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Analyzing Nutritional Impacts of Price and Income Related Shocks in Malawi: Simulating Household Entitlements to Food

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ANALYZING NUTRITIONAL IMPACTS OF PRICE AND INCOME RELATED SHOCKS IN MALAWI: SIMULATING HOUSEHOLD ENTITLEMENTS TO FOOD

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Abstract

The 2007/2008 food price crisis and the following global economic recession has (temporarily) increased the number of people to suffer from hunger. While the impacts can be measured with precision only ex post, for policy makers it is critical to get a sense of likely impacts ex ante in order to plan approaches to mitigate these impacts. In this paper we adopt a very simple micro-based simulation approach to analyze how changes in prices of specific food groups, such as maize prices or prices for staple foods, as well as how negative short-term household level income shocks affect the entitlements to calorie consumption of individuals and how these changes affect overall food poverty. We illustrate our approach using household survey data from Malawi. We find that food poverty is of serious concern with large within-country variations. We find that price shocks for staple foods have a very large impact on food security with particularly strong effects on poor net food buyers in rural and urban areas. This paper demonstrates that it is possible to estimate food security impacts of price and income shocks ex ante in a relatively straightforward fashion that can be done relatively quickly and that is suitable for cross-country assessments of the likely impacts of shocks on food security and the design of appropriate response measures.

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1 Introduction

The 2007/ 2008 food price crisis and the following global economic recession have (presumably) led to large increases 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 increase in food poverty and food insecurity as it reduces the entitlements households have to food. Indeed such entitlement failures are the key to explaining famines in the framework of Sen's entitlement approach (Sen, 1981). However, although there is a general agreement in the literature on the definition of food security, i.e. referring to effective access to food by individuals and households rather than just the availability of food in a country, it is exceedingly difficult to come up with reliable estimates of the impact of the food price and related crises on food insecurity and hunger. Although data availability has been improved within the last years, data limitations are still the main constraint analyzing impacts of income and price shocks on food security and food poverty. Due to their infrequent collection, analyzing household survey data for this purpose implies a time lag of several years between a majority of events and estimates of their effects. This further increases uncertainty in identification and overall 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 and identified those who become food insecure as a result of price and output crises, it is at least as important to identify those affected by short-term crises who might be threatened with acute hunger.

The most commonly used indicator in public debates of food insecurity is the Food and Agriculture Organization of the United Nations' (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 data directly measuring individual's access to food. Rather, it attempts to measure the access individuals have to calories in a country:[4] It first estimates a three year moving average of per capita calorie availability from food balance sheets, trade statistics, and assumptions about

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

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 is only available with a time lag of 2-3 years.[5] Therefore, this indicator is unsuitable to assess the impact of food price crises and economic recessions on hunger, and 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, 1981). Although food availability at the national level is a necessary condition for households to have access to food, it is not a sufficient condition. Households must also have enough resources to meet their basis needs and to acquire enough amount of food.[6]

The most direct alternative to measuring caloric shortfall is to analyze information from household surveys as to measure food availability and food insecurity on a per-day and per capita basis. Based on an analysis of household surveys, the International Food Policy Research Institute (IFPRI) has published an estimate of hunger in 12 sub-Saharan African countries (Smith et al 2006). 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 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. 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 availability directly at the household level, one does not need to rely on a problematic assumption about the distribution of calories within the country. Also, population groups affected can be directly identified and the indicator is thus particularly 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

[5] 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.

[6] For further discussions on 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.

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 readily available information in a food crisis, is limited.

To use these household surveys for assessing current short-term food security fluctuations nevertheless, one could use a survey-based approach to then simulate the impact of price and income changes on 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. Simulation results regarding 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 (Abdulai and Aubert (2004a, b), Bouis et al (1992), von Braun et al (1991), Strauss (1984), and Skoufias (2009)). These studies are based on rather detailed simulation methods that address this issue for individual countries. For example, Ecker and Qaim (2010) extended such an approach by going beyond calories and the authors also capture micronutrient deficiencies and estimate related price and income elasticities. They show that food price changes have differentiated impacts on the consumption of micronutrients. For example, higher maize prices can lead to a shift in the micronutrient composition towards cheaper food, which can reduce the consumption of certain micronutrients. They also find that changes in income can have micronutrient neutral effects despite affecting 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 increases 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 suitable for comparisons over a larger range of countries to assess the likely 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 Sen's entitlement approach, which has proven to be the most robust way to understand famines. Sen (1981) 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 will 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 food and non-food basket (e.g. Ravallion, 1994), income poverty increases if people lose income or if prices for their basket go up, again the issues we are interested in.

In particular, we adopt a very simple simulation approach to analyze how changes in prices of specific food groups such as maize or staple food as well as how negative short-term income shocks on household income affect the calorie consumption[7] of individuals and how these changes affect food poverty in the very short-term.

One should be aware upfront that this approach is based on a very simple parametric estimation of the relationship between income and food consumption, which does not explicitly account for any behavioral changes of the household induced by price or 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 react to changing relative prices. Some households might change their food basket in the shorter-term as a result of lower resource endowments and shift from expensive to more affordable food items in order to secure their minimum energy requirements and 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 in detail (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 behavioral responses, we can directly analyze within-country differences of effects by socioeconomic characteristics, since different groups likely differ in their ability to switch to other foods.

We use calorie consumption per day and per capita as an indicator of food security. To illustrate our approach, we use household survey data from Malawi to first determine the

[7] Note that we use the terms food and calorie consumption and food and calorie availability interchangeably in this paper. For a discussion of conceptual differences, see section 3.4.

share of households that have insufficient command over calories and then estimate the impact of rising food prices and various income shocks on caloric deficiency. In order to do that, first, data about food consumption from purchases, own production, gifts or in-kind payments are converted into metric units and subsequently into calories per capita and day. This information is then used to analyze the state of food security by socioeconomic characteristics. Second, we estimate the calorie-income relationship. Third, we use this relationship to estimate to what extent falling real incomes (brought about by rising prices or income shocks) will affect the number of calorie-deficient households. To verify the usefulness of our approach, we also apply calorie income and calorie price elasticities provided by Ecker and Qaim (2010) for the same data, and discuss differences to using our simple approach.

We find that food poverty is a serious concern in Malawi with large within-country variations. Price increases of maize and/or staple food increase food poverty, especially among the poorer and urban population who cannot shift their food consumption pattern towards other (mostly more expensive) food items. Income shocks have relatively larger and more uniform effects and also hit rural food producers very hard, who are less affected by maize price shocks. Comparisons with more complex method show that our very simple approach provides a good approximation of short-run effects that can be useful when designing timely measures to mitigate the impact of price and income shocks.

The rest of the paper is organized as follows. In section 2, we describe the empirical approach of estimating food poverty in terms of calorie per day and capita consumption and our strategy to simulate the effects of negative price and income shocks. 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 current food security and food poverty profiles and then present our simulation results. In section 5 we conclude and provide an outlook for further research.

2 Empirical Analyses of Income and Price Shocks on Food Availability

The empirical approach of the paper is divided into three parts. In the first part, we provide a description of food consumption per day and per capita at the national level. We further examine within country differences by population subgroups, which we will continue throughout this paper. In particular, we focus on differences in food consumption by region, rural and urban areas, income quintiles, and by sex and education of household heads. In doing so, we closely follow Smith et al (2007).

Parts two and three are closely in line with Sen's entitlement approach and consecutively focus on changes in endowments and in exchange rates of food. Accordingly, part two examines effects of negative income shocks (that affect all households equally) and part three examines effects of maize prices increases on food consumption and the risk of food poverty. For example, between 2005 and 2007, the global maize price rose by 80% (Anríquez et al 2010).

The simulations done in this paper largely build on the parametric estimate of the income-food consumption linkage, which we derive from household survey data. We take this relationship to estimate the impact of negative income shocks (for some simulations induced by price changes) on food availability. 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:

$$y_i \;=\; \beta_0 \;+\; \beta_1 \ln(x_i) \;+\; u_i, \qquad (1)$$

where y_i refers to the per capita and day calorie availability of household i, and $\ln(x_i)$ to the log of household i's income/expenditure per capita. After having estimated equation (1) we are able to predict changes in the calorie per day and per capita if income changes as a result of negative income or later as a result of price shocks. In this paper, we assume a uniform income shock affecting all households the same (in percentage terms); of course one could simulate other income shocks as well. The changes in food availability per day and capita are obtained by applying equation (2).

$$y_i^{new} = \; y_i^{actual} - \beta_1[\ln(x_i) - \ln(x_i^*)] \qquad (2)$$

In equation (2), the new (after shock) amount of calories per day and capita $y_i^{new}$is obtained by subtracting β_1 (from equation (1)) times the term in brackets from the currently observed amount of calories per day and capita, y_i^{actual}. These 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 has occurred. The 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 to show which groups would most strongly be affected by the respective income shock.

To model the impacts of price shocks, 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 affected by increases in prices. Accordingly, we study how increases in maize prices affect the risk of food poverty. In this paper, we assume a price increase of maize by 100% and compare our findings to a uniform income shock of 50%. To examine the effect of price changes on food availability in our framework, we will simulate the effect if the food price shock is treated as an equivalent income shock, implicitly allowing households to adjust to the rising food prices. In order to do that, we are first calculating the household-specific income equivalent of the price shock (i.e. maize quantity purchased*maize price increase), and then investigate how this income shock reduces calorie availability applying the parametric estimate introduced before. As opposed to a uniform income shock, this will effectively mean households that purchased more maize initially will be more heavily affected by the shock.

To analyze food poverty 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

To illustrate our simple simulation approach, we use household survey data from Malawi. In particular, we use 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 IHS-2 is nationally representative and based on a two-stage stratified sampling design (NSO 2005). The IHS-2 comprises 11,280 households, and includes a module on food consumption based on purchases, own production, and gifts for 108 food items and with a recall period of 7 days. An additional advantage of the survey is that the data collection covers a one year period (from March 2004 through March 2005). This allows capturing seasonality effects and associated variances of agricultural production and consumption and makes the observed food availability quantities more precise and reliable.[8]

3.2 Estimates of Food Availability

As measure of food availability we use calorie availability per day and per capita. This indicator is based on the conceptual framework for food and nutrition security described by

[8] See section 3.4 on data limitations below.

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), and Ecker and Qaim (2010).

The household information on food consumption comes from own production, purchases and gifts or in kind transfers.[9] Quantities of food items converted into calories were provided by Ecker and Qaim. To convert physical quantities consumed as reported in the survey, all quantities are converted into standard weight units before converting these standardized units to calories using conversion factors of the World Food Dietary Assessment System (FAO 2010a). Since there are no conversion factors for Malawi, the authors used conversion factors from Senegal and Kenya.

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 expressed in per day terms and 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 have to assume that food is distributed according to needs between all household members.[10]

3.3 Estimation of food poverty

Typically, food insecurity indicators are measures at the household or individual level 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.

To determine this on the level of households, a household's observed calorie consumption needs to be compared to an 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 the age and sex composition of households. To assess whether a household member lacks sufficient calorie intake per day, we use international age and sex specific standard recommendations and requirements for individuals provided by the

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[9] See Table A2. 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.

[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.

FAO, WHO and UNO (2001). The information is used to calculate household-specific reference values. In particular, we apply recommended mean energy intakes (RMEI) also used by Ecker and Qaim (2010), who analyze nutritional impacts of policies in Malawi.

We define a household (and all its members) as food deprived if its amount of consumed calories per day falls below the (age and sex specific) food requirement threshold for that household. Overall food poverty is then calculated as the percentage of households or individuals that fall below their food poverty thresholds.

3.4 Data Limitations

Our estimates of food consumption on a per day and capita basis have certainly some drawbacks, which we now discuss (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 quantities, which results in lower accuracy of the data (Deaton and Grosh 2000). However, in the survey used for this study, the recall period of 7 days is relatively short, so that the data are presumably quite accurate.

Second, we aggregate quantities of food consumption from several sources, e.g. home production, purchase and 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 spoiled or wasted, 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 reported as being consumed is available, we cannot address this issue with our data.[12]

Third, 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 seasonal dynamics of food production. However, in Malawi the data collection covers a one-year period (e.g. for Malawi from March 2004 through March 2005). This captures seasonality and variances of agricultural production and consumption. To exploit this rich information, we will undertake a calorie availability assessment also by different seasons.

Fourth, an issue arises when converting quantities of food items into grams or kilograms; for some specifications of quantities, no conversion factors are available. Depending on the

[11] See Table A2.

[12] However, the questionnaire specifically asks for items consumed in the recall period (rather than purchased or received), which limits the potential bias as overestimation of actual calorie intakes and errors are assumed to be non-systematic.

frequencies of observation, dropping this information can reduce the sample size and might bias our estimates. However, in the case of Malawi, 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.

Fifth, another issue arises when using generally defined cut-offs to calculate the prevalence of food poverty (see, e.g. Svedberg 2000 and Ecker and Qaim 2010 for a detailed discussion). Although we use minimum calorie requirements that account for the sex and age composition of households, which is commonly done in the literature, we need to assume that all individuals with the same sex and at the same age have equal daily calorie requirements. Thus, we do not account for differences in the physical status of individuals, for example, or perform any adjustments for their health status, both of which would affect the minimum daily calorie requirements.

Sixth, the indicator of per day and per capita calorie availability based on a 7 day recall period is just a snapshot of the current food situation of a household and does neither allow to address whether the household has access to food at all times nor does it take into account food preferences of the household (Smith et al. 2006). In addition, our indicator cannot address the quality of food available, which is taken into account by Ecker and Qaim (2010) for example.

Being aware of these data limitations and of the assumption to be made in order to estimate 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 actual calorie intake 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 changes of food security for different groups of households as a result of price and income shocks.

4 Results and discussion

4.1 Food Availability Profiles

In this section, we present the national and subgroup specific estimates of food consumption. Sampling weights are used to produce summary statistics. Table 1 shows the food consumption per day and per capita for Malawi (2004/2005). The total mean calorie availability is 2361 kcal per capita per day.[13]

[13] Our results are somewhat different from the findings of Ecker and Qaim (2010), which is due to differences in handling raw data and dealing with outliers. In particular, Ecker and Qaim (2010) report mean calories of 2171 and energy deficiency

Figure 1 shows the non-parametric probability density function of household's per capita calorie consumption. The distribution appears lognormal due to the extended right tail. The vertical line shows the mean of the minimum dietary requirement for Malawi (see next section).

Before we have a closer look at food poverty, Table 1 already provides some interesting results with respect to within-country differences in calorie per capita consumption per day by socioeconomic characteristics. Only 12% of the population lives in urban areas compared to 88% in rural areas. As expected due to higher levels of income poverty, rural food availability per capita and day is lower than urban food availability. 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).[14] Table 1 also shows some variations by geographical regions in Malawi. The South, home to around half of the urban population, shows much higher availability of calories per capita than the Centre and the North of Malawi.

Table 1 additionally reveals some interesting differences between female-headed and male-headed households. Female-headed households show, on average, a higher level of calorie per capita availability (2429kcal compared to 2341kcal). Regarding education of household heads, higher educational levels are associated with higher mean per capita calorie consumption. However, these mean values do not allow drawing any firm conclusion about differences in food poverty and food security between these subgroups as caloric requirements and other relevant characteristics might differ across groups (see below).

Table 2 shows calorie availabilities per day and per capita by five food groups, namely staple food, pulses, vegetable and fruits, animal products, and meal complements.[15] Table 2 reveals that by far the largest amount of calories stems from staple food, where 74% of all per capita calories are sourced from. The second largest calorie resource in Malawi is pulses, which provides 12% of per capita calories, followed by meal complements which includes oils and fats, beverages, sugar, and spices (9%). Interestingly, the share of calories that come from more expensive animal products is rather low, which is probably linked to very low incomes that make such products unaffordable for many households.

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of 34.8% while we estimate mean calories of 2361 and energy deficiency of 29%. In addition, comparing the means of the calories per capita per day in our sample with national estimates of the FAO (2005-07) reveals also some differences. In Malawi, the FAO estimates are considerably lower than our estimates (see discussion on the differences between survey estimates of food poverty and FAO estimates below).

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

[15] For the frequencies and shares of households that consumed each food item within these food groups, see Table A3.

Next, we take a closer look at how food availability and food composition differ across income groups, in our case defined as total expenditure quintiles. Table 3 reveals a clear pattern: it shows that monetary poverty and calorie consumption are positively correlated. The poorest quintile consumes less than half of the calories of the richest quintile, shown by the $5^{th}:1^{st}$ quintile ratio in Table 3, and the poorest 40% of the population consume fewer than 2,000 calories per capita and per day. Furthermore, 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. The share of staple food decreases with household expenditure, whereas calorie shares from animal products and meal complements increase. These findings illustrate the importance of staple foods, especially among the poor, and already indicate how changes in staple food prices likely increase food insecurity among vulnerable population groups.

As described in the previous section, the data allow capturing seasonality 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 2 shows considerable variations in calorie availability, quantity of maize consumption and maize prices by months of the year. The first panel shows variations in calorie consumption per day and capita. For example, the mean calorie consumption in February declines below 2200 calories per day and capita. Average maize prices range from 20 to 26 Malawi Kwacha per kilo and average consumption of maize per capita and day ranges from 380 to 470 grams over the year. Hence, seasonality effects exist and 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 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, the severity index, and additionally the Gini coefficient by population subgroups. Table 4 reveals that food insecurity is a major concern in Malawi and food consumption is characterized by highs risks of food poverty and malnutrition. 28.3% of the population falls below the minimum daily calorie requirement threshold.

[16]To further illustrate how seasonality affects food availability for socioeconomic subgroups, Table A4 shows the levels of food consumption per day and capita by month, income quintiles and by urban and rural areas.

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 terms of the depth of food poverty at the national level, Table 4 shows that a severity index of 0.027.

Table 4 presents interesting within-country variations in food poverty and inequality by socioeconomic characteristics. We find large within country variations in food poverty, for example between rural and urban areas. Whereas less than 20% percent of the urban population was calorie deprived in 2004/2005, calorie deficiency was around 30% in rural areas, reflecting the overall worse access to food markets as well as lower level of incomes in rural areas (see below). In rural areas, calorie deficiency is also more unequally distributed, as shown in the higher Gini coefficient.

Next, we take a closer look at differences in food poverty by income quintiles. 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. The poorest quintile shows a food poverty headcount of almost 70% compared to 7.6% of the richest quintile. The same strong income gradient is found for food inequality within these quintiles. The Gini coefficient within quintile decreases with levels of income, suggesting that particularly among the income poor there is substantial variation in food deficiency. However, besides the clear observable correlation between income and food consumption, we can also see that food poverty and income poverty is not the same thing at all and the correlation is far from perfect. Indeed, food deprivation is a major concern also at higher income levels. 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, for example, that some 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 Malawi is in fact food-deprived; these households might 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. 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 more into merit goods, such as health and education, and food. If the women are the decision maker over resource allocation within the household, then this household might be less vulnerable to food poverty than male-headed households (Haddad et al 1997). However, in Malawi, we find no differences in food poverty between female and male-headed households.

At the same time and as expected, education matters for food security. As found by other studies, higher levels of education within the households are negatively correlated with undernutrition and undernourishment (see, e.g. Bhalotra and Rawlings 2011, 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.

4.3 Simulation results

In this section we present our simulation results of price changes and income shocks in line with Sen's entitlement approach. Table 5 shows the results for food poverty based on the poverty headcount, the poverty gap, and the severity index. In particular, the table presents the actual poverty rates from Table 4, and those estimated after the price induced income shock following a maize price increase by 100%, and those after a uniform negative income shock of 50%.

Starting with the maize price increase, households are expected to shift their calorie composition from maize to other products if the maize price increases. Since we do not explicitly model behavioral changes and thus do not know how exactly the calorie food item composition would be affected by the shock, we ask what the effective income loss from the price increase would be. Since the food budget will only be affected for the share of maize that is purchased (rather than consumed from own production or gifts), the effective income loss can be approximated by the price increase for maize times the quantity that is purchased. This approximation does not consider potential income gains for farm households selling their market surplus, nor opportunity costs of households that continue to consume their own produce instead of selling it at the market for higher prices. However, the majority of households in Malawi are net consumers of food more generally and of maize also: even though three quarters of rural households produce maize, on average, the net position of rural households expressed relative to their total income is around minus 7% (for urban households, this is minus 10% of total income). The median rural household has a balanced net position, i.e. it consumes as much maize as it produces.

Using this approximation, the maize price increase of 100% would be similar to an average reduction in income by 6.8%; but the income reduction would differ substantially according to spending patterns. The poor as well as urban households, both of whom tend to purchase more maize, would be hit hard, facing a higher relative income loss than non-poor rural households, for example. Based on the methodology described in section 2, we can then apply equation (2) from section 2 to the household specific income shock. As a result of this maize price shock, the food poverty rate is estimated to increase by 3.4 percentage points from 28.3 to 31.7 percent.

The second shock we analyze is a 50% uniform negative income shock, which corresponds to a (substantial) decrease in the overall endowments in line with Sen's entitlement approach. In fact, given that the maize price shock worked out to imply a much lower average income shock (6.8%), the average effect of the income shock on food poverty should be much larger; but since, in contrast to the income shock, the maize price shock hits households in very differently (depending on their maize purchases), studying the differential effect and comparing that to the uniform income shock is particularly instructive. Figure 3 shows the relationship between calorie per day per capita consumption and household expenditure in Malawi. For this scenario also, we can apply equation (2) from section 2 to simulate effects on the calorie per capita consumption, again leaving all other things constant.[17]

Table 5 shows that a uniform large negative income shock would, as expected, considerably increase food poverty, from 28.3 to 56.3%. Also the poverty gap and the severity index would increase considerably. One should note that this assessment could underestimate the severity of impacts of such a drop in incomes. Since it is based on the estimated calorie-income relationship, we ignore food quality issues. As households are facing lower incomes, their calorie consumption might fall only a little, but their nutritional status is more heavily affected. This is because these fewer calories are likely of lower quality than before, e.g. consisting more of staple crops and less on diversified and higher quality calories.

Table 5 also presents simulation results by different socioeconomic characteristics. First, we can observe large variations between urban and rural areas and geographical regions. Second, although, the simulation is based on very simplistic and strong assumptions, we can

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[17] Regression result for equation (1) $y_i = \beta_0 + \beta_1 \ln(x_i) + u_i$ are: $\widehat{\beta_0} = 1391\ (s.e.\,114), \widehat{\beta_1} = 966\ (s.e.\,31)$. Standard errors are robust to clustering on level of primary sampling units.

observe that an increase in food prices as well as a negative income shock would most strongly affect the poorer population subgroups. But this is more so in the case of the price shock. For the poorest quintile, the price shock increases food poverty by 5 percentage points, while it raises it by less than 1 percentage point in the richest quintile. The income shock shows a much less strong differential (25 p.p. increase for poorest versus 17 for richest quintile), due to the higher reliance of the poor on maize purchases. Fourth, differential effects of income and price shock are quite visible by region. While the income shock hits rural and urban areas in similar ways, the price shock hits urban areas a lot more (increase of food poverty by 6.5p.p. compared to 3 p.p. in rural areas), again emphasizing the role of greater food purchases in urban areas. Fourth, more 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 6 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 find that price increases and income shocks would increase food inequality in Malawi; this means that a reduction of income or higher prices will hit the poor harder as the reduced income (directly via the income shock or indirectly via the food price shock) has a larger impact on calorie consumption than among the rich. This can also be seen by the effects by quintile. For the richest quintile, the impact of food prices and incomes on inequality in food poverty is much smaller than for the poorest quintile. There are also small differences in the direction of change in inequality. Of particular note is that with the income shock food inequality would increase more in rural than urban areas, while with the maize price shock, the reverse is the case. It thus appears that poor urban dwellers are more affected by the price shock as they spend a large share of their income on maize while the income shock has a more uniform effect.

In this context, the distribution of calorie availability per day and capita, and in particular, the mean and inequality of the distribution allow 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, keeping inequality constant (i.e. moving the distribution to the right)? Second, what would be the reduction in inequality needed, holding the mean of the current distribution constant (i.e. squeezing the distribution), to achieve the same food availability? Figure 4 graphically illustrates these two simulations. The vertical line refers to the average household-specific per capita recommended mean energy requirement (RMEI). The sample mean of this threshold, adjusting for the age and sex distribution of the population, is 1702 calories per capita and day. The (dashed) vertical line refers to the mean of the distribution (2361). 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 from 0.237 to 0.092. Second, eliminating 95% of food poverty by increasing the mean with equal inequality would have to increase the mean by 750 calories per day and per capita. Both are of course rather drastic changes, but smaller reductions in food poverty via higher mean availability and lower inequality are clearly possible; the results also show that the best route to tackling this issue would likely be a combination of both, higher mean calorie availability as well as lower inequality, or 'pro-poor growth' in caloric consumption.

Finally, Table 7 shows the seasonal effects on food poverty. As indicated in Figure 2, food poverty varies by months. The lowest levels of actual food poverty are found in the months from July to October; and the highest in February. Interesting to note is that this seasonal structure is not automatically translated into the food poverty outcomes of the simulations. Low food poverty months can also be relatively more affected by negative shocks compared to high food poverty periods. However, on average, high food poverty months show higher impacts of negative price and income shocks.

Since our assumptions as discussed in section 2 are rather simple, and accounting for behavioral responses likely changes the picture we compare our simulation findings to a scenario that explicitly considers behavioral responses following price and income shocks. To do that, we apply calorie-income and calorie-price elasticities to our data. The elasticities were kindly provided by Ecker and Qaim (2010), who base their estimation on a complex demand system model that notably takes into consideration quality effects, measurement errors in self-reported price data and differentiated responses by different population subgroups (income quintiles and urban/rural residence). Figure 5 illustrates the distributional effects of the simulations; we apply the calorie-income elasticities to the income equivalent of a 100% maize price shock as reported before, and we apply the calorie-price elasticities to the 100% maize price shock directly. Regarding the price shock, we produce two estimates. In one, we apply the price shock to the entire consumption of maize, as is commonly done (also by Ecker and Qaim, 2010). But this surely overestimates the impact of a price increase on food deprivation as many households produce maize themselves and are thus much less affected by the price increase. In a second estimation we then apply the effect of the price increase only to maize purchases, which we think is a much more realistic assumption.

Three findings are worth noting here: First, our preferred simulation as well as the calorie-income elasticity robustness check represent more of a shift in the calorie distribution than a change in its shape. Second, as compared to the calorie-income elasticity scenario, our 'regular' income equivalent price shock scenario yields lower effects on food poverty in terms of calorie deficiency prevalence, yet the differences are very small.

Third, it matters a great deal whether we apply the price elasticities to all maize consumption or just to maize purchases. If they are applied to the entire maize consumption, we find very strong effects on the distribution that is now shifted below the average energy requirement in its entirety, yielding food deficiency rates of 90% of the population. But, as argued above, this is clearly an overestimate as the maize price increase only affects food purchases rather than all of food consumption. When applying the price elastiticies to food purchases, the use of elasticities still yields greater food deficit than our simplified method, but the differences are now much smaller and the shape of the distribution is also now not much different.

In summary, our simplified method compares quite well with a more involved estimation of price and income elasticities if those are applied to net purchases (rather than overall consumption) of food, although it appears to (slightly) underestimate the effect of a price shock on food poverty.

5 Conclusion

The food price crisis 2008 and 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 consumers. 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. This is relevant because 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 taking 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 ex ante, exemplified in the case of Malawi, which is a rather straight-forward tool that could also be used with other countries. In particular, we have developed a very simple simulation approach to analyze how changes in prices of specific food groups such as maize prices or prices for staple foods as well as how negative short-term shocks on household income affect the calorie consumption of individuals and how these changes affect food poverty in the very short-term. All that is needed is a past household survey and information on the nature of the price and/or income shock. We used information on calorie per day and capita consumption from household survey data in Malawi to investigate the impact of price and income shocks on food consumption and food poverty. Thereby, we focused on within-country differences by socioeconomic characteristics. This type of analysis 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 maize price increases have a particularly large impact on food poverty, since maize is the most important staple food in the Malawian diet. Universal income shocks affect populations differently than price shocks with important repercussions for adequate response measures. When disaggregating the impact by population groups, we find that urban households and the poor are particularly affected by price shocks. We also show that only substantial 'pro-poor growth' in caloric expenditures would overcome existing food poverty, given low mean expenditures and high levels of inequality.

When comparing the results with more complex estimates based on elasticities derived from complex modeling of demand systems, we find that the results do not differ substantially suggesting that our simplified method can provide a very useful rough approximation of likely impacts for policy-makers concerned with designing appropriate response measures.[18]

As surveys of the type we use here are available in most poor countries (at least at irregular intervals), analyses of this type can be quickly performed to analyze the likely impact of changes in incomes or food prices in order to design appropriate mitigation policies.

[18] A more thorough comparative assessment of our approach here, the approach by Ecker and Qaim and a welfare theoretic approach (using the compensating variation) also supports our suggestion that our methods provide a good approximation of effects, also at a more disaggregated level. See Rischke (2014) for more details.

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Tables and Figures

Table 1: Food consumption per day per capita in Malawi

	Mean	SD	Min	Max	N
Malawi					
Total	**2361**	**991**	**503**	**5000**	**10370**
Area					
Urban	2601	953	676	4999	1280
Rural	2326	991	503	5000	9090
Region					
North	2084	1048	503	4999	1570
South	2489	995	507	5000	3912
Centre	2312	958	538	4998	4888
Household headship					
Male headed	2341	975	503	4999	8022
Female headed	2429	1041	514	5000	2348
Education of household head					
Head has no education	2281	992	514	5000	2797
Head has primary education	2357	971	506	4999	4080
Head has secondary education	2651	986	503	4989	1072

Source: Malawi Second Integrated Household Survey 2004/2005, authors' calculation.

Table 2: Food consumption per day per capita by food group

	Malawi (2004)	
	Calories	**Calorie share**
Staple foods	1734	0.74
Pulses	295	0.12
Vegetables and fruits	71	0.03
Animal products	98	0.04
Meal complements	231	0.09

Source: Malawi Second Integrated Household Survey 2004/2005; 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)	1496	1957	2353	2768	3232	2.16
	Quintile					
Share of total consumption (calories)	1	2	3	4	5	
Staple foods	0.82	0.77	0.74	0.70	0.66	0.81
Pulses	0.11	0.12	0.12	0.14	0.12	1.10
Vegetables and fruits	0.03	0.03	0.03	0.03	0.03	0.90
Animal products	0.03	0.03	0.04	0.04	0.06	1.93
Meal complements	0.05	0.07	0.09	0.11	0.14	3.14

Source: Malawi Second Integrated Household Survey 2004/2005; author's calculations.

Table 4: Food poverty and inequality in Malawi

	Headcount	Poverty gap	Severity index	Gini coefficient
Total	0.283	0.071	0.027	0.237
Area				
Urban	0.188	0.035	0.010	0.206
Rural	0.297	0.076	0.029	0.241
Region				
North	0.401	0.126	0.056	0.272
Centre	0.226	0.057	0.022	0.226
South (Eastern in Uganda)	0.291	0.064	0.021	0.231
Income				
Quintile 1	0.668	0.188	0.075	0.200
Quintile 2	0.346	0.077	0.027	0.182
Quintile 3	0.193	0.046	0.017	0.187
Quintile 4	0.124	0.025	0.008	0.186
Quintile 5	0.076	0.016	0.006	0.176
Household headship				
Female headed household	0.283	0.070	0.026	0.243
Male headed household	0.283	0.071	0.027	0.235
Education of household head				
Head has no education	0.323	0.082	0.030	0.243
Head has primary education	0.256	0.064	0.025	0.231
Head has secondary education	0.174	0.039	0.013	0.212

Note: The mean threshold of the recommended mean energy requirement (RMEI) in Malawi is 1703. Income quintiles are calculated based on household expenditure per capita.
Source: Malawi Second Integrated Household Survey 2004/2005; author's calculations.

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

	Headcount			Poverty gap			Severity index		
Variable	***Actual***	**Income shock (minus 50%)**	**Maize price shock (100%) as income shock**	***Actual***	**Income shock (minus 50%)**	**Maize price shock (100%) as income shock**	***Actual***	**Income shock (minus 50%)**	**Maize price shock (100%) as income shock**
Total	0.283	0.563	0.317	0.071	0.240	0.090	0.027	0.142	0.039
Area									
Urban	0.188	0.500	0.252	0.035	0.166	0.060	0.010	0.079	0.024
Rural	0.297	0.572	0.326	0.076	0.250	0.094	0.029	0.151	0.041
Region									
North	0.401	0.664	0.435	0.126	0.337	0.146	0.056	0.232	0.071
Centre	0.226	0.496	0.246	0.057	0.198	0.070	0.022	0.114	0.031
South	0.291	0.584	0.336	0.064	0.241	0.088	0.021	0.135	0.035
Wealth									
Quintile 1	0.668	0.931	0.735	0.188	0.522	0.253	0.075	0.352	0.122
Quintile 2	0.346	0.752	0.403	0.077	0.298	0.096	0.027	0.164	0.037
Quintile 3	0.193	0.526	0.221	0.046	0.185	0.051	0.017	0.098	0.019
Quintile 4	0.124	0.349	0.135	0.025	0.112	0.027	0.008	0.056	0.009
Quintile 5	0.076	0.244	0.081	0.016	0.072	0.017	0.006	0.035	0.006
Household headship									
Female headed household	0.283	0.535	0.315	0.070	0.234	0.089	0.026	0.139	0.038
Male headed household	0.283	0.572	0.318	0.071	0.241	0.090	0.027	0.143	0.039
Education of household head									
Head has no education	0.323	0.596	0.354	0.082	0.265	0.107	0.030	0.159	0.048
Head has primary education	0.256	0.543	0.290	0.064	0.222	0.080	0.025	0.130	0.034
Head has secondary education	0.174	0.461	0.200	0.039	0.161	0.046	0.013	0.083	0.016

Note: An increase in Maize price by 100% is translated into a mean income reduction of 6.8% on average .
Source: Malawi Second Integrated Household Survey 2004/2005; author's calculations.

Table 6: Simulation results on Food Inequality in Malawi

Variable	Gini coefficient		
	Malawi (2004)		
	Actual	Income shock (minus 50%)	Maize price shock (100%) as income shock
Total	0.237	0.322	0.250
Area			
Urban	0.206	0.278	0.224
Rural	0.241	0.328	0.253
Region			
North	0.272	0.367	0.284
Centre	0.226	0.300	0.235
South	0.231	0.322	0.247
Income			
Quintile 1	0.200	0.330	0.230
Quintile 2	0.182	0.268	0.189
Quintile 3	0.187	0.254	0.189
Quintile 4	0.186	0.244	0.187
Quintile 5	0.176	0.219	0.177
Household headship			
Female headed household	0.243	0.328	0.257
Male headed household	0.235	0.320	0.248
Education of household head			
Head has no education	0.243	0.336	0.261
Head has primary education	0.231	0.311	0.242
Head has secondary education	0.212	0.282	0.218

Note: An increase in Maize price by 100% is translated into an income reduction of 6.8% on average

Source: Malawi Second Integrated Household Survey 2004/2005; author's calculations

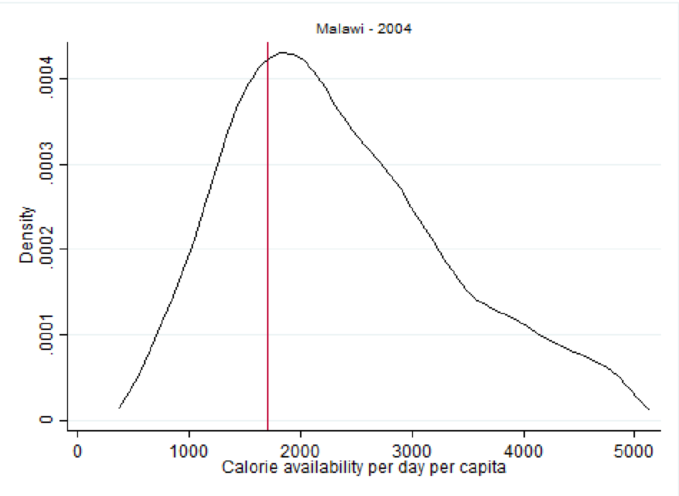
Table 7: Seasonality effects on food poverty in Malawi

	N	*Actual*	Income shock (minus 50%)	Maize price shock (100%) as income shock
March 04	806	0.29	0.53	0.31
April 04	858	0.30	0.54	0.32
May 04	739	0.29	0.57	0.30
June 04	887	0.28	0.55	0.29
July 04	669	0.25	0.51	0.28
August 04	1,032	0.24	0.51	0.26
September 04	960	0.25	0.56	0.30
October 04	832	0.25	0.56	0.31
November 04	716	0.28	0.55	0.33
December 04	602	0.29	0.59	0.35
January 05	516	0.30	0.60	0.35
February 05	855	0.36	0.64	0.41
March 05	898	0.31	0.62	0.35

Note: An increase in Maize price by 100% is translated into an income reduction of 6.8 % on average.

Source: Malawi Second Integrated Household Survey 2004/2005; author's calculations

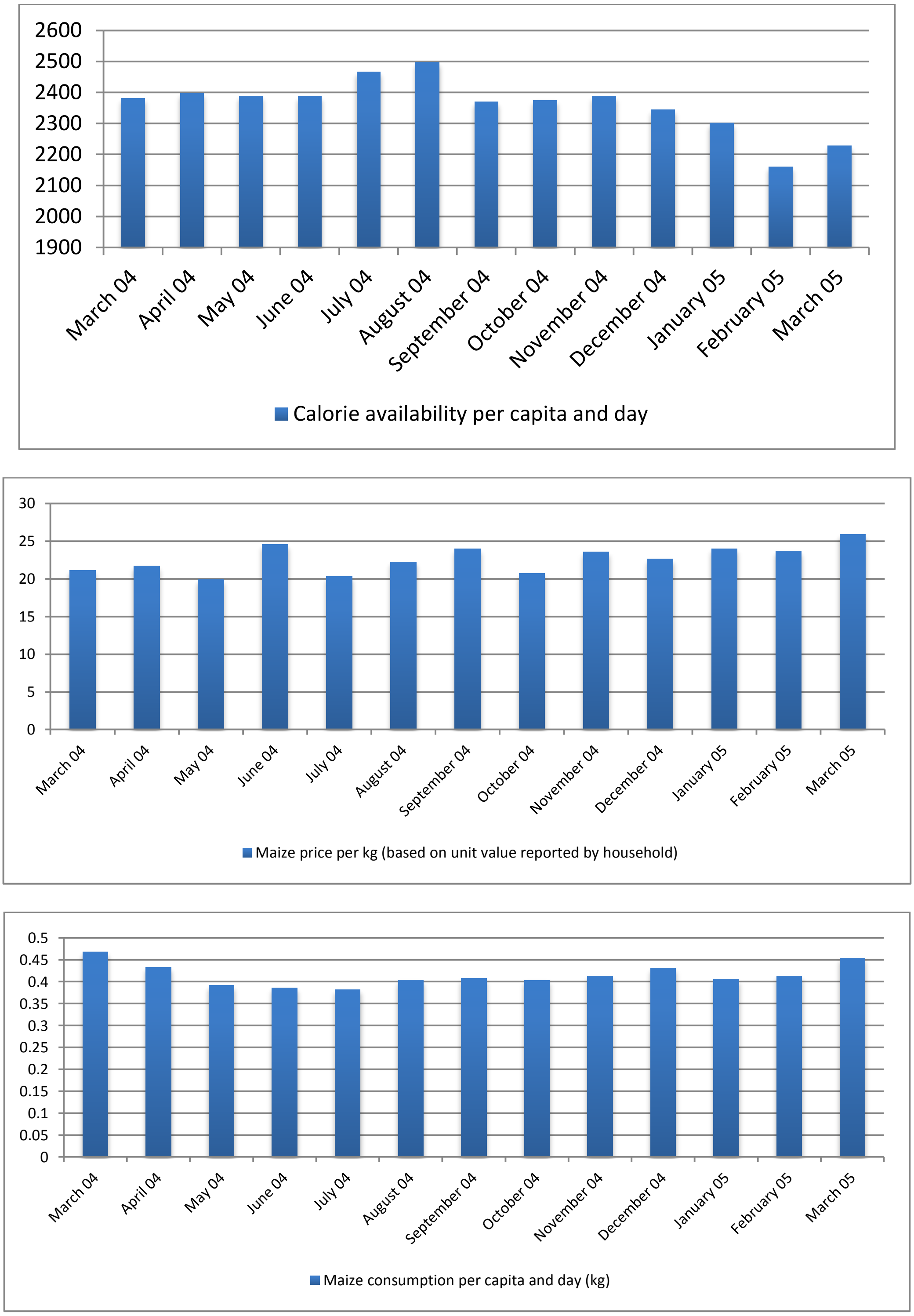
Figure 1: Density of calorie intake per capita per day



Note: The vertical line refers to the average per capita recommended mean energy requirement (RMEI) . The mean RMEI threshold in the sample is 1702.

Source: Malawi Second Integrated Household Survey 2004/2005; author's calculations.

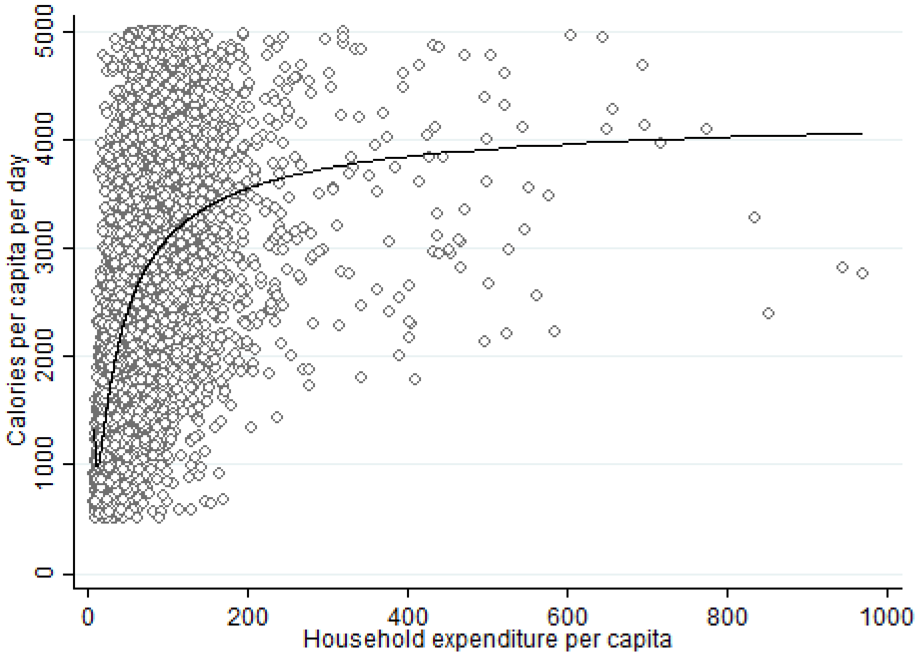
Figure 2: Seasonality effects



Source: Malawi Second Integrated Household Survey 2004/2005; author's calculations.

Figure 3: Relationship between calorie intake and household expenditure

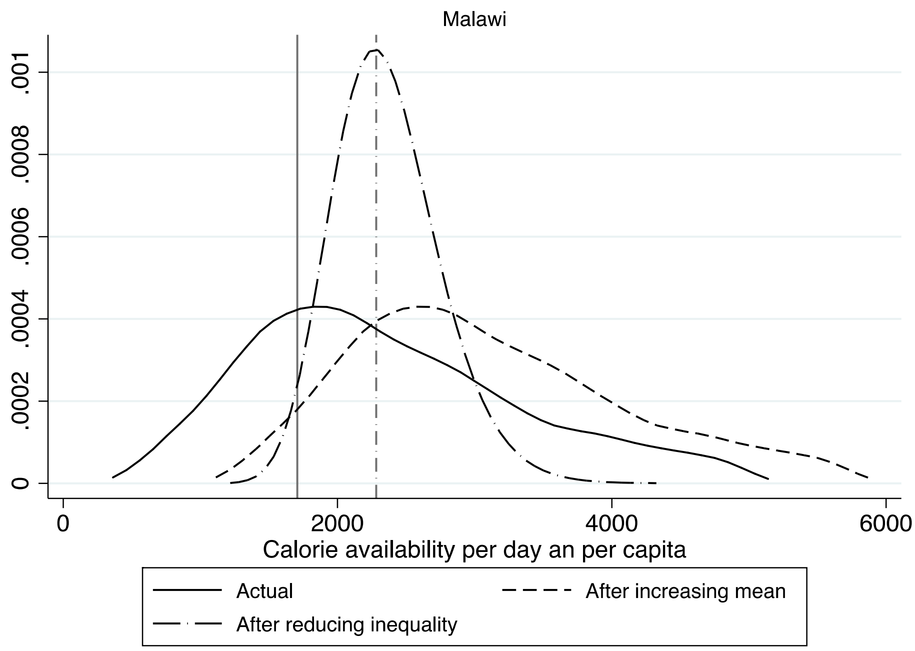
(Malawi – 2004/2005)



Note: Fitted curve from fractional polynomial regression of p.c. calories per day on p.c. expenditure

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

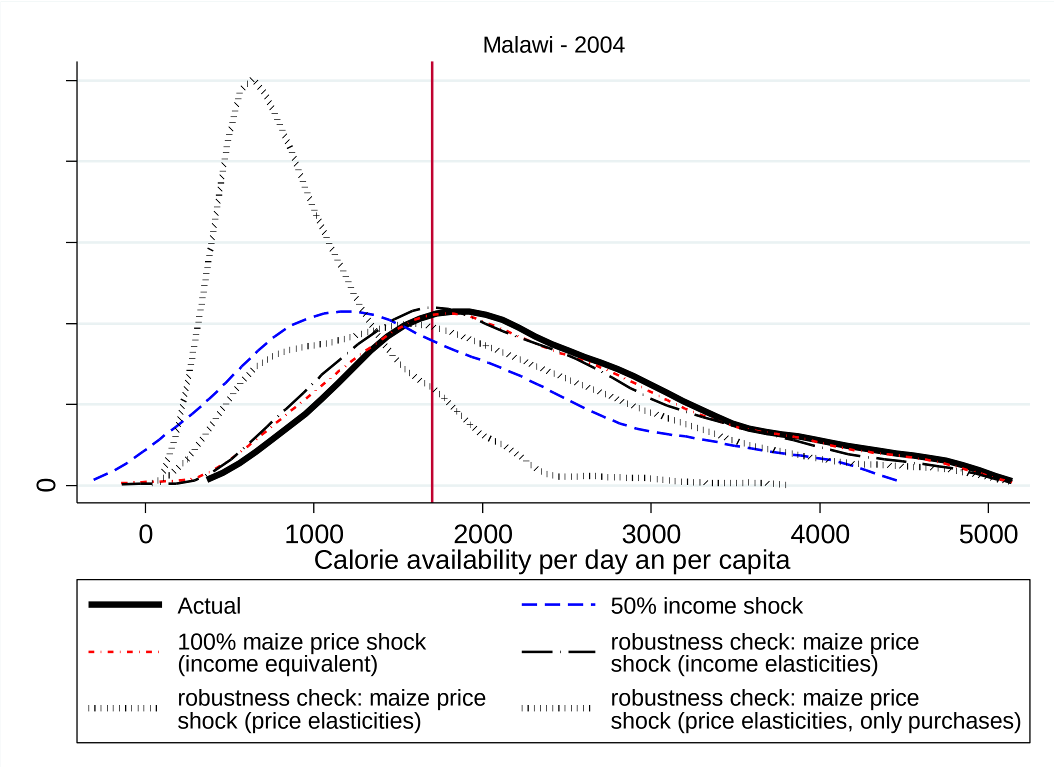
Figure 4: Densities of poverty simulations



Note: The left vertical line refers to the average per capita dietary intake requirement. The mean threshold of the recommended mean energy requirement (RMEI) in the sample is 1703. The dashed vertical line refers to the mean of the distribution (2361). 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 0.237 to 0.092. Second, eliminating 95 % poverty by increasing the mean with equal inequality would mean increasing the mean by 750 calories per day and per capita.

Source: Malawi Second Integrated Household Survey 2004/2005; author's calculations.

Figure 5: Densities of calorie availability per capita and day after shocks



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: Sample characteristics

Variable	Mean
Urban (=1)	0.129
Rural (=1)	0.871
Household size	4.695
Female headed household (=1)	0.226
Household head has no education (=1)	0.277
Household head has primary education (=1)	0.491
Household head has secondary education (=1)	0.105
Number of households	*10370*

Source: Malawi Second Integrated Household Survey 2004/2005; author's calculation.

Table A3: Food items and consumption frequencies

Staple foods	Freq.	% of hh	Animal products	Freq.	% of hh
Maize ufa mgaiwa (normal flour)	6,538	0.63	Eggs	2,510	0.24
Maize ufa refined (fine flour)	5,797	0.56	Dried fish	6,530	0.63
Maize ufa madeya (bran flour)	660	0.06	Fresh fish	2,374	0.23
Maize grain (not as ufa)	1,445	0.14	Beef	748	0.07
Green maize	3,124	0.30	Goat	1,044	0.10
Rice	2,481	0.24	Pork	543	0.05
Finger millet (mawere)	146	0.01	Chicken	1,659	0.16
Sorghum	573	0.06	Other poultry - guinea fowl, doves, etc	163	0.02
Pearl millet (mchewere)	103	0.01	Small animal ,Äì rabbit, mice, etc.	525	0.05
Wheat flour	48	0.00	Termites, other insects	284	0.03
Bread	1,264	0.12	Tinned meat or fish	16	0.00
Buns, scones	2,289	0.22	Fresh milk	915	0.09
Biscuits	822	0.08	Powdered milk	370	0.04
Spaghetti, macaroni, pasta	52	0.01	Butter	19	0.00
Breakfast cereal	242	0.02	Chambiko - soured milk	168	0.02
Infant feeding cereals	68	0.01	Yoghurt	105	0.01
Cassava tubers	4,453	0.43	Cheese	8	0.00
Cassava flour	987	0.10	Infant feeding formula (for bottle)	23	0.00
White sweet potato	2,550	0.25	Eggs - boiled (vendor)	70	0.01
Orange sweet potato	1,087	0.10	Chicken (vendor)	92	0.01
Irish potato	868	0.08	Meat (vendor)	222	0.02
Potato crisps	55	0.01	Fish (vendor)	483	0.05
Cocoyam (masimbi)	99	0.01	**Meal complements**		
Maize - boiled or roasted (vendor)	298	0.03	Margarine	239	0.02
Chips (vendor)	853	0.08	Sugar	5,682	0.55
Cassava - boiled (vendor)	333	0.03	Sugar Cane	3,618	0.35
Mandazi , doughnut (vendor)	2,338	0.23	Cooking oil	5,060	0.49
Pulses			Salt	10,138	0.98
Bean, white	1,612	0.16	Spices	184	0.02
Bean, brown	4,389	0.42	Yeast, baking powder, bicarbonate of so	1,877	0.18
Pigeonpea (nandolo)	2,210	0.21	Tomato sauce (bottle)	39	0.00
Groundnut	3,612	0.35	Hot sauce (Nali, etc.)	131	0.01
Groundnut flour	2,605	0.25	Jam, jelly, honey	33	0.00
Soyabean flour	403	0.04	Sweets, candy, chocolates	736	0.07
Ground bean (nzama)	599	0.06	Tea	2,974	0.29
Cowpea (khobwe)	1,246	0.12	Coffee	118	0.01
Vegetables and fruits			Squash (Sobo drink concentrate)	343	0.03
Plantain, cooking banana	654	0.06	Fruit juice	145	0.01
Onion	3,208	0.31	Freezes (flavoured ice)	473	0.05
Cabbage	1,810	0.17	Soft drinks	1,151	0.11
Tanaposi/Rape	4,436	0.43	Chibuku/Napolo (commercial traditional-	267	0.03
Nkhwani	6,971	0.67	Bottled/canned beer	102	0.01
Chinese cabbage	603	0.06	Local sweet beer (thobwa)	1,658	0.16
Other cultivated green leafy vegetables	2,366	0.23	Traditional beer (masase)	1,021	0.10
Gathered wild green leaves	1,366	0.13	Wine or commercial liquor	18	0.00
Tomato	7,850	0.76	Locally brewed liquor (kachasu)	557	0.05
Cucumber	805	0.08			
Pumpkin	2,368	0.23			
Okra/Therere	3,045	0.29			
Mango	1,433	0.14			
Banana	3,903	0.38			
Citrus , orange, etc.	1,187	0.11			
Pineapple	77	0.01			
Papaya	1,210	0.12			
Guava	1,357	0.13			
Avocado	914	0.09			
Wild fruit (masau, mlambe, etc.)	452	0.04			
Apple	95	0.01			

Note: Conversion of quantities to calories by Ecker and Qaim (2010). % of hhs refers to % of household that consumed item.
Source: Malawi Second Integrated Household Survey 2004/2005; author's calculation.

Table A4: Seasonality effects on food poverty

	Actual	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	Urban	Rural
March 04	0.29	0.64	0.39	0.24	0.15	0.06	0.15	0.31
April 04	0.30	0.68	0.44	0.26	0.13	0.09	0.11	0.32
May 04	0.29	0.70	0.39	0.19	0.12	0.05	0.18	0.31
June 04	0.28	0.76	0.39	0.18	0.11	0.04	0.16	0.29
July 04	0.25	0.70	0.46	0.19	0.17	0.04	0.23	0.26
August 04	0.24	0.64	0.32	0.18	0.15	0.12	0.13	0.26
September 04	0.25	0.59	0.31	0.18	0.09	0.10	0.21	0.26
October 04	0.25	0.61	0.24	0.18	0.10	0.07	0.13	0.27
November 04	0.28	0.71	0.34	0.17	0.12	0.09	0.13	0.30
December 04	0.29	0.68	0.37	0.13	0.10	0.08	0.24	0.30
January 05	0.30	0.64	0.29	0.21	0.11	0.06	0.20	0.32
February 05	0.36	0.71	0.31	0.21	0.12	0.09	0.29	0.37
March 05	0.31	0.64	0.31	0.16	0.11	0.07	0.30	0.31

Source: Malawi Second Integrated Household Survey 2004/2005; author's calculation.