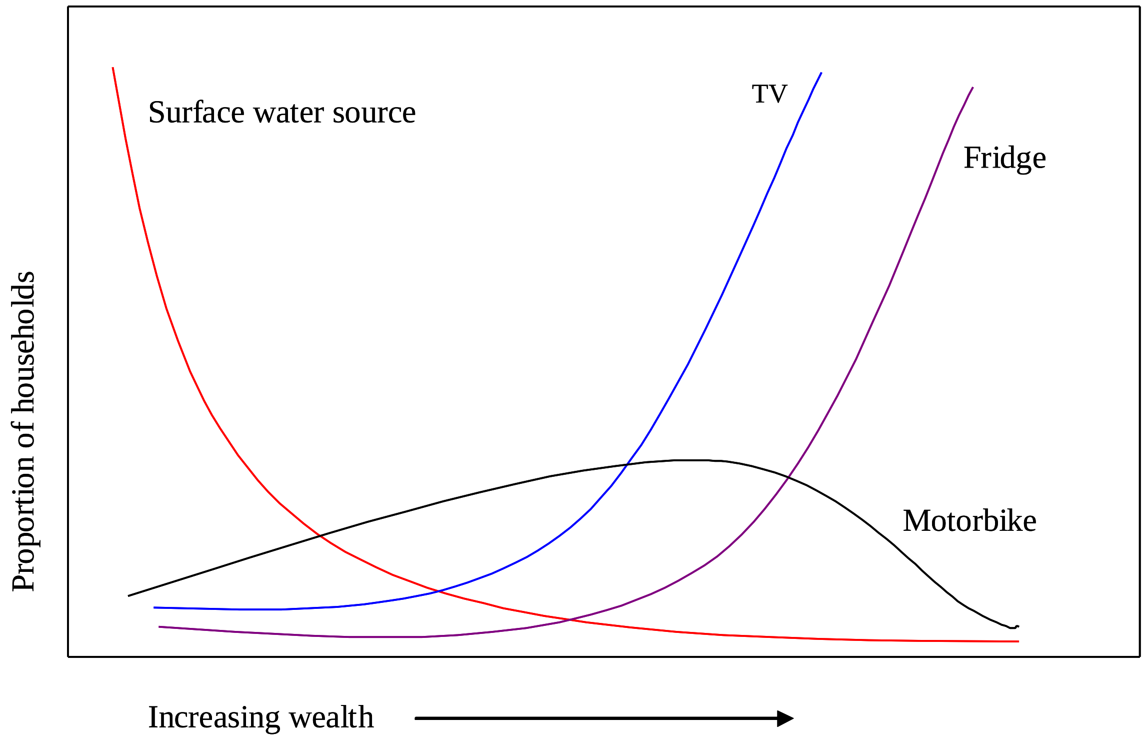

Figure 2.4: Assumed distribution of assets and services
Source: Adapted from Rutstein and Johnson (2004:4)

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. Most studies employ a range of indicators that may include variables for access to electricity, drinking water source, type of toilet facility, floor and other housing materials and ownership of a range of durable assets such as a radio, television, bicycle, motor vehicle and refrigerator (Falkingham & Namazi, 2002).

From the literature, four common methods for assigning weights to the variables are apparent: (1) Principal Component Analysis (Filmer & Pritchett, 1994; Filmer & Pritchett, 1999; Filmer & Pritchett, 2001; Zeller *et al*., 2001; Bollen *et al*., 2002; Larrea & Freire, 2002; Schellenberg *et al*., 2003; Zeller *et al*., 2003; McKenzie, 2005; Hong & Mishra, 2006; Hong *et al*., 2006; Lindelow, 2006; Rutstein, 2008), (2) Principal Factor Analysis (Sahn & Stifel, 2000, 2003; Naschold, 2005), (3) a simple sum of assets (Hatloy *et al*., 2000; Montgomery *et al*., 1999; Garenne & Hohmann-Garenne, 2003), and (4) the inverse of the proportion of households with the asset or service (Morris *et al*., 2000; Azzarri *et al*., 2005). The use of *ad hoc* weights (Rutstein & Johnson, 2004), weights based on the value of the included asset (Bollen *et al*., 2002), and hierarchical ordered probit analysis (Ferguson *et al*., 2002) have also been used.

The use of Principal Component Analysis (PCA) for the selection of weights of the variables within the asset-based index has received much attention (Filmer & Pritchett, 1994; Filmer & Pritchett, 1999; Filmer & Pritchett, 2001; Zeller *et al*., 2001; Bollen *et al*., 2002; Schellenberg *et al*., 2003; Zeller *et al*., 2003; Rutstein & Johnson, 2004; McKenzie, 2005; Lindelow, 2006; Rutstein, 2008), with the work by Filmer and Pritchett (1994, 1999, 2001) being popular in the area of development economics. PCA is a standard multivariate technique with the purpose of aggregating information spread in many numeric measures (Kolenikov & Angeles, 2009). It is used to extract, from a set of variables, the orthogonal linear combination of the variables that most effectively capture the common information (Filmer & Pritchett, 1999). It is a means of disaggregating a covariance or correlation matrix into a set of orthogonal components equal in number to the number of variates included (Lawley & Maxwell, 1962). The technique was developed in the field of psychometrics in the early 20th century (Kolenikov & Angeles, 2009, citing Pearson, 1901, and Hotelling, 1933). The approach allows each asset or variable to have its own weight, the weight being the result of the PCA rather than based on any information regarding the asset such as its value (Bollen *et al*., 2002). The weights are, thus, the standardized first principal component of the variance-covariance matrix of the observed household assets (Sahn & Stifel, 2000). The first principal component gives an index providing maximum discrimination between households, with the assets that vary most across the households having the larger weights (McKenzie, 2005). An asset that no household owns or one that all households own will have a zero weighting in the first principal component as it explains none of the variation across households (McKenzie, 2005).

The aim of the Filmer and Pritchett (1994, 1999, 2001) studies was to investigate the effect of household wealth on educational attainment. Various country DHS data were used. A linear index was constructed from asset ownership indicators as a proxy of wealth and a modified version of PCA was used to derive the weights (Filmer & Pritchett, 1999). In their application to DHS data from India (Filmer & Pritchett, 1999), 21 variables were included in the index, falling into three categories: household ownership of consumer durables (eight variables), characteristics of the household's dwelling (12 variables) and an ownership of land variable. The variables with multiple categories, such as source of drinking water, were transformed into a set of dummy variables representing ownership of, or access to, the variable or not. PCA was then applied to the resulting set of binary indicators. The first principal component was used as the weights for the index assuming that household wealth explains the maximum variance in the asset variables (Filmer & Pritchett, 1999). Once the weights were calculated the value of the index, for each household, was estimated by summing the values of the weights for each asset owned, divided by its particular standard deviation (SD). The households were then assigned to a category (percentiles of the population) on the value of their asset index. The categories were defined as poor (the bottom 40 per cent), middle (the next 40 per cent) and rich (the top 20 per cent). Table 2.3 reports the assets and the corresponding factor scores, means and standard deviations for each asset category for the Indian asset index (Filmer & Pritchett, 2001). In the example, ownership of a clock would increase the value of the asset index by 0.54 and ownership of a car by 1.21, while the use of biomass for fuel would decrease the index by 0.67. The first principal component explained 26 per cent of the variance in the assets included in the index.

Filmer and Pritchett (1999) tested the reliability of the asset index and concluded that it performed well on three levels. First, the index was internally coherent as the averages of the indicators differed clearly across the poor, middle and rich categories for each variable. Second, the index was robust to the assets or indicators included, as similar results were obtained when different subsets of the variables were used in its construction. The rank correlation coefficient was used to test for robustness. As an additional check the application was performed using principal factor analysis to assign the variable weights; both methods produced similar results. Lastly, the index produced reasonable comparisons with other estimates of state-level poverty.

Table 2.3: Scoring factors for variables entering the asset index, India, 2001

	Scoring Factors	Mean	SD	Scoring factor / SD
Own clock/watch	0.270	0.533	0.499	0.54
Own bicycle	0.130	0.423	0.494	0.26
Own radio	0.248	0.396	0.489	0.51
Own television	0.339	0.209	0.407	0.83
Own sewing machine	0.253	0.182	0.385	0.66
Own motorcycle/scooter	0.249	0.082	0.274	0.91
Own refrigerator	0.261	0.068	0.252	1.04
Own car	0.129	0.012	0.107	1.21
Drinking water from pump/well	-0.192	0.609	0.488	-0.39
Drinking water from open source	-0.041	0.040	0.195	-0.02
Drinking water from other source	-0.002	0.019	0.138	-0.01
Flush toilet	0.308	0.217	0.412	0.75
Pit toilet/latrine	0.040	0.086	0.280	0.14
None/other toilet	0.001	0.001	0.029	0.03
Main source of lighting electric	0.284	0.510	0.500	0.57
Number of rooms in dwelling	0.159	2.676	1.957	0.08
Kitchen a separate room	0.183	0.536	0.499	0.37
Main cooking fuel biomass	-0.281	0.776	0.417	-0.67
Dwelling all high-quality materials	0.309	0.237	0.425	0.73
Dwelling all low-quality materials	-0.273	0.483	0.500	-0.55
Own > acres land	0.031	0.115	0.319	0.10

Source: Adapted from Filmer and Pritchett (2001: 118)

While Filmer and Pritchett (1994, 1999, 2001) support the use of PCA to provide a statistical solution to the problem of how to weight the indicators within an asset-based index, there are criticisms regarding their methodology. One such criticism focuses on the application of PCA to binary data. Kolenikov and Angeles (2009) discuss this in detail and suggest possible solutions. They argue that the use of binary or dummy variables in PCA introduces spurious correlations because the dummy variables produced from the same factor are negatively correlated.

The DHS wealth index is an attempt to capture existing data in the DHS so as to determine a household's relative economic status (Rutstein & Johnson, 2004). The DHS index is constructed using the Filmer and Pritchett methodology - principal component analysis using the SPSS (Statistical Package for the Social Sciences) factor analysis procedure (Rutstein & Johnson, 2004). Once again it is assumed that the possession of assets and access to certain services is related to the economic position of the household in the country (Rutstein, 2008).

In the example, of the 20 per cent of the population with the lowest wealth index none used electricity, while 56.7 per cent of the top wealth quintile used electricity. About 43 per cent of the lowest wealth quintile used the bush or a field as a latrine while only 0.8 per cent of the top wealth quintile did so. The example shows how ownership of assets and access to services can be used to differentiate households, assuming that dissimilar levels of wealth are the cause of differences in asset ownership and access to services.

A criticism of the DHS wealth index is that it is too urban in its construction as many of the assets and services used in the surveys are owned by urban populations (Rutstein, 2008). Rutstein (2008) suggests that a possible solution to this problem is to include questions in the standard questionnaires that are able to ascertain rural stores of wealth, such as the size of landholdings and the number and type of farm animals owned. Other solutions would be to use rural and urban specific indices or to calculate the wealth quintiles by type of area. Separate indices could then be scaled to allow for comparison, so that a given score on each index refers to the same level of wealth (Rutstein, 2008). A second criticism arises from the inability of the index to distinguish the very poor from the poor (Rutstein, 2008; McKenzie, 2005). In response, Rutstein (2008) suggests using deciles in place of quintiles or adding questions regarding the possession of furniture items that the extremely poor may not own, such as chairs, tables and beds.

The PCA methodology has also been adopted by the World Bank for use in its reports on socio-economic differences in health, nutrition and population (HNP) within developing countries (Gwatkin *et al*., 2007a). The World Bank index for Kenya 2003, contained almost 70 variables. The advantage of including a number of variables in the index is that the degree of variation across the wealth scores is increased with the addition of assets which, in turn, facilitates a more regular distribution of individuals across the wealth quintiles (Gwatkin *et al*., 2007a). However, a possible disadvantage is that this method of item selection results in the inclusion of information regarding publicly-provided services such as electricity, water and sanitation which may not be useful indicators of private household wealth but rather a function of location (Gwatkin *et al*., 2007a). However, in the case of electricity, Montgomery *et al*. (1999) argue that given the possibilities afforded by batteries, generators and electrical line taps it is reasonable to include electricity in the list of assets. Another area of possible difficulty is the interpretation of the results. The index is relative and individuals or households are grouped into quintiles depending on their wealth score; this presents a problem for comparison of groups between countries or areas. The lowest quintile of one country may be considerably worse off (have lower asset scores) that the lowest quintile of another country (Gwatkin *et al*., 2007a).

Schellenberg *et al*. (2003) undertook an investigation into socio-economic inequalities in health in African countries. PCA was used to develop a relative index of household socio-economic status (SES) using weighted scores of information on income sources, the education level of the household head and ownership of household assets (Schellenberg *et al*., 2003). The authors point out that the asset index is a relative measure of SES within the area assessed and the results cannot be easily compared directly to other poverty assessment methods or results from other areas.

McKenzie (2005) investigated the potential of measuring household inequality in living standards using asset indicators. Using data from Mexico's national income and expenditure survey for the third quarter of 1998, McKenzie (2005) developed an asset index using PCA to derive the weights of the asset indicators or variables. McKenzie (2005) discusses two potential problems that may arise with the use of asset indices: clumping and truncation. Clumping occurs when not enough asset indicators are used and households are clumped into a few small groups (McKenzie, 2005). In the extreme, if only one indicator was used, there would be two groups - owners and non-owners. Truncation is the case when indicators, which allow for the differentiation between the very poor and poor, or the upper middle class and the rich, are not present (McKenzie, 2005). The problem of truncation is also discussed by Rutstein (2008). As a solution, McKenzie (2005) suggests adding more indicators into the index.

Houweling *et al*. (2003) investigated whether the choice of SES indicator affected the measurement of health inequality among children in developing countries. PCA was used to generate the weights for all of the selected indices, but each index differed in the inclusion of indicators. The first asset index followed the World Bank methodology. The three alternate indices were constructed by leaving out: (1) all water supply and sanitation items; (2) items under (1) and all housing items; and (3) items under (2) and electricity (Houweling *et al*., 2003).

The four indices were compared on the variance explained by the first principal component for each one and whether it was possible to stratify the population into five, about equally large, wealth groups based on the index. Cross-tabulations were then used to calculate the percentage of households remaining in the same quintile, moving to the adjoining quintiles and moving to the two furthest quintiles. Table 2.4 shows the percentage of variance explained by the first principal component for each of the indices. The proportion of variance explained is the lowest for the World Bank index for each of the study countries. Excluding items from the list of variables tended to increase the per cent of variance explained by the first principal component. The ability to stratify the sample population into equally sized quintiles became more difficult as the number of assets included in the index was decreased. From the movement of households between quintiles (for Uganda and Indonesia), it is clear that the categorisation of households into wealth groups was sensitive to the measure of SES.

Table 2.4: Percentage of variance explained by the first principal component for each index for 10 countries

Country	WB Index	Index 1	Index 2	Index 3
Bolivia	17	20	43	43
Brazil	13	15	40	43
Cameroon	20	29	28	36
Chad	19	30	39	38
Indonesia	14	17	31	32
Kenya	17	23	37	37
Malawi	18	24	25	27
Pakistan	20	27	38	40
Tanzania	16	24	36	36
Uganda	12	19	25	23

Source: Houweling *et al*. (2003: 5)

Table 2.5 shows the results of movement of households to other wealth groups when using the alternative indices as compared to the World Bank index, for Indonesia and Uganda. When using Wealth Index 1 instead of the World Bank index for Indonesia, 73 per cent of households remained in the same wealth group, 27 per cent moved by one wealth group and no households changed by two or more wealth groups. Largest changes occurred when Index 2 and 3 were used, where, on average, 47 per cent of households shifted to another quintile. From their study Houweling *et al*. (2003) concluded that the choice of indicators affected the magnitude of the observed health inequalities, which was in contrast to the Filmer and Pritchett (1999) study that found the ranking of households to be robust to the assets included in the index (Houweling *et al*., 2003).

Table 2.5: Movement of households to other wealth quintiles when using alternative indices as compared to the World Bank index, Indonesia and Uganda

Country	Wealth Index	% in same wealth group	% moving 1 wealth group	% moving 2 or more wealth groups
Indonesia	Index 1	73	27	0
	Index 2	53	38	9
	Index 3	50	37	13
Uganda	Index 1	72	24	3
	Index 2	56	35	9
	Index 3	54	36	10

Source: Houweling *et al*. (2003: 6)

Lindelow (2006) undertook a study to determine the sensitivity of measured health inequality to the choice of welfare indicator. The analysis was based on data from the Living Standards Survey for Mozambique for the year 1996-97. The welfare indicators compared in the study were per capita consumption, a money metric welfare indicator and an asset index constructed using PCA. The health outcomes used were hospital visits, health facility visits, child immunizations, pregnancy controls and medically supervised visits. The first form of evaluation was to compare the distribution of wealth quintiles, where the quintiles were defined on the basis of consumption and the asset index. The results showed, with the exception of health centre visits, that the utilization of health services was far more equally distributed when the households were ranked by consumption than by the asset index (Lindelow, 2006). Similar results were reported when concentration curves were used to compare inequality of health service use under the two different welfare indicators. If consumption is used as the welfare proxy, the conclusion can be drawn that although there is some inequality in health service use, the inequality is fairly moderate for all services, whereas if the asset index is used to proxy SES the inequality is much greater (Lindelow, 2006). This result points to the fact that consumption and the asset index measure different things, or are different proxies for the same underlying variable (Lindelow, 2006). It is not possible to conclude which proxy is better, but rather to accept that proxy choice is most likely to depend on data availability rather than conceptual concerns (Lindelow, 2006).

Studies by Zeller *et al*. (2001, 2003) also make use of PCA based indices. Several studies have considered the relationship between household socio-economic status and the under-nourishment of children using a PCA based asset index as a proxy of household wealth (Larrea & Freire, 2002; Hong & Mishra, 2006; Hong *et al*., 2006; Uthman, 2008). The studies conclude that household SES does affect the nourishment of children from households in developing countries.

Principal Factor Analysis has also been used to generate the weights associated with an asset-based index. Sahn and Stifel (2000) undertook a comparison of poverty over time within and between African countries. The problem of accurately calculating household expenditure was the motivation for developing an asset index as an alternative measure of welfare. The index is based on the premise that there is a common factor behind ownership of assets and that factor analysis could be used to define the factor as a weighted sum of individual assets. Factor analysis is similar to PCA, but differs in that it does not force all of the components to completely explain the correlation structure between the assets (Sahn & Stifel, 2000). The method of factor analysis accounts for the covariance of the assets in terms of fewer hypothetical common factors compared to PCA (Lawley & Maxwell, 1962). Sahn and Stifel (2000) used data from the first round of DHS for a number of African countries in the study. Table 2.6 shows the asset index weights by country and for the pooled sample using factor analysis.

Table 2.6: Asset variables and the corresponding weights by country and for the pooled sample

Assets	Cameroon	Ghana	Kenya	Madagascar	Mali	Senegal	Tanzania
Durables							
Radio	0.095	0.103	0.075	0.123	0.082	0.052	0.161
TV	0.249	0.340	0.196	0.266	0.312	0.312	0.169
Refrigerator	0.208	0.350	0.142	0.125	0.183	0.274	0.216
Bicycle		0.023	0.008				0.024
Motorized transport	0.082	0.073		0.132	0.126	0.095	0.160
Characteristics							
Piped drinking water	0.190	0.132	0.225	0.253	0.172	0.131	0.149
Surface drinking water	-0.056	-0.098	-0.154	-0.143	-0.010	-0.014	-0.093
Flush toilet	0.169	0.117	0.259	0.201	0.066	0.146	0.134
No toilet facilities	-0.038	-0.020	-0.064	-0.148	-0.068	-0.100	-0.058
Floor-low quality	-0.148	-0.060	-0.220		-0.234	-0.099	-0.247
Education of head	0.144	0.056	0.040	0.064[a]	0.142	.124[a]	0.149

[a] Dummy variable for household head with some education

Table 2.6 ***Continued***

Assets	Togo	Uganda	Zambia	Zimbabwe	Pooled
Durables					
Radio	0.099	0.121	0.086	0.062	0.098
TV	0.410	0.202	0.127	0.105	0.297
Refrigerator	0.197	0.129	0.086	0.087	0.212
Bicycle	0.020	0.011		0.009	
Motorized transport	0.152	0.035	0.042	0.049	0.049
Characteristics					
Piped drinking water	0.132	0.243	0.242	0.256	0.189
Surface drinking water	-0.057	-0.067	-0.061	-0.031	-0.074
Flush toilet	0.433	0.180	0.199	0.459	0.205
No toilet facilities	-0.130	-0.055	-0.080	-0.089	-0.075
Floor-low quality	-0.037	-0.311	-0.272	-0.073	-0.168
Education of head	0.127	0.188	0.123	0.039	0.054[a]

[a] Dummy variable for household head with some education

Source: Sahn and Stifel (2000: 2129)

The countries were then ranked on the basis of the welfare index and the results compared to other indicators of poverty and national economic attainment. From the results, Sahn and Stifel (2000) concluded that the use of factor analysis to measure poverty is a useful alternative to large surveys of household consumption and budgets. However, the authors found, on comparison to the rankings generated using PCA, that the two methods (PCA and factor analysis) ranked households similarly, with a Spearman rank correlation between the two indices of about 0.98 for each of the samples. Sahn and Stifel (2000) explain that an advantage of such an asset index is that the use of money metric measures of welfare that depend on, often questionable, price deflators can be avoided.

Sahn and Stifel (2003) evaluated an asset index derived from a factor analysis of household assets using data collected from Living Standards Measurement Studies and similar surveys for 11 countries, to ascertain its potential as a measure of household economic wealth. The results showed that the household rankings based on the asset index were less consistent with the ranking by reported expenditures than the household rankings using predicted expenditures. However, as Sahn and Stifel (2003) explain, the method of predicting expenditures is prone to errors as a result of recall bias, home production, poorly trained enumerators and unreliable price deflators. The results also showed that the asset index was a valid predictor of child nutrition outcomes. It was concluded that, in the case of child nutrition, there was no evidence that reported or predicted expenditures served as a better proxy for economic welfare than the asset index (Sahn & Stifel, 2003). For many of the samples, the asset index performed as well as, if not better than, the reported expenditures in predicting child nutrition outcomes (Sahn & Stifel, 2003).

Naschold (2005) undertook a study to identify asset poverty thresholds with an application to Pakistan and Ethiopia. For the purposes of the study it was necessary to summarize assets into an asset index. Naschold (2005) used principal factor analysis, following Sahn and Stifel (2000), to construct the asset index. In the study, poverty and welfare were defined based on assets rather than income and consumption, and the author gives a number of reasons for doing so. First, the economic welfare of a household is dependent on its asset reserves as it is the accumulation of assets over time that enables a household to earn sufficient income to move out of poverty. Second, asset levels are less volatile than income and, thus, are closer to a measure of long-term economic welfare than income. Third, surveys are inclined to measure asset holdings more accurately than income or consumption measures. Before attempting the principal factor analysis, the author conducted two tests to determine whether there was a strong enough correlation in the data to allow for meaningful factor analysis. The tests used were Barlett's test for sphericity and the Kaiser-Meyer-Olkin Measure for Sampling Adequacy. Both tests suggested the data were suitable for factor analysis (Naschold, 2005).

Asset indices have been constructed using a simple sum of assets owned by the household (Hatloy *et al*., 2000; Montgomery *et al*., 1999; Garenne & Hohmann-Garenne, 2003). Hatloy *et al*. (2000) analysed the associations between a number of food security measures and socio-economic status (SES) for households in Koutiala, Mali. A score of SES was generated for each household based on the possession of 14 different household items. Table 2.7 is a list of the 14 household items and the percentage of sample households in possession of the various items at the time of measurement. The score was generated by a straightforward count of possessions (one point was given for possession of each of the items). Based on the asset score the households were divided into tertiles of high (a score of 7-10), medium (a score of 4-6) and low (a score of 0-3) SES.

Table 2.7: Percentage of sample households possessing different items included in the SES index, Koutiala, Mali, 1994/95

Item	Urban (n= 327)	Rural (n= 487)
Latrine	100	60
Radio	77	73
Motorcycle	44	40
Bicycle	33	91
Donkey/cart	32	85
Ox/plough	22	93
Sheep/goats	20	76
Electricity	15	3
Cattle	10	46
Television	9	1
Refrigerator	7	0
Video	5	0
Car	4	1
Tractor	1	1
SES score		
SES1 (0-3 possessions)	57	13
SES2 (4-6 possessions)	30	48
SES3 (7-10 possessions)	14	39

Source: Hatloy *et al*. (2000: 60)

The results showed that there were associations between food security measures and SES and associations between the food security measures and the nutritional status of children in the households of Koutiala. There was a high degree of homogeneity in SES in the rural areas of Koutiala and there was a higher prevalence of agricultural equipment in the rural areas causing a larger number of rural households to be classified as having a higher SES than their urban counterparts. This result highlights the necessity of creating socioeconomic scores adapted to different contexts (Hatloy *et al*., 2000). A second potential problem with the simple sum method is that assets of different values are equally weighted (Bollen *et al*., 2002); therefore, a household owning a number of inexpensive items may be ranked on the same level of wealth as a household owning more expensive items.

Montgomery *et al*. (1999) investigated the use of proxy variables to measure living standards by evaluating the performance of the proxy measures in relation to consumption expenditures per adult. Comparisons were also drawn between the effects of alternative proxies on fertility, child mortality and childrens' education and those of consumption per adult. Living Standards Measurement Study (LSMS) data for five developing countries were used in the analysis as they consist of information pertaining to proxy measures as well as household consumption expenditures. The three proxy measures considered by Montgomery *et al*.

(1999) were (1) a simple summation of the number of items present in the household, (2) a measure specified with dummy variables for each distinct value of the items, and (3) a measure in which each item is a separate variable. Only the third measure was compared to consumption expenditure in predicting fertility, child mortality and children's education. From the analysis results Montgomery *et al*. (1999) found that the proxy measures were weak predictors of consumption per adult as the partial R^2 values were very low. However, the proxy measures still provided useful information in that they showed that consumption is relevant to household behaviour (Montgomery *et al*., 1999). Two factors add to the support of proxy measures: first, there is significant variability in consumption expenditures per adult, meaning that even weak proxies for consumption are able to show that consumption is relevant, and secondly, the power of the proxy measures is strengthened by large sample size and demographers generally have access to relatively large samples (Montgomery *et al*., 1999).

Garenne and Hohmann-Garenne (2003) considered a wealth index, based on a score derived from the sum of ownership of, or access to, 15 socioeconomic indicators, to screen families at higher risks of infant and child mortality in Morocco. The score was based on characteristics of housing and household goods easily collectable in the field. The 1992 Moroccan DHS was used as a source of data. The aim of the study was to provide a relatively simple tool to define socioeconomic levels that correlate with a health outcome indicator: the under-five child mortality rate (Garenne & Hohmann-Garenne, 2003). The score was constructed by recoding the variables as dummy variables: coded one for the value linked to a higher socioeconomic status and zero otherwise. The final score was then just the sum of the dummy variables. Five groups were defined, ranked by increasing value of the score, and close to the five quintiles. The score results were compared to the results obtained by other studies using PCA. The main finding of the study was that the score was able to discriminate between families with higher and lower risks of child mortality. Its discriminating power was found to be equivalent to that of more complex procedures such as discriminant analysis and PCA (Garenne & Hohmann-Garenne, 2003). A limitation of discriminant analysis, argued by Garenne and Hohmann-Garenne (2003), is that such techniques use complex coefficients, or weightings, with no empirical meaning and are likely to change significantly when applied to other samples. Advantages of the simple sum method include: (1) the technique is simple and only requires a spreadsheet for analysis, (2) it can be replicated in any country with a demographic survey, and (3) it could be used for comparisons over time if the list of variables is unchanged (Garenne & Hohmann-Garenne, 2003).

The last method of generating the weights for the variables included in an asset-based index discussed in this study is to use the reciprocal of the share of households owning the particular item in the total sample. Morris *et al*. (2000) used such a technique in their study of the validity of proxy measures of household wealth and income for health surveys in rural Africa. The score was constructed by assigning a weight to each of the items in the list of assets equal to the reciprocal of the proportion of the study households owning one or more of the item. The number of units of the asset owned by the household was then multiplied by its corresponding weight and the product over all possible assets was summed for each household. The approach was based on the assumptions that households with greater wealth or resources would purchase a larger number of consumer durables and households would be progressively less likely to own a certain item the higher its monetary value (Morris *et al*., 2000). Data from Malawi, Mali and Cote d'Ivoire were used to construct and test the measure. The simple asset scoring tool was compared to a more complex monetary valuing method of generating weights and it was found that the derived weights from both techniques correlated highly ($r \geq 0.74$) (Morris *et al*., 2000). From their analysis, Morris *et al*. (2000) concluded that the simple asset score gave a quantitative indication of the overall value of a household's assets relative to other households. The score was limited in that it did not include house and land ownership in its list of variables, two assets that are of particular importance to rural households (Morris *et al*., 2000).

Azzarri *et al*. (2005) applied the Morris index to Albanian households over two years, 2002 and 2003. The analysis found urban households to control more assets than rural households for each consumption quintile and the 2003 index to be higher than the 2002 index across all quintiles.

Bollen *et al*. (2002) investigated the consequences of using different proxies of SES on the impact of economic status and other factors of fertility. Five measures of SES were compared through the use of an ordinary least squares (OLS) model to predict the number of children ever born: (1) household expenditures, (2) a simple sum of goods owned, (3) a sum of the estimated value of the goods owned, (4) a sum of the median value of the goods owned, and (5) a PCA based index of goods owned. The analysis was based on data from the Ghana

Living Standards Survey 1988-89 and the Peru Living Standards Survey 1985. The first model included only religion, ethnicity, place of residence and age; each model thereafter included these variables plus education and one of the five proxies of SES, except for model 3, which included occupation as a proxy of economic status. For the Ghanaian sample the results of the analysis showed mixed results with some coefficients of the explanatory variables being affected by the choice of proxy measure and some not (Bollen *et al*., 2002). Similarly, the Peruvian sample analysis showed shifts in some of the variable coefficients, but these changes were not greater than double the standard errors of the coefficients (Bollen *et al*., 2002). The general conclusions drawn about the effects of the explanatory variables on fertility levels would be similar regardless of the SES proxy used (Bollen *et al*., 2002).

The relative fit of each of the models was examined using the Bayesian Information Criterion (BIC): the model with the smallest (most negative) BIC is the best fitting model (Bollen *et al*., 2002). The results showed the PCA-based asset index to have the lowest BIC (-1103.633 for Ghana and -1469.847 for Peru). The simple sum of assets measure had the next lowest BIC value (-1098.075 for Ghana and -1459.222 for Peru). Included in the comparison was a set of asset-based indices generated using the same four methods, but including a fewer number of goods. These measures were shown, in terms of the BIC, to perform not as well as their counterparts including a greater number of assets (they consistently had higher BIC values than the same measure including fewer assets) (Bollen *et al*., 2002). Bollen *et al*. (2002) concluded that choice of the SES proxy altered the results, albeit not by a large amount, and the PCA-based asset index had the best model fit. Including a greater number of assets in the index also increased its performance (Bollen *et al*., 2002).

A review of the literature shows that statistically weighted asset-based indices have the potential for providing welfare rankings of the population. They can be used to group a population into levels of socio-economic status and thus are useful in focusing attention onto more vulnerable groups of the population. However, they are relative measures and do not give absolute levels of poverty. An advantage of using an asset index as a measure of wealth or SES is that the data can be quickly and easily collected in a single household interview providing a convenient means of summarizing the socio-economic situation of a household or individual (Lindelow, 2006). A second advantage of using an asset index as a measure of wealth is that assets are less prone to fluctuations than income or consumption, thus making it a better measure of long-term household wealth (Lindelow, 2006). A drawback of the asset index measure, as pointed out by Filmer and Pritchett (1999), is the problem of rural/urban comparisons: the DHS asset index has been criticised for being too urban in its construction (Rutstein, 2008). Rutstein (2008) suggests that a possible solution to the problem is to include questions in the standard questionnaires that are considered able to ascertain rural stores of wealth, such as the size of landholdings and the number and type of farm animals owned. Alternatively, rural and urban specific indices could be used or wealth quintiles could be calculated by the type of area (Rutstein, 2008).

In conclusion, sections 2.1 and 2.2 of the chapter give evidence of the role assets play in a household's ability to cope with risk. Therefore, if asset ownership could be 'measured', the outcome would give an indication of a household's resilience. In section 2.3 a number of studies regarding asset-based indices were reviewed. From the literature consulted, it can be concluded that asset-based indices have the potential to provide welfare rankings of a population, thus giving an indication of the wealth of assets owned by a particular household. This, in turn, could be used as a relative indication of household resilience. An asset-based index could be used to estimate a wealth or socio-economic status score for a household, which could then be used as an indicator of the relative resilience of the particular household, based on the premise that the level of asset ownership is an indication of a household's ability to cope with risk.

CHAPTER 3: REVIEW AND SELECTION OF RESEARCH METHODOLOGY

In this chapter of the study, the research methodology and data used to develop a tool for the measurement of household resilience – based on asset ownership – are described. From the discussion in chapter two, it is clear that the level and nature of assets owned by a household could be used as a proxy of its resilience. It was concluded that a socio-economic status (SES) score, based on asset ownership and estimated using an asset-based index, could be used as an indicator of household resilience. The SES score could then be used to classify a chosen population into categories representing relative levels of household resilience. From the review of literature presented in section 2.3, it is clear that there are a number of methods of constructing an asset-based index: no single method has been widely accepted as being superior to the rest in estimating household SES. To this end, four methods of constructing an index of socio-economic status (SES) have been selected for comparison in this study: three versions of Principal Component Analysis (PCA) and a simple sum of assets technique.

The chapter is organised as follows: Section 3.1 is a description of the data and Section 3.2 discusses the four methods of index construction, including the selection and weighting of variables. The last section details the process of estimating individual household SES scores and the classification of households into resilience groups.

3.1 Description of the Data

The data used in the study were taken from the household component of the Demographic and Health Surveys (DHS) for six African countries. The DHS are large, nationally representative household surveys with a focus on obtaining nationally representative and cross-nationally comparable household level data on fertility, use of family planning methods and services, child mortality, and maternal and child health. The surveys are an extensive, reliable source of data for health and demographic analysis in developing countries (Kolenikov & Angeles, 2009). The DHS programme, undertaken by Macro International with support from the United States Agency for International Development (USAID) and other organizations, has conducted surveys in roughly 75 countries across Africa, Asia, Latin America, the Middle East and the former Soviet Union (Gwatkin *et al*., 2007a). The DHS data are available for public access from the DHS website (www.measuredhs.com).

The focus of the DHS is household health and demographics. However, since 1990 the surveys have included two sets of questions related to the economic status of the household. For the first set of questions, households are asked to report on the ownership of various assets, such as a radio, television, refrigerator or bicycle. The second set of questions revolves around the characteristics of the household, for example the source of drinking water, type of toilet facility, access to electricity and the types of materials used in the construction of the house.

In this study, the DHS household data from six African countries (Macro International Inc., 2010) were used to construct indices of socio-economic status (SES) in an attempt to develop a tool for the measurement of household resilience in these countries. In the Human Development Report (UNDP, 2009) countries are listed in order of the per cent of the population living below U.S. $1.25 per day. The countries included in this study were chosen by grouping the African countries appearing in the report into three categories - rich, middle and poor - based on their UNDP (2009) poverty ranking. Two countries from each category with a DHS version V – the most recent round of DHS surveys - were selected for analysis. The six countries 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). Table 3.1 compares the African countries appearing in the Human Development Report (UNDP, 2009) by poverty ranking and DHS version. The highlighted countries are the ones chosen for the study.

3.2 Construction of the Socio-Economic Status Index

The construction of the SES index involved two main undertakings. Firstly, the indicators or variables for inclusion in the index were selected. Studies in which asset indices have been used as a measure of wealth or SES (see Chapter 2) and the availability of relevant variables in the DHS data sets were used as a guide in the selection of variables for this study. The second undertaking was to weight the indicators included in the index. A number of methods have been suggested in the literature for the weighting of variables in a SES index. These are outlined in Chapter 2. Since there is no set methodology for assigning weights to indicators in an index of SES, this study applies four different approaches (three versions of PCA, and a simple sum of assets method) in an attempt to examine differences in the measurement of household resilience as a result of using different weighting procedures.

Table 3.1: Comparison of African countries by poverty ranking and DHS version

	Country	Poverty Ranking	DHS version	Year
Rich	Egypt	<2	V	2008
(<33.33)	Morocco	2.5	IV	2003/4
	Tunisia	2.6	I	1988
	Gabon	4.8	IV	2000
	Kenya	19.7	V	2008/9
	Cote D'Ivoire	23.3	III	1998/9
	South Africa	26.2	III	1998
	Ghana	30	V	2008
	Cameroon	32.8	IV	2004
	Senegal	33.5	IV	2005
Middle	Botswana	31.2	N/A	N/A
(<66.66)	Gambia	34.3	N/A	N/A
	Ethiopia	39	V	2005
	Lesotho	43.4	IV	2004
	Benin	47.3	V	2006
	Guinea Bissau	48.8	N/A	N/A
	Namibia	49.1	V	2006/7
	Mali	51.4	V	2006
	Uganda	51.5	V	2006
	Congo	54.1	V	2005
	Burkina Faso	56.5	IV	2003
	Democratic Republic of Congo	59.2	V	2007
	Chad	61.9	IV	2004
	Central African Republic	62.4	III	1994/5
	Swaziland	62.9	V	2006/7
	Zambia	64.3	V	2007
	Nigeria	64.4	V	2008
	Niger	65.9	V	2006
Poor				
(>66.66)	Madagascar	67.8	V	2008/9
	Guinea	70.1		
	Malawi	73.9	IV	2004
	Mozambique	74.7	IV	2003
	Rwanda	76.6	V	2005
	Burundi	81.3	I	1987
	Liberia	83.7	V	2007
	Tanzania	88.5	V	2007/8

Source: Adapted from UNDP (2009) and Measure DHS

3.3.1 Selection of the Variables

There is no 'best practice' for selecting variables for inclusion in an index of household wealth or SES (Montgomery, 2000). The aim is to select those variables that best distinguish between levels of SES for households. PCA and related techniques are proposed as a means of assigning weights to the selected indicators; therefore, the chosen variables must also meet the requirements of PCA. There is ambiguity regarding the type of data (continuous, normal or ordinal) appropriate for PCA (this is discussed under section 3.3.2 below). However, once the indicators have been selected the manner in which they are coded or quantified can be altered at a later stage to meet analysis requirements.

A number of variables for inclusion in an asset index have been indentified in similar studies, as discussed in Chapter 2. These generally include durable assets owned by the household, such as a radio or bicycle; access to certain services, for example, source of water and sanitation facilities; and characteristics of the dwelling, such as the roof and floor materials. There is little clear guidance on the optimum number of indicators to include in an index of SES with similar studies including anywhere from 11 variables (Schellenberg *et al.*, 2003) to 68 (Gwatkin, 2007b). Angeles and You (2007) conducted a review of the number and type of variables included in the DHS that could be used to estimate SES indices (Kolenikov & Angeles, 2009). From the 76 surveys considered (1994-2007), the average number of variables used to calculate a SES index was 20, with a range of 11 to 42, the average number of dichotomous variables included was 12, with a range of five to 32, the average number of categorical variables included was seven, with a range of three to 16, and the average number of numeric variables included was two (Kolenikov & Angeles, 2009, citing Angeles & You, 2007).

In the DHS data, information is collected on durable asset ownership, access to services and infrastructure and characteristics of the dwelling, all of which could be included in the analysis as variables. Rutstein and Johnson (2004) suggest that all household assets and utility services should be included, with the justification that the greater the number of indicator variables, the better the distribution of households. However, PCA works best when the variables are correlated and the distribution of the variables varies across households (Vyas & Kumaranayake, 2006). The indicators or variables that are more unequally distributed between households are given a greater weight in the PCA (McKenzie, 2003). A variable with a low standard deviation would carry a low weight in the PCA. For example, if an asset was owned by all or none of the households, it would exhibit no variation across households, have a standard deviation of zero, obtain a zero weighting in the PCA and, thus, be of little use in differentiating levels of SES between households (Vyas & Kumaranayake, 2006).

Therefore, as a first step in the selection of the indicator variables for inclusion in the index, descriptive analyses were carried out for all possible variables from each of the chosen countries' DHS datasets. While descriptive analyses assist the selection of variables, they are also a useful tool for detecting issues such as missing values and coding errors (Vyas & Kumaranayake, 2006). However, the mean and standard deviation estimates are only useful for the durable asset variables with only two categories, such as owns a radio or does not. The mean and standard deviation for the durable asset variables, as well as the number of missing values for all variables, were then examined. The correlations between variables were also considered, as an indication of the variable's suitability for PCA. The variables for inclusion in the index were chosen based on these statistics. Variables with high levels of missing values were excluded. The index variables were chosen separately for each of the six countries as the variables available in the DHS samples differed across countries.

Two problems associated with PCA-based asset indices are clumping and truncation (McKenzie, 2005). Clumping is defined as the grouping of households into a small number of distinct clusters, and truncation as a more even distribution of socio-economic status (SES), but spread over a narrow range (McKenzie, 2005). The occurrence of these two problems can make it more difficult to differentiate between socio-economic groups. Vyas and Kumaranayake (2006) suggest that the distribution of asset ownership, housing characteristics and access to utilities and infrastructure can give an early indication of the potential presence of these two problems. A possible solution to these two problems is to add more variables to the analysis that are relevant in assessing household SES (Vyas & Kumaranayake, 2006), especially those variables that capture inequality between households (McKenzie, 2005).

3.3.2 Weighting of the Variables

As is clear from Chapter 2, PCA is a widely used means of generating the weights for the variables included in the asset index with the methodology used by Filmer and Pritchett (1994, 1999, 2001) being the most used. However, Kolenikov and Angeles (2009) argue that the method of PCA was originally intended for use with continuous data and that its application to dichotomous data, as done by Filmer and Pritchett (1994, 1999, 2001), is not appropriate and may introduce spurious correlations to the results. The next three sub-sections discuss PCA, support for and against its application to non-continuous data, the method adopted by Filmer and Pritchett (1994, 1999, 2001) and the alternative as proposed by Kolenikov and Angeles (2009). Following the discussion of PCA is an introduction to nonlinear PCA and the method of equal weights which may also be used as a means of assigning weights to the variables of an asset index.

3.3.2.1 Principal Component Analysis

PCA is a statistical, multivariate technique that linearly transforms a group of correlated variables into a relatively smaller group of uncorrelated variables that capture most of the information in the original group of variables (Dunteman, 1989:7; Jolliffe, 2004:1). The technique of PCA was first described by Pearson in 1901 and further elaborated by Hotelling in 1933 (Tintner, 1952:102; Dunteman, 1989:7; Manly, 1994:76; Jolliffe, 2004:7).

In mathematical terms, PCA creates uncorrelated components from an initial set of *n* correlated variables, where each component is a linear weighted combination of all the initial variables (Vyas & Kumaranayake, 2006). Thus, PCA takes a set of variables, X_1 through to X_n and computes linear combinations of them that represent *m* dimensions or principal components (PCs):

$$PC_1 = a_{11}X_1 + a_{12}X_2 + ... + a_{1n}X_n \tag{3.1}$$

$$PC_m = a_{m1}X_1 + a_{m2}X_2 + ... + a_{mn}X_n \tag{3.2}$$

where a_{mn} represents the weight or component loading for the *m*th principal component and the *n*th variable. The principal components are ordered with respect to their variation so that the first principal component would account for the greatest variation in the original variables (Dunteman, 1989: 10; Manly, 1994:76). However, the following condition is applied:

$$a^2_{11} + a^2_{12} + ... + a^2_{1n} = 1 \tag{3.3}$$

so that the variance of the PC cannot be increased by simply raising the value of any one of the component loadings (Manly, 1994:78). Similarly, the second PC is derived so that its variance is as large as possible, although smaller than that of PC_1, subject to the constraint that the sum of the squares of the component loadings is equal to one (Manly, 1994:78). The proportion of the total variance explained by each PC is calculated as the Eigenvalue of the PC divided by the number of variables in the initial data set, since the sum of the Eigenvalues for all the PCs is equal to the number of variables in the original data set (Kim & Mueller, 1994:86; Vyas & Kumaranayake, 2006). Details of the derivation and properties of PCA can be found in Jackson (1991), Manly (1994) and Joliffe (2004), among others.

PCA is based on the assumption that the initial variables are linearly related, but if this is not the case then PCA is inappropriate (Koutsoyiannis, 1977:436). PCA requires that the original variables be measured at least at the interval level as implied by the use of the covariance or correlation matrix as the basic input for factor analysis (Stevens, 1946). Therefore, the use of PCA with non-interval data may be inappropriate. There are a number of different selection criteria for deciding how many PCs should be retained so as to account for the maximum amount of variation in the initial set of variables (Kim & Mueller, 1994:110; Jolliffe, 2004:112). It may be difficult to interpret the PCs or to identify which dimension of the data a particular PC is capturing.

However, in a number of its applications, as discussed in Chapter 2, PCA is used with dichotomous data (categorical data) (Filmer & Pritchett, 1994, 1999, 2001; Rutstein & Johnson, 2004; Gwatkin *et al.*, 2007a). There are a number of measurement scales of variables and they can be generally classified into four broad categories (Gujarati, 2003:30-31). The measurement scale is a ratio scale when the ratio of two values for the same variable and the distance between the two values are meaningful quantities and there is a natural ordering of the values along the scale (Gujarati, 2003:30-31). An interval scale variable satisfies the last two properties of the ratio scale, the distance between two values of the variable is meaningful and the scale has a natural ordering (Gujarati, 2003:31). An ordinal scale variable satisfies only the property of natural ordering and the distances between categories are not meaningful quantities (Gujarati, 2003:30-31). Each variable has a number of categories which may be represented by labels or numbers with a specific ascending or descending order (Linting, 2007); for example, 'weight' measured not in kilograms but categorized as underweight, average or overweight (Rao & Caligiuri, 1993:97).

Variables with a nominal measurement scale have none of the features of a ratio scale (Gujarati, 2003:30-31) and are measured in unordered categories (Linting, 2007). Nominal scale variables could be gender, religion or race (Rao & Caligiuri, 1993:97). Often, only a distinction between numeric and categorical data is made. The term categorical generally refers to nominal and ordinal measurement scales while numeric refers to variables measured on an interval or ratio scale (Linting, 2007). Reference is also made to continuous variables which are those measured on equal interval scales (interval or ratio scales) (Rao & Caligiuri, 1993:97). Dichotomous or binary variables (eg. dummy variables) are those variables that take only two values, such as one for yes and zero for no (Gujarati, 2003:581). Dichotomous, binary and dummy variables fall into the group of categorical variables (Gujarati, 2003:297). Kolenikov and Angeles (2009) argue that PCA was developed for multivariate normal data and it is best used with continuous data, although they suggest if PCA is to be used with categorical data, ordinal data is preferable to dichotomous data.

Kim and Mueller (1994:141-143) briefly discuss the use of PCA with non-continuous data and explain that PCA is not defined for ordinal variables and that the distortions in data scaling caused by dichotomies and ordinal data will distort the correlations between variables and, hence, the PCA results. However, they indicate that the correlation coefficients are fairly robust to the distortions resulting from the use of ordinal data. They conclude that as long as the distortions introduced by assigning numerical values to ordinal categories are not substantial, the ordinal variables can be treated as continuous variables. They recommend, in the case of ordinal data, that it is best to use a large number of categories, as doing so will reduce the distortion.

Two further conditions are given that, if met, may justify the use of PCA with ordinal data: (1) if the analysis is used to find general dimensions in the data, and (2) if the underlying correlations among the variables are believed to be moderate (less than 0.6 or 0.7) (Kim & Mueller, 1994:143). Kim and Mueller (1994:142) advise against the use of PCA with dichotomous data. Gower (1966) explains that the use of PCA is not appropriate for unordered qualitative data (nominal data), but does give support for the application of PCA to dichotomous data. Kim and Rabjohn (1980) regard the explanatory variables as generally thought of as continuous variables and that binary or polytomous data are inconsistent with the factor analysis model. Dunteman (1989) uses an example based on categorical data in his discussion of PCA. Chandola *et al.* (2009) consider multivariate techniques such as PCA to be inappropriate for categorical data.

In the discussion of PCA for discrete data, Jolliffe (2004:339) explains that, while variances, covariances and correlations are relevant to multivariate normal variables and the linear functions of ordinal and dichotomous variables are more difficult to interpret than the linear functions of continuous variables, the basic objective of PCA, which is to summarize most of the variation in the original variables, can be achieved regardless of the nature of the original variables. Linting (2007) explains that for nominal and ordinal variables, category labels cannot be treated as numbers; therefore, common calculations such as standard deviations and correlations applied to categorical data do not lead to reasonable results. PCA is based on the assumptions that variables have at least an interval level of measurement and are linearly related to one another (Linting, 2007). In the case of categorical data, these assumptions may be violated and the application of standard PCA to such data may lead to serious problems (Linting, 2007). Linting (2007) argues that if PCA is performed on categorical data without checking if the assumptions are violated, it becomes uncertain as to whether the results are reliable. Linting (2007), among others (Meulman *et al*., 2004a; Meulman *et al*., 2004b; Linting *et al*., 2007; Costantini *et al*., 2010; Mair & de Leeuw, 2010; Manisera *et al*., 2010), suggest the use of nonlinear PCA as a means of dealing with categorical data. Nonlinear PCA is discussed in Section 3.3.2.2.

While not specific to PCA, Labovitz (1967) suggests that assigning numbers to ordinal data and treating them as interval data is acceptable, but that the process may be accompanied by a small amount of error. Labovitz (1970) advises that the use of more than three categories is preferred and dichotomizing or trichotomizing variables should be avoided. Mayer (1971) discusses the effects of treating ordinal data as continuous and concludes that it may be highly unreliable. Bollen and Barb (1981) and Johnsen and Creech (1983) investigated the outcomes of applying concepts and measures designed for continuous data to categorical data, although they do not specifically consider PCA. Bollen and Barb (1981) considered the differences in the correlation coefficients between two normally distributed continuous variables and the same two variables collapsed into a number of smaller categories and found the differences to be small especially when five or more categories were used. Johnson and Creech (1983) explain that categorization error occurs when continuous variables are measured by indicators with only a few categories, and concluded from their study that the estimates tend to be biased and inefficient especially when less than five categories are used.

From the literature there does not appear to be a definitive answer on whether PCA is appropriate for use with non-continuous data. As a result of this lack of consensus, and since the data used in this study consist of non-continuous variables, four methods of weighting the variables were used: the Filmer and Pritchett (1994, 1999, 2001) method using dummy variables, the alternative proposed by Kolenikov and Angeles (2009) using ordinal data, nonlinear PCA using Categorical PCA (as available in the Statistical Package for the Social Sciences), and the method of equal weights. The results from the four different methods were then compared.

(a) Filmer and Pritchett (2001) Method of PCA

The first method of generating the weights for the index of SES followed that of Filmer and Pritchett (1994, 1999, 2001). The chosen variables that were in a categorical form were transformed into dichotomous variables by creating a dummy variable for each category of the categorical variable. PCA was then performed on the 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.

(b) Kolenikov and Angeles (2009) Method of PCA

The second method of index construction, with regards to generating the weights for the indicators, was taken from Kolenikov and Angeles (2009). They argue that one of the assumptions underlying PCA is that the input variables are multivariate normal; thus, when the data are discrete the assumption is violated. The problems associated with discrete data have received attention in many studies including Bollen and Barb (1981), Johnson and Creech (1983), Labovitz (1967, 1970), Mayer (1971) and Kim and Mueller (1994). Kolenikov and Angeles (2009) point out that, while discrete data violate distributional assumptions of PCA, they also tend to have high skewness and kurtosis.

The Filmer and Pritchett (1994, 1999, 2001) methodology applies PCA to a set of dummy variables. The motivation for this may have been the recommendation to use individual dichotomous variables whenever the categorical variable is to be used in a regression analysis (Kolenikov & Angeles, 2009). Kolenikov and Angeles (2009) explain that while this makes sense when the variables are explanatory, in the case of PCA the input variables should be considered as dependent since the variability in the assets is caused by variability in wealth and not the other way around. Kolenikov and Angeles (2009) describe how the inclusion of dummy variables in a PCA analysis introduces spurious correlations as the dummy variables produced from the same factor are negatively correlated. The PCA procedure then has to take into account both the original correlations between the variables and the spurious correlations created by the dummy variables (Kolenikov & Angeles, 2009). Because of this, the PCA method may not be able to recover the wealth dimension from the data, as the directions of greater variability may correspond to the spurious correlations (Kolenikov and Angeles, 2009).

Kolenikov and Angeles (2009) undertook a study to examine the behaviour of different PCA procedures with discrete data as a means of generating the weights for an index of SES. The Bangladesh 2000 DHS data were used in an empirical application. The first procedure was to apply the Filmer and Pritchett methodology, using dummy variables to represent the different categories. The second approach used PCA based on the ordinal variables. The categorical variables were recoded into order so that the category of lowest SES (eg. no toilet facility) was represented by a one, the next level of SES, a two (eg. bucket toilet) and so on, rather than converting the categorical variables to dummy variables. These recoded variables were then treated as if they were continuous variables. The third approach made use of polychoric PCA using a package for polychoric correlations developed by one of the authors and conducted with Stata software (Kolenikov & Angeles, 2009). The definition of polychoric or polyserial correlations is given as: "*the maximum likelihood estimates of the correlation between the unobserved normally distributed continuous index variables underlying their discretized versions*" (Kolenikov & Angeles, 2009:135). An explanation of polychoric correlations is given in Kolenikov and Angeles (2009:135-138). The correlation matrix was obtained by combining the pairwise estimates of the polychoric correlations and standard PCA was then applied to the correlation matrix – the Eigen problem for the estimated correlation matrix was solved (Kolenikov & Angeles, 2009). The results from the empirical application are given in Table 3.2.

From the results Kolenikov and Angeles (2009) concluded that dividing the categories into sets of dummy variables, as suggested by Filmer and Pritchett (1994, 1999, 2001), leads to a reduction in performance, according to all the performance measures used. The most heavily affected measure was the per cent of variance explained, which was underestimated (Kolenikov & Angeles, 2009). The use of the polychoric correlations leads to a gain in the accuracy of the estimate of the variance explained; however, the misclassification rates and the rank correlations of the welfare indices were not substantially different between the ordinal and polychoric versions of PCA (Kolenikov & Angeles, 2009).

Table 3.2: Wealth index weights for different versions of the PCA, Bangladesh 2000

Variable	Filmer & Pritchett	Ordinal	Polychoric Scoring weight	Polychoric Eigenvector
Source of drinking water		0.2919		0.2856
Surface well, lake, pond or stream (1)	0.0000		-0.6267	
Tube well (2)	-0.2617		-0.0130	
Piped outside (3)	0.0859		0.4604	
Piped inside (4)	0.3150		0.5980	
Source of non-drinking water		0.3095		0.2571
Surface well, lake, pond or stream (1)	0.0000		-0.3077	
Tube well (2)	-0.1277		0.0786	
Piped outside (3)	0.0858		0.3829	
Piped inside (4)	0.3420		0.5076	
Type of toilet facility		0.3094		0.2917
No facility (1)	0.0000		-0.4084	
Open latrine (2)	-0.0649		-0.1317	
Pit latrine (3)	-0.0752		0.0371	
Water sealed (4)	0.0044		0.2228	
Septic tank/toilet (5)	0.3089		0.5104	
Has electricity	0.2837	0.3506	0.5671	0.3451
Has radio	0.1640	0.2272	0.4019	0.2443
Has television	0.3016	0.3584	0.6541	0.3663
Has bicycle	0.0441	0.1011	0.2231	0.1278
Has motorcycle	0.1116	0.1365	0.6838	0.2728
Main floor material		0.3986		0.3918
Earth/bamboo (1)	0.0000		-0.1120	
Wood (2)	0.0051		0.3969	
Cement/concrete (3)	0.3718		0.6042	
Main wall material		0.3773		0.3417
Natural (1)	0.0000		-0.2112	
Rudimentary/tin (2)	-0.0754		0.2070	
Brick/cement (3)	0.3532		0.5097	
Main roof material		0.3004		0.3054
Earth/bamboo (1)	0.0000		0.4227	
Wood (2)	-0.1130		0.0530	
Cement/concrete (3)	0.2909		0.0551	
Percent variance explained	24.11	39.23	56.09	

Source: Kolenikov and Angeles (2009)

Overall, Kolenikov and Angeles (2009) recommended that if there is a reliable ordering of the categories then the ordinal PCA procedure should be used. Even if the variables are not ordered in a standard way, such as a Likert scale with approximately equal distances between categories, it would be worthwhile recoding them in such a way. The polychoric procedure should be used if the proportion of variance explained is of importance (Kolenikov & Angeles, 2009). Kolenikov and Angeles (2009) suggest that the Filmer and Pritchett procedure should be used only when there is no information pertaining to the ordering of the categories.

From the recommendations of Kolenikov and Angeles (2009), the ordinal PCA procedure was adopted as the second approach to constructing an index of SES in this study. The categorical variables as well as the dichotomous variables were recoded to start at one with an interval of one between each category. 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 & Angeles, 2009). The higher number was linked to a higher level of SES. For example, the variable *type of toilet facility* would keep its four categories, but be recoded to: a one for *no facility/bush/ field*, a two for *traditional pit latrine*, a three for *ventilated improved pit latrine* and a four for *flush toilet*. Thereby, an order of SES is forced onto the categorical variables. Standard (linear) PCA was then applied to the transformed ordinal data as if they were continuous data, using SPSS version 15.0 for Windows.

3.3.2.2 Nonlinear Principal Component Analysis

Nonlinear PCA makes use of optimal quantifications to transform category labels into numeric values, such that the strength of the relationships between the quantified variables is optimized, while simultaneously performing standard PCA on the quantified data (Linting *et al*., 2007). This is achieved by the minimization of a least-squares loss function (Linting *et al*., 2007). The model estimation and optimal quantification are alternated using an iterative algorithm that converges to a stationary point where the optimal quantifications of the categories no longer change (Linting *et al*., 2007).

Computer software capable of performing nonlinear PCA is available, such as CATPCA, a procedure in SPSS Categories 10 onwards (Meulman *et al*., 2004a; Meulman *et al*., 2004b). A detailed discussion of the mathematics of nonlinear PCA is given by Gifi (1990), Meulman *et al*. (2004b) and Linting (2007). Briefly, if H is an $n \times m$ data matrix consisting of the observed scores of n persons on m variables and the variables are not measured on a numeric scale or are expected to be nonlinearly related to each other, then a nonlinear transformation of the variables is required (Linting *et al*., 2007). During the transformation process, each category of the variable receives an optimally scaled value, known as a category quantification (Linting *et al*., 2007). The $n \times m$ matrix Q, in which the observed scores for each person are replaced by their category quantifications, is then substituted for the data matrix H (Linting *et al*., 2007). Nonlinear PCA is then performed by minimizing a least-cost function in which the observed data matrix H is replaced by matrix Q. The least-cost function, as used in CATPCA, is given in equation (3.9) (Linting *et al*., 2007). If X is the $n \times p$ matrix of component scores, with p the number of components, and if A is the $m \times p$ matrix of component loadings, with its j^{th} row indicated by a_j, the loss function that can be used in

PCA for the minimization of the difference between the original data and the principal components can be expressed (in matrix notation) as:

$$L_2(\mathrm{Q, A, X}) = n^{-1}\sum_{j=1}^{m} \mathrm{tr}\,(q_j a'_j - \mathrm{X})'\,(q_j a'_j - \mathrm{X}) \qquad (3.9)$$

where tr denotes the trace function that sums the diagonal elements of a matrix (Linting *et al*., 2007). The loss function (equation 3.9) is subject to a number of constraints (Linting *et al*., 2007): (1) the transformed variables are standardized, so that $q'_j q_j = n$, which ensures that the component loadings in a_j are correlations between variables and components; (2) the object scores are restricted by requiring $\mathrm{X'X} = n\mathrm{I}$, where I is the identity matrix, which is to avoid the minor solution A = 0 and X = 0; and (3) the object scores are centred, thus $1'\mathrm{X} = 0$, with '1' indicating a vector of ones.

Optimal scaling assigns a numerical quantification to the categories of each variable; in this way standard procedures can be used to obtain solutions from the quantified variables (Meulman *et al*., 2004a). The optimal quantification process is necessary for nonlinear PCA of non-numeric values as the variance of the variables cannot be established and PCA requires an estimation of such variance (Linting *et al*., 2007). The quantifications are optimal in the sense that the overall variance accounted for in the transformed variables is maximized, given the number of components (Manisera *et al*., 2010). In nonlinear PCA, the correlations are computed between the quantified variables, not between the original observed variables (Linting *et al*., 2007). Therefore, and in contrast to linear PCA, the correlation matrix in nonlinear PCA is not fixed, but is dependent on the type of quantification, called an analysis level, that is selected for each of the variables in the analysis (Linting *et al*., 2007).

There are several analysis or scaling level options in nonlinear PCA and the analysis level does not have to equal the measurement level of the variable; the analysis level depends on the preference of the researcher (Costantini *et al*., 2010). However, each of the three analysis levels – nominal, ordinal and numeric - have different properties and requirements (Linting *et al*., 2007). In the case of a nominal analysis level the only requirement is that persons who scored the same category on the original variable should receive the same quantified value (Linting *et al*., 2007). A multiple nominal scaling level allows a variable to obtain a different optimal quantification in each principal component (Costantini *et al*., 2010). For an ordinal analysis level the same requirement as for the nominal analysis level applies, but, additionally, the quantification of the categories should respect the ordering of the original variables (Linting *et al*., 2007). Both of these requirements hold for a numeric analysis level; moreover, the quantified categories must maintain the relative spacing of the original categories, which is achieved by standardizing the variable (Linting *et al*., 2007). If a nominal analysis is specified, and the resulting quantifications are in the same order as the original categories, then an ordinal analysis level would give identical transformations (Linting *et al*., 2007). If all the variables in the analysis are specified at a numeric analysis level, nonlinear PCA approximates linear PCA (Linting, 2007). A nominal analysis level allows nonlinear PCA the most freedom in quantifying a variable, while a numeric analysis level is the most restrictive. To this end, the analysis would obtain the highest variance accounted for (VAF) when all variables were analyzed nominally and the lowest when all variables were analyzed numerically (Linting *et al*., 2007). The VAF is the sum of the squared component loadings, which, in turn, are the correlations between the quantified variables and principal components (Meulman *et al*., 2004b; Linting *et al*., 2007).

Spline transformations, which utilize smooth functions, can be used instead of nominal and ordinal analysis levels, which utilize step-functions and can be quite irregular. A monotonic spline transformation is more restrictive than an ordinal one, but less restrictive than a linear transformation. It requires the categories to show the same original order, as ordinal analysis would; however, the transformation must also show a smooth curve (Linting *et al*., 2007). A nonmonotonic spline can be used instead of a nominal analysis level as the nonmonotonic spline will yield a smoother transformation than the possibly irregular transformations resulting from a nominal analysis level (Linting *et al*., 2007). Transformation plots can be used to show the relationship between the quantifications (y-axis) and the original categories (x-axis) (Meulman *et al*., 2004a). The line connecting the category quantifications indicates the variable's transformation (Linting *et al*., 2007). Transformation plots are useful in determining how appropriately the selected optimal scaling level performs (Meulman *et al*., 2004a). A linear transformation plot results when a variable is treated as numerical, while variables treated as ordinal result in a non-decreasing transformation plot (Meulman *et al*., 2004a). Transformation plots of variables treated at the nominal analysis level that are U-shaped (or the inverse) display a quadratic relationship (Meulman *et al*., 2004a).

Comparing linear PCA and nonlinear PCA, many similarities are revealed. Both methods provide component loadings, component scores and Eigenvalues, where the Eigenvalues are overall summary measures that indicate the VAF by each component. Thus, the output resulting from a nonlinear PCA and a linear PCA can be compared (Costantini *et al*., 2010). For both methods each principal component (PC) can be seen as a composite variable summarizing the original variables, with the Eigenvalue indicating the success of the summary (Linting *et al*., 2007). The main difference between the two methods is that in linear PCA the PCs are the weighted sums or linear combinations of the original variables, whereas in nonlinear PCA they are the weighted sums of the quantified variables. In other words, linear PCA analyses the measured variables directly, while in nonlinear PCA the measured variables are quantified during the analysis (Linting *et al*., 2007). There is a computational difference between the two methods regarding the nestedness of the components. For linear PCA the solutions are nested for different dimensions: corresponding components in p and p+1 dimensions are equal. The concept of the nestedness of the components is discussed in detail by Linting *et al*. (2007). Simply, in linear PCA consecutive maximization of the variance accounted for in p components is identical to simultaneous maximization, therefore the solutions are nested for different values of p. However, this is not the case for CATPCA: consecutive and simultaneous maximization gives different results; therefore, the solutions are not usually nested over different values of p (Linting *et al*., 2007). Linting *et al*. (2007) point out that, in practice, the differences between the components of a p-dimensional solution and the first p components of a p+1-dimensional solution are often small.

Applications of nonlinear PCA are found in Eurelings-Bontekoe *et al*. (1996), Beishuizen *et al*. (1997), van der Ham *et al*. (1997), de Haas *et al*. (2000), Huyse *et al*.(2000), Zeijl *et al*. (2000), Hopman-Rock *et al*. (2001), Arsenault *et al*. (2002), de Schipper *et al*. (2003) Costantini *et al*. (2010) and Manisera *et al*. (2010). de Haas *et al*. (2000), de Schipper *et al*. (2003), Costantini *et al*. (2010) and Manisera *et al*. (2010) use the CATPCA procedure from SPSS to perform their analysis while Eurelings-Bontekoe *et al*. (1996), van der Ham *et al*. (1997), Huyse *et al*.(2000), Zeijl *et al*. (2000), Hopman-Rock *et al*. (2001) and Arsenault *et al*. (2002) use the PRINCALS procedure also from SPSS and the precursor to CATPCA. The study by Beshuizen *et al*. (1997) uses the HOMALS procedure, which is equivalent to factor analysis but for non-linear multivariate analysis.

In this study, CATPCA using SPSS version 15.0 for Windows was used to perform nonlinear PCA on the variables selected for the wealth index for each of the chosen countries. A nominal scaling level was used for all variables in the analysis and inspection of the transformation plots showed the categorical variables to be non-linear and non-ordered and the dichotomous variables to be linear and ordered. An ordinal or numeric scaling level could be used for the dichotomous variables, but an exploration of this showed that changing the scaling level for the dichotomous variables has no effect on the solution. To this end, a nominal scaling level was maintained for all the variables in each of the country analyses. The results were then compared to those obtained using standard PCA following both the Filmer and Pritchett (1994, 1999, 2001) method and the ordinal variable method suggested by Kolenikov and Angeles (2009).

3.3.2.3 Equal Weights

As an alternative to using 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 SES, as done by Hatloy *et al*. (2000), Montgomery *et al*. (1999) and 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 small TV 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 SES 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.

3.3.3 Missing Values

There are a number of options for dealing with values missing in data (Schafer & Graham, 2002). Gwatkin *et al*. (2007b) replaced missing values with the mean value for that variable. However, replacing missing values with mean scores leads to a reduction in the variation of the data (Schafer & Graham, 2002) and increases the potential for clumping and truncation (Vyas & Kumaranayake, 2006). In a study by Cortinovis *et al*. (1993) (cited by Vyas & Kumaranayake, 2006), households with missing values were excluded from the analysis (case deletion). However, this may lead to bias towards households with a higher SES as missing data may occur more frequently in households of lower SES. Case deletion is especially inefficient in multivariate analyses involving many items, as low rates of missing values on each item may cause large proportions of the sample to be discarded (Schafer & Graham, 2002), thereby reducing sample sizes and lowering the statistical power of the results (Vyas & Kumaranayake, 2006). In the study by Vyas and Kumaranayake (2006), the percentage of households with missing data was less than one per cent and missing values were replaced with the mean for that variable.

The CATPCA application of SPSS provides four options for handling missing values. The most advanced is that of passive treatment which only takes into account the non-missing data when the loss function is minimized (Meulman *et al*., 2004b). The option of passive treatment results in only those entries in the data that contain valid values being used in the analysis; thus a household with a missing value on one variable does not contribute to the solution for that variable, but it does contribute to the solution for all other variables for which it has valid values (Linting *et al*., 2007). This strategy is possible in nonlinear PCA, because the CATPCA solution is derived from the data itself and not from the correlation matrix, which cannot be computed with missing values (Linting *et al*., 2007). If passive treatment of missing values is chosen, the transformed dataset has missing values where the original dataset had missing values (Manisera *et al*., 2010). Linting *et al*. (2007) used the method of passive treatment to deal with missing values in their data.

A second option for the handling of missing values available in CATPCA is to treat the missing values as an extra category. This extra category then obtains a quantification that is independent of the analysis level of the variable (Linting *et al*., 2007). The option is useful when a person leaves out an answer to a certain question for a specific reason, which then distinguishes her from someone who does answer (Linting *et al*., 2007). The method is also advantageous in that it allows the researcher to deal with variables that include categories such as “no response” or “don’t know” as well as numerical or ordinal categories (Linting *et al*., 2007). The other two options are to: exclude objects or cases with missing values, or to impute the missing values using the value of the modal category (Meulman *et al*., 2004b). In this study, missing values were replaced with the mean for the specific variable in question across all methods.

3.4 Estimation of Household Socio-Economic Status Scores and Classification into Wealth Groups

Once the indicator weights had been estimated and the index of SES constructed, the index was applied to the individual households and a score for each household calculated. The SES score for each household was estimated using Equation (3.10):

$$A_j = f_1 \text{ x } (a_{j1} - a_1) / (s_1) + ... + f_N \text{ x } (a_{jN} - a_N) / (s_N) \tag{3.10}$$

where A_j was the SES score for household *j*, f_1 was the component loading generated by PCA for the first variable, a_{j1} was the j^{th} household's value for the first variable, and a_1 and s_1 were the mean and standard deviation, respectively, of the first variable over all the households.

The households were then sorted into quintiles of the population based on the value of their SES scores, following Houweling *et al*. (2003), Rutstein and Johnson (2004), Hong *et al*. (2006), Hong and Mishra (2006), Lindelow, (2006), Vyas and Kumaranayake (2006), Gwatkin *et al*. (2007b), Uthman (2008) and Kolenikov and Angeles (2009). The use of quintiles as group cut-off points assumes that the distribution of SES is uniform. If the differences in mean socio-economic score between adjoining households are even, then SES is uniformly distributed in the sample (Vyas and Kumaranayake, 2006). The process was repeated for each of the weighting methods, and differences in the classification of households between the four methods were estimated and discussed for each of the chosen countries.

CHAPTER 4: METHOD EVALUATION

In Chapter three, four methods of constructing an index of socio-economic status (SES) were discussed; three indices based on principal component analysis (PCA) and a simple sum of assets index. In this chapter, the four methods are assessed, in terms of several assessment criteria, by comparing the construction and application of each index to demographic and health survey (DHS) data from six African countries (Egypt, Kenya, Mali, Uganda, Liberia and Tanzania). The assessment characteristics were used to evaluate the reliability and appropriateness of each of the methods in an attempt to determine which method is the most suitable for the construction of a SES index as an indicator of household resilience.

The results from the application of each of the four methods to the six sets of country household data are discussed in the following sections with regards to each of the assessment characteristics. The results are given as summary tables of the performance of the four methods across the six countries for each assessment criterion. ‘Dichot. PCA’ refers to the method of applying PCA to the variables coded into dichotomous variables, as put forward by Filmer and Pritchett (2001). ‘Ordinal PCA’ indicates that the method used in the construction of the SES index is the one suggested by Kolenikov and Angeles (2009) of applying PCA to the variables once the categories of each variable have been ranked in order of SES. ‘CATPCA’ refers to the method of applying non-linear or categorical principal component analysis to the variables coded as done for the ordinal PCA method, and ‘Simple sum’ indicates that the SES score has been calculated by adding/counting the number of assets owned by the household.

4.1 Country Data Description

The selection of the six countries for the analysis was discussed in Chapter 3. Table 4.1 lists the six chosen countries along with the date of the corresponding DHS dataset, its size and the number of variables considered appropriate as an index of SES, for each country. The selection of the variables for inclusion in the different country indices was also discussed in Chapter 3. The number of missing values for each variable, the number of categories for each of the categorical variables and the mean and standard deviation for the dichotomous variables were all considered during the selection of the variables. These descriptives are given in Table 4.2, for the Tanzanian DHS dataset, as an example.

Table 4.1: Country descriptives

Country	Year	Sample size (*N*)	No. of variables
Tanzania	2007/8	8497	15
Liberia	2007	6824	21
Uganda	2006	8870	21
Mali	2006	12998	16
Kenya	2008/9	9057	16
Egypt	2008	18968	27

Source: Macro International Inc. (2010)

Table 4.2: Descriptive statistics for the Tanzanian DHS, 2007/8 (*N*=8497)

Variable	No. of missing values	No. of 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)

The last column of table 4.2 shows the expected sign of the component loading for each of the variables of the first principal component (PC) generated by PCA of the variables. From the literature and previous studies presented in Chapter 2, it was expected that all the component loadings of the first PC will be positive. All the variables should be positively correlated with a household's level of SES, as access to better sanitation, ownership of many assets and good quality housing materials should all increase a household's wealth. However, a negative sign on the component loading for bicycle has been reported in past studies (McKenzie, 2005; Gwatkin, 2007b). A negative component loading on bicycle was expected, since bicycle ownership increases with increasing wealth, only up to a point, after which bicycle ownership decreases with increasing wealth as households substitute motorized vehicles for bicycles. Vyas and Kumaranayake (2006) explain that ownership of a bicycle may be more strongly correlated with variables that are expected to be associated with a lower level of wealth, such as poorer sanitary conditions and lower quality housing materials. This may occur especially when the indices have been constructed for combined rural and urban locations: the asset represents wealth in some parts of the area, but not others (Vyas & Kumaranayake, 2006).

When each of the categories for the categorical variables were recoded to dummy variables, as for the dichotomous PCA method (Filmer and Pritchett, 2001), negative component loadings were expected for those variables linked to a lower SES. For example, a main floor material of grass or mud would be expected to carry a negative component loading on the first PC as it would be associated with a relatively poor household, while a main floor material of tile would have a positive component loading for the first PC and be associated with a relatively wealthier household.

4.2 Principal Component Analysis Results

For the three PCA based methods, the sign and size of the component loadings, the Eigenvalue of the first principal component (PC) and the proportion of variance accounted for (PVAF) by the first PC were considered. The underlying assumption in this study is that household long-run wealth explains the maximum variance and covariance in the selected set of variables. To this end, the first PC was of most interest and its component loadings were used as the weights in the index of SES. The Eigenvalue for each PC is an indication of the proportion of variation in the total data explained by that PC (Vyas & 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 PC (Kolenikov & Angeles, 2009). In a study of Indian households, Filmer and Pritchett (2001) found that the first PC explained approximately 26 per cent of the variance in their index. Of the studies reviewed in Chapter 2, the first PC accounted for a range from 12 per cent (Houweling *et al.*, 2003) to 27 per cent (McKenzie, 2005). Kolenikov and Angeles (2009) obtained a PVAF for the first PC of 24.11 per cent when using the Filmer and Pritchett dichotomous variables method and a PVAF of 39.23 per cent when using the ordinal variables method, for data from Bangladeshi households. Table 4.3 is a summary of results from the PCA of the chosen variables for the three PCA based methods across all six countries. The number of variables included in each of the indices is given in the first section of the table for all four methods.

The boxes indicate the highest values for the respective characteristics across the six countries.

Table 4.3: PCA results across the six countries

Characteristic	Method	Country					
		Tanzania 2007/8	Liberia 2007	Uganda 2006	Mali 2006	Kenya 2008/9	Egypt 2008
No. Vs	Dichot. PCA	61	77	78	41	84	53
	Ordinal PCA	15	21	21	16	16	27
	CATPCA	15	21	21	16	16	27
	Simple sum	9	15	15	12	10	24
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	$\boxed{5.36}$	$\boxed{6.50}$	$\boxed{7.34}$	$\boxed{5.46}$	$\boxed{6.88}$	$\boxed{5.51}$
	Simple sum	n/a	n/a	n/a	n/a	n/a	n/a
PVAF (%)	Dichot. PCA	24.20	$\boxed{31.89}$	22.28	20.34	20.42	$\boxed{25.16}$
	Ordinal PCA	30.66	30.28	30.46	32.48	39.8	20.34
	CATPCA	$\boxed{35.76}$	30.94	$\boxed{34.93}$	$\boxed{34.15}$	$\boxed{43.01}$	20.79
	Simple sum	n/a	n/a	n/a	n/a	n/a	n/a
Desirable monotonicity	Dichot. PCA	No, except for toilet facility	No	No	No	No, except for drinking water & toilet facility	No
	Ordinal PCA		n/a	n/a	n/a	n/a	
	CATPCA		n/a	n/a	n/a	n/a	
	Simple sum		n/a	n/a	n/a	n/a	

Where: 'No. Vs' is the number of variables included in the respective index and PVAF is the proportion (as a percentage) of variance accounted for by the first principal component for the particular index.
Source: Author's 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 countries, while the dichotomous PCA method had the highest PVAF values for Liberia and Egypt. The PVAF, by the first PC for the ordinal PCA method, was the lowest of the three methods across all six countries.

Since it is assumed that the first PC is an index of wealth, a variable with a positive component loading should be associated with a relatively higher level of SES. Conversely, a variable carrying a negative component loading should be associated with a relatively lower level of SES. Kolenikov and Angeles (2009) refer to the conformance of PCA weights to an expected ordering of SES as the component loadings displaying a desirable monotonicity. A

PCA that generates component loadings displaying a desirable monotonicity could be considered a relatively more reliable estimation process than one that does not (Kolenikov & Angeles, 2009).

Determining the desirable monotonicity of the component loadings is not easy for the ordinal PCA and CATPCA methods as the individual categories were not given component loadings, whereas for the dichotomous PCA method each category was recoded to form its own dichotomous variable. The component loadings generated by the dichotomous PCA method were examined for each of the countries and the observations, in terms of desirable monotonicity, are summarised in the last section of Table 4.3. For Tanzania and Kenya, the variables relating to the type of toilet facility used by the household did show a desirable monotonicity: the component loadings followed an expected ordering of value or SES. For example, the component loading for *flush to a piped sewer system* was larger than the component loading for f*lush to a septic tank* and the variable *no facility/bush/field* had the lowest component loading of the variables relating to type of toilet facility for Tanzania. The component loadings did not show a desirable monotonicity for all the variables for any country. The SES index is meant to provide maximum discrimination between households with the assets that vary most across households receiving heavier weights (McKenzie 2004:233). Therefore, an asset that all households own, or one that no households own, would be given a zero weight in the first PC. This would explain the lack of desirable monotonicity observed in many of the PC loadings and suggests that perhaps the characteristic of desirable monotonicity is not a useful means of assessment.

4.3 Stability of the Principal Component Analysis Solutions

In an attempt to discover instability in the PCA solution of their study, Manisera *et al*. (2010) performed a stability analysis in order to identify any categories or variables causing instability in their solution. They used non-linear or categorical PCA in their study. In this study, for the purpose of comparison, a stability analysis was performed for all three of the PCA methods. The stability analysis entailed running PCA on 10 subsets of size $0.75N$ drawn from the total sample and comparing the solutions with regards to the per cent of variance explained and the component loadings. The position of the component loadings in relation to a reference line on a graph of the first PC versus the second PC was used as an indication of stability. If the solution was stable, the 10 estimated component loadings of 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 ten estimated component loadings for each variable on the graph.

Stability analysis results from this study for the Ugandan household data using the dichotomous PCA method of weight estimation (Figure 4.1) and the ordinal PCA method (Figure 4.2) are shown below.

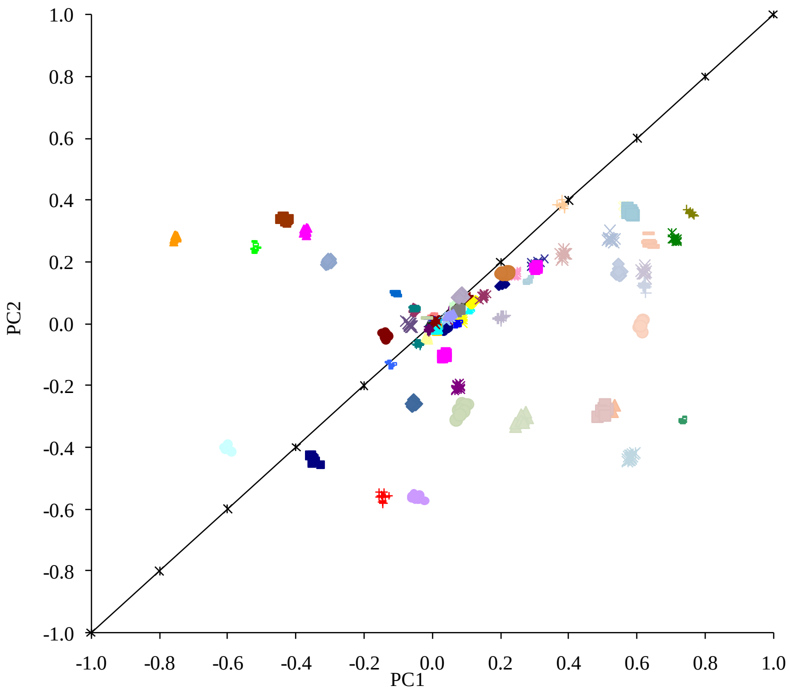

Figure 4.1: Stability analysis results for the repetition of PCA of dichotomous variables for 10 subsamples (0.75*N*), Uganda 2006 (*N*=8870)
Source: Author's calculations

In Figure 4.1 each of the colours represented one of the 78 variables included in the dichotomous PCA analysis. From the graph, it was clear that the PCA solution was unstable: there was a large spread in points across the reference line. For a number of the variables, the 10 estimated component loadings were not all either above or below the reference line. The instability was likely a result of the inclusion of a number of poorly populated variables in the analysis. For example, the blue circles near the centre of the graph represent the variable *cooking fuel is biogas*, only six households (0.1 per cent) used biogas. In order to improve the stability of the analysis, poorly populated categories, such as *cooking fuel is biogas* in the Ugandan case, of a similar nature could be grouped, or particularly unstable variables excluded from the analysis (Manisera *et al.*, 2010). In this study, for the purpose of comparison between methods, categories were not grouped. Conversely, in Figure 4.2, all the points were either above or below the reference line – each colour represented one of the 21 variables included in the index – indicating that the CATPCA solution for the Ugandan data was stable.

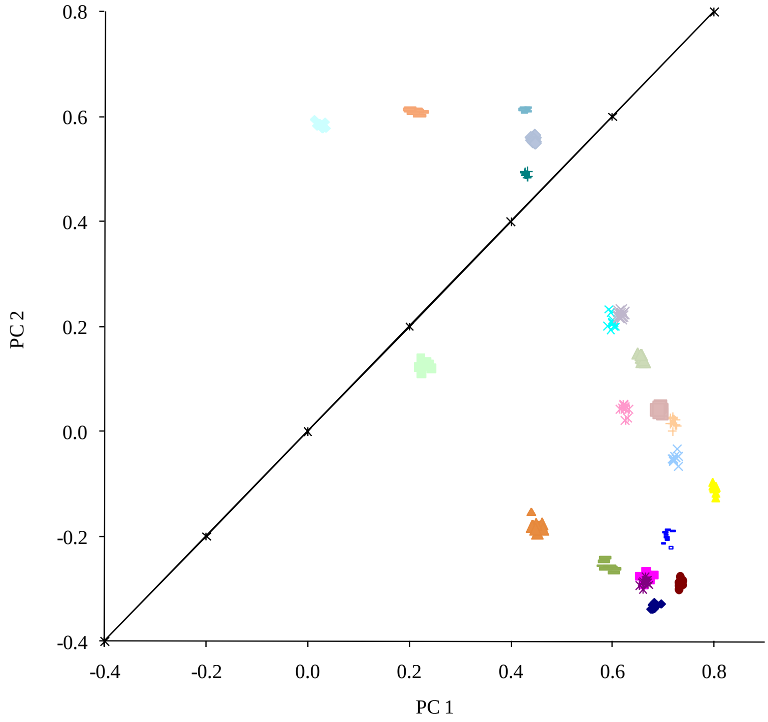

Figure 4.2: Stability analysis results for the repetition of CATPCA on ordinal variables for 10 subsamples (0.75*N*), Uganda 2006 (*N*=8870)
Source: Author's calculations

The individual country results for the stability analyses are presented in Table 4.4. The CATPCA method produced stable solutions for all of the countries except Kenya. The component loadings for the variables *has a motorcycle/scooter* and *has a mobile phone* fell across the reference line for a few of the 10 CATPCA repetitions for the Kenyan sample. According to Manisera *et al*. (2010), this is an indication of an unstable solution. The ordinal PCA solutions were stable for two of the six country datasets, Mali and Kenya, whereas the dichotomous PCA solutions were not stable for any of the six countries. The instability was 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.

The stability of the dichotomous PCA solution could be improved by grouping a number of similar categories into one before coding them into dichotomous variables so as to reduce the number of poorly populated variables included in the analysis. For example, from the Ugandan example discussed previously, the category *cooking fuel is biogas* could be grouped with other similar cooking fuel categories such as *cooking fuel is LPG* or *natural gas* to form a single more highly populated variable.

Table 4.4: Stability analysis results for each method, by country

Method	Country					
	Tanzania 2007/8	Liberia 2007	Uganda 2006	Mali 2006	Kenya 2008/9	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 Vs	Stable
Simple sum	n/a	n/a	n/a	n/a	n/a	n/a

Source: Author's calculations

4.4 Socio-Economic Status Estimation and Household Classification Results

For the three PCA-based methods the estimated component loadings were then used to calculate a SES score for each household. For the simple sum method, the SES score was the sum of the number of assets owned by the household. The households were then classified into quintiles based on the value of their SES score. This was repeated for each method across all the countries. The first quintile contained the 20 per cent of households with the lowest SES scores while the fifth quintile contained the 20 per cent of households with the highest SES scores. According to Vyas and Kumaranayake (2006), if SES is uniformly distributed, the difference in the mean SES score between adjoining quintiles should be even.

An example of the results of the estimation of household SES scores and the classification of households into quintiles based on the SES score is given in Table 4.5, from the Malian household analysis, using the CATPCA weight estimation method. From Table 4.5 it appears that SES was not distributed uniformly across households from Mali in 2006, using the CATPCA method. The difference in mean SES score between quintiles four and five was much greater than between the other quintiles.

Table 4.5: SES score descriptives by quintile, Mali 2006 (*N*=12998)

Quintile (Q)	1	2	3	4	5	Total
N	2599	2599	2600	2600	2600	12998
Mean	-3.933	-2.970	-2.033	0.028	8.906	0.000
Difference btw Qs		0.964	0.936	2.061	8.878	
Standard deviation	0.398	0.225	0.317	1.014	5.912	5.367
Minimum	-5.685	-3.416	-2.540	-1.410	2.199	-5.685
Maximum	-3.416	-2.540	-1.410	2.199	29.428	29.428

Where: 'Difference btw Qs' is the difference between the mean SES scores for the quintiles.
Source: Author's calculations

A frequency histogram of SES scores across households can also be used as an indication of the distribution of SES. Figure 4.3 is the frequency histogram of SES scores generated using the Filmer and Pritchett (2001) PCA method across the Malian households for 2006.

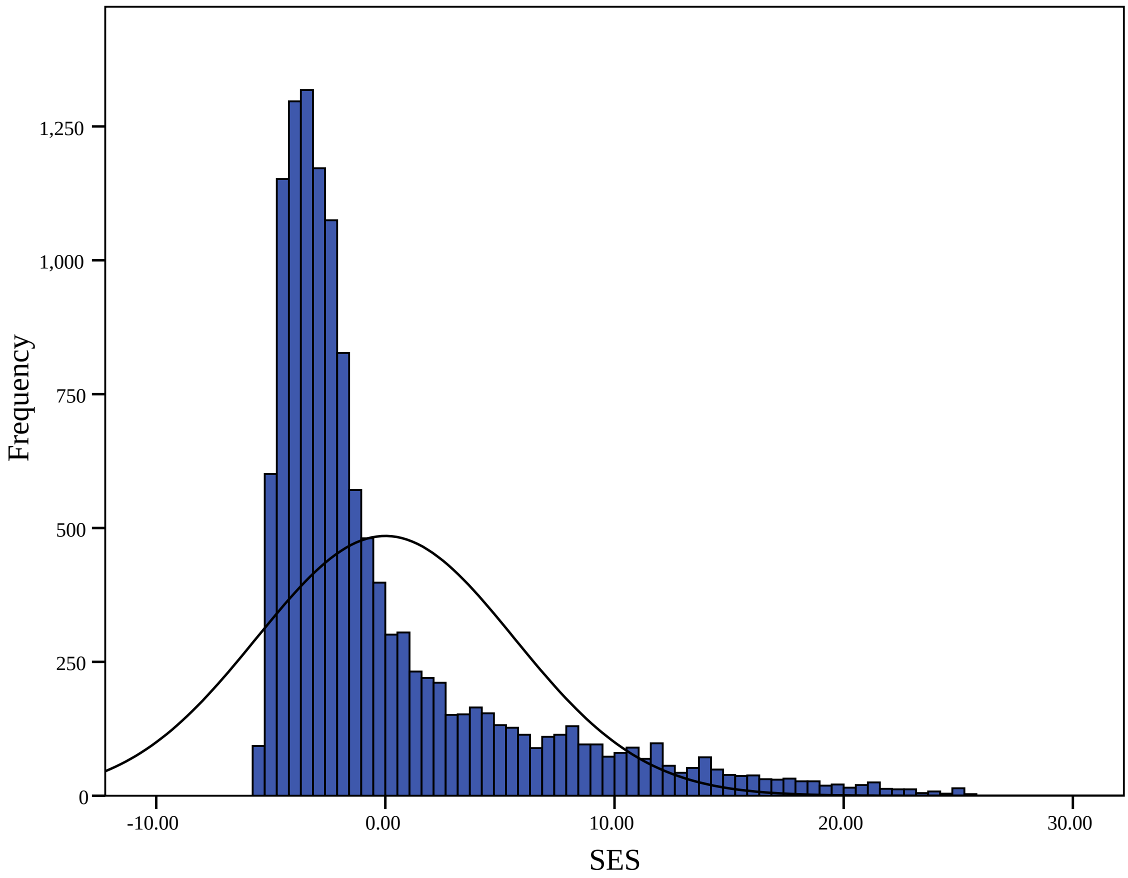

Figure 4.3: Frequency histogram of SES scores, Mali 2006 (*N*=12998)
Source: Author's calculations

The figure shows the lack of uniformity suggested by the differences in mean SES score across households. Many more households had low SES scores and only a few households had relatively high SES scores – the distribution of scores is skewed to the right. The assumption of uniformity was not appropriate in this case suggesting that the use of quintiles as cut-off points was not suitable for classifying the study households into wealth groups.

The estimated household SES scores for the first and last quintiles for each of the six countries are given in Table 4.6. The PCA indices of SES were relative measures of SES and the variables used in the construction of the indices differed across the countries; therefore, the household SES scores were not directly comparable across countries. However, the scores were comparable across methods within the individual countries.

Table 4.6: Mean household SES scores for the total sample, quintile 1 (Q1) and quintile 5 (Q5) for all methods across the six countries

Characteristic	Method	Country					
		Tanzania 2007/8	Liberia 2007	Uganda 2006	Mali 2006	Kenya 2008/9	Egypt 2008
Mean SES score	Dichot. PCA	0	0	0	0	0	0
	Ordinal PCA	0	0	0	0	0	0
	CATPCA	0	0	0	0	0	0
	Simple sum	1.75	3.29	3.99	2.24	2.79	11.51
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: Author's calculations

From the estimated SES scores for households across the six countries, it was evident that the various methods generated SES scores that differed from one another, and that the SES scores resulting from the use of the ordinal PCA method and the CATPCA method were the most similar. For each method, the lowest mean SES score for quintile one occurred for a different country, as indicated by the boxes. For example, Liberia had the lowest mean SES score for quintile one by the dichotomous PCA method (-9.5), but it did not have the lowest mean SES score for quintile one by any of the other methods. Uganda had the highest mean SES score for the fifth quintile by all the methods (indicated by the boxes in Table 4.6) except the simple sum method. These results suggested that the three PCA based methods performed similarly for higher levels of SES. However the SES scores did still differ from one another even at the higher levels of SES. The mean SES score for quintile one was the lowest for the dichotomous PCA method across all six countries, and the mean SES score across quintile five was the highest for the dichotomous PCA index for four of the six countries.

Table 4.7 is a summarised description of the differences in the mean SES scores between the quintiles and the frequency histograms for the distribution of SES across the six countries for all four methods. The distribution of SES scores was uneven for all four methods across all six countries, except for Egypt where the differences in mean SES between the quintiles were more equal than for any of the other countries and the SES frequency histograms showed a less-skewed distribution. For each country, the SES distribution was less skewed and the differences in mean SES scores between the quintiles were more equal for the simple sum method than for the others.

Table 4.7: SES score distribution of the total sample of households for all methods across the six countries

Characteristic	Method	Country					
		Tanzania 2007/8	Liberia 2007	Uganda 2006	Mali 2006	Kenya 2008/9	Egypt 2008
Differences in mean SES score across Qs	Dichot. PCA	Unequal	Unequal	Unequal, difference between Q4 & Q5 is great	Unequal	Unequal	Unequal, but only mildly
	Ordinal PCA	Unequal	Unequal	Unequal, difference between Q4 & Q5 is great	Unequal, but similar differences btw Qs 1 to 3	Unequal	Unequal, but only mildly
	CATPCA	Unequal	Unequal	Unequal, difference between Q4 & Q5 is great	Unequal, but similar differences btw Qs 1 to 4	Unequal	Unequal, but only mildly
	Simple sum	Similar except for Q4 & Q5	Similar except for Q4 & Q5	Similar except for Q4 & Q5	Similar except for Q4 & Q5	Similar except for Q4 & Q5	Similar except for Q1 & Q2
Frequency Histogram	Dichot. PCA	Right skewed	Right skewed	Right skewed	Right skewed	Slightly right skewed	Almost normal curve
	Ordinal PCA	Right skewed	Right skewed	Right skewed	Right skewed	Right skewed	Almost normal curve
	CATPCA	Right skewed	Right skewed	Right skewed	Right skewed	Right skewed	Almost normal curve
	Simple sum	Right skewed	Right skewed	Slightly right skewed	Right skewed	Slightly right skewed	Almost normal curve

Source: Author's calculations

4.5 Internal Coherence

Filmer and Pritchett (2001) put forward a means of evaluating the reliability of the SES index, which they refer to as the internal coherence of the index. Internal coherence can be established if there is a difference in average ownership of, or access to, the variables across the groups of households. Using three classification groups - poor, middle and rich - Filmer and Pritchett (2001) found large differences across the groups for almost all the index variables. For example, 96 per cent of the ‘poor’ used biomass as a cooking fuel, whereas only 22 per cent of the ‘rich’ did so.

By way of example, the results of the analysis of the Malian household data undertaken in this study, using the dichotomous PCA method of index construction, are discussed in detail below. A summary of the internal coherence of the four methods across all six countries is then presented. Of the households in each of the first three quintiles, greater than 40 per cent obtained drinking water from an unprotected well, only the fifth quintile was different to the other quintiles in that 30 per cent of households had water piped into the dwelling and 36 per cent used a public tap or standpipe as a source of drinking water. Regarding the variables related to the type of toilet facility, quintile one was characterized by no facility/bush/field (76 per cent), more than 60 per cent of the households in each of the second to fourth quintiles used a traditional pit latrine and greater than 50 per cent of households in quintile five used a ventilated improved pit latrine. The variables relating to the type of toilet facility did not show internal coherence across all five quintiles; rather they were able to distinguish between three groups, quintile one, quintiles two to four and quintile five. For the variables relating to the type of floor material, the first four quintiles were similar and characterized by a floor material of earth or sand, only the fifth quintile differed noticeably with more than 70 per cent of households having a dwelling with a cement floor. For the first four quintiles, the main material used as cooking fuel was wood – more than 78 per cent of households in each quintile. Only for the fifth quintile did the frequency of wood use drop substantially: 44 per cent of households in the fifth quintile used charcoal as a cooking fuel and only 51 per cent used wood.

Considering the durable asset variables, houses in the first quintile were characterized by a lack of ownership of assets: 33 per cent of households owned a radio, 34 per cent owned a bicycle and 2 per cent owned a motorcycle or scooter - no other assets were owned by households in the first quintile. Across quintiles two to four, asset ownership was similar with more than 70 per cent of households owning a radio and more than 48 per cent owning a bicycle for each quintile. In contrast, all of the asset variables were owned by at least some of the households in the fifth quintile, with 88 per cent possessing a radio and 59 per cent owning a motorcycle or scooter. Ownership of a television increased between the fourth and fifth quintiles: only 28 per cent of households in the fourth quintile owned a television, whereas 75.5 per cent of households in the fifth quintile did so. No households in quintiles one to four owned a refrigerator, while 21 per cent of households in the fifth quintile did so.

In terms of internal coherence for the Malian dataset using the dichotomous PCA method of SES index construction, there were relatively large differences in ownership of, or access to, the various variables between the first and the fifth quintiles, but there was not always much distinction between adjacent quintiles. Similarly, as shown in Table 4.5, there was a difference in mean SES score of 0.96 between quintile one and two, but a difference in mean SES score of 8.88 between quintile four and five. These results suggested that the index of SES constructed here using Malian households was able to distinguish between the 'poor' and the relatively 'richer', but the index was not able to separate out the households in-between quintiles one and five with as much clarity. Forcing the Malian households into five equally sized groups may not have been the best means of classifying the households based on the estimated SES score, since a larger proportion of the sample had relatively low SES scores. The five groups did not display the desired internal coherence and applying arbitrary cut-off points, such as the quintile split, did not reflect the clustered nature of the Malian data.

Table 4.8 presents the observations made with regards to internal coherence for the four methods across the six countries. The observations were made by comparing the frequency of household access to or ownership of each of the variables across the five quintiles. As suggested by Filmer and Pritchett (2001), internal coherence can only be concluded if there is a difference in asset ownership across the quintiles. Internal coherence could not be concluded for all, or even the majority, of variables for any of the methods across all the countries. In almost all instances, quintile five was distinct from the other quintiles, but there was often similarity in the frequency of access to, or ownership of, the variables between quintiles one to four.

The simple sum method appeared to be the best at separating households into five 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. From these results, it is suggested that grouping the households into five equally populated categories is not an appropriate means of household classification when using an index of SES, regardless of the method of index construction. This conclusion is strengthened by the SES distribution results, discussed previously, which indicated that SES was not evenly distributed across households for any of the countries, except perhaps for Egypt.

Table 4.8: Internal coherence (a difference in frequency of access to or ownership of the variables between quintiles) for each of the methods across the six countries

Method	Country		
	Tanzania 2007/8	Liberia 2007	Uganda 2006
PCA - dichot.	Generally there is a difference between Q1 & Q5, the distinction between the middle Qs is poor, a few asset Vs show internal coherence	Not apparent over 5 Qs, possibly 3 groups distinct. The V *roof material* & the assets show some internal coherence	Generally there is a difference between Q1 & Q5, but the distinction between the middle Qs is poor
PCA - ordinal	Generally there is a difference between Q1 & Q5, the distinction between the middle Qs is poor, a few asset Vs show internal coherence	Not apparent over 5 Qs, possibly 3 groups distinct. The V *roof material* & the assets show some internal coherence	Generally there is a difference between Q1 & Q5, but the distinction between the middle Qs is poor
CATPCA	Generally there is a difference between Q1 & Q5, the distinction between the middle Qs is poor, a few asset Vs show internal coherence	Not apparent over 5 Qs, possibly 3 groups distinct. The V *roof material* & the assets show some internal coherence	Generally there is a difference between Q1 & Q5, but the distinction between the middle Qs is poor
Simple sum	3 of the variables show internal coherence	5 of the variables show internal coherence	4 of the variables show internal coherence

Table 4.8: ***continued***

Method	Country		
	Mali 2006	Kenya 2008/9	Egypt 2008
PCA - dichot.	The 5 Qs are not distinct from one another except for Q 5, at least 2 Qs for each V are similar	Not apparent over 5 Qs. The V *roof material* & the assets show some internal coherence	Not much distinction across Qs for the categorical Vs, the asset Vs show some internal coherence
PCA - ordinal	The 5 Qs are not distinct from one another except for Q 5, at least 2 Qs for each V are similar	Not apparent over 5 Qs. The Vs *toilet facility* & *floor material* as well as the assets show some internal coherence	Not much distinction across Qs for the categorical Vs, the asset Vs show some internal coherence
CATPCA	Not apparent over 5 Qs, Q5 is distinct from the other Qs. The V *toilet facility* shows some internal coherence	Not apparent over 5 Qs. The Vs *toilet facility* & *floor material* as well as the assets show some internal coherence	Not much distinction across Qs for the categorical Vs, the asset Vs show some internal coherence
Simple sum	3 of the variables show internal coherence	4 of the variables show internal coherence	4 of the variables show internal coherence

Source: Author's calculations

4.6 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. In their study, they compared household classifications when different subsets of variables were used in the construction of the index. Filmer and Pritchett (2001) compared the classification of households using all the variables to classifications using indices based on: (1) all the variables except those related to drinking water and toilet facilities; (2) ownership of durable assets, housing quality, number of rooms, and land ownership; and (3) only the durable asset variables. Filmer and Pritchett (2001) found that the index produced similar classifications when the different subsets of variables were used in its construction. This was determined by comparing the percentage of households classified into the poorest 40 per cent when all the assets were included in the index and when only a subset of the variables was used. Filmer and Pritchett (2001) found that almost none of the households classified into the poorest group by the 'all variables index' would be classified into the richest group by any of the indices including only a subset of the variables. Filmer and Pritchett (2001) report finding similar results for the middle and rich groups.

In a study of health inequality among children in developing countries, Houweling *et al*. (2003) investigated whether the categorisation of households into wealth groups was sensitive to the inclusion of asset variables. The study was reviewed in Chapter 2, Section 2.2. When all the indicators available to Houweling *et al*. (2003) were included in the index - 39 variables – the PCA generated a first PC that explained 16 per cent of the variation in the variables using data from Tanzania. For the same Tanzanian data, but using only the asset indicators - 10 variables - the first PC explained 36 per cent of the variation in the variables. However, Houweling *et al*. (2003) concluded that, while reducing the number of variables included in the index tended to increase the percentage of variance explained, the ability of the index to stratify the sample households into equally-sized quintiles decreased as items were excluded from the index.

The robustness of the SES index in this study was assessed through comparisons of household classifications using all the variables to classifications based on three subsets of variables, where

- base index refers to all the variables;
- index A contains all the variables except those relating to drinking water (Dw) and toilet facilities (Tf);
- index B contains the asset variables only; and
- index C contains the categorical variables only.

Indices A and B follow the Filmer and Pritchett (2001) choice of variables for an analysis of robustness. Index C (the categorical variables only) was chosen as a comparison to the asset variables only subset in order to determine the effect of using only categorical or only dichotomous data.

Comparisons were made between the household classifications across all five of the quintiles to determine if the different indices classified households similarly for each quintile, some of the quintiles or none of the quintiles. Robustness was only considered for the PCA-based methods. As an example of the individual robustness assessment, results from this study for the Kenyan household analysis using the CATPCA method, are presented and discussed. Table 4.9 is a summary of the Eigenvalues and PVAF values obtained from the PCA of the different sets of variables. The PVAF by the first PC of the categorical variables only index was the highest of the three indices, and it was higher than the PVAF by the first PC of the base index. As pointed out by Houweling *et al*. (2003), reducing the number of variables included in the index tended to increase the proportion of variance accounted for by the first PC. This explained why the first PC for the categorical variables index had the highest PVAF – the categorical variables index contained the fewest variables.

Table 4.9: Eigenvalue and PVAF (per cent) results for the first PC of CATPCA of all the variables and each of the subsets of variables, Kenya 2008/9 (*N*=9057)

	All Vs	Asset Vs	Categorical Vs	Vs excl. Dw&Tf
Eigenvalue	6.881	3.486	3.744	5.700
No. Vs	16	10	6	14
PVAF	43.008	34.855	62.405	40.713

Where: 'No. Vs' is the number of variables included in the analysis and PVAF is the percentage of variance explained by the first principal component.
Source: Author's calculations

Table 4.10 shows the comparisons in household classification 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 SES 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 the index of all variables excluding the variables for drinking water and toilet facilities. This was to be expected as these two indices only differed by two variables: whereas the asset variables only index had six variables less and the categorical variables only index had 10 variables less than the base index.

Table 4.10: 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)

	Base method: All Vs	Asset Vs	Cat. Vs	All Vs excl. Dw & Tf
Q1	100.0	66.9	61.2	88.0
Q2	0.0	27.0	26.8	12.0
Q3	0.0	5.9	12.0	0.0
Q4	0.0	0.2	0.0	0.0
Q5	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0

Source: Author's calculations

The asset variables only and categorical variables only indices classified households much less similarly than the index of all variables excluding drinking water and toilet facility, namely 67 per cent and 61 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 of the asset variables only index and none in quintile four of 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. Filmer and Pritchett (2001) found similar results for the 'middle' and 'rich' groups in their investigation. In this study, the classification similarities seen for the first quintile deteriorated for the second and third quintiles. A maximum of 75 per cent of households classified into quintile two by the base method were classified into quintile two by the all variables excluding drinking water and toilet facility index and only 40.5 per cent appeared in quintile two of the asset variables only method. Results were similar for quintile three. Classification similarities improved for quintile four and were higher across all the subset variables indices for quintile five (a minimum classification similarity of 83 per cent). Filmer and Pritchett (2001) used three categories for the household classifications; this study used five groups (quintiles). The more similar classifications obtained by Filmer and Pritchett (2001) may be explained by the difference in the number of classification categories.

The results showed that the index of SES 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, but classification similarities deteriorated for the middle quintiles. Reducing the number of classification groups could have improved the robustness of the index. These results suggested that the indices of SES constructed here, using different subsets of variables and household data from Kenya, were better able to distinguish between the 'poorer' and the relatively 'richer', but they did not separate out the households in the middle quintiles with the same clarity. Forcing the households into five equally sized groups may not have been the best means of classifying the households based on the estimated SES scores. A similar conclusion could be drawn for all the PCA-based index construction methods across the six countries. Table 4.11 presents a comparison of the robustness of each of the three PCA-based indices to changes in the variables included, for the six countries. The minimum and maximum classification similarity rates are given for each index (compared to the base index) for each variable weighting method for all six countries. Considering Tanzania 2007/08, 79.1 per cent of the households classified into quintile two by the base method were also classified into quintile two by Index A (the index of all variables excluding source of drinking water and type of toilet facilities). This is the lowest classification rate between the base index and Index A for the dichotomous PCA method for Tanzania.

The index of all the variables, excluding source of drinking water and type of toilet facility, most similarly classified the households to the base index of the three indices across the six countries, except for Mali. The reason was most likely due to the similarity in the number and type of variables included in the base index and the index of all the variables, excluding source of drinking water and type of toilet facility; the two indices only differed by two variables: source of drinking water and type of toilet facility.

Generally, across all the countries and index construction methods, classification similarities and hence the robustness of the indices declined for the middle quintiles. The results implied that an index of SES 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 the 'poorer' and 'richer' categories with the same clarity.

Table 4.11: Summary of method robustness: minimum and maximum classification similarities (per cent) between the base index and the three subsets of variables indices, for each variable weighting method, across all six countries

Method	Index	Country					
		Tanzania 2007/8	Liberia 2007	Uganda 2006	Mali 2006	Kenya 2008/9	Egypt 2008
PCA - dichot.	A	Min: 79.1 (Q 2)	Min: 73.7 (Q 2)	Min: 80.0 (Q 2)	Min: 49.1 (Q 2)	Min: 78.1 (Q 2)	Min: 60.4 (Q 3)
		Max: 94.0 (Q 5)	Max: 94.1 (Q 5)	Max: 95.7 (Q 5)	Max: 92.6 (Q 5)	Max: 93.2 (Q 5)	Max: 95.0 (Q 5)
	B	Min: 22.1 (Q 3)	Min: 30.7 (Q 3)	Min: 34.5 (Q 2)	Min: 23.8 (Q 3)	Min: 34.0 (Q 3)	Min: 49.5 (Q 3)
		Max: 74.9 (Q 5)	Max: 77.2 (Q 5)	Max: 75.9 (Q 5)	Max: 79.9 (Q 5)	Max: 78.7 (Q 5)	Max: 94.1 (Q 5)
	C	Min: 66.7 (Q 2)	Min: 49.0 (Q 2)	Min: 53.3 (Q 2)	Min: 38.7 (Q 2)	Min: 63.7 (Q 2)	Min: 0 (Q 1 & 5)
		Max: 92.6 (Q 5)	Max: 82.3 (Q 5)	Max: 86.6 (Q 5)	Max: 82.7 (Q 5)	Max: 84.2 (Q 1)	Max: 48.4 (Q 3)
PCA - ordinal	A	Min: 62.0 (Q 2)	Min: 85.2 (Q 2)	Min: 73.3 (Q 2)	Min: 48.7 (Q 2)	Min: 72.7 (Q 2)	Min: 75.8 (Q 3)
		Max: 93.1 (Q 5)	Max: 93.3 (Q 5)	Max: 96.7 (Q 5)	Max: 93.6 (Q 5)	Max: 94.8 (Q 5)	Max: 97.1 (Q 5)
	B	Min: 21.9 (Q 3)	Min: 40.4 (Q 3)	Min: 52.5 (Q 3)	Min: 39.3 (Q 3)	Min: 31.1 (Q 3)	Min: 60.6 (Q 3)
		Max: 81.4 (Q 5)	Max: 83.1 (Q 5)	Max: 87.0 (Q 5)	Max: 89.5 (Q 5)	Max: 87.3 (Q 5)	Max: 96.2 (Q 5)
	C	Min: 51.5 (Q 2)	Min: 36.1 (Q 2)	Min: 35.3 (Q 3)	Min: 40.6 (Q 2)	Min: 53.9 (Q 3)	Min: 41.4 (Q 2)
		Max: 85.5 (Q 5)	Max: 77.9 (Q 5)	Max: 75.8 (Q 5)	Max: 93.0 (Q 5)	Max: 85.0 (Q 5)	Max: 64.6 (Q 1)
CATPCA	A	Min: 62.0 (Q 2)	Min: 79.1 (Q 2)	Min: 68.0 (Q 2)	Min: 40.6 (Q 2)	Min: 75.3 (Q 2)	Min: 74.9 (Q 3)
		Max: 92.7 (Q 5)	Max: 93.4 (Q 5)	Max: 95.0 (Q 5)	Max: 93.0 (Q 5)	Max: 93.5 (Q 5)	Max: 97.1 (Q 5)
	B	Min: 24.6 (Q 3)	Min: 42.1 (Q 3)	Min: 45.8 (Q 3)	Min: 31.3 (Q 3)	Min: 37.5 (Q 3)	Min: 64.0 (Q 3)
		Max: 78.1 (Q 5)	Max: 82.0 (Q 5)	Max: 81.7 (Q 5)	Max: 88.5 (Q 5)	Max: 86.9 (Q 5)	Max: 93.8 (Q 5)
	C	Min: 52.1 (Q 2)	Min: 38.8 (Q 2)	Min: 44.9 (Q 3)	Min: 44.9 (Q 2)	Min: 44.4 (Q 2)	Min: 38.4 (Q 3)
		Max: 89.7 (Q 5)	Max: 78.2 (Q 5)	Max: 83.1 (Q 5)	Max: 79.1 (Q 5)	Max: 83.4 (Q 5)	Max: 66.0 (Q 1)

Where: A is the index of all variables excluding source of drinking water and type of toilet facilities, B is the index of asset variables only, C is the index of categorical variables only and Q is quintile.
Source: Author’s calculations

The results from the robustness analysis once again implied that forcing the households into quintiles was not the most suitable means of classifying the households into levels of SES.

4.7 Household Classification Comparisons

The classifications of households into quintiles by the four indices were compared 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. For example, considering the classification differences for quintile one between the CATPCA index (base method) and the other three indices for the Liberian data (Table 4.12), of the households classified into quintile one by the base method, 93.3 per cent were also classified into quintile one by the ordinal PCA method, 86.7 per cent by the dichotomous PCA method and 73.2 per cent by the simple sum index. 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. All of the households classified into quintile one by the base method appeared in either quintile one (93.3 per cent) or quintile two (6.7 per cent) by the ordinal PCA method; the ordinal PCA method classified households most similarly to the CATPCA index for quintile one of the Liberian households.

Table 4.12: Household classification comparisons (percentages) between the CATPCA index and the three alternate indices, for quintile one, Liberia 2007 (*N*=6824)

Q1	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: Author’s calculations

Similarly, classification similarities between the CATPCA index and the ordinal PCA method were greater than 87 per cent across all of the quintiles. The simple sum index classifications were the most different to the CATPCA index classification, especially for quintiles three and four: only 39 per cent of the households classified into quintile three by the CATPCA method appeared in the same quintile by the simple sum index, the classification similarities were only marginally higher for the fourth quintile (46 per cent). Summary results from classification comparisons between all the methods across the six countries - Table 4.13 – showed similar trends.

Table 4.13: Household classification comparisons between the four SES indices across the six country analyses

Method	Country Tanzania 2007/8	 Liberia 2007	 Uganda 2006
Dichot. PCA	Similar to CATPCA & ordinal PCA, but with classification similarities low for Q2 & Q3	Similar to CATPCA & ordinal PCA, but with classification similarities low for Q2 & Q3	Similar to CATPCA (>74.1% for all Qs)
Ordinal PCA	Similar to CATPCA (>73.6% for all Qs), similarities with all methods are less for the middle Qs	Similar to CATPCA (>87% for all Qs)	Similar to CATPCA (>64.6% for all Qs)
CATPCA	Similar to PCA - ordinal (>73.6% for all Qs) &to PCA - dichot, esp. for Qs 1,3 & 4	Similar to PCA - ordinal (>87% for all Qs)	Similar to PCA - dichot (>74.1% for all Qs)
Simple sum	Relatively low classification similarities with the other methods (a highest classification similarity of 64.6%)	Relatively low classification similarities with the other methods, especially for the middle Qs	Relatively low classification similarities with the other methods, especially for the middle Qs (a highest classification similarity of 78.2%)

Table 4.13: *continued*

Method	Country Mali 2006	 Kenya 2008/9	 Egypt 2008
Dichot. PCA	Most similar to the PCA - ordinal method for Q1 to 3, and to the CATPCA method for Q4 & 5. Classification similarities are low for the CATPCA method for Q2 & 3	Similar to CATPCA & PCA - ordinal (>79.8% for all Qs)	Similar to CATPCA (>78.4% for all Qs)
Ordinal PCA	Most similar to the PCA - dichot. method for Q1 & 2, and to the CATPCA method for Q 3 to 5, classification similarities are relatively lower for Q2 & 3, but high for Q5	Similar to CATPCA & PCA - dichot. (>84% for all Qs, except Q3 for PCA- dichot.)	Similar to CATPCA (>89.7% for all Qs), also high similarities for dichot - PCA
CATPCA	Most similar to PCA - ordinal, but classification similarities for Q 2 & 3 are relatively low	Similar to PCA - ordinal & PCA - dichot. (>84% for all Qs)	Similar to PCA - ordinal (>89.7% for all Qs)
Simple sum	Relatively low classification similarities with the other methods, especially for the middle Qs (a highest classification similarity of 77.4%)	Relatively low classification similarities with the other methods, especially for the middle Qs (a highest classification similarity of 77.6%)	Relatively low classification similarities with the other methods, especially for the middle Qs (a highest classification similarity of 68.7%)

Source: Author's calculations

In general, the three PCA-based indices classified households relatively similarly to each other, especially for the first and last quintiles. Across the six countries, 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).

4.8 Conclusions

This chapter was motivated by a lack of consensus in the literature on the most appropriate means of generating the weights of the variables for inclusion in an index of household SES. In a number of recent examples, linear PCA has been applied to dichotomous and categorical variables extracted from household surveys. However, there is some contention as to whether the application of linear PCA to non-continuous data is appropriate. Arguments around this point are discussed in Chapter three of the study. In response, it was decided to investigate four methods of constructing an index of SES: three PCA-based methods and a simple sum of assets technique. The objective was to determine which of the four methods of weighting the variable for inclusion in an index of SES, was the most reliable and appropriate for estimating a household's level of resilience. The four methods were applied to six sets of country household data. A number of assessment characteristics relating to indices of SES, as suggested in the literature, were evaluated in an attempt to compare the performance of the four methods and their respective classifications of households into quintiles.

The main conclusions that can be drawn from the method comparisons are as follows. 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 SES scores estimated using each of the four indices differed from one another in terms of the mean SES scores across quintiles and the difference between the minimum and maximum scores for each method. The distribution of SES 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 SES distribution was less skewed and the differences in mean SES scores between the quintiles 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 SES score 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.

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. The simple sum of assets method produced a distribution of SES scores showing the most uniformity and performed somewhat better in terms of internal coherence than the other methods. 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 SES 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 makes use of only the asset (dichotomous) variables.

There is another conclusion that can be drawn from this analysis and relates to the classification of households into quintiles. The use of quintiles as group cut-off points assumes that the distribution of SES is uniform. It is clear from the SES score frequency histograms and the differences in mean SES scores across quintiles, that the distribution of SES across households was not uniform by any of the methods. Therefore, the use of quintiles as group cut-off points is not appropriate. Applying the quintile split did not reflect the clustered nature of the household data. An alternate means of classifying the households into groups reflecting a particular level of SES could be to apply cluster analysis to the SES scores derived for each country. Cluster analysis is a procedure that aims to identify homogenous groups or clusters of cases in datasets (Norusis, 2008:359). Cluster analysis was applied to the household SES scores estimated by the CATPCA method for each country and the results are discussed in the next chapter.

CHAPTER 5: HOUSEHOLD CLASSIFICATION BY CLUSTER ANALYSIS

In Chapter 4 of the study, four methods of constructing an index of socio-economic status (SES) were compared in an attempt to establish the most reliable and appropriate method for the estimation of household SES scores as an indication of household resilience. From the comparison it was concluded that no single method, of the four considered in this study, was 'better' than the others across all of the assessment criteria and the method of choice depends on the preference of the user. However, it was shown that SES was not evenly distributed across all households for the six countries of analysis and, therefore, the use of quintiles as household classifications was inappropriate. To supplement the previous chapter, this chapter applies cluster analysis as an alternate method of classifying households into different categories of SES. The aim of this chapter is to investigate cluster analysis as a means of grouping households based on estimated SES scores.

The chapter is organised as follows. The first section briefly introduces cluster analysis. Section 5.2 presents and discusses the results of k-means cluster analysis of the estimated household SES scores using five clusters. The next section considers k-means cluster analysis of the household SES scores, but with solutions of two and then three clusters. The chapter closes with a conclusion of the usefulness of cluster analysis in classifying households into groups of differing SES based on estimated household SES scores from Chapter 4.

5.1 Cluster Analysis

Cluster analysis is a technique used to identify homogenous groups of cases in multivariate datasets (Norusis, 2008:359). The cases are grouped based on the values of the selected variables so that 'similar' cases fall into the same group or cluster (Manly, 1994:128). Hierarchical Cluster Analysis and Partitioning Cluster Analysis are two common approaches to clustering. Hierarchical Cluster Analysis involves the calculation of distances from each case to all other cases and the formation of groups based on these distances by either agglomeration or division (Garson, 2010). In partitioning, group centres are chosen after data inspection and cases are allocated to the nearest group. New centres are then estimated and a case will move to a new group if it is closer to that group's centre rather than its current group centre. Cases move into and out of groups at different steps in the process until the number of groups stabilizes (Manly, 1994:129).

The k-means cluster analysis technique is suggested for medium to large sample sizes as it is less computer intensive than hierarchical cluster analysis (Garson, 2010). K-means clustering falls into the group of cluster analyses involving partitioning (Manly, 2005:126). K-means clustering was chosen for the analysis of the country household data in this study as dataset sizes exceed 1000 cases. Garson (2010) suggests k-means cluster analysis is appropriate when *N* exceeds 1000. Fairly arbitrary group centres are chosen and the distances of each case from the mean vector of *k* suggested clusters are compared (Morrison, 2005:355). The cases are allocated to the nearest group and new group centres are calculated representing the averages of the cases in the group (Manly, 2005:126). The process continues iteratively and cases move between groups until all the cases are in clusters with minimum distances to their mean vectors (Manly, 2005:127; Morrison, 2005:355).

5.2 K-means Cluster Analysis with Five Clusters

In Chapter 4, quintiles were used as classification groups: each household was grouped into a quintile based on its SES score. In order to compare household classifications by cluster analysis to the original SES 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 SES scores by the CATPCA method – from Chapter 4 – using the k-means cluster analysis option in the Statistical Package for the Social Sciences (SPSS) version 15.0 for Windows.

From the results of the cluster analysis five-cluster solution it was clear that for none of the six countries did the k-means analysis result in five clusters of equal size (quintiles). The results from the k-means, five cluster analysis appear in Table 5.1 where the percentage of households allocated to each of the five clusters is shown. The country results are presented in order of the 2009 Human Development Report (UNDP, 2009) poverty rankings. In the discussion, ‘poor’ refers to countries with relatively high 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 SES.

For the five-cluster solution, a larger proportion of the households in each country sample were allocated to the group of lowest SES for the four ‘poorest’ countries of the study, and to the second level of SES for the two relatively better-off countries of the study. The highest

SES level group (cluster 5) contained the lowest per cent of households for all six of the countries.

Table 5.1: 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 (%)					Total (%)
		1	2	3	4	5	
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: Author's calculations

Of the proportion of households allocated to cluster 5, 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 in the study. The results showed that a greater proportion of households fell into relatively lower levels of SES. This is in contrast to the assumption of uniformity of SES 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.

Considering the internal coherence of the clusters, in comparison to the quintile classifications generated using the CATPCA SES index, the internal coherence was somewhat improved especially for the asset variables. However, the internal coherence remained poor for a number of the categories of the categorical variables, due to the low frequency of positive responses for these categories. Grouping similar categories prior to analysis could further improve the internal coherence of the CATPCA five-cluster solution. The differences between the mean SES scores of the clusters were still not even with the cluster analysis approach. However, they were more similar than for the quintile classification.

Garson (2010) defines three 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. In this study, the fifth cluster of each of the six countries tended to be rather small for the k-means five-cluster solution, 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 SES levels for the six countries investigated in this study.

The second criterion suggested by Garson (2010) is that of cluster meaningfulness. 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 SES score was used to cluster the households, therefore, differing levels of household SES should be discernable between the five clusters. The frequency of ownership of or access to the variables used to estimate the SES scores should have coincided with different levels of household SES across the clusters. The clusters should have shown internal coherence to be truly meaningful. As discussed, the internal coherence of the solution was improved by using cluster analysis rather than quintiles. However, not all of the variables showed internal coherence across all five clusters. The internal coherence of the solution could possibly be improved by requesting fewer clusters from the cluster analysis procedure.

The third of Garson's (2010) criteria involves cross tabulation of the clusters by variables known from theory to correlate with the concept which the clusters are meant to reflect. The cross tabulation should reveal the expected level of association between the clusters and the variables. In this case it would be useful to cross tabulate the cluster variable with a variable(s) representing household wealth to ensure that the clusters did represent different levels of household SES. However, the demographic and health surveys do not include information regarding household income or wealth, other than the asset variables already used to calculate the household SES scores.

5.3 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 SES scores 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 5.2.

Table 5.2: 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 (%)		Total (%)
		1	2	
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: Author's calculations

For all of the countries, the larger proportion of households was allocated to the first cluster - the cluster representing the lowest SES level. For three of the six countries, over 80 per cent of the households were allocated to the first cluster. Once again, the results showed that SES was not evenly distributed across households for any of the six countries. 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 5.3.

Table 5.3: 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 (%)			Total (%)
		1	2	3	
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: Author's calculations

For five of the six countries of analysis, the first cluster contained the greatest per cent of households; only for Egypt 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 for all of the countries except Egypt (less than 15 per cent). Once again, this may indicate the use of too many clusters in the solution; however, reducing the number of clusters used – as shown by the two-cluster solution – did not improve the solution.

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

The application of cluster analysis as a means of classifying a set of households into groups representing a certain level of SES appeared to be more useful than the use of quintiles: both in that it did not assume an even distribution of SES – 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 levels of SES. Cluster analysis of the household SES 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. In Chapter six the ability of the resilience score, developed in this study, to capture changes in household resilience over time is investigated.

CHAPTER 6: A COMPARISON OF HOUSEHOLD SOCIO-ECONOMIC STATUS OVER TIME

In Chapter 5 it was concluded that an index of socio-economic status (SES) could be used, along with cluster analysis, as a broad indication of changes in household SES. In this chapter, the results from the application of an index of SES to the demographic and health survey (DHS) household data for a number of African countries from two different time periods and the resulting classification of households into SES groups by cluster analysis are presented and discussed. The aim was to compare the results for each country over the two time periods to determine if the SES index with household classification by cluster analysis was able to pick up changes in household SES over time in the chosen countries. Additionally, the literature regarding national poverty estimates was consulted to compare trends in household SES observed in this study, with changes in poverty reported in the literature. The five countries chosen for the analysis were the original countries used in Chapter 4 without Liberia. The Liberian DHS survey before the most recent one was undertaken in 1984 and did not contain information on household assets and, therefore, could not be used to compare changes in SES over time; it was thus excluded from this analysis.

In the first section of this chapter the results of the classification of households into SES groups by country and year, based on the estimated SES scores generated using the Categorical Principal Component Analysis (CATPCA) method (see Chapter 4) are presented and discussed. The classification results for each country from the two different years of DHS data are compared. The process was repeated using the simple sum method to calculate the household SES scores and the results are discussed in Section 6.2. Section 6.3 reports poverty estimates in the respective countries by alternate studies in an attempt to find support for the trends in household SES observed in this study.

6.1 Country Comparison over Time – Categorical Principal Component Analysis

The index of SES applied in this section was constructed by means of the CATPCA method. The households were classified into five groups representing different levels of SES using k-means cluster analysis of the estimated SES scores. The cluster sizes – as percentages of the total population – are presented by country and year in Table 6.1. The SES score results are not presented here, but can be found in Appendix B. Comparisons were drawn between the SES scores of the two different years. However, there were slight differences in the variables included in the construction of the indices between the years. Therefore, direct comparisons of the SES scores were not entirely reliable and should not be given too much attention. In the discussion below the terms poor, rich and forms thereof are used loosely to describe differences in SES level: the estimated SES scores are relative to one another within each data set and give no indication of absolute levels of poverty or wealth.

Table 6.1: Cluster sizes (per cent of total sample) by country and year, based on the estimated household SES scores using the CATPCA index and k-means cluster analysis with five clusters

Country	Year	Cluster (%)					Total (%)
		1	2	3	4	5	
Egypt	2005	8.3	24.0	34.7	22.5	10.5	100.0
	2008	10.4	31.6	30.9	19.4	7.7	100.0
Kenya	2003	43.3	30.9	14.1	7.6	4.1	100.0
	2008	30.3	32.6	19.9	12.2	5.0	100.0
Mali	2001	57.4	28.7	7.8	3.9	2.2	100.0
	2006	65.8	19.3	8.9	4.0	1.9	100.0
Uganda	2000	43.2	30.5	16.0	7.5	2.8	100.0
	2006	45.3	31.9	12.7	6.9	3.2	100.0
Tanzania	2004	61.8	21.2	10.0	4.6	2.4	100.0
	2007	58.0	24.9	9.0	6.4	1.7	100.0

Note: Relative household wealth increases from cluster one to cluster five.
Source: Author's calculations

For three of the five countries of analysis, the results showed an increase in the per cent of households allocated to the lowest level of SES (cluster 1) from the earlier time period to the more recent period. For Kenya and Tanzania there was a decrease in the per cent of households allocated to the lowest SES level. The results also indicated that the per cent of households allocated to the group of highest SES level (cluster 5) decreased from the earlier time period to the more recent one for three of the five countries of analysis. For Kenya and Uganda, the per cent of households assigned to cluster five increased slightly.

The cluster containing the greatest per cent of households for the 2005 Egypt analysis was the third cluster, whereas for the 2008 analysis the largest cluster was the second cluster. This result suggests, along with the increase in the percentage of households allocated to the first cluster from 2005 to 2008, that there was a decrease in the SES level of households in Egypt between 2005 and 2008. This conclusion was reflected in a slight decrease in the maximum SES score between 2005 (18.77) and 2008 (18.1) and the lower mean SES score for the fifth cluster of the 2008 period. The minimum SES score increased from 2005 (-19.96) to 2008 (-17.30) and the mean SES score of the first cluster was actually higher for the 2008 year. It could be concluded for Egypt that a greater per cent of the population was poorer in 2008 than in 2005, yet the poorest were better off in terms of SES. The differences in mean SES scores between the clusters were more similar for the 2008 analyses compared to the 2005 results, suggesting that the distribution of SES was more even in 2008 that in 2005. The conclusions drawn from the results assume that the household samples used in the analyses were a reliable reflection of the entire population.

For Kenya, there was a decrease in the percentage of households allocated to the first cluster and an increase in the number of households allocated to all the other clusters between 2003 and 2008. For the 2003 analysis, the largest percentage of households was allocated to the first cluster whereas for 2008 the largest cluster was the second one. The maximum SES score was higher for 2008 (23.14) than 2003 (20.42) and so was the mean SES score for the fifth cluster. However, the minimum SES score was lower for 2008 than 2005; similarly the mean SES score for the first cluster was lower for 2008 than 2005. For Kenya, it could be concluded that a lower percentage of the population was extremely poor in 2008 than in 2003, yet the poorest were worse off in 2008 as shown by the lower minimum SES score and lower mean SES score for cluster one for the 2008 year. The differences in the mean SES scores between clusters were more similar for the 2003 analysis suggesting that the distribution of SES across households was more even in 2003 than in 2008. There was a greater difference between the minimum and maximum SES scores for 2008 (32.92) than for 2005 (27.06), which implies a more unequal distribution of SES for 2008.

The results for Mali suggest there was an increase in extreme poverty between 2001 and 2006 as shown by the increase in the proportion of households allocated to the first cluster. The poorest were worse off as indicated by a lower minimum SES score as well as a lower mean SES score for the first cluster for 2006 compared to 2001. The per cent of households allocated to the fifth cluster decreased from 2001 (2.2 per cent) to 2006 (1.9 per cent), and the richest households appear to have been better off in 2006 than 2001 as both the mean SES score for the fifth cluster and the maximum SES score were higher in 2006 than in 2001.

The Ugandan results indicate an increase in extreme poverty between 2000 and 2006, although the change is slight – 43.2 per cent of the population fell into the first (relatively poorest) cluster for the 2000 period and 45.3 per cent for the 2006 period; there was also a slight decrease in mean SES score for the first cluster between 2000 (-4.28) and 2006 (-5.21). Additionally, there was a small increase in the per cent of households assigned to the fifth (relatively wealthiest) cluster between 2000 (2.8) and 2006 (3.2) and an increase in the mean SES score for the fifth cluster from 2000 (18.65) to 2006 (23.60). The differences in mean SES between clusters were more similar for the 2000 analysis, suggesting that household SES in Uganda was more evenly distributed in 2000 than in 2006.

For Tanzania, from 2004 to 2007, there was a decrease in the proportion of households allocated to the lowest level of SES as well as a decrease in the per cent of households falling into the relatively richest category. These changes were relatively small. The mean SES score for both the first (poorest) and fifth (wealthiest) clusters decreased slightly from 2004 to 2007 as did the minimum SES score for the total sample. From these observations it could be concluded that overall the level of SES decreased from 2004 to 2007 for households in Tanzania. The differences in mean SES score between the clusters were relatively alike for the two time periods, suggesting that the distribution of SES was similar in 2004 and 2007.

The discussion above demonstrates how the index of SES combined with k-means cluster analysis could be used to monitor changes in household SES status over time. This SES measurement tool, however, only gives an indication of adjustments in the proportion of households falling into the relative categories of SES over time and does not give any indication of the actual level of SES represented by the clusters. The estimated SES scores are relative and their values are not directly comparable between countries: the actual levels of SES represented by the clusters for one country are not necessarily the same for another and the scores do not indicate actual levels of poverty or wealth.

6.2 Country Comparison over Time – Simple Sum

The CATPCA method of asset weight estimation is time consuming as the variables have to be recoded twice – once before CATPCA is applied and once after – to achieve the final ordering of the categories and weights for each variable. The additional recoding processes may introduce a number of computational errors into the analysis if care is not taken to check each step of the process. Alternatively, the simple sum method of weight estimation does not require the variables to be recoded as only the dichotomous variables are used in their binary form. As such, the simple sum method is quicker to apply and less susceptible to computational error. In order to investigate the possibility of using the simple sum method instead of the CATPCA method, the comparison of household SES over time was repeated using the simple sum method of weight estimation. The results are presented in Table 6.2 as the per cent of households allocated to each cluster by country and year.

Table 6.2: Cluster sizes (per cent of total sample) by country and year, based on the estimated household SES scores using the simple sum index and k-means cluster analysis with five clusters

Country	Year	Cluster (%)					Total (%)
		1	2	3	4	5	
Egypt	2005	3.9	15.6	56.6	18.8	5.1	100.0
	2008	3.7	15.8	58.9	18.4	3.3	100.0
Kenya	2003	54.9	31.8	5.9	6.7	0.7	100.0
	2008	32.3	33.2	28.4	5.3	0.8	100.0
Mali	2001	20.5	59.4	15.1	3.7	1.2	100.0
	2006	42.8	45.2	8.7	2.3	1.0	100.0
Uganda	2000	47.5	34.2	13.0	4.0	1.3	100.0
	2006	22.0	53.1	16.3	6.1	2.5	100.0
Tanzania	2004	29.2	59.9	6.9	3.4	0.6	100.0
	2007	23.3	66.6	7.0	2.8	0.3	100.0

Note: Relative household wealth increases from cluster one to cluster five.
Source: Author's calculations

For four of the five countries analysed, the trends in the changes of the per cent of households allocated to the first and fifth clusters and the location of the largest cluster differ between the CATPCA and simple sum method; only for Kenya were they similar.

For Kenya, both methods showed a decrease in the per cent of households allocated to the relatively poorest cluster from 2003 to 2008 and an increase in the proportion of households allocated to the relatively wealthiest cluster. The largest cluster was the first cluster for 2003 and the second cluster for 2008 based on the classifications by both of the methods. The same conclusions for Kenya can be drawn from the results based on both the CATPCA and simple sum methods: a lesser per cent of the population was extremely poor in 2008 than in 2003; however, the poorest were worse off in 2008. The distribution of SES across households was more even in 2003 than in 2008 for both methods.

For Egypt, the results from the household classification based on the simple sum method showed that the per cent of households in the first cluster decreased by 0.2 percentage points from 2005 to 2008, whereas the results from the CATPCA-based classification showed an increase of 2.1 percentage points in the per cent of households in the poorest cluster between the two years of analysis. Both methods showed a decrease in the per cent of households allocated to the fifth cluster from 2005 to 2008. For the simple sum method, there was a decrease in the mean SES score for the relatively poorest and relatively wealthiest clusters which suggests, respectively, that the level of extreme poverty worsened and the level of extreme wealth decreased; assuming that the sum of a household's assets are a reflection of its wealth, which is unlikely to be accurate. The CATPCA results showed a reduction in both extreme poverty and wealth between 2005 and 2008.

Discrepancies between the results of the two methods could be found, for Mali, in that the CATPCA method results indicated a possible worsening in extreme poverty – as shown by a reduction in the mean SES score for cluster one between 2001 and 2006 as well as a lower minimum SES score for 2006, whereas the simple sum method results implied a potential reduction in the level of extreme poverty. However, comparing the SES scores from the two years was not entirely reliable as the variables included in the respective indices varied for the two time periods due to changes in the Demographic and Health Surveys over time. Similarly, the results from the two methods were not in agreement for Uganda: the CATPCA method results showed an increase in the per cent of households allocated to the first cluster from 2000 to 2006, whereas the simple sum method results indicated a decrease in the per cent of the extreme poor. For Tanzania, both methods showed a decrease in the proportion of households allocated to the first cluster and a decrease in the per cent of households falling into the fifth cluster. However, the CATPCA method indicated that the first cluster was the largest for both years, whereas the simple sum method results showed the second cluster to be the largest for both time periods.

It is clear from the previous discussion that the changes in the proportion of households allocated to the different levels of SES differ depending on the method of index construction. In this case, using the CATPCA method produced different, and often opposite, trends in the movement of households between levels of SES over time to the simple sum method. While the simple sum method offers a quicker, easier means of constructing an index of SES it uses less information and this omission of information clearly affects the classification results. This outcome supports the conclusion from Chapter 4 that the method of index construction does affect the household classification outcomes; additionally it also affects the trends in the movement of households between clusters over time. In other words, not only does the method of index construction affect the actual cluster sizes, it also affects the direction of changes in the cluster sizes over time. More research and attempts to validate either method are required before a conclusion can be drawn as to which of the methods – CATPCA or simple sum – is more appropriate as a means of assessing household SES as an indicator of household resilience.

6.3 Poverty Estimates by Alternate Studies and Methods

The literature regarding the poverty and welfare of households within the countries of analysis was consulted in an attempt to find evidence in support of the results obtained in this study. The aim was to link alternate estimates of changes in national poverty for the chosen countries to the conclusions drawn from the comparisons of SES over time conducted in this chapter. An attempt was made to gather country poverty estimates from the Millennium Development Goals (MDG) Reports to keep in line with the poverty estimates used in the first chapter of this study.

From sections 6.1 and 6.2, the comparison of SES levels over time for Egypt showed an increase in the proportion of poor households between 2005 and 2008 by the CATPCA method, but the extreme poor were better off in 2008 than in 2005 as shown by a reduction in the mean SES score for cluster one as well as a fall in the minimum SES score from 2005 to 2008. The results from the simple sum method were not in agreement and showed a slight decrease in the proportion of poor households in Egypt over the same period, but a worsening in extreme poverty. Both methods showed a reduction in the per cent of households falling into the fifth cluster as well as a slight reduction in the mean SES score for cluster five and a decrease in the maximum SES score. The distribution of SES across households was not shown to change significantly between 2005 and 2008 by either method.

The Millennium Development Goals Report for Egypt for 2010 (Ministry of Economic Development – Egypt, 2010) reflected a three percentage point fall in the incidence of poverty in Egypt between 2005 and 2008. The incidence of poverty is calculated as the proportion of the population living below US$1.25 per day (Ministry of Economic Development – Egypt, 2010). This outcome is in line with the conclusions drawn from the simple sum results, but in contrast to results of the CATPCA method. The Egypt Human Development Report (HDR) for 2008 (UNDP, 2008) puts the poor, as a percent of the total population, at 20.7 per cent for 2004 and 19.6 per cent for 2006 based on the national poverty line for Egypt. The 2010 HDR indicates that 21.6 per cent of the population was poor in the 2008/09 period. These figures suggest an increase in the percent of the poor in Egypt between

2005 and 2008, which is in line with the conclusions drawn from the CATPCA results, but in contrast to results of the simple sum method.

For Kenyan households, the conclusions regarding changes in SES were similar for both the CATPCA and simple sum methods as discussed in the previous two sections. Briefly, for the period 2003 to 2008 in Kenya, the results suggest a decrease in the per cent of poor households; however the poorest of the poor were worse off. There was an increase in the level of wealth of the relatively richest cluster and a small increase in the per cent of wealthier households. The inequality in the SES of households appeared to worsen over the time period considered.

Similar conclusions were drawn from a study conducted by the World Bank in Kenya over the 1997-2005/06 time period (World Bank, 2008). The study showed a decrease in poverty by 5.5 per cent, but no reduction in the severity of poverty, and concluded that the poorest of the poor lost out in absolute terms. There was an increase in the income levels of the rich and inequality worsened. The study used the cost of buying the amount of calories sufficient to meet the recommend daily nutritional requirements and minimal non-food needs as a poverty threshold. The conclusions drawn from the World Bank analysis (World Bank, 2008) lend support to the results obtained in this study. However, outcomes of an investigation of poverty dynamics in Kenya over the 1997 to 2007 period by Suri *et al*. (2009) are somewhat different. Suri *et al*. (2009) also found a decrease in the proportion of the poor – poverty levels fell from 50 per cent to 37.6 per cent from 1997 to 2007 – however, their estimates showed an increase in the incomes of the poorest of 30 per cent and they concluded that the poorest of the poor were better off in 2007 than in 1997. Suri *et al*. (2009) defined an individual as poor if he/she fell below a pre-determined level of economic welfare. The incomes of the richest were found to have decreased by 20 per cent. The results from the Suri *et al*. (2009) study differ from the conclusions drawn from the changes in SES estimated for Kenya in this study. However, the time periods considered in each of the three studies discussed here differ slightly, which may account for a portion of the difference in outcomes.

For both the CATPCA and simple sum methods, the results for Mali indicate an increase in the per cent of poor households during the 2001 to 2006 period. Conversely the Poverty Reduction Strategy Paper for Mali 2006 (IMF, 2008) reports a decline in poverty between 2001 and 2005 that is attributed mainly to a fall in urban poverty. The paper indicates that there was also a reduction in the severity of poverty. This outcome is consistent with the conclusion drawn from the simple sum method results of a lessening in the level of extreme poverty. However, the CATPCA method results implied that the level of extreme poverty worsened in Mali between 2001 and 2006.

From the comparison of household SES estimates and rankings for Uganda for 2000 and 2006, it was concluded, from the CATPCA method results, that the per cent of poor households increased during the time period; additionally the level of extreme poverty increased and the distribution of household SES became more uneven over time. Conversely, the per cent of poor households in Uganda was shown to have decreased over the same period by the simple sum method. The level of extreme poverty appeared to have fallen and the distribution of household SES became more even over the 2000 to 2006 period according to the simple sum method results. Clearly, the two methods did not always produce the same outcomes. The results were similar for the two methods in that they both showed the per cent of rich households to increase from 2001 to 2006; additionally, the level of wealth of the richest cluster appeared to increase during the chosen time period.

The 2010 Millennium Development Goals Report for Uganda (Ministry of Finance, Planning and Economic Development - Uganda, 2010) reported poverty headcounts of 34 per cent (the per cent of the population living below one US dollar per day) for the 1999/2000 period and 31 per cent for the 2005/2006 period. These estimates indicated that there was a three percentage point drop in the per cent of the population living below the one US dollar per day poverty line between 1999/2000 and 2005/2006. This finding is in support of the conclusions drawn from the simple sum method results, but does not match the CATPCA method results.

The results of the Tanzania analysis using the CATPCA method and the simple sum method were not entirely in agreement. By both methods, the per cent of poor households and the per cent of rich households decreased from 2004 to 2007, but the level of wealth of the richest cluster was shown to have decreased by the CATPCA method and increased by the simple sum method. By the CATPCA method the level of poverty worsened while the simple sum method showed no change in the level of poverty. The evenness of the distribution of SES across Tanzanian households appeared unchanged between 2004 and 2007 by the CATPCA method, whereas the simple sum method showed a more uneven distribution in 2007.

The midway evaluation of the Millennium Development Goals for Tanzania (2000 - 2008) showed a decline of approximately 1.4 percentage points in the proportion of the population living below one US dollar per day between 2003/2004 and 2006/2007 (Poverty Eradication & Economic Empowerment Division, United Republic of Tanzania, 2008). These results support the findings in this study of a fall in the per cent of poor households in Tanzania between 2004 and 2007 by both the CATPCA and simple sum methods. Similarly, the Poverty and Human Development Report 2009 for Tanzania indicated that there was a fall in the proportion of households living on less than one US dollar per day between 2001 and 2007 (Research & Analysis Working Group, United Republic of Tanzania, 2009).

In this chapter, comparisons were made between estimated levels of household SES over time for five African countries. Two methods of generating the household SES scores were used for the same country data as a second comparison. The poverty literature was then consulted in an attempt to link changes in SES over time observed in this study to poverty estimates by alternate studies and methods. In summary, Table 6.3 compares the direction of changes in the per cent of the population allocated to the relatively poorest cluster over time by the CATPCA and simple sum methods to poverty trends reported in the various country MDG documents.

Table 6.3: The direction of changes in the per cent of the population allocated to the relatively poorest cluster over time by the CATPCA and simple sum methods compared to trends in poverty estimates reported in various MDG documents

Method	Increase/decrease in the proportion of poor households over time				
	Egypt	Kenya	Mali	Uganda	Tanzania
CATPCA	↑	↓	↑	↑	↓
Simple sum	↓	↓	↑	↓	↓
MDG Report	↓	n/a	n/a	↓	↓

Source: The increase/decrease for the CATPCA and simple sum methods are based on the author's calculations using the estimated household resilience scores and reflect increases or decreases in the per cent of households allocated to the relatively poorest cluster for each country over time. The increase/decrease for the MDG Report row was taken from the country MDG reports available from www.undp.org/mdg/reports.shtml. 'n/a' indicates that a MDG report for that time period was not available.

It was found that the two methods of generating the SES scores – the CATPCA and simple sum methods (refer to Chapter 4) – did not consistently produce the same results and, therefore, the conclusions regarding the changes in the per cent of the poor and the level of poverty over time did not always coincide. For Egypt, the results of the CATPCA and simple sum methods differed and support could be found in the literature for the conclusions drawn from the simple sum results. For Kenya, both methods produced similar results, for which support could be found in poverty estimates reported by the World Bank (2008) and Suri *et al.* (2009). The CATPCA and simple sum methods both showed similar changes in the per cent of the poor in Mali. However, the results were in contrast to trends reported by the IMF (2008). For Uganda, the CATPCA and simple sum method results differed and support for the simple sum method results and conclusions was found in the 2010 Millennium Development Goals Report for Uganda (Ministry of Finance, Planning and Economic Development - Uganda, 2010). Lastly, the results produced by the CATPCA and simple sum methods for Tanzania were in agreement with one another regarding changes in the per cent of the poor between 2004 and 2007. These results were supported by poverty estimates and trends reported by the Tanzania government in two separate documents (Poverty Eradication & Economic Empowerment Division, United Republic of Tanzania, 2008; Research & Analysis Working Group, United Republic of Tanzania, 2009).

From these comparisons it was clear that neither the CATPCA method nor the simple sum method received more support than the other and in the case of Mali, neither method was supported by the literature considered. Even within the poverty literature consulted there were differences in estimated poverty levels. The methods and data sources used to estimate the poverty levels were of considerable diversity. From the previous discussion, it is clear that these differences affect the outcomes to such an extent that different methods of estimating poverty levels and trends can produce contrasting results. Sabry (2009) suggests that if a large proportion of the population under study is considered to live near the chosen poverty line, then the variations in poverty estimates could be exaggerated as even slight differences in methodology could have large effects on the estimated numbers of the poor.

In conclusion, this chapter has shown that the SES index with household classification by cluster analysis was able to detect changes in household SES over time in the five chosen countries and often support for these changes could be found in the poverty literature. However, the choice of methodology – CATPCA vs. simple sum - in estimating the household SES scores did affect the results, producing, at times, contrasting conclusions regarding poverty changes in a number of countries. The simple sum method received more support from the poverty literature than the CATPCA method.

The index of SES with household classification by cluster analysis was developed as a means of estimating a score representing a household's level of resilience. The resilience score and the classification of households into SES groups is an attempt to identify a household's level of vulnerability and to track changes in household resilience over time. From the results of this chapter, it can be concluded that the classification of households into SES groups, by an estimated resilience score, does detect changes in household SES over time in the five chosen countries.

However, it is as yet unclear whether the changes observed are accurate reflections of changes in household resilience within the country and what specifically has resulted in the changes. Additionally, the household SES scores are relative to one another and not directly comparable across countries or over time, unless identical variables are used in each analysis. Therefore, the resilience score is limited in its ability to identify a household's level of vulnerability as the same score for households in two different analyses does not necessarily represent the same level of SES. However, the index of SES and the classification of households into SES groups by cluster analysis developed in this study was able to detect changes in SES over time and, therefore, may be used to monitor changes in household resilience. Future research is required to confirm whether the observed changes in household SES are accurate reflections of changes in household resilience, or whether the scores vary over time due to other factors or influences.

CONCLUSIONS AND RECOMMENDATIONS

This study set out to develop a household resilience score to identify households with low resilience and measure progress towards improved household resilience. Resilience is the ability of households to cope with risk. The purpose of the study originated from the first objective of the Framework of African Food Security (FAFS) of improved household risk management, and the indicator of progress towards this objective – proposed by the FAFS - a resilience score. The FAFS is the third pillar of the Comprehensive African Agricultural Development Programme (CAADP) established to stimulate agricultural growth in Africa. Progress made through the FAFS will contribute to the overall CAADP objective of achieving a growth rate sufficient to reach the first Millennium Development Goal.

From the literature it was clear that the assets owned by a household could potentially be used as a proxy for resilience. Therefore, an asset-based index could be used to estimate a socio-economic status (SES) score for a household, as an indicator of the relative resilience of the particular household, based on the premise that the level of asset ownership is an indication of a household's ability to cope with risk. It was proposed that the household resilience score could be estimated using an index of household asset ownership and access to certain facilities. Within the aim of the study were two objectives; the first, was to develop an asset-based index for use in the estimation of household socio-economic scores as an indication of household resilience, by comparing several methods of asset-based index construction. The second was to apply the index to data, from two different time periods for several African countries, to evaluate the ability of the resilience score to measure progress towards improved household resilience.

From a review of the literature related to asset-based indices it became clear that a number of methods of constructing such indices are available and no single method has been shown to be better than the others. Consequently, in this study, four methods of constructing an asset-based index were applied to the same data and the results compared. The data 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).

The decision to compare four different methods was motivated by a lack of consensus in the literature on the most appropriate means of constructing an index of SES. The four methods of index construction considered in this study were:

- the application of linear PCA to the chosen variables coded into dichotomous variables, as put forward by Filmer and Pritchett (2001);
- a method proposed by Kolenikov and Angeles (2009) of applying linear PCA to the variables once the categories of each of the categorical variables have been ranked in order of SES;
- the application of non-linear or categorical principal component analysis (CATPCA) to the variables as coded for the Kolenikov and Angeles PCA method; and
- a simple sum of assets technique.

The results from the application of each of the four indices to the country data were compared across several assessment criteria.

The comparison of methods showed that no single method of index construction outperformed the others across all of 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. The simple sum method produced a distribution of SES scores displaying the most uniformity as well as performing somewhat better in terms of internal coherence than the other methods. Generally, all four methods were robust to changes in the variables included in the index for the first and fifth quintiles: classification similarities declined across the middle quintiles. It was concluded that the choice of index construction method depends on the objective of the researcher in terms of which of the assessment characteristics is deemed most important. The time period available for analysis and the type of data to be analysed are further considerations. Of the four methods investigated, the simple sum method was the quickest to apply.

From the SES score frequency histograms and the differences in mean SES scores across quintiles, it was clear that the distribution of SES was uneven by all the methods for the countries analysed. The use of quintiles as group cut-off points assumes that the distribution of SES is uniform. Therefore, the use of quintiles as group cut-off points was not appropriate for the six countries analysed. The application of an arbitrary cut-off point, such as the quintile split, did not reflect the clustered nature of the household data. As an alternate to the quintile split, cluster analysis could be applied to the SES scores derived for each country. Cluster analysis is a technique that can be used to identify homogenous groups or clusters of cases in datasets. It was applied to the household SES scores estimated by the CATPCA method for each country.

The k-means cluster analysis technique was used in this study. K-means cluster analysis of the estimated SES scores by the CATPCA method with two, three and five clusters was investigated. A comparison of the two, three and five cluster solutions showed that the two cluster solution was not useful as the majority of the households were allocated to one broad cluster. The three cluster and five cluster solutions produced a better distribution of households: the three cluster solution resulted in slightly better cluster sizes, but the five cluster solution offered a more detailed separation of households into SES groups. The five cluster solution also provided a more even distribution of households with the differences in mean SES scores between clusters being more similar to one another than for the three cluster solution.

For the five-cluster solution, a larger proportion of the households in each country sample were allocated to the group of lowest SES for the four 'poorest' countries of the study (Tanzania, Liberia, Uganda and Mali), and to the second level of SES for the two relatively better off countries of the study (Kenya and Egypt). The highest SES level group (cluster 5) contained the lowest per cent of households for all six of the countries. Of the proportion of households allocated to cluster 5, the lowest per cent occurred for Tanzania – the 'poorest' country in the study – and the largest per cent for Egypt – the 'richest' country of study. The results showed that a greater proportion of households fell into relatively lower levels of SES, which is in contrast to the assumption of uniformity of SES made when using the quintile cut-off approach. The cluster analysis better reflected the clustered nature of the household data compared to the quintile cut-off method. The application of cluster analysis as a means of classifying a set of households into groups representing different levels of SES appears to be more effective than the use of quintiles: both in that it does not assume an even distribution of SES – as the use of quintiles does - and, if observed over time, it could provide a clear indication of changes in the per cent of households falling into the different groups of SES. In a further investigation of the use of cluster analysis in classifying households into groups of differing SES, it would be useful to validate the measure using data that include both the type of variables used to estimate an index of SES and information regarding household income and wealth and to run cross tabulations between the estimated cluster variable and variables of household income and wealth.

With regards to the first objective of the study, of developing a resilience score as a means of *identifying* households with a low resilience, it is important to note that the SES scores estimated using the principal component techniques were relative to one another and were not absolute values. As such, the same SES score for two households from different analyses did not necessarily represent the same level of resilience. The estimated scores could not be used to identify households at an absolute level of SES, but rather to identify households within a population that were more (or less) resilient than other households within the same population. The actual level of resilience depends, not only on the quantity of assets owned, but also the quality of the assets and their usefulness as a coping mechanism which may differ between and within countries. Accordingly, the estimated resilience scores should not be compared across countries. Firstly, because different variables were used in the construction of the country indices and the weights calculated for each variable using the PCA-based methods are relative to the other variables included in the index. Secondly, the actual value of a particular asset in coping with a shock depends on the nature of the shock and differs between and within countries and over time. If the shock is such that all households in an area are affected the resilience value of assets would fall as all households attempted to sell their assets. The resilience value of assets cannot be generalised across types of shocks, countries or time. This limits the usefulness of the tool in identifying vulnerable households as each time the measure is applied the resilience value of the chosen assets would have to be assessed for the specific area at that point in time in order to link an absolute level of resilience to the relative resilience score.

The second objective of the study was to develop a household resilience score that could be used to *measure progress* towards improved household resilience. The index of SES along with k-means cluster analysis was applied to household data from two different time periods for five African countries to determine whether the tool was able to detect changes in household SES over time and, therefore, whether the tool could be used to monitor changes in household resilience over time. The comparison of SES over time was conducted using both the CATPCA index and the simple sum index. The observed changes in SES between the two survey years for each country were then compared to changes in national poverty estimates for the respective countries over a similar time period.

From the results, changes in SES between the two survey periods were evident for both methods, as shown by changes in the per cent of households allocated to the five clusters of SES over time, as well as by changes in the mean SES score for each cluster and changes in the minimum and maximum SES scores for the country sample. However, the changes in SES over time were not consistently the same by the two methods. The simple sum index predicted trends in poverty over time more similarly to those reported in the literature considered than the CATPCA index.

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. Additionally, tracking the movement of a single household from one cluster to another over time could show the effect of policy interventions on a particular household's livelihood. 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.

The resilience score developed in this study was constructed using, and applied to, country level data. This means that rural and urban households were grouped together and the variables chosen for inclusion in the index were meant to reflect the resilience of both rural and urban households. Variables such as the ownership of livestock and farm implements were excluded from the analysis as they only represent wealth in the rural areas of the country. It is possible that rural households may have received lower SES scores in the analysis, not because they were less resilient than their urban counterparts, but because the types of assets they owned were not included in the analysis. The ability of the SES score to reflect household resilience could be improved by constructing separate rural/urban indices. There is, however, a trade-off in terms of the simplicity of country level indices and the additional expense of obtaining specialized information and data for location-specific indices.

The study made use of data on household asset ownership and access to services available in the DHS to develop a resilience score, based on the premise that asset ownership is an indication of a household's ability to cope. However, for assets to be useful as a coping mechanism they should have limited risk, a reasonable return and, importantly, they must retain their value during a shock (Dercon, 2001). These characteristics were not considered in this study and, therefore, it is likely that the actual resilience of the households analysed has been misjudged. Future research is required to investigate the nature of various household assets in an attempt to ascertain the effectiveness of a particular asset as a household coping mechanism. The nature of household assets, in terms of their potential return, associated risk and their ability to be mobilised during a shock, should be studied within a specific context: identical assets may not represent the same level of resilience to households across geographical locations or time.

Changes in household SES status over time were estimated for five African countries by comparing the per cent of households allocated to each of five clusters based on the estimated SES scores for the two most recent DHS data sets for each country. The period of time between the two years of analysis ranged from three years (Egypt) to six years (Uganda). An aspect for future research would be to determine how long it takes changes in household resilience, due to policy changes or programme interventions, to be reflected by changes in asset ownership and, therefore, changes in the estimated SES scores. This length of time is important as it influences the usefulness of the resilience measure in monitoring changes in household resilience: if the time taken for changes in household resilience to be reflected in the estimated SES scores is relatively long, then the tool may not be particularly useful, as it would only show changes in resilience long after they have occurred. A fuller understanding of the dynamic relationship between asset ownership and household resilience is required.

The use of assets as a means of identifying vulnerable households is not recommended unless combined with a detailed understanding of the asset-resilience relationship in the particular context. However, the resilience score developed in the study did display an ability to track changes in household poverty over time and could be used as a measure of progress towards improved household resilience. The resilience score tool has potential to measure progress towards improved household resilience and could be useful to policy makers in analysing the impact of household risk management interventions. Results from the application of the resilience measure over time could be used to inform future poverty and food insecurity interventions. The tool could give an indication of which risk management interventions are relatively more effective and should be continued and those that should be removed or modified. Future research is recommended, especially with regards to the actual value to a household of a particular asset in coping with a shock and how this value differs by location, over time and with different types of shocks.

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APPENDICES

APPENDIX A: SUMMARY OF FOOD SECURITY MEASURES

Indicator	Principles	Advantages	Disadvantages
Food Supply ~Haddad *et al* .,1997; Hoddinott, 1999; Wolfe & Frongillo, 2001; Webb & Thorne-Lyman, 2006; Perez-Escamilla & Segall-Correa, 2008	~Per capita energy availability calculated from food supply ~ Inputs: food balance sheets, energy intake coefficient of variation, single cut ~off point	~ Inexpensive ~ Data widely available	~ Do not consider problems of access to food and diet quality ~ High measurement error ~ Low standardization of data collection
Individual caloric intake ~Maxwell, 1996; Hoddinott, 1999; Migotto *et al* ., 2005; Swindale & Ohri-Vachaspati, 2005; Perez-Escamilla & Segall-Correa, 2008	~ Individual caloric consumption ~ Inputs: observation or recall over reference period, food consumption tables, nutrient requirements	~ Accurate measure of individual access to food ~ Captures intra-household differences in food consumption	~ Data collection expensive and time ~consuming ~ Difficult to estimate individual nutrient requirements ~ Requires reliable food consumption tables
Household caloric intake **~**Hoddinott, 1999; Coates *et al* ., 2007	~ Household food consumption estimated from recall of meals prepared ~ Inputs: recall over reference periods, food consumption tables, nutrient requirements	~ Based on recall; less time ~consuming, lower level of skill required by enumerators	~ Does not capture foods eaten outside of the household, or wastage within the household ~ Intra -household food consumption differences are not identified
Experiential -based ~Frongillo, 1999; Bickel *et al* ., 2000; Derrickson *et al* ., 2000; Tarasuk, 2001; Wolfe & Frongillo, 2001; Kaiser *et al* ., 2002; Nord *et al* ., 2002; Webb *et al.* , 2002; Coates *et al* ., 2003; Frongillo *et al* ., 2003; Gulliford *et al* ., 2003; Perez-Escamilla *et al* ., 2004; Coates *et al* ., 2006a, 2006b; Frongillo & Nanama, 2006; Melgar-Quinonez *et al* ., 2006; Swindale & Bilinsky, 2006; Coates *et al* ., 2007; Hackett *et al* ., 2007; Gonzalez *et al* ., 2008; Melgar-Quinonez & Hackett, 2008; Rafiei *et al* ., 2009	~ Household food security status estimated from household perception of its food insecurity ~ Inputs: survey to capture household perceptions, algorithm to covert scales into categories	~ Lower cost and quicker once survey has been developed ~ Comparable across countries if survey is standardized ~ Gives an understanding of the cause of food insecurity	~ Subject to intentional misreporting by respondents ~ Difficult to determine and standardize cut-off points ~ May require adaptation for each context

Appendix A: *Continued*

Indicator	Principles	Advantages	Disadvantages
Anthropometry ~Frankenberger, 1992; Cogill, 2003; Migotto *et al*., 2005; Scaramozzino, 2006; Perez-Escamilla & Segall-Correa, 2008	~ Body dimensions used to estimate levels of malnutrition ~ Inputs: weight, height, age	~ Highly standardized ~ Inexpensive ~ Frequently applied in national surveys (secondary data sources)	~ Nutritional status indicator, not specific to food security ~ 'Late' indicator of nutrition problems ~ Requires accurate data on individuals' age
Dietary diversity ~Hatloy *et al*., 1998; Hoddinott & Yohannes 2002; Ruel, 2002; Swindale & Ohri-Vachaspati, 2005; Swindale & Bilinsky, 2006; Faber *et al*. 2008	~ Number of food groups consumed over a given period ~ Inputs: household surveys	~ Data relatively simple and inexpensive to collect ~ Found to be correlated with other measures of food security ~ Comparable across regions	~ Does not capture food quantities therefore the severity of food insecurity can not be discerned
Income/ expenditure ~Migotto *et al*., 2005; Perez-Escamilla & Segall-Correa, 2008	~ Calories available to the household based on expenditure ~ Inputs: expenditure on food & other goods, foods consumed and their market value, food consumption tables	~ Can give an indication of the source of the food insecurity, diet quality vs. quantity ~ Identifies vulnerable households as well as food insecure ones	~ Indicates food availability ~ Data collection is costly and time consuming ~ Difficult to estimate food consumed outside the household

Appendix A: ***Continued***

Indicator	Principles	Advantages	Disadvantages
Coping strategies ~Hoddinott, 1999; Maxwell *et al* ., 1999; Christiaensen & Boisvert, 2000; Maxwell *et al* ., 2003; Hendriks, 2005; Maxwell *et al* ., 2008	~Assessment of a households' responses when faced with a food shortage ~ Inputs: household surveys, weightings of different behaviors	~ Easy and quick to implement ~ Captures vulnerability aspect ~ Easily understood by enumerators and respondents	~ Subjective measure ~ Context specific therefore results not comparable across regions
Vulnerability ~Webb *et al* ., 1994; Riley, 2000; Seaman, 2000; Devereux, 2001; Stephen & Downing, 2001; WFP, 2002; Scaramozzino, 2006	~ Dynamic, measures potential of falling into food insecurity in the future ~Inputs: household surveys, food security outcome indicators, production, climate, market and education information	~ Provide an early warning to potential food security allowing more time for intervention	~ Extensive data needs ~ Problems regarding selection and weighting of variables
Composite measures ~Christiaensen & Boisvert, 2000; Christiaensen *et al* ., 2000; Wolfe & Frongillo, 2001; Rose & Charlton, 2002; von Braun, 2007; Gentilini & Webb, 2008; Jacobs, 2009	~ Index of food security indicators ~ Inputs: food security and related indicators	~ Indices are generally comparable ~ Provides a relatively quick overview of the food security situation	~ Usefulness of the index depends on the reliability and accuracy of the indicators used ~ Problems regarding selection and weighting of indicators

Source: Author’s review of related literature

APPENDIX B: ESTIMATED SES SCORES BY THE CATPCA AND SIMPLE SUM METHODS, ACROSS FIVE AFRICAN COUNTRIES, FOR TWO TIME PERIODS

Egypt 2005 (CATPCA)

Cluster (C)	4	2	1	5	3	Total
N	1834	5274	7622	4936	2306	21972
%	8.3	24.0	34.7	22.5	10.5	100.0
Mean	-11.27	-5.09	-0.61	4.96	12.00	0.00
Difference btw Qs		6.18	4.48	5.57	7.04	
Standard deviation	2.37	1.49	1.44	1.79	2.59	6.38
Minimum	-19.96	-8.27	-2.93	2.16	8.52	-19.96
Maximum	-8.28	-2.93	2.15	8.52	18.77	18.77

Egypt 2008 (CATPCA)

Cluster	2	4	5	3	1	Total
N	1979	5998	5853	3672	1466	18968
%	10.4	31.6	30.9	19.4	7.7	100.0
Mean	-9.00	-3.62	0.50	5.26	11.82	0.00
Difference btw Qs		5.38	4.11	4.76	6.56	
Standard deviation	2.15	1.33	1.28	1.60	2.50	5.60
Minimum	-17.29	-6.41	-1.67	2.81	8.53	-17.30
Maximum	-6.41	-1.67	2.80	8.51	18.10	18.10

Egypt 2005 (Simple sum)

Cluster (C)	4	1	2	5	3	Total
N	861	3418	12441	4128	1124	21972
%	3.9	15.6	56.6	18.8	5.1	100.0
Mean	3.71	7.94	11.62	14.71	17.91	11.64
Difference btw Qs		4.22	3.68	3.09	3.20	
Standard deviation	1.42	1.07	1.05	0.78	1.20	3.07
Minimum	0.00	5.83	9.80	13.19	16.37	0.00
Maximum	5.64	9.74	13.12	16.23	23.00	23.00

Egypt 2008 (Simple sum)

Cluster (C)	4	5	1	2	3	Total
N	694	2995	11167	3494	618	18968
%	3.7	15.8	58.9	18.4	3.3	100.0
Mean	3.60	7.96	11.64	14.63	17.64	11.51
Difference btw Qs		4.36	3.68	2.99	3.01	
Standard deviation	1.41	1.05	1.04	0.75	0.90	2.88
Minimum	0.00	6.00	9.88	13.17	16.27	0.00
Maximum	5.27	9.49	13.12	16.04	22.00	22.00

Kenya 2003 (CATPCA)

Cluster (C)	5	2	3	4	1	Total
N	3706	2645	1206	650	354	8561
%	43.3	30.9	14.1	7.6	4.1	100.0
Mean	-4.30	-0.63	4.28	9.95	16.85	0.00
Difference btw Qs		3.67	4.90	5.67	6.91	
Standard deviation	1.17	1.21	1.57	1.79	2.06	5.64
Minimum	-6.64	-2.45	1.86	7.19	13.45	-6.64
Maximum	-2.46	1.85	7.17	13.43	20.42	20.42

Kenya 2008 (CATPCA)

Cluster	3	4	5	2	1	Total
N	2741	2955	1800	1105	456	9057
%	30.3	32.6	19.9	12.2	5.0	100
Mean	-6.51	-2.05	3.13	9.09	18.04	0.00
Difference btw Qs		4.46	5.18	5.97	8.95	
Standard deviation	1.54	1.38	1.61	2.00	2.46	6.73
Minimum	-9.78	-4.22	0.66	6.27	13.70	-9.78
Maximum	-4.22	0.65	6.25	13.67	23.14	23.14

Kenya 2003 (Simple sum)

Cluster (C)	1	2	5	3	4	Total
N	4695	2722	508	573	63	8561
%	54.8	31.8	5.9	6.7	0.7	100.0
Mean	0.60	2.28	4.00	5.46	7.06	1.71
Difference btw Qs		1.68	1.72	1.46	1.60	
Standard deviation	0.49	0.45	0.04	0.50	0.25	1.57
Minimum	0.00	1.71	3.44	5.00	7.00	0.00
Maximum	1.37	3.06	4.34	6.00	8.00	8.00

Kenya 2008 (Simple sum)

Cluster (C)	3	4	5	2	1	Total
N	2926	3009	2575	476	75	9057
%	32.3	33.2	28.4	5.3	0.8	100
Mean	0.49	2.48	4.72	7.45	9.11	2.79
Difference btw Qs		1.99	2.25	2.73	1.66	
Standard deviation	0.50	0.50	0.76	0.50	0.32	2.15
Minimum	0.00	2.00	3.60	7.00	9.00	0.00
Maximum	1.44	3.44	6.03	8.03	10.00	10.00

Mali 2001 (CATPCA)

Cluster (C)	5	1	4	2	3	Total
N	7077	3543	964	479	268	12331
%	57.4	28.7	7.8	3.9	2.2	100.0
Mean	-2.25	0.22	5.15	11.19	18.04	0.00
Difference btw Qs		2.47	4.93	6.04	6.85	
Standard deviation	0.77	0.97	1.63	1.74	2.23	4.24
Minimum	-4.77	-0.94	2.81	8.33	14.78	-4.77
Maximum	-0.95	2.81	8.32	14.76	23.34	23.34

Mali 2006 (CATPAC)

Cluster	4	2	1	5	3	Total
N	8555	2513	1162	522	246	12998
%	65.8	19.3	8.9	4.0	1.9	100.0
Mean	-2.81	1.20	7.11	13.97	22.19	0.00
Difference btw Qs		4.02	5.91	6.86	8.22	
Standard deviation	0.97	1.44	1.79	2.17	2.85	5.37
Minimum	-5.69	-0.75	4.30	10.77	18.34	-5.69
Maximum	-0.75	4.30	10.76	18.29	29.43	29.43

Mali 2001 (Simple sum)

Cluster (C)	4	2	1	3	5	Total
N	2530	7322	1865	461	153	12331
%	20.5	59.4	15.1	3.7	1.2	100.0
Mean	0.00	1.49	3.25	5.42	7.27	1.67
Difference btw Qs		1.49	1.76	2.17	1.85	
Standard deviation	0.02	0.50	0.43	0.49	0.45	1.44
Minimum	0.00	0.88	2.45	5.00	6.64	0.00
Maximum	0.68	2.31	4.11	6.23	8.00	8.00

Mali 2006 (Simple sum)

Cluster (C)	1	5	4	2	3	Total
N	5563	5869	1136	300	130	12998
%	42.8	45.2	8.7	2.3	1.0	100.0
Mean	0.61	2.60	5.73	8.39	10.38	2.24
Difference btw Qs		1.99	3.13	2.66	1.99	
Standard deviation	0.49	0.73	0.80	0.51	0.65	2.05
Minimum	0.00	1.70	4.22	7.07	10.00	0.00
Maximum	1.47	4.17	7.04	9.00	12.00	12.00

Uganda 2000 (CATPCA)

Cluster(C)	2	4	5	1	3	Total
N	3409	2405	1264	587	220	7885
%	43.2	30.5	16.0	7.4	2.8	100.0
Mean	-4.28	-0.57	4.50	10.53	18.65	0.00
Difference btw Qs		3.71	5.08	6.03	8.12	
Standard deviation	1.20	1.26	1.54	1.90	2.99	5.59
Minimum	-7.79	-2.36	2.10	7.72	14.78	-7.79
Maximum	-2.36	2.09	7.71	14.74	26.23	26.23

Uganda 2008 (CATPCA)

Cluster	1	3	1	4	2	Total
N	4022	2826	1126	614	282	8870
%	45.3	31.9	12.7	6.9	3.2	100
Mean	-5.21	-0.52	6.19	14.32	23.6	0.00
Difference btw Qs		4.69	6.71	8.13	9.28	
Standard deviation	1.54	1.62	2.13	2.51	3.12	7.24
Minimum	-8.7	-2.78	3.03	10.59	19.32	-8.70
Maximum	-2.78	3.02	10.54	19.22	31.43	31.43

Uganda 2000 (Simple sum)

Cluster(C)	5	1	2	4	3	Total
N	3748	2698	1028	312	99	7885
%	47.5	34.2	13.0	4.0	1.3	100.0
Mean	0.46	2.42	4.32	6.40	8.40	1.97
Difference btw Qs		1.96	1.90	2.09	2.00	
Standard deviation	0.50	0.49	0.47	0.49	0.60	1.85
Minimum	0.00	1.97	3.42	6.00	8.00	0.00
Maximum	1.42	3.31	5.16	7.00	10.00	10.00

Uganda 2006 (Simple sum)

Cluster(C)	1	3	4	5	2	Total
N	1949	4709	1449	543	220	8870
%	1949.0	4709.0	1449.0	543.0	220.0	8870.0
Mean	0.43	3.53	6.73	9.87	12.65	3.99
Difference btw Qs		3.10	3.20	3.14	2.77	
Standard deviation	0.50	1.08	0.80	0.81	0.75	2.99
Minimum	0.00	2.00	5.15	8.56	12.00	0.00
Maximum	1.70	5.09	8.09	11.00	15.00	15.00

Tanzania 2004 (CATPCA)

Cluster (C)	5	1	3	4	2	Total
N	6021	2062	969	446	237	9735
%	61.8	21.2	10.0	4.6	2.4	100.0
Mean	-3.02	0.87	6.04	12.95	20.02	0.00
Difference btw Qs		3.89	5.17	6.91	7.07	
Standard deviation	0.98	1.31	1.76	2.05	2.24	5.33
Minimum	-5.67	-0.98	3.69	9.75	16.73	-5.67
Maximum	-0.99	3.67	9.75	16.66	26.49	26.49

Tanzania 2007 (CATPCA)

Cluster	3	5	2	4	1	Total
N	4925	2114	767	544	147	8497
%	58.0	24.9	9.0	6.4	1.7	100
Mean	-3.22	0.73	6.05	12.48	19.74	0.00
Difference btw Qs		3.95	5.32	6.42	7.26	
Standard deviation	1.09	1.36	1.75	1.92	2.69	5.29
Minimum	-6.02	-1.17	3.60	9.48	16.29	-6.02
Maximum	-1.19	3.57	9.48	16.23	27.37	27.37

Tanzania 2004 (Simple sum)

Cluster (C)	5	2	3	1	4	Total
N	2838	5837	671	330	59	9735
%	29.2	60.0	6.9	3.4	0.6	100
Mean	0.00	1.48	3.39	5.46	7.08	1.35
Difference btw Qs		1.48	1.91	2.07	1.62	
Standard deviation	0.03	0.50	0.49	0.50	0.28	1.33
Minimum	0.00	1.00	2.44	5.00	7.00	0.00
Maximum	0.61	2.11	4.04	6.00	8.00	8.00

Tanzania 2007 (Simple sum)

Cluster (C)	3	2	4	5	1	Total
N	1982	5661	594	239	21	8497
%	23.3	66.6	7.0	2.8	0.2	100
Mean	0.00	1.87	4.44	6.23	8.19	1.75
Difference btw Qs		1.87	2.57	1.78	1.96	
Standard deviation	0.05	0.78	0.50	0.42	0.40	1.52
Minimum	0.00	1.00	4.00	6.00	8.00	0.00
Maximum	0.87	3.12	5.12	7.00	9.00	9.00