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# ANALYZING NUTRITIONAL IMPACTS OF PRICE AND INCOME RELATED SHOCKS IN MALAWI AND UGANDA

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**Abstract:** The recent food price crisis and the following global economic recession have led to large increase in the number of people to suffer from hunger. While the impacts can be measured with precision ex post, for policy-makers it is critical to get a sense of likely impacts ex ante to plan approaches to mitigate these impacts. In this paper we adopt a very simple simulation approach to analyze how changes in prices of specific food groups such as maize prices or prices for staple food as well as how negative short-term income shocks on household affect the calorie consumption of individuals and how these changes affect food poverty. We illustrate our approach using household survey data from Malawi and Uganda. We find that food poverty is of particular concern in Malawi and Uganda and we find large variations within countries in food poverty. We find that price shocks for staple foods have a very large impact on food security in both countries while the impact of income shocks is considerably smaller. Moreover, we find that the food security impacts of price shocks are substantially larger in Malawi than Uganda as people in this country rely much more on staple foods for their caloric consumption. This paper demonstrates that it is possible to estimate food security impact of price and income shocks ex ante in a relatively straight-forward fashion that can be done relatively quickly for cross-country assessments of the likely impacts of shocks on food security.

**Keywords: Economic recession, huger, food poverty, food security, income shock. Malawi, Uganda**

**JEL Classification: Q01, Q15, D13, I32**

## 1. Introduction

The recent food price crisis and the following global economic recession have (presumably) led to large increase in the number of people to suffer from hunger (FAO 2008, 2009, 2011a). The major concern related to recent increases in food prices as well as of negative income shocks, which affects many household in Sub-Saharan Africa, is the possible reduction in food calorie availability on a per capita basis resulting in increasing food poverty and food insecurity. However, although there is a general agreement in the literature on the definition of food security, i.e. meaning the access to food by individuals and households and not only the availability of food in a country, at the same time, it is exceedingly difficult to come up with reliable estimates of the impact of the food price and related crises on hunger. Although data availability has been improved within the last years, data limitations are still the main constraint analyzing impact of income and price shocks on food poverty. As a result, one will only know the impact of the food price crisis on food security and poverty when household surveys from the affected countries are analyzed. This will imply a time lag of several years between the event and the estimates of its effect and makes the information much less useful for policy-makers.

As argued by de Haen et al. (2011), to be useful for a comprehensive assessment of food insecurity, indicators of food insecurity should provide answers to at least three questions, namely: Who are the food-insecure? How many are they? And where do they live? If the purpose of the measurement goes beyond assessment and includes the design of policy responses, the indicators should also help answering the more ambitious question: Why are people food insecure? While that paper dealt with chronic food insecurity, identifying those who become food insecure as a result of price and output crises, it is at least as important, if not more important to identify those affected by short-term crises who might be threatened with acute hunger.

The most commonly used indicator used in public debates of food insecurity is the FAO indicator of undernourishment which calculates the number of people with insufficient caloric access and which is also used to monitor MDG 1. The FAO indicator is based on food supply at the national level and not on direct data of individual's access to food. It attempts to measure the access individuals have to calories in a country.[2] Thus it first estimates a three year moving average of per capita calorie availability from food balance sheets, trade statistics, and assumptions about waste, then applies a distributional assumption to account for inequality in caloric availability, and then identifies the share of the population that has fewer calories than recommended by a norm. At best, it is a rough proxy for the long-term availability of calories in a country, and it only available with a time lag of 2-3 years.[3] Therefore, this indicator is unsuitable to assess the impact of food crises and economic recessions on hunger as the only driver of changes in hunger over time in a country using this FAO approach is the mean caloric availability which is largely driven by agricultural production and exports, and little affected by changes in people's entitlements to food (see de Haen et al. 2011; Sen, 1983). Although food availability at the national level is a necessary condition for households to have access to food, it is not a sufficient

[2] As stated in the SOFI Report 2011, the FAO is currently revising the FAO measure of hunger to provide more frequent updates and include more information (FAO 2011a).

[3] There have been attempts to use this general approach to provide more timely assessments of impacts, but the methods used have not been validated so far. See de Haen et al. (2011) for a discussion.

condition. Households must also have enough resources to meet their basis need and acquire enough amount of food. There is a broad literature that debates the limitations of the FAO approach to measure hunger based on national estimates of food supply for policymaking and planning interventions (see, e.g. Svedberg 2000, 2003; Aduayom and Smith 2001; Senauer 2003; Klasen 2003, 2008; de Haen et al. 2011).

The most direct alternative to measuring caloric shortfall is to analyze information from household surveys to measure food availability and food insecurity on a per day and per capita basis. Recently, the International Food Policy Research Institute (IFPRI) has published an estimate of hunger in 12 sub-Saharan African countries (Smith et al 2006). Based on an analysis of household surveys the authors found that in the late 1990s 59 percent of the population was food energy deficient. This result was in stark contrast to estimates by the Food and Agriculture Organization of the United Nations (FAO), based on food balance sheets for the same countries, the same period and using the same criterion of energy deficiency as an indicator of undernourishment. The FAO prevalence estimate was 36 percent, hence significantly lower.[4] Not only did the two methods differ with respect to the mean level of undernourishment, the ranking of the 12 countries differed as well. In other words, there is not even a close correlation between the two estimates. This example of divergent estimates of hunger, measured with the same criterion, namely food energy deficiency, suffices to raise interest in a thorough comparative assessment of the various methods used to estimate hunger.

As argued by de Haen et al. (2011), using food consumption surveys has a range of advantages vis-à-vis the FAO method. As one measures caloric deficiency directly, one does not need to rely on a problematic assumption about the distribution of calories. Also, the groups affected can be directly identified and the indicator is actionable and useful for policy purposes. The main problem, for the use as a measure of short-term assessments of food insecurity, is that these surveys take place rather infrequently, are costly, and often necessitate many months of fieldwork and data cleaning before they are available for analysis; they may be the best approach for an ex post assessment, but the time lags are substantial so that their use for policy-makers, who need actionable information in a food crisis, is limited.

To use these surveys nevertheless for assessments of short-term food security fluctuations, one could also use this household-survey based approach to then simulate the impact of price and income changes on this caloric shortfall. Since these surveys also contain information on food prices and household incomes or total expenditures, calorie price and income elasticities can be estimated for the population as a whole as well as for population subgroups. These elasticities, together with the results on household food security, can then be used to predict changes in the prevalence of undernourishment due to price and income changes (see de Haen et al. 2011). There is an increasing body of literature that estimates price elasticities of food demand in Africa (see, e.g. Abdulai and Aubert (2004a, b) for Tanzania, Bouis et al (1992) for Kenya, von Braun et al (1991) for Rwanda, Strauss (1984) for Sierra Leone, and Skoufias (2009) for Mexico). These studies are based on rather detailed simulation methods that address this issue for individual countries. For example, Ecker and Qaim (2010) have recently extended such an approach, which goes beyond

[4] For the respective numbers by country, see Table A1.

calories and also captures micronutrient deficiencies and related price and income elasticities. They show that food price changes have different impacts on the consumption of micronutrients. For example, higher maize prices can lead to a shift in the micronutrient composition towards cheaper food that reduces the consumption of certain micronutrients. They also find that changes in income have micronutrient neutral effects of calorie consumption. Alderman (1986) and Anríquez et al (2010 and 2010a) have also used household survey data to assess the possible effects of staple food price increases on household's food consumption and undernourishment. The authors find that food price increase reduce the mean calorie availability and increase inequality in its distribution, therefore, worsening the situation of those who were already most vulnerable to food insecurity.

While these are excellent ways of pursuing this issue in some detail, it may be useful to use slightly less involved methods over a larger range of countries to assess the impact of food and economic crises on hunger. This is what we plan to do here. The aim is therefore to provide an approach that allows for a timely, ex ante, and cross-country comparable assessment of the impact of price and income shocks on food security.

The advantage of this approach (vis-à-vis the FAO method) is that it links the issue of food insecurity directly to the Sen's entitlement approach which has proven to be the most robust way to understand famines. Sen (1983) identified changes in endowments (such as employment opportunities or assets) or changes in the 'exchange entitlement mapping' that turn endowments into food as the key drivers of famines. In other words, famines occur because people lose their asset base due a crisis or they starve because food prices have increased (relative to the price of labor or other products), exactly the issues we like to analyze here.

Another advantage of this approach is its close linkage to empirical assessments of income poverty. As many poverty lines are actually based on a certain pre-defined basket (e.g. Ravallion, 1994), income poverty increases if people lose incomes or prices for their basket has gone up, again the issues we are particularly interested in.

In particular, we adopt a very simple simulation approach to analyze how changes in prices of specific food groups such as maize prices or prices for staple food as well as how negative short-term income shocks on household income affect the calorie consumption of individuals and how these changes affect food poverty in the very short-term.

One should be aware that this approach is based on a very simple parametric estimation between income and food consumption, which does not take into account any behavioral changes of the household induced by the negative income shocks. We thus assume that households are unable to deal with food price increases by substituting towards other foods. While we believe this to be a reasonable assumption in the very short term, in the medium term households will surely shift their food consumption habits to reflect relative prices. And some households might change their food basket in the shorter-term as a result of lower resource endowments from expensive food items to more affordable food items in order to secure their minimum energy requirements to maintain their physical health and activity. However, the objective of this paper is not to estimate income and price elasticities of food demand and thus study these behavioral responses (see, e.g. Ecker and Qaim 2010) but to investigate, in line with Sen's entitlement approach, how a negative income shock changes the entitlements to food for the country and for population subgroups in the very short-run. By excluding any behavioral responses, we can direct assess differences in changes by socio-economic subgroups in crisis situations, where the ability to switch to other foods is not easily possible. Our assessment will not include these second-round adjustments (which have been analyzed in some detail in the in-depth studies mentioned above), but focus on the first-order impact of income and price shocks.

This information already provides us with very important new insight with respect to ensure food security within countries as it identifies immediately how a crisis affects the ability of households to command food[5].

In doing so, we use calorie consumption per day and per capita as an indicator of food security and investigate food poverty, and the impact of price and income shocks on food consumption and food poverty. Thereby, we take into account within-country differences by socioeconomic characteristics. To illustrate our approach, we use household surveys from Malawi and Uganda to first determine the share of households that have insufficient command over calories and then estimate the impact of rising food prices and various income shocks on this caloric deficiency. First, data about food consumption from purchases, own production, gifts or in-kind payments are converted into metric units and converted into calories per capita and day. This information is then used to analyze food security and insecurity of individuals and by socioeconomic characteristics. Second, we will estimate the calorie-income relationship. Third, we will use this relationship to estimate to what extent falling real incomes (brought about by rising prices or various income shocks) will affect the number of calorie-deficient households.

For our country case studies, we find that food poverty is of particular concern in Malawi and Uganda and we find large variations within countries in food poverty. Price increases (either local or international) of maize and/or staple food increases food poverty, especially among the poorer population who cannot shift their food consumption pattern towards other (mostly more expensive) food items. We also find that short-term negative income shocks increases food poverty. More specifically, we find that price shocks for staple foods have a very large impact on food security in both countries while the impact of income shocks is considerably smaller. Moreover, we find that the food security impacts of price shocks are substantially larger in Malawi than Uganda as people in this country rely much more on staple foods for their caloric consumption.

The rest of the paper is organized as follows. In section 2, we describe the approach of the empirical analysis of estimating food poverty based on calorie per day and capita consumption and how we simulate how negative price and income shocks would affect food poverty. In Section 3, we describe the data we use for our analysis and discuss some of their advantages and limitations. In section 4, we present the results, starting with food security and food poverty profiles and then present our simulation results. In section 5 we conclude and provide an outlook for further research.

[5] As we are only considering entitlements to food, we are unable to study the impact of physical availability (or lack thereof) of food in a particular market, assuming that ultimately this would be captured by the price response.

## 2. Empirical Analyses of Income and Price Shocks on Food Availability

The empirical approach of the paper is divided into three steps. In a first step, we provide a description of food consumption per day and per capita across the countries in our sample at the national level as well as examine within country differences by population subgroups. In particular, we focus on differences in food consumption by region, rural and urban areas, income quintiles, sex of the household head, and by education of the household head. In doing so, we closely follow the report of Smith et al (2007). The descriptive analysis provides us with first insights of level of food availability and variations within and across countries.

After the description of the level and distribution of food availability across and within countries, in a second step, we then attempt to examine changes in endowments and exchange rates of food in line with Sen's entitlement approach on food consumption and thus on the risk of food poverty. We start with changes in household's endowments situation. We study how a negative income shock (that affects all households equally) changes the food availability of the country and identify, which population subgroups suffer most from such an income shock and which population subgroups are less affected. In doing so, we adopt a very simple approach to simulate the impact of short-term shocks on household food consumption.

We know from the empirical literature on food security and undernutrition that income and undernourishment and undernutrition are closely related. Higher incomes are associated with lower rates of undernutrition and undernourishment, i.e. higher levels of food availability (see, e.g. Sibrián 2009). Figure 1a shows the relationship between calorie consumption versus GDP per capita for several countries of the world in the year 2005 based on data from the FAO statistics on food security (FAO 2011b) and from the World Development Indicators (World Bank 2010). Figure 1a shows a strong positive correlation between calories per day and capita and GDP per capita PPP. With increasing income levels, food consumption is also rising, while largest increases are found at relatively lower levels of income. At higher level of GDP per capita (around 20,000 USD PPP), the increases decline. The graph indicates a relationship between GDP per capita and food availability that follows a logarithmic function. Figure 1b illustrates this, by showing the relationship between the log calories per day and per capita and log GDP per capita. The fitted correlations line shows a clear linear positive relationship (see also Sibrián 2009).

We take this relationship to estimate the impact of negative income shocks on food availability using household survey data. In particular, we apply a simple OLS regression of calories per day and per capita on log household income/expenditure assuming the following functional form based on the aggregated data from Figure 1:

$$\hat{y}_i = \underset{(\text{s.e. } 19.72)}{\underset{112}{\beta_0}} + \underset{(\text{s.e. } 171.73)}{\underset{306}{\beta_1}} \ln(x_i) + u_i, \qquad (1)$$

where $\hat{y}_i$ refers to the estimated calorie availability of individual i, and $\beta_1 \ln(x_i)$ to the log of household income/expenditure per capita of household *i*. The results provided here are the regression results based on the macro information from Figure 1. After having estimated equation (1) for each country, we are able to predict changes in the calorie per day and per capita if income changes as a result of a negative income shock. The changes in food availability per day and capita are obtained by applying equation (2).

$$y_{new} = y_{actual} - [\beta_1 \ln(x_i - x_i^*)] \quad (2)$$

In equation (2), new (after shock) quantity of calories per day and capita $y_{new}$ are obtained by subtracting from the actual observed quantity $y_{actual}$ amount of calories that are assumed to decrease as a results of changes in income before and after the shock $\Delta x_i = x_i - x_i^*$, where $x_i^*$ is the income after the negative shock have occurred. Using the coefficient $\beta_1$ from equation (1), we are then able to calculate the amount of calories of household *i*. Graphically, the negative income shock corresponds to a downshift of the estimated line between income and calorie per capita in Figure 1a. This new (after shock) distribution of calorie availability per day and capita can then be used to calculate food poverty at the national level as well as by socioeconomic characteristics. This allows us to study, first, how a negative income shock changes the amount of food available on a per day and per capita basis, and, second, to examine, which population subgroups are most strongly affected by such income shocks.

In a third step, we attempt to examine how changes in exchange rates of food can increase the risk of food poverty across countries and within countries by population subgroups. In doing so, we introduce a very simplistic approach to study changes in food consumption if prices of certain food items or food groups increase as observed in recent years in many developing regions. For example, between 2005 and 2007, the global maize price rose by 80% (Anríquez et al 2010).

We proceed as follows. The most important calorie resource in many African countries is staple foods, e.g. maize, which was at the same time most strongly affects by increases in prices. In line with these recent price increases, we study how increases in staple food prices in general and maize prices in particular affect the risk of food poverty. In this paper, we assume a priced increase of staple food or maize by 100%. To examine the effect of price changes on food availability, assuming no behavioral responses to these changes, we simply assume that households are forced to consume that actual percentage change less of staple food (maize). This means that a price increase by 100% is translated into halving the amount of calories consumed from staple food (maize).

Again, this is clearly an extreme assumption as households are likely to reduce their consumption of more expensive foods and non-food items more than that of staple foods. But the aim is here first to see the first round impact of affected populations to be able to identify them clearly. Using this assumption, we obtain a new (after price increase) calorie per day and per capita distribution for each country for which we can then calculate any types of food poverty indicators across countries and also by population subgroups. As already mentioned above, we do not address any behavioral changes as response to price changes. This simple simulation has the aim to illustrate how chances in the exchange rate of food (items) within Sen's entitlement approach can increase the risk of food poverty within a country and of specific population subgroups leaving all other things constant.

We are aware that this assumption might be ultimately too strong. In a robustness check we will simulate the effect if the food price shock is treated as an equivalent income shock allowing households to adjust to the rising food prices in their 'normal' pattern of expenditure. More concretely, we are first calculating the household-specific income shock the maize price increase induced (maize quantity*maize price), and then investigate how this income shock reduces caloric availability assuming the normal spending patterns of households; this will effectively mean that households that consumed more maize will be more heavily affected by the shock.

To analyze food poverty across countries and within countries across population subgroups, we apply the FGT class of poverty indicators (Foster et al 1984) to our observed and simulated calorie per day and capita distribution, but in principle any poverty measures could be applied. An addition, we also provide the Gini coefficient to assess inequality in food consumption.

## 3. Data

### *3.1. Data Sources*

Smith et al (2006) have shown in great detail the advantages of household survey data over the national FAO estimates to analyze food security and food poverty across countries and within countries across population subgroups. The advantages have been summarized recently by Haen et al (2011), chief among which is that it measures food insecurity directly at the household level and thus generates actionable information that can be used to design and monitor intervention programs. Another advantage of relying on household survey data to analyze food security is that household surveys contain rich information on the socioeconomic characteristics of the household and individuals allow to disaggregate the analysis and to study within country differences by population subgroups. The socioeconomic characteristics we examine in this paper are region of the residence, urban or rural residence, economic status measures by household wealth quintiles, sex of household head, and educational attainment of the household head.

On the other hand, to analyze food consumption at the household and/or per capita level imposes critical and ambitious data requirements.[6] First, household surveys usable for calculating food availability must include a module on food consumption containing the consumption at least of production and purchases of several food items as well as respective amounts in standardized units. Second, to analyze variations in food availability and food poverty by population subgroups, the survey must include a module on socioeconomic characteristics such as income, education, and region. Although the availability of living standard surveys have been increased extensively within the last years, there are still many countries, for which national representative surveys including information on food consumption and socioeconomic characteristics are missing, especially in Sub-Sahara Africa. Therefore, data limitations are still the mayor constraint for the kind of analysis done in this paper.

To illustrate our simple approach to analyze the relationship between calorie consumption per capita and shocks in food prices and negative income shocks, we use household survey data from Malawi and Uganda.

[6] See also Smith et al (2006) for a related discussion.

The Malawi data comes from the Second Integrated Household Survey (IHS-2) 2004/2005 conducted by the National Statistical Office of Malawi and the World Bank. The survey is part of the Living Standard Measurement Surveys (LSMS). The HIS-2 is national representative, based on a two-stage stratified sampling design (NSO 2005). The IHS comprises 11,280 households in urban and rural areas. The recall period for food consumption is 7 days. The HIS-2 includes a module on food consumption based on purchases, own production, and gifts for 108 food times.[7]

The Uganda data comes from the Uganda National Household Survey 2005/2006 (UNHS) conducted by the Uganda Bureau of Statistics (UBOS). The UNDHS collects information on socioeconomic characteristics at the household and community level as well as information on agriculture. The data set contains around 7,400 households in urban and rural areas based on a selection of a sample of about 750 Enumeration Areas (EAs). Information on food consumption is based on purchases, own production and in kind transfers for 61 foot items. The recall period for food consumption is 7 days.

Besides the fact that the data for Uganda and Malawi include both a module on food consumption as well as on a socioeconomic module, an additional advantage of the Malawi Integrated Household Survey 2004/2005 and the Uganda National Household Survey (2005/2006) is that the data collection covers a one year period (e.g. from March 2004 through March 2005 in Malawi and May through April in Uganda). This captures the seasonality and variances of agricultural production and consumption and makes the observed food availability quantities more precise.[8]

### *3.2. Estimates of Food Availability*

Before we are able to examine across country and within country variations in food availability and food poverty, we need to calculate food availability at the per capita level. As measure of food availability we calculate calorie availability per day and per capita. This indicator is based on the conceptual framework for food and nutrition security described by Smith et al (2007) based on Frankenberger et al (1997) and UNICEF (1998). In calculating our food availability indicator we closely follow the approach of Anríquez et al (2008), Smith and Subandoro (2007), Sibrián et al (2008), Ecker and Qaim (2010).

The household information on food consumption comes from own production, purchases and gifts or in kind transfers.[9] Often these quantities are reported in non-metric units such as bunches or cans. Anríquez et al (2008), Smith and Subandoro (2007) provide a detailed description on how to calculate food consumption. In a first step, to calculate calorie consumption for each household member, all quantities of consumed food items are converted into standard units, in our case grams. In a second step, to calculate calorie intake amounts consumed by household members based on the reported food quantities, we use conversion factors of the World Food Dietary Assessment System (FAO 2010a). Since there are not particular conversion factors for Malawi, we rely on conversion factors from Senegal and Kenya.

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[7] See Table A2 for information on the data sources by country.
[8] See section 3.4 on data limitations blow.
[9] See Table A2.

For each household in our sample we then aggregate the total amount of calories consumed within the recall period (7 days) into five main food groups, namely staple food, pulses, vegetables and fruits, animal products, and meal complements. For each household, the total amount of calorie availability is then divided by the household size to obtain calorie availability per capita per day. Since we do not know from our data how the available amount of food is distributed between household members, we assume that food is equally distributed between all household members.[10]

### 3.3. Estimation of food poverty

Typically, food insecurity indicators are measures at the household level or at a per capita based on quantities of calorie consumption (see, Smith and Subandoro (2006) for a detailed description of food security indicators). To estimate food poverty, we focus on the measure of undernourishment. A household member is defined as undernourished if her or his calorie consumption falls below its minimum dietary energy requirement. We proceed as follows.

In order to categorize a household (or individual) as food poor, the actual observed calorie consumption of the household (or individual) needs to be compared with a energy requirement threshold. Depending on the definition of food poverty, this threshold quantifies the necessary (minimum) or recommended (average) energy requirement (Anríquez et al 2010a). The threshold needs to take into account differences between age and sex of the individual. To assess whether a household member lacks of sufficient calorie intake per day, we use international standard recommendations and requirements for individuals provided by the FAO and WHO. The information provides household-specific reference values of calories that takes into account the household size as well as the sex and age of household members. In particular, to calculate calorie recommendations and requirements, we apply the recommended mean energy intakes (RMEI) used by Ecker and Qaim (2010) to analyze nutritional impacts of policies in Malawi, which are based on information from the FAO, WHO, and UNO (2001). Based on the mean energy requirements we can then define a sex- and age-specific food poverty line of minimum calorie intake per day and per capita.

We define a household member as food deprived if her or his amount of consumed calories per day is below the age and sex specific food requirement. Food poverty is then calculated as the percentage of individuals that fall below the age- and sex-specific food poverty line.

### 3.4. Data Limitations

Our estimates of food consumption on a per day and per capita basis has certainly some drawbacks, which should be addressed (see also Ecker and Qaim 2010 for a similar discussion). First, the information on food consumption is based on retrospective answers of consumed food of several different food items and its respective quantities. Especially if the recall period is long, the respondent might not be able to remember the exact

[10] We define outlier as cases where the amount of calories per day per capita as +/- 2 standard deviations from the mean quantity of calories. Outliers were then dropped from the sample. The second exclusion criterion is whether the daily energy was greater than 12,000 calories per capita (Smith et al 2007). Then this observation is also coded as missing.

quantities, which results in lower accuracy of the data (Deaton and Grosh 2000). However, in both surveys we use for this study, the recall period is with 7 days relatively short, so that the data are presumably quite accurate.

Second, we aggregate the quantities of food consumption from several sources, e.g. home production, purchase in kind.[11] From this aggregation, we do not know whether all available food is actually consumed by household members or whether some of the food is fed to pets, given to guests of the household or also whether part of the food is degenerated, which might lead to an overestimation of actual calorie intakes (Bouis and Haddad 1992; Bouis 1994; Smith and Subandoro 2007). Since no information on the actual use of the food consumption is available, we cannot address this issue.

Third, from the questionnaires, no information is available on how the food quantities are distributed between family members. Therefore, we assume that the total amount of food consumption is equally distributed within the household, ignoring any intra-household inequality (e.g. gender-specific discrimination). Haddad and Kanbur (1990) already have shown that ignoring intra-household differences in the allocation of food quantities can lead to biased results in food poverty outcomes. However, since any assumption about intra-household food allocation would be on a purely arbitrary basis, we have to bypass this issue by assuming that there is no intra-household inequality and the total food is allocated equally between all household members.

Fourth, the seasonality of food consumption can lead to an over or underestimation of total food consumption in single-round household surveys, because they often do not capture the seasonal dynamics of food production. However, the data for Uganda and Malawi the data collection cover a one year period (e.g. for Malawi from March 2004 through March 2005). This captures the seasonality and variances of agricultural production and consumption. Therefore, we also undertake a calorie availability assessment at different seasons in the year to study the differences, an issue we will also investigate below.

Fifth, an issue arises to problems when converting quantities of food items into grams or kilograms. For some specifications of quantities, no conversion factors are available. Depending on the frequencies of observation, dropping this information can reduce the sample size and might bias our estimates. The most complete information is available for the Malawi data. Here, the conversion of units and quantities of food items based on the conversion factors from the World Food Dietary Assessment System (FAO 2010a) did not lead to many missing values. The same holds for Uganda. Although no conversion factors are available for Uganda, we combined information of conversion factors from the FAO (2010a) with conversion factors from the neighbor country Tanzania (MUHAS 2008) that show similar pattern of food times and units. Also here, we did not lose much information due to unconvertible units.

Sixth, another issue when using household survey data to calculate calorie intakes and deficiencies on a per capita basis it the use of generally defined cut-offs to calculate prevalence of food poverty (see, e.g. Svedberg 2000 and Ecker and Qaim 2010 for the more specific discussion). Although we use minimum calorie requirements that take into account

[11] See Table A2.

the sex and age of the individual, we need to assume that all individuals with the same sex and at the same age have equal daily calorie requirements. Thus, using the commonly available applied requirement cut-offs from the literature, we cannot take into account differences in the physical status of the individuals, for example, any adjustments for the health status, which would affect the minimum daily calorie requirements.

Seventh, the indicator of calorie access on a per day per capita basis based on a 7 day recall periods is just a snapshot of the current food situation of this households and does not allow to address whether the household has access to food all times nor does it take into account food preferences of the household (Smith et al. 2006). In addition, our indicator does not address the quality of food availability, which is taken into account by Ecker and Qaim (2010).

Being aware of the limitations of the data and of the assumption to be made in order to calculate calorie intakes per day and per capita, all results should be treated with caution and in the light of the described limitations and assumptions. However, since the availability of representative data on calorie consumption is still very limited in developing countries and since we do not attempt to calculate exact calorie changes for a particular household, the use of household survey data can provide interesting and important insights on within the debate on how to ensure food security in developing countries.

## 4. Results and discussion

### *4.1. Food availability profiles*

In this section, we present the national estimates of food consumption for each country and also by socioeconomic characteristics. Table 1 shows the food consumption per day and per capita for Malawi (2005) and Uganda (2006). In Malawi, the total mean food per day and capita availability is 2300 calories, which is slightly higher than in Uganda, were the mean total quantity is 2276 calories. In both countries, the standard deviations of the calorie estimates are quite similar as well as the minima and maxima values, whose range roughly from 400 calories to 6,500 calories per day and capita. Our results of food poverty for Malawi are similar to the findings of Ecker and Qaim (2010). Comparing the means of the calories per capita per day in our sample with national estimates of the FAO (2005-07) reveals differences in both countries. In Malawi, the FAO estimates are considerably lower than our estimates (2130), whereas in Uganda our estimates are quite close to the FAO estimates (2250) (see discussion on the differences between survey estimates of food poverty and FAO estimates below).

Figure 2 shows the non-parametric probability density function of individual's calorie consumption by country. We can see that in Uganda, the distribution is skewed to the left compared to Malawi where the calories per capita are more normally distribution across the population. But besides these differences, in principle Figure 2 confirms the findings of Smith et al (2006) who found similar distributions of per capita calorie consumption. The vertical line shows the mean of the minimum dietary requirement in the respective countries indicators the share of the population that is food deprived (see next section).

Before we have a closer look at food poverty, Table 1 already provides some interesting results with respect to differences in calorie per capita consumption per day within countries by socioeconomic characteristics. Part of the variations naturally depends on the differences in the shares of the socioeconomic subgroups within the population.[12] In both countries less than 20% of the populations live in urban areas compared to more than 80% in rural areas. As expected, rural food availability is lower than urban food availability in Malawi and Uganda. This result is already important from a food security perspective, because rural dwellers are physically more active than urban dwellers and would typically need to consume more calories in order to meet their higher energy requirement (Higins and Alderman 1997).[13] However, as Table 2 shows, although the rural population, on average, needs more they have less than the urban population. Table 1 also shows some variations between the geographical regions in Malawi and Uganda. In Malawi, the South shows much higher availability of calories per capita than the Centre and the North of Malawi. In Uganda, the Eastern region seems to better off, on average, than the other geographical regions.

Table 1 additionally reveals some interesting differences between female headed and male headed households between Malawi and Uganda. Whereas female headed households in Malawi show, on average, a lower level of calorie per capita availability (2287 compared to 2384), the opposite is found in Uganda, where female headed households have higher calorie per capita consumption than male headed households. A similar picture in both countries is found for education of the household head. Higher educational level of the household head is associated with higher mean per capture calorie consumption. However, the mean values of calorie per capita do not allow making any firm conclusion about differences in food poverty and food security between these subgroups as the caloric requirements might differ between the groups (see below).

Table 2 shows the descriptive statistics of calorie availability per day and per capita for Malawi and Uganda by five food groups, staple food, pulses, vegetable and fruits, animal product, and meal complements.[14] Table 2 reveals that the largest amount of calories stems from staple food in Malawi, where 72% of all per capita calories are based on staple food. The second largest calorie resource in Malawi is pulses, which provides 15% percent of the per capita calories, followed by meal complements (12%). Interesting is that in Malawi the share of calories that come from more expensive animal products is rather low. In Uganda the calorie resources are more equally distributed across food groups. Here, staple foods account 'only' for 26% of the calories, compared to the large share in Malawi. Interestingly, in Uganda, the calorie resource from meal complements, including sugar, tea, salt, food eaten out, is quite high.[15]

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[12] Table A3 in the Appendix presents the socioeconomic characteristics of the countries. Both in Malawi, as well as in Uganda, the share of the urban population is considerably lower than the rural population share. Differences in the socioeconomic characteristics between Malawi and Uganda are only small, meaning that both countries show similar characteristics.

[13] Our minimum dietary requirement level cannot address this issue because it takes not into account differences in the actual activity level of a person.

[14] For the frequencies and shares of each food item, see Table A4 for Malawi and A5 for Uganda.

[15] See also Table A5 for the respective food item shares.

Next, we have closer look at how food availability differs across income groups, in our case defined as total expenditure quintiles. Table 3 shows the calorie per capita consumption by expenditure quintiles and also the shares of food consumption by food group and income quintiles in Malawi and Uganda. Table 3 reveals a clear pattern in both countries. Table 3 shows that poverty and undernourishment are positively correlated. In Table 3 quintile 1 refers to the poorest, quintile 5 to the richest population quintile. Per capita calorie consumption increases with income/expenditure. In Malawi, the poorest quintile consumes less than half of the calories of the richest quintile, shown by the 5:1 ratio in Table 3. In Uganda, the difference is also observable, but to a lesser extent. Here, the 5:1 ratio is 1.56. This mirrors that in Malawi, the poorest 40% of the population consume less than 2,000 calories per capita and per day, whereas in Uganda, only the poorest 20% of the population falls below the 2,000 calories cut-off. What is also interesting is that the share of food consumption by food groups differs between income groups. The poorest population groups have the highest share in calories from staple food resulting in a 5:1 ratio of 0.81 in Malawi. Although changes across income groups are not very large, they are sizable and we can observe that the share of staple food decreases with household income/expenditure, whereas shares of calories from animal products and meal complements increase. In Uganda, the variations of calorie shares by income quintiles is different, reflecting the findings from Table 2, which already has shown the relatively low share of staple food. In addition, the share remains constant across income quintiles, whereas, with increasing income, the share of animal products increases, i.e. it nearly doubles between the poorest and richest quintile (ratio 5:1 of 1.94 in Table 3). As we will analyze in the next section, this findings already give an indication of how changes in staple food prices can increase food insecurity among the poor population.

As described in the previous section, the data also provides the possibility to control for seasonal effects in calorie per capita availability. In high food price times the most vulnerable population subgroups with respect to food insecurity might be particularly affected by further food price increases or negative income shocks. To illustrate this, Figure 3 shows the variations in calorie availability, quantity of maize consumption, and maize price variations by months of the year. Figure 3 reveals considerable variations across months. The first panel shows variations in calorie consumption per day and capita. For example, in Uganda, the mean calorie consumption in June declines below 2000 calories per day and capita. In both countries maize prices were highest in April (third and forth panel). This is translated in to lower shares of maize consumption in both countries (second penal). Hence, seasonality effects are existent, which also might have impacts on food poverty over the year.[16]

### 4.2. Food Poverty Profiles

In this section, we present food poverty and food inequality profiles for Malawi and Uganda by socioeconomic characteristics. Table 4 shows the food poverty estimates for calorie per capita consumption. In particular, Table 4 shows the poverty headcount, the poverty gap, and the severity index both for Malawi and Uganda. In addition, Table 4 also shows the Gini coefficient for both countries by socioeconomic population subgroups. Table 4 reveals that

[16] To further illustrate how seasonality affects food availability for socioeconomic subgroups, Table A6 shows the levels of food consumption per day and capita for Uganda and Malawi by month, income quintiles and by urban and rural areas.

food insecurity is a major concern in both countries. Food consumption in Malawi and Uganda is characterized by highs risks of food poverty and malnutrition. In Malawi, 29.4% of the population falls below the minimum daily calorie requirement threshold and in Uganda the food poverty headcount is 39%.

The prevalence of food poverty in Malawi is similar to FAO estimates for Malawi on the share of undernourished population, which was estimated to be 29% (2005-07) (FAO 2010b), based national food balance sheet data (FAO and WFP 2009). In contrast, the estimates for Uganda are much higher than the FAO estimates (FAO 2010b), which were at 21% in 2005-07. However, as Ecker and Qaim (2010) have already argued, and which is shown by Smith et al (2006), the FAO data can lead to an underestimation of food poverty.[17] In addition, when comparing the results of our countries with results on prevalence of child undernutrition from Demographic and Health Surveys (DHS) reveals that that the FAO numbers might be underestimated for Uganda. Child undernutrition in Uganda 2006 was 31.5% (based on the height-for-age z-score below minus 2 standard deviations from the reference population).

However, even if FAO estimates might underestimate food poverty in Uganda, our findings are in contrast to other studies that show relatively lower levels of food poverty in Uganda compared to other African countries (see, e.g. Smith et al 2006 who uses the 1999/2000 Uganda National Household Survey). The relatively stable situation in Uganda and the great agricultural production potential of the country and also its stable political situation and fast-growing economic (Resnick 2004) would have expected lower levels of food poverty. Partly, this high poverty rates are data driven. The minimum dietary recommendation threshold differs between the two countries, depending on the age and sex structure of the sample. In Uganda the mean of the recommended minimum calorie intake is 1710 compared to 1680 in Malawi. Higher means of the food poverty line can lead to higher levels of poverty, because we do not take into account any distributional aspects of the allocation of food within households and simply divide by the total amount of calories available by the household size. If there many large households with member that have a 'high' recommended minimum calorie threshold, then dividing by the household size can lead to higher food poverty.[18]

Looking at the depth of food poverty at the national level, Table 4 shows that the high poverty headcount ratios in Uganda are translated into high values of the poverty gap and of the severity index. This means that food poverty in both countries is not a temporary concern indicating a problem of chronic poverty. The results for the Gini coefficient shows that, on average, both countries show quite similar levels of food inequality in calorie per day and capita consumption. In Malawi, the Gini coefficient is 0.240 and in Uganda it is 0.268.

Table 4 presents interesting variations in food poverty and inequality within countries by socioeconomic characteristics. Both countries show a large within country variation in food poverty. In Malawi, large differences exist between rural and urban areas. Whereas 20%

[17] See Smith et al (2006) on the discussion of the sources of the discrepancies between FAO estimates and calorie availability estimates based on household survey data.

[18] Another reason might be that Uganda has experienced a bad year in terms of food production, which will then especially affect the calories consumed from on production (this will be checked).

percent of the urban population was food deprived in 2005, more than 30% were deprived in rural areas reflecting the overall worse access to food markets as well as lower level of incomes in rural areas (see below). In contrast, in Uganda, the differences between urban and rural are much smaller, whereas large variations exist between the main regions.

Next, we take a closer look at differences in food poverty by income quintiles. In both countries, we find a clear income gradient. Income is negatively correlated with levels of food poverty, indicating that increases in income reduce the risk of food poverty. This is especially true for Malawi, where the poorest quintile shows a food poverty headcount of almost 70% compared to 7% of the richest quintile. Although the differences in Uganda are smaller, also here the poorest quintile shows a poverty rate of around 60% compared to still 26% of the richest quintile. The same strong income gradient is found for food inequality. The Gini coefficient decreases with levels of income. However, besides the clear observable relationship between income and food consumption, we can also see that food poverty and income poverty is not the same thing at all and the correlations is far from perfect. Also at higher levels of income, food deprivation is a major concern in both countries. This is an important finding, but also requires careful interpretation. In particular, it may be the case that this is partly due to measurement error in food consumption or overall consumption. It could be the case that households are underestimating their food expenditures which leads to higher food poverty. This might be particularly the case for richer groups who have a more diversified diet, spend more on food outside of the home, and who maybe track their food expenditures less carefully than poorer households. But it could also be the case that a significant share of households in richer wealth groups in Uganda is in fact food-deprived; these households would then have sufficient assets, but not enough current income to consume enough food. This requires further analysis.

Table 4 also presents food poverty by sex of the household head. Household headship is also important for food security. Female-headed households are often assumed to be more vulnerable to food insecurity because of time and resource constraints compared to male headed households (Caldwell et al 2003). On the other hand, women tend to invest into beneficial households goods, such as health and education, and food. If the women are the decision maker over resource allocation within the household, then it this household might be less vulnerable to food poverty than male headed households (Haddad et al 1997). These competing effects are reflected in our results. In Malawi, no differences in food poverty exist between female and male headed households. In contrast, In Uganda, male headed households show lower levels of food poverty than female headed households suggesting that the resource constraint of female headed households dominates.

As expected, education matters for food security. As found by other studies, higher levels of education within the households is negatively correlated with undernutrition and undernourishment (see, e.g. Bhalotra 2009, 2010). The argument here is twofold. First, better-educated households might be able to better process information and to acquire skills in order to invest in health and consume healthy food, and second, better-educated households are, on average, richer than poor-educated households. Table 4 shows that with increasing educational levels of the household head, food poverty rates decrease in Malawi and Uganda, while a stronger effect is observable in Malawi.

### *4.3. Simulation results*

In this section we present our results of the simulation of price changes and income shocks in line with Sen's entitlement approach on food poverty and food inequality in Uganda and Malawi. Table 5 and 6 show the results for food poverty based on the poverty headcount, the poverty gap, and the severity index for Malawi and Uganda, respectively. In particular, the table presents the actual poverty rates from Table 4 and the poverty rates for the staple price increase by 100%, the maize price increase by 100%, and the negative income shock by minus 50%.

Starting with changes in the food price increase (thus changing the exchange entitlement mapping of translating incomes into food), Table 5 and 6 reveal that increases in food staple food prices would have a strong impact on food poverty, keeping everything constant and ignoring behavioral changes. The first shock we analyze is an increase in staple foods prizes by 100%. If staple food prices would increase in Malawi, this would increase food poverty, measured by the poverty headcount, to 85%, which would be almost three times higher than the observed actual rate. In Uganda, such an increase would be less strong but would also increase food poverty by more than 10 percentage points (0.390 to 0.501). The differences between Malawi and Uganda with respects to changes in food poverty when staple food prices rise reflect that in Malawi staple foods is the main calorie resource for the population. Thus, Malawi is assumed to be much more vulnerable to changes in staple food prices than Uganda (see Table 2).

The second shock we simulate is an increase of the maize price by 100%. As maize is part of staple foods, the effect on food poverty is expected to be lower than the effect of an overall staple food price increase. Table 5 and 6 show that a maize price increase by 100% would also have a considerable effect on food poverty in Malawi and Uganda although the effect would be lower than the effect of general price increase of staples food, because the households are less dependent on maize than on staple foods in general. Nevertheless, the impact would be sizable, especially in Malawi (0.294 to 0.571). Both price shocks increases would also have effects on the depths poverty, measured by the poverty gap and the severity index. Not only would a price increase food insecurity, it is also very likely that the depth of food poverty will increase resulting in a higher share of individuals that are chronically food poor.

As we have argued above, it may be too extreme an assumption that households simply reduce staple food or maize consumption by the amount of the food price increase, it may be more realistic to assume that the maize or staple food price increase is equivalent to an income shock that depends on the importance of maize or staple foods in the diet. As described in the methodology, we assume that households will shift their calorie composition from maize to other product if the maize price increases. Since we do not know how exactly the past shock calorie food item composition would be, we ask what the income would be needed (new price maize x quantity) to maintain the same calorie consumption level. Hence, we assume that the price shock can be translated into an negative income shock, which is a weaker assumption than the direct reduction of maize consumption by the amount of the price increase. In particular, Tables 5 and 6 show how a maize price increase by 100% is translated into an income shock given the quantity of maize that was consumed by the household before the price increase (see Table 2). For Malawi the maize price increase would be similar to a reduction in income by 36% in Malawi and 23% in Uganda. If we do this, the effect is much smaller, but still substantial in Malawi where food poverty increases by eight percentage points. Interestingly, in Malawi, although the mean income reduction is smaller than in the simulation where all households are hit by a 50% income reduction, the effect in food poverty is higher. This is because especially the poor and food vulnerable populations consume a higher share of maize and hence, these subgroups are particularly affected by the negative shock (Table 5).

The third shock we analyze is an overall negative income shock, which corresponds to a decrease in the overall endowments in line with Sen's entitlement approach. Following the methodology describes in section 2, Figure 4 shows the relationship between calorie per day per capita consumption and household expenditure in Malawi and Uganda. In both countries, we can identify a similar relationship in the micro data than the relationship that has been found for the macro data in Figure 1. Calories per day per capita increase with household expenditure, while increases are diminishing at higher levels of household expenditure, indicating that the relationship follows a logarithmic function. Based on the estimation equation (1) we can apply equation (2) from section 2 to simulate how an overall negative income shocks would decrease the calorie per capita consumption, again leaving all other things constant and ignoring behavioral responses of households.[19]

Tables 5 and 6 show that a negative income shock would have a considerable impact on food poverty. In Malawi, food poverty would increase by around 6 percentage points and in Uganda by 2 percentage points. Also the poverty gap and the severity index would increase considerably. One should note that this assessment underestimates the severity of impact of such a drop in incomes. As it is based on the estimated calorie-income relationship, we ignore food quality issues. So as households are facing lower incomes, their calorie consumption falls only a little leading to the observed higher levels of food poverty. But their nutritional status is more affected as these fewer calories are of lower quality than before, consisting more of staple crops and less on higher quality calories.

What we are also interested in is how price and income shocks affect population subgroups within countries differently. Table 5 and 6 present the simulations results also by different socioeconomic characteristics. First, we can observe large variations between urban and rural areas and geographical regions both in Malawi as well as in Uganda. Interestingly, after a general staple foods price increase, the urban population would have a similar (higher) food poverty rate than the rural population in Malawi indicating that the urban population would be relatively more affected, because they started at a lower poverty level. Second, although, the simulation is based on very simplistic and strong assumptions, we can observe in both countries that an increase in food prices as well as a negative income shock would most strongly affect the poorer population subgroups. Third, similar effects are found for food price changes and negative income shocks on food poverty by sex of the household head and also by educational attainment of the household head.

Table 7 shows the simulation results of price and income shocks on food inequality. Although results are less dramatic with respect to food inequality than food poverty, we still

[19] The results of regression of equation (1) [$\hat{y}_i = \beta_1 \ln(x_i)$] for $\beta_1$ are: $\beta_1$=606.34 (s.e. 2.01) in Malawi and $\beta_1$=181.65 (s.e. 0.46) in Uganda.

find that price increases would increase food inequality. This holds especially in Malawi, when maize price increases would increase and in Uganda when staple foods in general would get more expensive. As expected price shocks would have a higher impact on food inequality than income shocks because price shocks take explicitly the food shares of food groups into account. Table 7 also shows the impacts of a maize price shock that is translated into a negative income shock on inequality. Interestingly, this worsens the inequality situation in Malawi because the poorer subgroups are relatively more affected as they have a higher share of maize consumption.[20]

To illustrate the distributional effects of our simulations of negative price and income shocks, Figure 5 shows the density distributions of the actual calorie consumption as well as after the respective shock in Malawi and Uganda. Two findings are worth noting here: First, income shocks are distributionally more neutral than price shocks. Second, as already found in the tables, the distributional effects of the simulations are more profound in Malawi and in Uganda. Especially the staple price shock has a considerable effect on the distribution. Given that Malawi consumes a larger share of staple food, these large distributional effects are, therefore, not unexpected.

In this context, the distribution of calorie availability per day and capita, and in particular, the two parameters mean and inequality of the distribution allows us to analyze what would be needed to eliminate food poverty (or, given the long tail of the distribution, it is more realistic to assume that one eliminates, say, 95% of food poverty). Two simulations are interesting to analyze here, First, what increase in the mean food availability would be needed to shift 95% of the population out of food poverty, keep inequality constant (i.e. move the distribution to the right). Second, what would be the needed reduction in inequality holding the mean of the current distribution constant (squeezing the distribution). Figure 6, graphically illustrates these two simulations. The left vertical line refers to the average per capita dietary intake requirement for each country. The mean threshold of the recommended mean energy requirement (RMEI) in the sample is 1680 for Malawi (2004), and 1707 for Uganda (2006). The right vertical line refers to the mean of the distribution (2308 in Malawi and 2276 in Uganda). Analyzed is a simulation where food poverty remains at a level of 5%. First, achieving this by a reduction in inequality with equal mean would mean reducing the Gini in Malawi from 0.237 to 0.092 an in Uganda from 0.268 to 0.033. Second, eliminating 95% of food poverty by increasing the mean with equal inequality would mean increasing the mean by 750 calories per day and per capita in Malawi and 1150 in Uganda.

Finally, Table 8 shows the seasonal effects on food poverty. As indicated in Figure 3, food poverty varies by months both in Uganda as well as in Malawi. The lowest level of actual food poverty in Uganda was found in September and in August in Malawi; and highest in January (Uganda) and February (Malawi). Interesting to note is that this seasonal structure is not automatically translated into the poverty outcomes of the simulations. Whereas is Uganda, food poverty levels after the simulations were also highest in the periods where the actual food poverty was high, in Malawi, the pattern is less clear. Low food poverty months can also be relatively more affected by negative shocks than high food poverty periods and

[20] Differences in the Gini coefficient in Malawi between the actual data and the staple price increase are only existent at the fourth decimal place.

vice versa. However, on average, high food poverty months show higher impacts of negative price and income shocks.

## 5. Conclusion

The food crisis 2008 and the resurgent food prices in 2010 and 2011 have reminded the world that food prices can have dramatic impacts on poverty and hunger. Even in countries where the majority of the population lives and works in agriculture, rising food prices can have negative impacts as most households, including most rural households, are net food purchasers. As a result, negative income and price shocks negatively affect many households in Africa and increase hunger and poverty. While this is well understood, it is hard to come up with reliable ex ante estimates of the impacts of such shocks. And waiting for the ex post data to emerge (either at the aggregate level, as in the FAO hunger measure; or at the micro level using food consumption surveys) prevents policy-makers from talking timely action.

In this paper, we have developed a simple and readily usable method to estimate the impact of income and price shocks on hunger in Africa, which is a rather straight-forward tool that could also be used with other countries. In particular, we developed a very simple simulation approach to analyze how changes in prices of specific food groups such as maize prices or prices for staple food as well as how negative short-term income shocks on household income affect the calorie consumption of individuals and how these changes affect food poverty in the very short-term. We used information on calorie per day and capita consumption from household survey data in Malawi and Uganda to investigate food poverty and the impact of price and income shocks on food consumption and food poverty. Thereby, we focused on within-country differences by socioeconomic characteristics. This can then be used either to predict the impact of food and income crises as they arise in order to plan mitigation measures, or they can be used to identify vulnerable populations and install safety net programs to reduce the impact of future shocks.

We find that staple food price increases have a particularly large impact on food poverty, particularly in Malawi, slightly less so in Uganda. Income shocks have a smaller impact, but here we ignore the impact of changing food quality (just focusing on calories). When disaggregating the impact by population groups, it is of particular note that urban households and the poor are particularly affected by price shocks.

Clearly, our assumptions are rather simple and further robustness checks are required. A next step would be to undertake further robustness checks and extend the analysis to more countries to see whether this approach is indeed usable for a large sample of countries for a quick assessment of the impact of shocks on food security in Africa.

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## Tables and Figures

**Table 1: Food consumption per day per capita**

| Country | Mean | SD | Min | Max | N |
|---|---|---|---|---|---|
| **Malawi** | | | | | |
| **Total** | **2308** | **983** | **503** | **5000** | **11993** |
| *Area* | | | | | |
| Urban | 2559 | 951 | 676 | 4999 | 1441 |
| Rural | 2271 | 982 | 503 | 5000 | 10552 |
| *Region** | | | | | |
| North | 1854 | 960 | 503 | 4864 | 1059 |
| South | 2285 | 919 | 510 | 4996 | 2590 |
| Centre | 1986 | 811 | 538 | 4998 | 2986 |
| *Household headship* | | | | | |
| Female headed household | 2287 | 966 | 503 | 4999 | 9448 |
| Male headed household | 2384 | 1040 | 514 | 5000 | 2545 |
| *Education of household head* | | | | | |
| Head has no education | 2230 | 983 | 514 | 5000 | 3146 |
| Head has primary education | 2366 | 975 | 503 | 4999 | 6034 |
| Heads has secondary education | 2603 | 990 | 503 | 4989 | 1222 |
| | | | | | |
| **Uganda** | | | | | |
| **Total** | **2276** | **1192** | **412** | **6651** | **6890** |
| *Area* | | | | | |
| Urban | 2366 | 1185 | 415 | 6651 | 1484 |
| Rural | 2258 | 1192 | 412 | 6646 | 5406 |
| *Region* | | | | | |
| Central | 2322 | 1185 | 413 | 6651 | 1892 |
| Eastern | 2486 | 1233 | 430 | 6646 | 1812 |
| Northern | 1888 | 1098 | 415 | 6603 | 1529 |
| Western | 2330 | 1162 | 412 | 6628 | 1657 |
| *Household headship* | | | | | |
| Female headed household | 2353 | 1248 | 412 | 6651 | 1888 |
| Male headed household | 2247 | 1169 | 413 | 6646 | 5002 |
| *Education of household head* | | | | | |
| Head has no education | 2218 | 1193 | 415 | 6651 | 1467 |
| Head has primary education | 2296 | 1173 | 413 | 6629 | 4101 |
| Heads has secondary education | 2456 | 1187 | 417 | 6629 | 1035 |

*Note*: *for Malawi, a large share has missing values with respect to the geographical region. This is the reason, why the means of each region falls below the national average and why the number of observations does not sum up to the national sample size.
*Source*: Malawi Second Integrated Household Survey 2004/2005, Uganda National Household Survey 2005/2006; author's calculations.

**Table 2: Food consumption per day per capita (by country and food group)**

| | Malawi (2004) | | Uganda (2005) | |
|---|---|---|---|---|
| | **Calories** | **Calorie share** | **Calories** | **Calorie share** |
| Staple foods | 1668 | 0.72 | 701 | 0.31 |
| Pulses | 339 | 0.15 | 303 | 0.13 |
| Vegetables and fruits | 89 | 0.04 | 539 | 0.24 |
| Animal products | 126 | 0.05 | 309 | 0.14 |
| Meal complements | 280 | 0.12 | 425 | 0.19 |
| **Total** | **2308** | **1** | **2276** | **1** |

*Source*: Malawi Second Integrated Household Survey 2004/2005, Uganda National Household Survey 2005/2006; author's calculations.

**Table 3: Food consumption shares by income quintiles**

| | Malawi (2004) | | | | | |
|---|---|---|---|---|---|---|
| | Quintile | | | | | |
| | 1 | 2 | 3 | 4 | 5 | Ratio 5:1 |
| Total consumption (calories) | 1458 | 1909 | 2304 | 2687 | 3181 | 2.18 |
| | Quintile | | | | | |
| Share of total consumption (calories) | 1 | 2 | 3 | 4 | 5 | |
| Staple foods | 0.79 | 0.75 | 0.72 | 0.69 | 0.64 | 0.81 |
| Pulses | 0.14 | 0.14 | 0.16 | 0.16 | 0.15 | 1.09 |
| Vegetables and fruits | 0.04 | 0.04 | 0.04 | 0.04 | 0.03 | 0.80 |
| Animal products | 0.05 | 0.04 | 0.05 | 0.06 | 0.08 | 1.67 |
| Meal complements | 0.08 | 0.10 | 0.12 | 0.13 | 0.18 | 2.31 |
| | Uganda (2005) | | | | | |
| | Quintile | | | | | |
| | 1 | 2 | 3 | 4 | 5 | |
| Total consumption (calories) | 1672 | 1932 | 2108 | 2441 | 2610 | 1.56 |
| | Quintile | | | | | |
| Share of total consumption (calories) | 1 | 2 | 3 | 4 | 5 | |
| Staple foods | 0.26 | 0.26 | 0.26 | 0.26 | 0.26 | 1.00 |
| Pulses | 0.14 | 0.12 | 0.11 | 0.11 | 0.10 | 0.71 |
| Vegetables and fruits | 0.22 | 0.23 | 0.22 | 0.22 | 0.22 | 1.00 |
| Animal products | 0.07 | 0.09 | 0.11 | 0.12 | 0.14 | 1.94 |
| Meal complements | 0.30 | 0.30 | 0.29 | 0.29 | 0.28 | 0.91 |

*Source*: Malawi Second Integrated Household Survey 2004/2005, Uganda National Household Survey 2005/2006; author's calculations.

**Table 4: Food poverty and inequality in Malawi and Uganda**

| Variable | Headcount | | Poverty gap | | Severity index | | Gini coefficient | |
|---|---|---|---|---|---|---|---|---|
| | Malawi | Uganda | Malawi | Uganda | Malawi | Uganda | Malawi | Uganda |
| Total | 0.294 | 0.390 | 0.074 | 0.121 | 0.028 | 0.121 | 0.240 | 0.268 |
| *Area* | | | | | | | | |
| Urban | 0.196 | 0.383 | 0.037 | 0.113 | 0.011 | 0.113 | 0.208 | 0.260 |
| Rural | 0.307 | 0.393 | 0.079 | 0.124 | 0.030 | 0.124 | 0.243 | 0.270 |
| *Region* | | | | | | | | |
| North | 0.449 | 0.538 | 0.144 | 0.193 | 0.065 | 0.091 | 0.274 | 0.287 |
| Centre | 0.234 | 0.390 | 0.059 | 0.117 | 0.022 | 0.049 | 0.224 | 0.264 |
| South (Eastern in Uganda) | 0.344 | 0.305 | 0.076 | 0.084 | 0.026 | 0.034 | 0.223 | 0.254 |
| Western | | 0.356 | | 0.104 | | 0.043 | | 0.260 |
| *Wealth** | | | | | | | | |
| Quintile 1 | 0.687 | 0.586 | 0.196 | 0.220 | 0.079 | 0.220 | 0.203 | 0.297 |
| Quintile 2 | 0.359 | 0.497 | 0.080 | 0.173 | 0.028 | 0.173 | 0.183 | 0.281 |
| Quintile 3 | 0.202 | 0.411 | 0.047 | 0.125 | 0.017 | 0.125 | 0.187 | 0.257 |
| Quintile 4 | 0.134 | 0.359 | 0.029 | 0.102 | 0.010 | 0.102 | 0.191 | 0.244 |
| Quintile 5 | 0.078 | 0.262 | 0.016 | 0.066 | 0.006 | 0.066 | 0.179 | 0.235 |
| *Household headship* | | | | | | | | |
| Female headed household | 0.292 | 0.404 | 0.072 | 0.129 | 0.026 | 0.129 | 0.247 | 0.277 |
| Male headed household | 0.294 | 0.386 | 0.074 | 0.119 | 0.028 | 0.119 | 0.238 | 0.265 |
| *Education of household head* | | | | | | | | |
| Head has no education | 0.334 | 0.420 | 0.085 | 0.134 | 0.031 | 0.134 | 0.246 | 0.268 |
| Head has primary education | 0.267 | 0.401 | 0.068 | 0.124 | 0.026 | 0.124 | 0.234 | 0.267 |
| Head has secondary education | 0.182 | 0.338 | 0.042 | 0.099 | 0.015 | 0.099 | 0.217 | 0.251 |

*Note:* The mean threshold of the recommended mean energy requirement (RMEI) in Malawi is 1680 and in Uganda 1707. *The quintiles of the wealth index are calculated based on household expenditure per capita. *Source*: Malawi Second Integrated Household Survey 2004/2005, Uganda National Household Survey 2005/2006; author's calculations.

## Table 5: Simulation Results on Food Poverty in Malawi (2004)

| | Headcount | | | | | Poverty gap | | | | | Severity index | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | ***Actual*** | **Staple price increase by 100%** | **Maize price increase by 100%** | **Income shock (minus 50%)** | **Maize price shock (100%) as income shock*** | ***Actual*** | **Staple price increase by 100%** | **Maize price increase by 100%** | **Income shock (minus 50%)** | **Maize price shock (100%) as income shock** | ***Actual*** | **Staple price increase by 100%** | **Maize price increase by 100%** | **Income shock (minus 50%)** | **Maize price shock (100%) as income shock*** |
| Total | *0.294* | 0.842 | 0.833 | 0.360 | 0.373 | 0.074 | 0.336 | 0.329 | 0.104 | 0.118 | 0.028 | 0.169 | 0.164 | 0.045 | 0.058 |
| *Area* | | | | | | | | | | | | | | | |
| Urban | *0.196* | 0.818 | 0.815 | 0.275 | 0.281 | 0.037 | 0.291 | 0.290 | 0.058 | 0.077 | 0.011 | 0.130 | 0.130 | 0.019 | 0.038 |
| Rural | *0.307* | 0.846 | 0.835 | 0.372 | 0.386 | 0.079 | 0.343 | 0.335 | 0.111 | 0.124 | 0.030 | 0.175 | 0.168 | 0.048 | 0.061 |
| *Region* | | | | | | | | | | | | | | | |
| North | *0.449* | 0.890 | 0.882 | 0.512 | 0.477 | 0.144 | 0.429 | 0.413 | 0.190 | 0.161 | 0.065 | 0.245 | 0.230 | 0.098 | 0.078 |
| Centre | *0.234* | 0.812 | 0.806 | 0.295 | 0.305 | 0.059 | 0.303 | 0.299 | 0.084 | 0.098 | 0.022 | 0.146 | 0.142 | 0.036 | 0.051 |
| South | *0.344* | 0.895 | 0.891 | 0.432 | 0.456 | 0.076 | 0.370 | 0.368 | 0.114 | 0.145 | 0.026 | 0.186 | 0.185 | 0.044 | 0.073 |
| *Wealth* | | | | | | | | | | | | | | | |
| Quintile 1 | *0.687* | 0.988 | 0.984 | 0.777 | 0.833 | 0.196 | 0.549 | 0.542 | 0.265 | 0.343 | 0.079 | 0.329 | 0.322 | 0.122 | 0.193 |
| Quintile 2 | *0.359* | 0.967 | 0.960 | 0.458 | 0.511 | 0.080 | 0.415 | 0.406 | 0.119 | 0.132 | 0.028 | 0.207 | 0.201 | 0.047 | 0.053 |
| Quintile 3 | *0.202* | 0.880 | 0.868 | 0.276 | 0.268 | 0.047 | 0.313 | 0.305 | 0.069 | 0.061 | 0.017 | 0.142 | 0.137 | 0.028 | 0.023 |
| Quintile 4 | *0.134* | 0.761 | 0.749 | 0.170 | 0.152 | 0.029 | 0.232 | 0.226 | 0.040 | 0.031 | 0.010 | 0.095 | 0.092 | 0.015 | 0.010 |
| Quintile 5 | *0.078* | 0.607 | 0.595 | 0.107 | 0.087 | 0.016 | 0.167 | 0.161 | 0.025 | 0.021 | 0.006 | 0.066 | 0.062 | 0.010 | 0.010 |
| *Household headship* | | | | | | | | | | | | | | | |
| Female headed household | *0.292* | 0.807 | 0.796 | 0.364 | 0.375 | 0.072 | 0.324 | 0.316 | 0.103 | 0.123 | 0.026 | 0.164 | 0.158 | 0.043 | 0.063 |
| Male headed household | *0.294* | 0.852 | 0.844 | 0.359 | 0.372 | 0.074 | 0.340 | 0.333 | 0.105 | 0.117 | 0.028 | 0.171 | 0.165 | 0.045 | 0.057 |
| *Education of household head* | | | | | | | | | | | | | | | |
| Head has no education | *0.334* | 0.855 | 0.842 | 0.403 | 0.439 | 0.085 | 0.356 | 0.348 | 0.119 | 0.151 | 0.031 | 0.184 | 0.179 | 0.051 | 0.080 |
| Head has primary education | *0.267* | 0.838 | 0.829 | 0.329 | 0.329 | 0.068 | 0.324 | 0.316 | 0.095 | 0.098 | 0.026 | 0.160 | 0.154 | 0.041 | 0.046 |
| Head has secondary education | *0.182* | 0.783 | 0.770 | 0.244 | 0.229 | 0.042 | 0.274 | 0.269 | 0.060 | 0.055 | 0.015 | 0.124 | 0.121 | 0.023 | 0.020 |

*Note:* The mean threshold of the recommended minimum energy requirement (RMEI) in the sample is 1680. *An increase in Maize price by 100% is translated into a mean income reduction of 36 % in Malawi.
*Source*: Malawi Second Integrated Household Survey 2004/2005; author's calculations.

## Table 6: Simulation Results on Food Poverty in Uganda (2006)

| | Headcount | | | | | Poverty gap | | | | | Severity index | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | *Actual* | Staple price increase by 100% | Maize price increase by 100% | Income shock (minus 50%) | Maize price shock (100%) as income shock* | *Actual* | Staple price increase by 100% | Maize price increase by 100% | Income shock (minus 50%) | Maize price shock (100%) as income shock | *Actual* | Staple price increase by 100% | Maize price increase by 100% | Income shock (minus 50%) | Maize price shock (100%) as income shock* |
| Total | *0.390* | 0.504 | 0.414 | 0.415 | 0.401 | 0.121 | 0.190 | 0.137 | 0.134 | 0.129 | 0.121 | 0.096 | 0.063 | 0.061 | 0.058 |
| *Area* | | | | | | | | | | | | | | | |
| Urban | *0.383* | 0.487 | 0.399 | 0.411 | 0.397 | 0.113 | 0.177 | 0.127 | 0.127 | 0.121 | 0.113 | 0.087 | 0.056 | 0.055 | 0.052 |
| Rural | *0.393* | 0.509 | 0.418 | 0.416 | 0.403 | 0.124 | 0.193 | 0.140 | 0.136 | 0.131 | 0.124 | 0.098 | 0.065 | 0.062 | 0.059 |
| *Region* | | | | | | | | | | | | | | | |
| Central | *0.390* | 0.505 | 0.417 | 0.418 | 0.405 | 0.193 | 0.188 | 0.137 | 0.130 | 0.125 | 0.091 | 0.094 | 0.063 | 0.057 | 0.054 |
| Eastern | *0.305* | 0.424 | 0.329 | 0.327 | 0.314 | 0.117 | 0.147 | 0.100 | 0.094 | 0.089 | 0.049 | 0.070 | 0.043 | 0.039 | 0.037 |
| Northern | *0.538* | 0.603 | 0.552 | 0.558 | 0.548 | 0.084 | 0.249 | 0.206 | 0.210 | 0.204 | 0.034 | 0.132 | 0.101 | 0.103 | 0.100 |
| Western | *0.357* | 0.507 | 0.385 | 0.382 | 0.366 | 0.104 | 0.188 | 0.120 | 0.117 | 0.110 | 0.043 | 0.094 | 0.053 | 0.051 | 0.047 |
| *Wealth* | | | | | | | | | | | | | | | |
| Quintile 1 | *0.586* | 0.673 | 0.610 | 0.606 | 0.598 | 0.220 | 0.293 | 0.238 | 0.238 | 0.236 | 0.220 | 0.161 | 0.119 | 0.120 | 0.120 |
| Quintile 2 | *0.497* | 0.594 | 0.517 | 0.515 | 0.505 | 0.173 | 0.244 | 0.191 | 0.188 | 0.183 | 0.173 | 0.130 | 0.094 | 0.092 | 0.089 |
| Quintile 3 | *0.411* | 0.521 | 0.435 | 0.437 | 0.422 | 0.125 | 0.197 | 0.143 | 0.137 | 0.132 | 0.125 | 0.100 | 0.066 | 0.060 | 0.057 |
| Quintile 4 | *0.359* | 0.474 | 0.380 | 0.381 | 0.367 | 0.102 | 0.169 | 0.117 | 0.112 | 0.105 | 0.102 | 0.082 | 0.051 | 0.047 | 0.043 |
| Quintile 5 | *0.262* | 0.398 | 0.290 | 0.287 | 0.271 | 0.066 | 0.129 | 0.079 | 0.074 | 0.068 | 0.066 | 0.058 | 0.032 | 0.028 | 0.025 |
| *Household headship* | | | | | | | | | | | | | | | |
| Female headed household | *0.404* | 0.515 | 0.428 | 0.426 | 0.414 | 0.129 | 0.196 | 0.145 | 0.142 | 0.138 | 0.129 | 0.099 | 0.068 | 0.066 | 0.064 |
| Male headed household | *0.386* | 0.501 | 0.410 | 0.412 | 0.398 | 0.119 | 0.188 | 0.135 | 0.132 | 0.126 | 0.119 | 0.095 | 0.062 | 0.059 | 0.056 |
| *Education of household head* | | | | | | | | | | | | | | | |
| Head has no education | *0.420* | 0.540 | 0.445 | 0.441 | 0.428 | 0.134 | 0.210 | 0.153 | 0.147 | 0.141 | 0.134 | 0.108 | 0.073 | 0.068 | 0.065 |
| Head has primary education | *0.401* | 0.510 | 0.422 | 0.426 | 0.411 | 0.124 | 0.193 | 0.140 | 0.137 | 0.130 | 0.124 | 0.097 | 0.064 | 0.061 | 0.057 |
| Head has secondary education | *0.338* | 0.462 | 0.360 | 0.373 | 0.352 | 0.099 | 0.168 | 0.113 | 0.111 | 0.104 | 0.099 | 0.082 | 0.050 | 0.048 | 0.043 |

*Note:* The mean threshold of the recommended minimum energy requirement (RMEI) in the sample is 1707. *An increase in Maize price by 100% is translated into a mean income reduction of 23% in Uganda.
*Source*: Uganda National Household Survey 2005/2006; author's calculations.

### Table 7: Simulation results on Food Inequality in Malawi and Uganda

| Variable | Gini coefficient Malawi (2004) | | | | | Gini coefficient Uganda (2004) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Actual* | Staple price increase by 100% | Maize price increase by 100% | Income shock (minus 50%) | Maize price shock (100%) as income shock* | *Actual* | Staple price increase by 100% | Maize price increase by 100% | Income shock (minus 50%) | Maize price shock (100%) as income shock* |
| Total | 0.237 | 0.237 | 0.239 | 0.256 | 0.267 | 0.268 | 0.295 | 0.267 | 0.261 | 0.259 |
| *Area* | | | | | | | | | | |
| Urban | 0.206 | 0.206 | 0.209 | 0.221 | 0.237 | 0.260 | 0.288 | 0.257 | 0.252 | 0.249 |
| Rural | 0.241 | 0.241 | 0.242 | 0.261 | 0.271 | 0.270 | 0.296 | 0.269 | 0.263 | 0.261 |
| *Region* | | | | | | | | | | |
| North | 0.272 | 0.272 | 0.268 | 0.300 | 0.285 | 0.284 | 0.305 | 0.281 | 0.281 | 0.280 |
| Centre | 0.222 | 0.222 | 0.221 | 0.240 | 0.251 | 0.263 | 0.295 | 0.265 | 0.256 | 0.254 |
| South | 0.222 | 0.222 | 0.224 | 0.243 | 0.268 | | | | | |
| Eastern | | | | | | 0.258 | 0.280 | 0.248 | 0.241 | 0.239 |
| Western | | | | | | 0.249 | 0.290 | 0.255 | 0.248 | 0.245 |
| *Wealth* | | | | | | | | | | |
| Quintile 1 | 0.200 | 0.200 | 0.201 | 0.227 | 0.266 | 0.297 | 0.324 | 0.299 | 0.298 | 0.299 |
| Quintile 2 | 0.182 | 0.182 | 0.185 | 0.200 | 0.196 | 0.281 | 0.301 | 0.280 | 0.277 | 0.275 |
| Quintile 3 | 0.187 | 0.186 | 0.187 | 0.202 | 0.187 | 0.257 | 0.292 | 0.259 | 0.253 | 0.251 |
| Quintile 4 | 0.186 | 0.186 | 0.189 | 0.198 | 0.186 | 0.244 | 0.278 | 0.246 | 0.240 | 0.237 |
| Quintile 5 | 0.176 | 0.176 | 0.179 | 0.186 | 0.179 | 0.235 | 0.262 | 0.228 | 0.220 | 0.216 |
| *Household headship* | | | | | | | | | | |
| Female headed household | 0.243 | 0.243 | 0.245 | 0.262 | 0.276 | 0.277 | 0.297 | 0.273 | 0.268 | 0.267 |
| Male headed household | 0.235 | 0.235 | 0.237 | 0.254 | 0.265 | 0.265 | 0.294 | 0.265 | 0.259 | 0.256 |
| *Education of household head* | | | | | | | | | | |
| Head has no education | 0.243 | 0.243 | 0.249 | 0.264 | 0.285 | 0.268 | 0.298 | 0.268 | 0.260 | 0.259 |
| Head has primary | 0.231 | 0.231 | 0.232 | 0.249 | 0.254 | 0.267 | 0.294 | 0.264 | 0.259 | 0.255 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| education | | | | | | | | | | |
| Head has secondary education | 0.212 | 0.212 | 0.219 | 0.228 | 0.225 | 0.251 | 0.281 | 0.244 | 0.238 | 0.234 |

*Note:* There is virtually no change in the Gini coefficients between the actual Gini and the after the simulation of the price increase of staple food. Since staple food is such a high share of food in Malawi (see Table 2), a general decline of calories from staple food by 50% does not only have a level effect but the distributional effect is only very small. Differences are observed at the third position after decimal point. Differences in the Gini coefficient in Malawi between the actual data and the staple price increase are only existent at the fourth decimal place.
*An increase in Maize price by 100% is translated into an income reduction of 23% in Uganda and 36 % in Malawi.
*Source*: Malawi Second Integrated Household Survey 2004/2005, Uganda National Household Survey 2005/2006; author's calculations

**Table 8: Seasonality effects on food poverty**

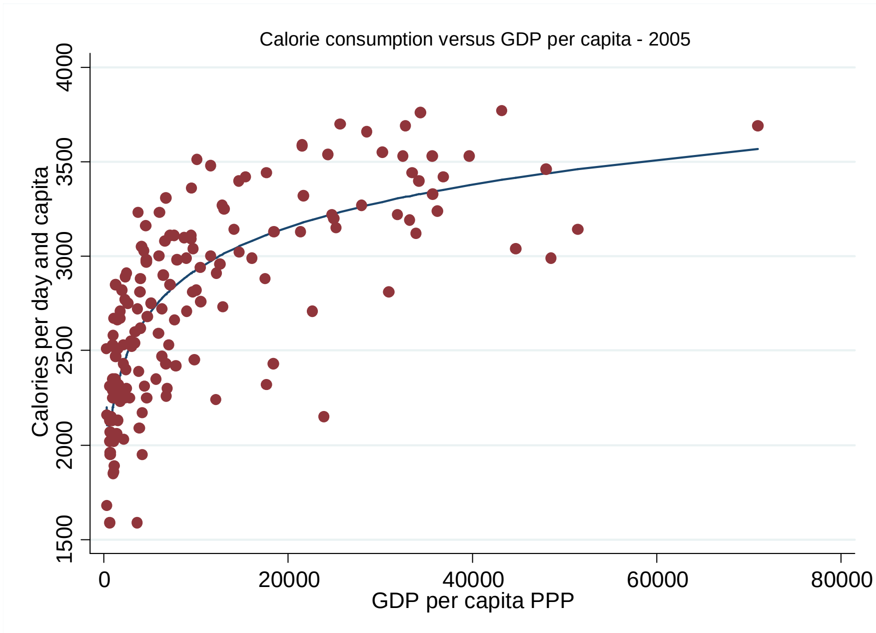
| | Uganda | | | | | | Malawi | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **N** | ***Actual*** | **Staple price increase by 100%** | **Maize price increase by 100%** | **Income shock (minus 50%)** | **Maize price shock (100%) as income shock*** | **N** | ***Actual*** | **Staple price increase by 100%** | **Maize price increase by 100%** | **Income shock (minus 50%)** | **Maize price shock (100%) as income shock*** |
| January | 3,892 | 0.443 | 0.545 | 0.465 | 0.462 | 0.450 | 516 | 0.304 | 0.874 | 0.818 | 0.382 | 0.413 |
| February | 2,849 | 0.396 | 0.523 | 0.428 | 0.415 | 0.399 | 855 | 0.358 | 0.902 | 0.891 | 0.447 | 0.496 |
| March | 4,262 | 0.394 | 0.509 | 0.429 | 0.417 | 0.402 | 1,704 | 0.299 | 0.854 | 0.852 | 0.367 | 0.387 |
| April | 2,377 | 0.420 | 0.539 | 0.460 | 0.448 | 0.432 | 858 | 0.298 | 0.815 | 0.810 | 0.378 | 0.353 |
| May | 2,233 | 0.309 | 0.442 | 0.344 | 0.332 | 0.319 | 739 | 0.295 | 0.827 | 0.821 | 0.372 | 0.353 |
| June | 3,003 | 0.366 | 0.484 | 0.406 | 0.389 | 0.374 | 887 | 0.277 | 0.838 | 0.833 | 0.343 | 0.333 |
| July | 2,512 | 0.422 | 0.552 | 0.455 | 0.444 | 0.433 | 669 | 0.253 | 0.812 | 0.806 | 0.336 | 0.317 |
| August | 3,844 | 0.443 | 0.584 | 0.484 | 0.467 | 0.452 | 1,032 | 0.244 | 0.820 | 0.804 | 0.296 | 0.322 |
| September | 3,096 | 0.380 | 0.503 | 0.411 | 0.404 | 0.386 | 960 | 0.251 | 0.854 | 0.845 | 0.342 | 0.353 |
| October | 3,283 | 0.404 | 0.498 | 0.431 | 0.422 | 0.415 | 832 | 0.252 | 0.834 | 0.825 | 0.337 | 0.364 |
| November | 3,806 | 0.401 | 0.541 | 0.431 | 0.422 | 0.408 | 716 | 0.281 | 0.832 | 0.828 | 0.355 | 0.388 |
| December | 2,160 | 0.431 | 0.571 | 0.453 | 0.456 | 0.441 | 602 | 0.289 | 0.836 | 0.832 | 0.384 | 0.409 |

*Note: * An increase in Maize price by 100% is translated into an income reduction of 23% in Uganda and 36 % in Malawi.*

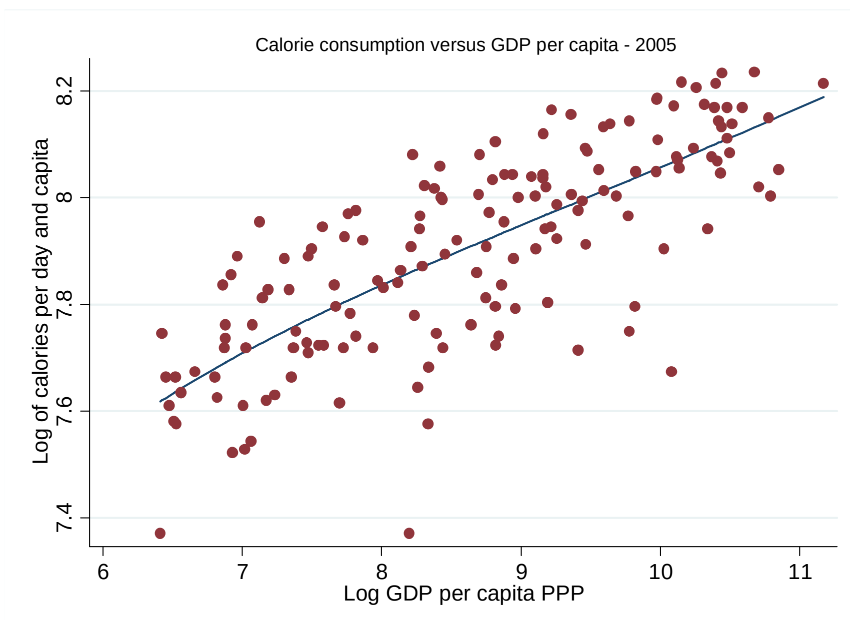
*Source*: Malawi Second Integrated Household Survey 2004/2005, Uganda National Household Survey 2005/2006; author's calculations

**Figure 1: Calorie per capita availability versus GDP per capita (2005)**

(a)

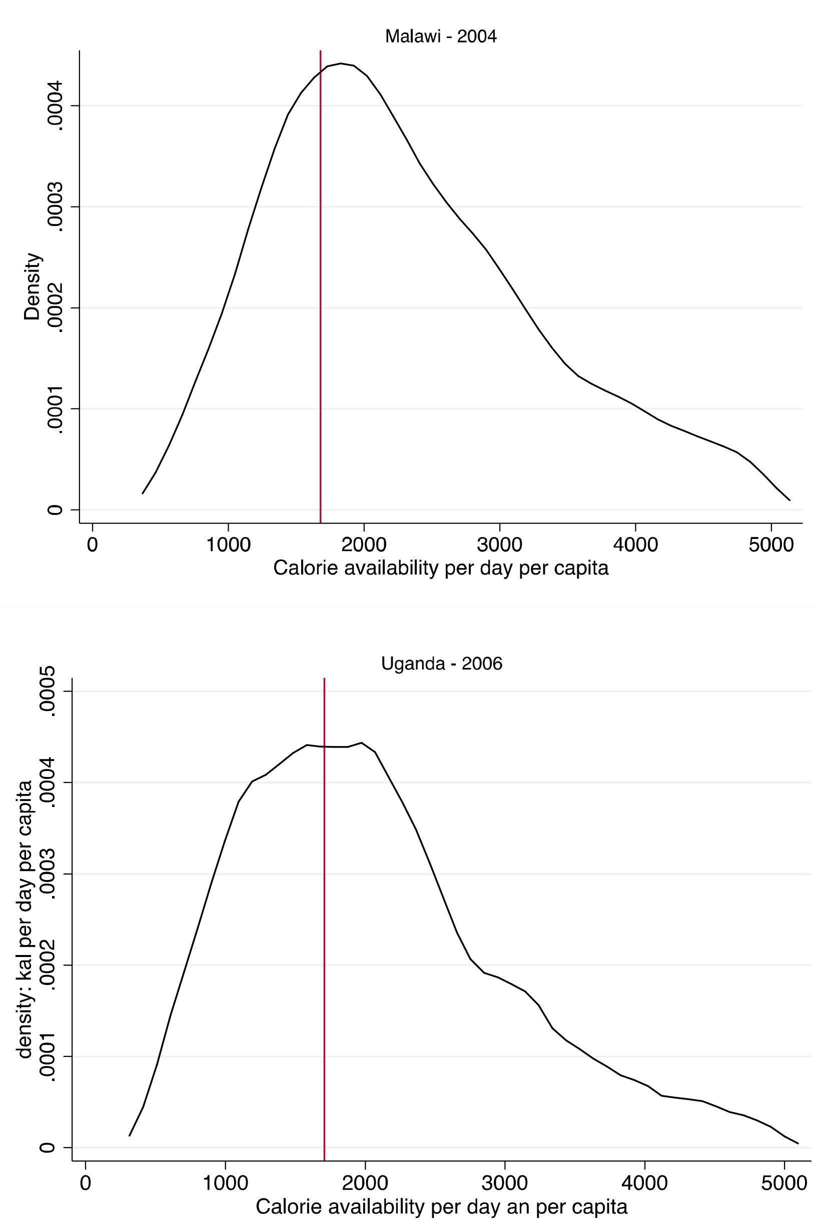



(b)



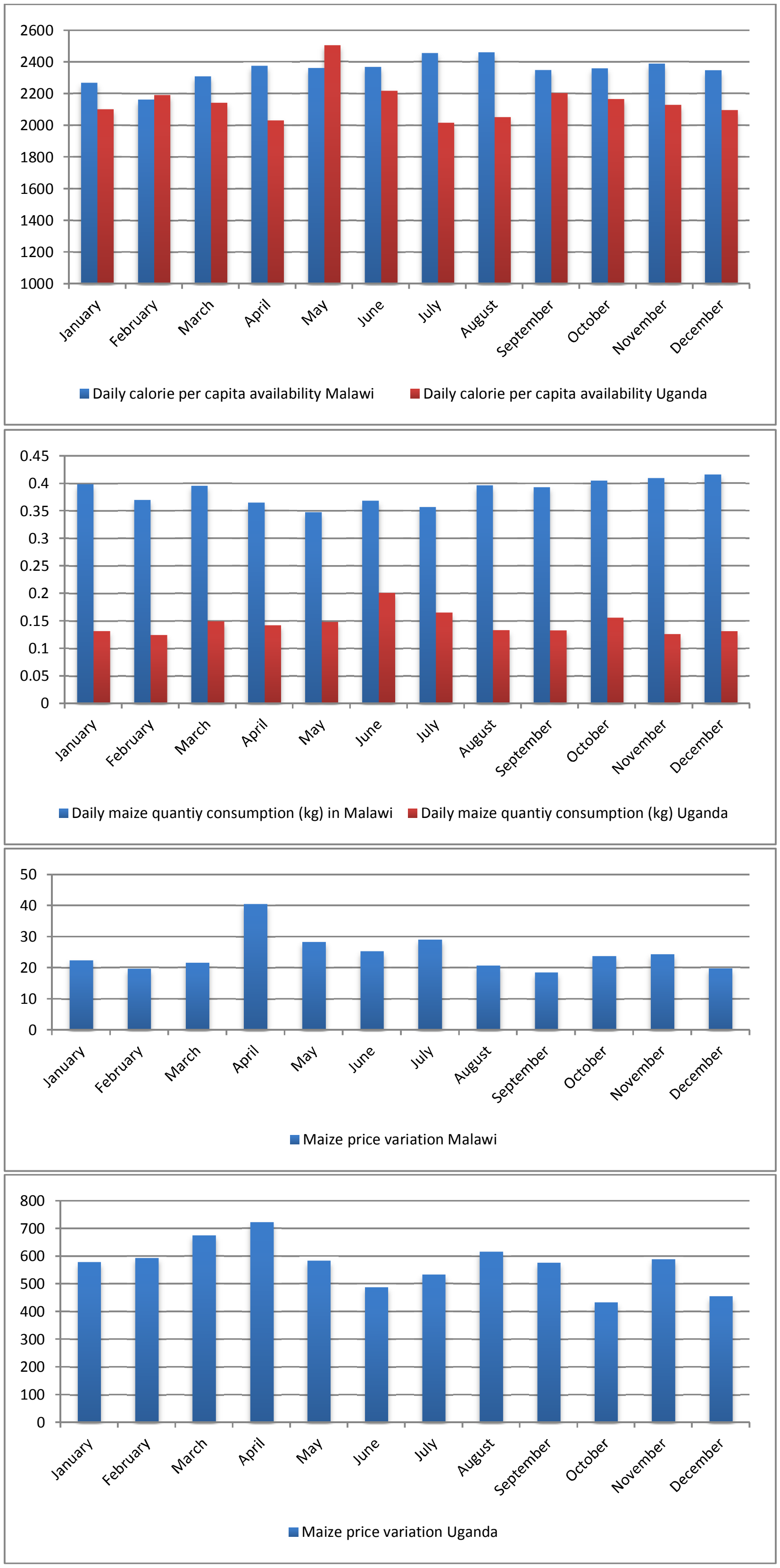

Source: WDI (2010), FAO (2010b); author's calculations

**Figure 2: Densities of calorie intake per capita per day**




Note: The vertical line refers to the average per capita dietary intake requirement for each country. The mean threshold of the recommended mean energy requirement (RMEI) in the sample is 1680 for Malawi (2004), and 1707 for Uganda (2006).
*Source*: Uganda National Household Survey 2005/2006, Malawi Second Integrated Household Survey 2004/2005; author's calculations.

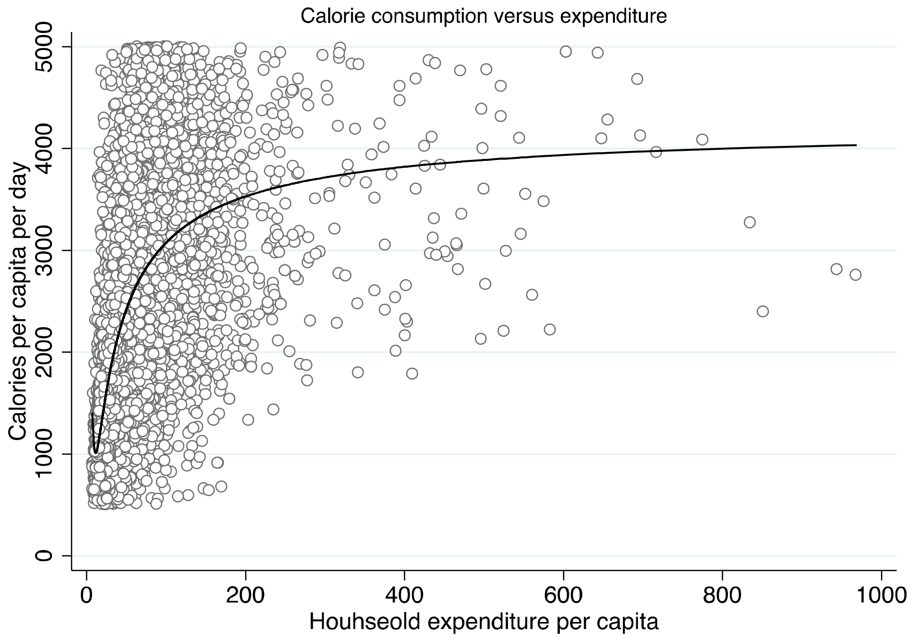
## Figure 3: Seasonality effects



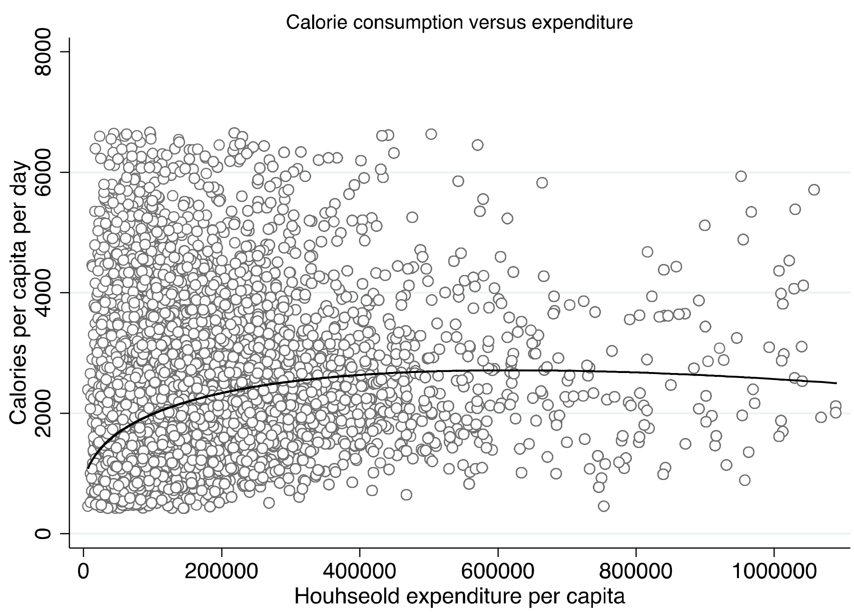

*Source*: Uganda National Household Survey 2005/2006, Malawi Second Integrated Household Survey 2004/2005; author's calculations.

**Figure 4: Relationship between calorie intake and household expenditure**

(a) (Malawi – 2004)

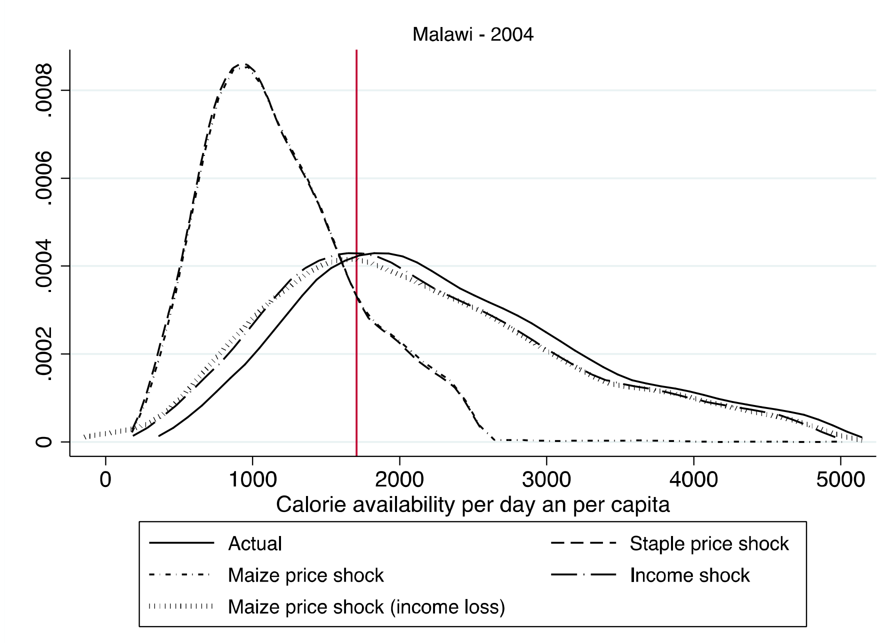


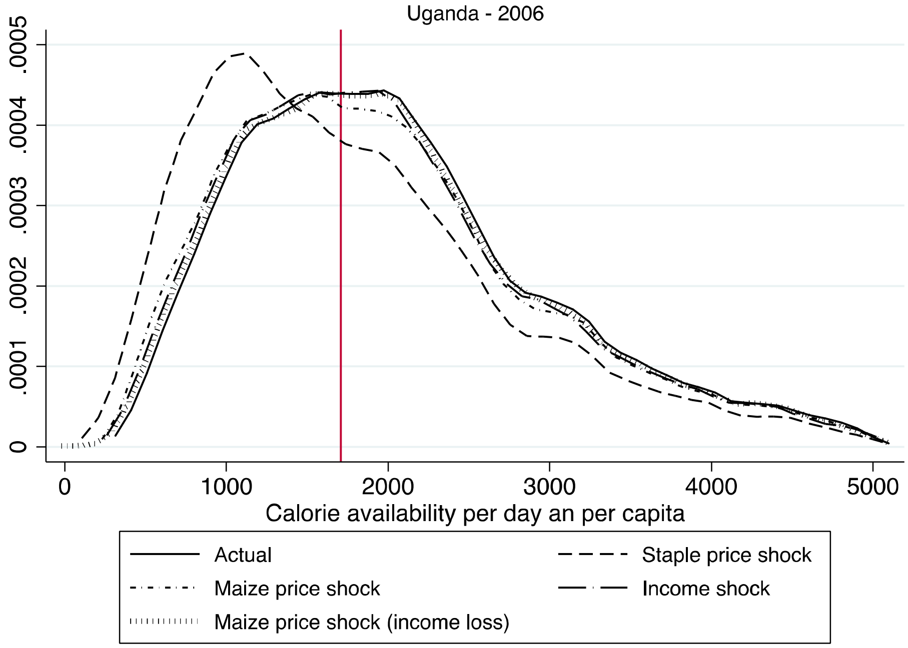

(b) (Uganda - 2006)




*Note:* for the estimation regression equation (1) $\hat{y}_i = \beta_1 \ln(x_i)$, the results for $\beta_1$ are: $\beta_1$=606.34 (s.e. 2.01) in Malawi and $\beta_1$=181.65 (s.e. 0.46) in Uganda.
*Source*: Uganda National Household Survey 2005/2006, Malawi Second Integrated Household Survey 2004/2005; calculation by the authors.

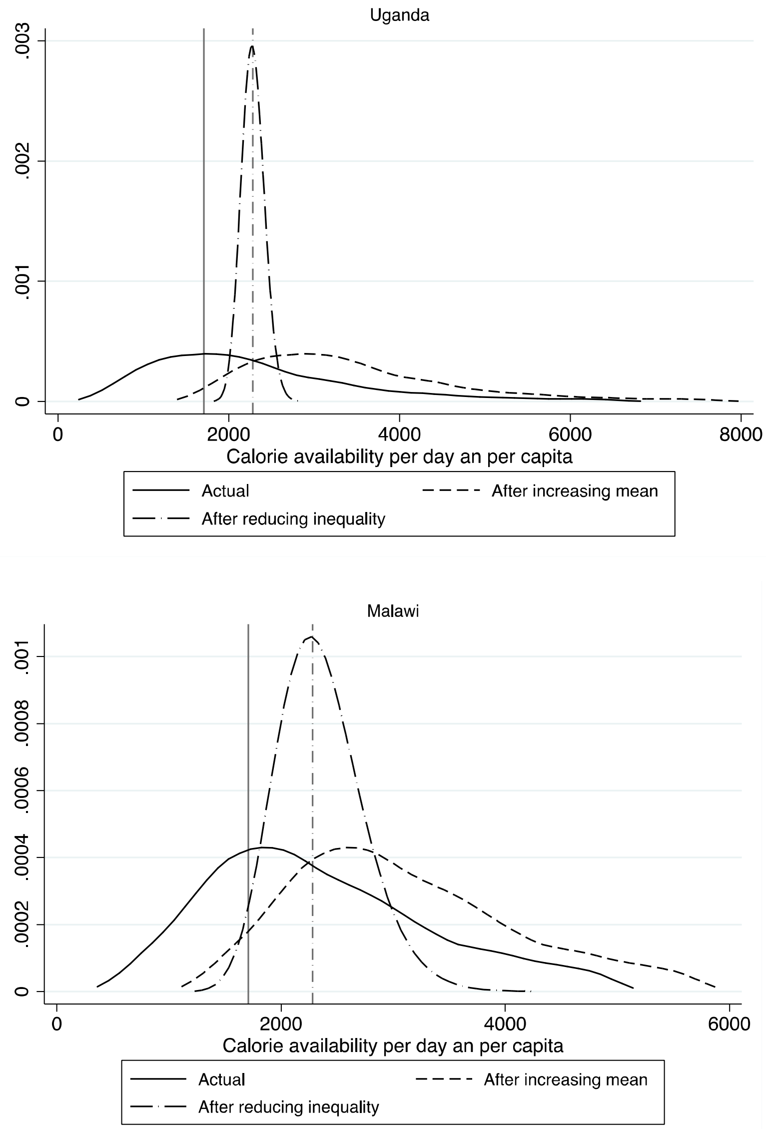
**Figure 5: Densities of calorie intake per capita per day after shocks**




Note: The vertical line refers to the average per capita dietary intake requirement for each country. The mean threshold of the recommended mean energy requirement (RMEI) in the sample is 1680 for Malawi (2004), and 1707 for Uganda (2006).
*Source*: Uganda National Household Survey 2005/2006, Malawi Second Integrated Household Survey 2004/2005; author's calculations.

## Figure 6: Densities of poverty simulations




Note: The left vertical line refers to the average per capita dietary intake requirement for each country. The mean threshold of the recommended mean energy requirement (RMEI) in the sample is 1680 for Malawi (2004), and 1707 for Uganda (2006). The right vertical line refers to the mean of the distribution (2308 in Malawi and 2276 in Uganda). Analyzed is a simulation where food poverty remains at a level of 5%. First, achieving this by a reduction in inequality with equal mean would mean reducing the Gini in Malawi from 0.237 to 0.092 an in Uganda from 0.268 to 0.033. Second, eliminating 95 % poverty by increasing the mean with equal inequality would mean increasing the mean by 750 calories per day and per capita in Malawi and 1150 in Uganda.
*Source*: Uganda National Household Survey 2005/2006, Malawi Second Integrated Household Survey 2004/2005; author's calculations.

## Appendix

**Table A1: FAO versus country estimates of hunger**

| Country | Year | Estimate of Food Deficiancy | FAO estimate | Year |
|---|---|---|---|---|
| Burundi | 1998 | 75 | 56 | 1997 |
| Ethiopia | 1999 | 76 | 62 | 1997 |
| Ghana | 1998 | 51 | 12 | 1997 |
| Guinea | 1994 | 45 | 19 | 1997 |
| Kenya | 1997 | 44 | 31 | 1997 |
| Malawi | 1997 | 77 | 36 | 1997 |
| Mozambique | 1996 | 60 | 48 | 1997 |
| Rwanda | 2000 | 65 | 38 | 2002 |
| Senegal | 2001 | 60 | 26 | 2002 |
| Tanzania | 2000 | 44 | 39 | 2002 |
| Uganda | 1999 | 37 | 23 | 1997 |
| Zambia | 1996 | 71 | 38 | 1997 |
| **Average** | | **59** | **36** | |

*Source*: Smith et al. 2006, World Development Indicators.

**Table A2: Data Sources**

| Country | Survey | Year | Number of households | Food sources for food consumption | Food consumption recall period | Number of food items |
|---|---|---|---|---|---|---|
| Malawi | Second Integrated Household Survey | 2004/2005 | 11,280 | Purchases, home production, gifts | 7 days | 108 |
| Uganda | Uganda National Household Survey | 2005/2006 | 7,421 | Purchases, home production, in kind | 7 days | 61 |

**Table A3: Sample characteristics**

| Variable | Malawi 2004 Mean | Uganda 2005 Mean |
|---|---|---|
| Urban (=1) | 0.126 | 0.211 |
| Rural (=1) | 0.874 | 0.789 |
| Household size | 4.952 | 6.865 |
| Female headed household (=1) | 0.212 | 0.233 |
| Household head has no education | 0.270 | 0.304 |
| Household head has primary education | 0.496 | 0.695 |
| Household head has secondary education | 0.104 | 0.137 |
| *Number of households* | *11280* | *7421* |

*Source*: Uganda National Household Survey 2005/2006, Malawi Second Integrated Household Survey 2004/2005; calculation by the authors.

**Table A4: Food items and frequencies – Malawi (2004)**

| Staple foods | Freq. | Percent | Animal products | Freq. | Percent |
|---|---|---|---|---|---|
| Maize ufa mgaiwa (normal flour) | 7,124 | 16.33 | Eggs | 2,819 | 13.38 |
| Maize ufa refined (fine flour) | 6,303 | 14.44 | Dried fish | 7,113 | 33.76 |
| Maize ufa madeya (bran flour) | 694 | 1.59 | Fresh fish | 2,626 | 12.46 |
| Maize grain (not as ufa) | 1,555 | 3.56 | Beef | 856 | 4.06 |
| Green maize | 3,383 | 7.75 | Goat | 1,199 | 5.69 |
| Rice | 2,782 | 6.38 | Pork | 618 | 2.93 |
| Finger millet (mawere) | 167 | 0.38 | Chicken | 1,863 | 8.84 |
| Sorghum | 632 | 1.45 | Other poultry - guinea fowl, doves, etc | 181 | 0.86 |
| Pearl millet (mchewere) | 119 | 0.27 | Small animal ,Äì rabbit, mice, etc. | 569 | 2.7 |
| Wheat flour | 62 | 0.14 | Termites, other insects | 304 | 1.44 |
| Bread | 1,456 | 3.34 | Tinned meat or fish | 20 | 0.09 |
| Buns, scones | 2,580 | 5.91 | Fresh milk | 1,049 | 4.98 |
| Biscuits | 943 | 2.16 | Powdered milk | 439 | 2.08 |
| Spaghetti, macaroni, pasta | 64 | 0.15 | Butter | 28 | 0.13 |
| Breakfast cereal | 266 | 0.61 | Chambiko - soured milk | 184 | 0.87 |
| Infant feeding cereals | 73 | 0.17 | Yoghurt | 126 | 0.6 |
| Cassava tubers | 4,889 | 11.2 | Cheese | 10 | 0.05 |
| Cassava flour | 1,065 | 2.44 | Infant feeding formula (for bottle) | 24 | 0.11 |
| White sweet potato | 2,826 | 6.48 | Eggs - boiled (vendor) | 92 | 0.44 |
| Orange sweet potato | 1,197 | 2.74 | Chicken (vendor) | 128 | 0.61 |
| Irish potato | 990 | 2.27 | Meat (vendor) | 273 | 1.3 |
| Potato crisps | 73 | 0.17 | Fish (vendor) | 550 | 2.61 |
| Cocoyam (masimbi) | 109 | 0.25 | **Meal complements** | | |
| Maize - boiled or roasted (vendor) | 347 | 0.8 | Margarine | 289 | 0.72 |
| Chips (vendor) | 1,007 | 2.31 | Sugar | 6,270 | 15.54 |
| Cassava - boiled (vendor) | 377 | 0.86 | Sugar Cane | 3,977 | 9.86 |
| Mandazi , doughnut (vendor) | 2,552 | 5.85 | Cooking oil | 5,613 | 13.92 |
| **Pulses** | | | Salt | 11,022 | 27.33 |
| Bean, white | 1,777 | 9.71 | Spices | 213 | 0.53 |
| Bean, brown | 4,775 | 26.08 | Yeast, baking powder, bicarbonate of so | 2,003 | 4.97 |
| Pigeonpea (nandolo) | 2,393 | 13.07 | Tomato sauce (bottle) | 47 | 0.12 |
| Groundnut | 4,026 | 21.99 | Hot sauce (Nali, etc.) | 145 | 0.36 |
| Groundnut flour | 2,844 | 15.54 | Jam, jelly, honey | 41 | 0.1 |
| Soyabean flour | 468 | 2.56 | Sweets, candy, chocolates | 815 | 2.02 |
| Ground bean (nzama) | 668 | 3.65 | Tea | 3,304 | 8.19 |
| Cowpea (khobwe) | 1,356 | 7.41 | Coffee | 142 | 0.35 |

| | | | | | |
|---|---|---|---|---|---|
| **Vegetables and fruits** | | | Squash (Sobo drink concentrate) | 392 | 0.97 |
| Plantain, cooking banana | 719 | 1.43 | Fruit juice | 178 | 0.44 |
| Onion | 3,564 | 7.08 | Freezes (flavoured ice) | 509 | 1.26 |
| Cabbage | 2,019 | 4.01 | Soft drinks | 1,371 | 3.4 |
| Tanaposi/Rape | 4,866 | 9.67 | Chibuku/Napolo (commercial traditional- | 328 | 0.81 |
| Nkhwani | 7,531 | 14.96 | Bottled/canned beer | 127 | 0.31 |
| Chinese cabbage | 668 | 1.33 | Local sweet beer (thobwa ) | 1,801 | 4.46 |
| Other cultivated green leafy vegetables | 2,537 | 5.04 | Traditional beer (masase ) | 1,099 | 2.72 |
| Gathered wild green leaves | 1,429 | 2.84 | Wine or commercial liquor | 21 | 0.05 |
| Tomato | 8,542 | 16.97 | Locally brewed liquor (kachasu ) | 627 | 1.55 |
| Cucumber | 891 | 1.77 | | | |
| Pumpkin | 2,595 | 5.16 | | | |
| Okra/Therere | 3,293 | 6.54 | | | |
| Mango | 1,532 | 3.04 | | | |
| Banana | 4,306 | 8.56 | | | |
| Citrus ‚Äì naartje, orange, etc. | 1,323 | 2.63 | | | |
| Pineapple | 92 | 0.18 | | | |
| Papaya | 1,334 | 2.65 | | | |
| Guava | 1,477 | 2.93 | | | |
| Avocado | 1,007 | 2 | | | |
| Wild fruit (masau, mlambe, etc.) | 490 | 0.97 | | | |
| Apple | 118 | 0.23 | | | |

*Note*: Conversion factors for Kcal per 100g are taken from Ecker and Qaim (2010).

*Source*: Malawi Second Integrated Household Survey 2004/2005; calculation by the authors.

**Table A5: Food items and frequencies – Uganda (2006)**

| Food Item/Group | Freq. | Percent | Kcal per 100g | Food Item/Group | Freq. | Percent | Kcal per 100g |
|---|---|---|---|---|---|---|---|
| **Staple foods** | | | | **Pulses** | | | |
| matooke | 2,593 | 2.70% | 116 | beans fresh | 961 | 1.00% | 306 |
| matooke | 539 | 0.60% | 116 | beans dry | 4,754 | 5.00% | 116 |
| matooke | 311 | 0.30% | 116 | ground nuts in shell | 112 | 0.10% | 567 |
| matooke | 226 | 0.20% | 116 | ground nuts shelled | 1,129 | 1.20% | 567 |
| sweet potatoes fresh | 3,772 | 4.00% | 74 | ground nuts pounded | 1,980 | 2.10% | 567 |
| sweet potatoes dry | 162 | 0.20% | 103 | peas | 705 | 0.70% | 322 |
| cassava fresh | 2,994 | 3.10% | 160 | simsim | 864 | 0.90% | 573 |
| cassava dry/flour | 1,645 | 1.70% | 314 | **Meal Complements** | | | |
| irish potatoes | 761 | 0.80% | 58 | sugar | 4,649 | 4.90% | 387 |
| rice | 1,884 | 2.00% | 358 | coffee | 392 | 0.40% | 200 |
| maize grains | 341 | 0.40% | 119 | tea | 4,475 | 4.70% | 1 |
| maize cobs | 982 | 1.00% | 59 | salt | 6,860 | 7.20% | 0 |
| maize flour | 4,400 | 4.60% | 362 | soda | 798 | 0.80% | . |
| bread | 1,407 | 1.50% | 274 | beer | 349 | 0.40% | 41 |
| millet | 1,372 | 1.40% | 328 | other alcoholic drinks | 1,273 | 1.30% | . |
| sorghum | 825 | 0.90% | 339 | other drinks | 419 | 0.40% | . |
| **Animal products** | | | | cigarettes | 670 | 0.70% | 0 |
| beef | 2,395 | 2.50% | 323 | other tobacco | 723 | 0.80% | 0 |
| pork | 411 | 0.40% | 537 | expenditures in restaurants on food | 1,248 | 1.30% | . |
| goat meat | 463 | 0.50% | 269 | expenditures in restaurants on soda | 322 | 0.30% | . |
| other meat | 110 | 0.10% | 376 | expenditures in restaurants on beer | 55 | 0.10% | . |
| chicken | 574 | 0.60% | 200 | other juice | 417 | 0.40% | . |
| fresh fish | 1,437 | 1.50% | 98 | other foods | 956 | 1.00% | . |
| dry/smoked fish | 1,965 | 2.10% | 335 | infant formula foods | 20 | 0.00% | 500 |
| eggs | 927 | 1.00% | 155 | cooking oil | 4,386 | 4.60% | 884 |
| fresh milk | 2,488 | 2.60% | 60 | ghee | 316 | 0.30% | 884 |
| **Fruits & Vegetables** | | | | margarine, butter | 267 | 0.30% | 716 |
| passion fruits | 899 | 0.90% | 43 | | | | |
| sweet bananas | 1,101 | 1.20% | 89 | | | | |
| mangoes | 751 | 0.80% | 65 | | | | |

| | | | |
|---|---|---|---|
| oranges | 497 | 0.50% | 47 |
| other fruits | 1,486 | 1.60% | 61 |
| onions | 5,099 | 5.40% | 40 |
| tomatoes | 5,022 | 5.30% | 21 |
| cabbages | 1,250 | 1.30% | 25 |
| dodo | 2,395 | 2.50% | . |
| other vegetables | 2,618 | 2.80% | 29 |

*Note*: Conversion factors for Kcal per 100g are taken from the survey questionnaire.
*Source*: Uganda National Household Survey 2005/2006; calculation by the authors.

## Table A6: Seasonality effects on food availability

| | Uganda | | | | | | | | Malawi | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Actual* | Quintile 1 | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 | Urban | Rural | *Actual* | Quintile 1 | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 | Urban | Rural |
| January | 0.443 | 0.663 | 0.549 | 0.489 | 0.426 | 0.249 | 0.442 | 0.445 | 0.443 | 0.642 | 0.287 | 0.213 | 0.114 | 0.063 | 0.321 | 0.197 |
| February | 0.396 | 0.556 | 0.503 | 0.367 | 0.358 | 0.345 | 0.368 | 0.480 | 0.396 | 0.714 | 0.314 | 0.210 | 0.123 | 0.087 | 0.365 | 0.289 |
| March | 0.394 | 0.608 | 0.477 | 0.414 | 0.390 | 0.302 | 0.398 | 0.372 | 0.394 | 0.642 | 0.340 | 0.203 | 0.136 | 0.065 | 0.309 | 0.230 |
| April | 0.420 | 0.576 | 0.598 | 0.461 | 0.345 | 0.370 | 0.415 | 0.443 | 0.420 | 0.678 | 0.435 | 0.260 | 0.126 | 0.092 | 0.322 | 0.112 |
| May | 0.309 | 0.468 | 0.380 | 0.347 | 0.250 | 0.243 | 0.318 | 0.282 | 0.309 | 0.704 | 0.391 | 0.194 | 0.124 | 0.045 | 0.311 | 0.180 |
| June | 0.366 | 0.568 | 0.443 | 0.359 | 0.311 | 0.270 | 0.354 | 0.400 | 0.366 | 0.763 | 0.394 | 0.181 | 0.111 | 0.039 | 0.293 | 0.164 |
| July | 0.422 | 0.607 | 0.563 | 0.477 | 0.352 | 0.204 | 0.422 | 0.423 | 0.422 | 0.703 | 0.459 | 0.191 | 0.172 | 0.036 | 0.255 | 0.227 |
| August | 0.443 | 0.672 | 0.503 | 0.426 | 0.450 | 0.264 | 0.447 | 0.419 | 0.443 | 0.638 | 0.317 | 0.180 | 0.145 | 0.122 | 0.261 | 0.125 |
| September | 0.380 | 0.510 | 0.475 | 0.425 | 0.374 | 0.231 | 0.404 | 0.308 | 0.380 | 0.594 | 0.313 | 0.179 | 0.090 | 0.105 | 0.258 | 0.207 |
| October | 0.404 | 0.615 | 0.494 | 0.370 | 0.284 | 0.303 | 0.413 | 0.368 | 0.404 | 0.605 | 0.243 | 0.178 | 0.102 | 0.069 | 0.266 | 0.131 |
| November | 0.401 | 0.620 | 0.508 | 0.356 | 0.319 | 0.287 | 0.413 | 0.345 | 0.401 | 0.708 | 0.339 | 0.173 | 0.122 | 0.091 | 0.304 | 0.133 |
| December | 0.431 | 0.444 | 0.575 | 0.508 | 0.439 | 0.220 | 0.391 | 0.555 | 0.431 | 0.680 | 0.367 | 0.133 | 0.104 | 0.084 | 0.298 | 0.239 |

*Source*: Uganda National Household Survey 2005/2006, Malawi Second Integrated Household Survey 2004/2005; calculation by the authors.