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A Comparative Analysis

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Predicting Welfare Effects of Food Price Shocks. A Comparative Analysis.

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Abstract

Following the 2007/09 and subsequent world food price shocks, a growing number of simulation studies predicted their implications on food security. Studies that only require pre-price-hike data and the specification of relevant price or income changes have been advocated as a potential tool to guide the planning and targeting of mitigation programs. A critical research gap remains with comparing simulation outcomes across studies that use different, established methods on the same subject. In this paper we examine the extent to which different simulation methods drive differences in similar outcome variables and in potential targeting efforts. For this we build on three simulation studies set in Malawi, using 2004/05 LSMS data. We harmonize simulation scenarios and systematically adjust relevant parameters for the methodological comparison. We find overlaps in simulation outcomes to depend on scenarios and time horizons under consideration and to be driven by the study context. In case of Malawi, for a reasonable set of price changes, mean outcomes on district levels are fairly robust to underlying methodologies.

Keywords

Food security, food price shock, income shock, simulation studies, predicting welfare effects

JEL Codes

C4, D6, I3

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1 Introduction

After their historic low in the early 2000s, food prices started to soar in 2006 and culminated in the world food price crisis of 2007/08. This experience has spurred interest in quantifying welfare effects of food price-hikes and in predicting their magnitude and distribution across space and time. Studies that only require pre-price-hike data and the specification of relevant price or income changes are of particular importance to policy makers because they can guide evidence-based planning and targeting of mitigation programmes. Since these studies rely on different methods and sets of assumptions, a critical research gaps remains with respect to comparing the simulation outcomes of different simulations studies on the same topic and in a similar context. This is to establish if and to which extent they might result in different and potentially conflicting policy recommendations. We address this gap by building on three simulation studies set in Malawi, which analyse welfare in terms of food security and household expenditure. All studies use the same 2004/05 household survey data but resort to methodologies of different complexity. In particular, we address the following research questions:

1. Do simulations based on different methodologies produce qualitatively different results at the level of districts (the lowest geographical level of representativeness)?
2. Does the overlap in prediction outcomes depend on the degree of price change under consideration?
3. Are similar household characteristics identified as relevant predictors of vulnerability towards food insecurity in the different simulation methods?

In order to allow insightful cross-study comparisons, we recalculate all predictions and harmonise simulation scenarios across methodologies. We use the following underlying studies: First, Ecker and Qaim (2011, henceforth EQ) analyse calorie and micronutrient deficiencies based on a demand system model. The authors allow for changing consumption patterns in response to price and income shocks and heterogeneous effects across income groups. Second, Harttgen and Klasen (2012, henceforth HK) simulate changes in calorie deficiencies based on a parametric estimate of the relationship between income and calorie consumption. While behavioural changes are not directly considered, this simulation approach is designed to be simple and thus to allow timely predictions suitable for cross-country comparisons. Finally, in my MA thesis (Rischke, 2010, unpublished, henceforth RR), I analyse welfare change in terms of the Compensating Variation (CV), the income needed to keep utility constant after allowing for heterogeneous substitution effects.[1]

While the methodological and theoretical merits and limitations of each approach are well known and thoroughly discussed by the respective authors, it remains unclear how they compare in predicting which regions and households are hit hardest by price shocks. Methodologically, there may be a trade-off between generating precise and timely assessments. The extent to which this affects prediction outcomes and potential targeting efforts is the main focus of this paper.

In this context, the selection of food security indicators is critical. A variety of indicators is available that serve to gauge different aspects of food security. These range from monetary access to physical availability of food, food intake, diversity and nutritional outcomes, the latter for example in terms of anthropometric

[1] Variations of this methodology have been used in the relevant literature, recent examples including Minot and Dewina (2013) and Van Campenhout *et al* (2013).

indicators. Indicators to guide policies need at least to reflect the potential scope and particular concern of interventions in question but additional information should ideally provide a more comprehensive picture. De Hean et al. (2011) differentiate between indicators of chronic food insecurity, which are usually related to problems of structural poverty, and indicators that capture short-term food insecurity, e.g. in emergency situations, which are partially overlapping. The studies compared in this paper focus on the latter category of food security indicators, reflecting their interest in situations of shocks. Another common ground of the studies analysed is their focus on short-term effects, which is motivated by predicting effects of food price shocks before more information might become available or before extensive mitigation strategies are adopted or structural adjustments take place. This is to say that second round, general equilibrium effects are not accounted for. We make no attempt to change these parameters but we will discuss the underlying assumptions and likely consequences.

The distribution of food security indicators by region and household characteristics is similarly important for policy makers who want to target possible countermeasures to those most affected. Targeting of policy efforts refers to the non-uniform distribution of available funds and is intended to increase the resources available for those in need or to reduce the costs of reaching the poor (Besley and Kanbur, 1990). Targeting can be done at a geographical level, within selected communities or both. There is a trade-off between costs and benefits of close-meshed targeting efforts related to cost-effectiveness of identifying and monitoring relevant eligibility criteria (Dorward *et al.*, 2008; Klasen and Lange, 2012) In this paper we focus on geographical targeting, i.e. on identifying most affected regions. Only when we turn to research question 3 will we also predict outcomes on the level of households and thus capture intra-regional variations.

Our findings suggest that differences between methods depend on the scenario under consideration: Differences between methods grow with increasing rates of simulated price changes. EQ's method produces significantly higher estimations of calorie deficiency rates compared to other methods. The differences we find are driven by the Malawian context that is characterised by relatively high levels of self-sufficiency in food production in rural areas, and at low levels of market sales. However, for a relevant set of price changes, differences between methods are fairly moderate. For instance, in the price change scenario equivalent to the five month period following the survey (or around 10% food price increases), the methods used do not strongly affect the distribution of energy deficiency rates across districts. This implies that geographical targeting would not strongly be affected. On the level of households, the methods largely converge on a set of household characteristics that are associated with estimated energy deficiency rates.

The paper is structured as follows: the next section provides a literature review. We then introduce our baseline studies in section 4.3, and provide a conceptual framework which will substantiate our hypotheses. Section 4.4 discusses data issues and the methodology for our comparative analysis. Section 4.5 presents our empirical results which are discussed further in section 4.6. Section 4.7 concludes.

2 Literature Review

Studying welfare effects of food price shocks on economic welfare, at least in the short-run, variations of the compensating variation approach are widespread in the empirical literature (e.g. Friedman and Levinsohn, 2001; Ivanic *et al.*, 2011; Minot and Goletti, 2000). This approach is rooted in the farm household model[2] and non-parametric estimation techniques as proposed by Deaton (e.g. 1989) are often used for approximating real income changes from cross-sectional data. The differences across these kind of studies relate to whether or not they consider behavioural effects, how they estimate elasticities if so, their assumptions about price transmissions from world to local food markets and differences between consumer and producer prices (Dawe and Maltsoglou, 2014) and price scenarios under study more generally (e.g. price changes of a single vs. multiple goods). In addition, some authors also include labour market effects in the model and allow wage rates to respond to price changes in the short-run (Ivanic and Martin, 2008). Behavioural responses on the consumer side, however, are often neglected on the grounds of arguing that they would have to be quite large in order to significantly change the results in the short-run (Friedman and Levinsohn, 2001; Minot and Dewina, 2013).

The study findings are context specific and their magnitude depends on the underlying assumptions and scenarios as outlined above. At the same time, they seem to point in the direction of negative welfare effects outweighing potential benefits of food price increases in developing countries (in the short-run), because large portions of households have been net consumers of food. In addition, poor households are often found to be particularly hard hit (Dawe and Maltsoglou, 2014; Minot and Dewina, 2013). This is exactly what Ivanic and Martin (2008; jointly with Zaman 2011) find, for example, when analysing the world food price shock of 2007/08 in nine and the price shock of 2010/11 in 28 low and middle-income countries respectively. They do not find short-term labour market effects to change the picture for the countries studied, which is why they consider these in their first and not in their second study. They do not consider behavioural effects, and extrapolate partial equilibrium poverty effects in low- and middle-income countries as a whole to be very high and a serious cause for concern.

Still, the question arises if and to what extent these effects differ in the long-run since theory suggests second round labour market effects might increase wages for agricultural labour, which could benefit rural poor and landless households (e.g. Ravallion, 1990). Comparing predictions on short-run and long-run effects of price shocks applying CV as well as general equilibrium models to the case of net food exporting Uganda, Van Campenhout *et al.* (2013) conclude that steadily increasing commodity prices can provide important incentives for structural change towards export oriented agriculture as a livelihood source in the long-run. At the same time, most vulnerable population groups and net consumers of food need to be protected against high prices, e.g. by promoting income earning opportunities. The authors further note the divergence of research findings across an array of studies done on the same subject and based on different methodologies, which underlines the relevance of our systematic comparison. In their own analysis, the results differ considerably between scenarios and range from welfare losses to considerable welfare gains, depending on the time horizon (short vs. long-run) and on the consideration of combined or only partial price changes (i.e. of single crops). In sum, these results call for a careful interpretation of simulation results and a justification of restricting the analysis to specific goods.

[2] Farm household model originally developed by Singh, Squire and Strauss (1986) (Sadoulet and de Janvry, 1995).

Studies analysing effects of price and income shocks on food security indicators directly rather than quantifying them in economic terms and in anticipation of secondary effects on nutrition, estimate the relationship between prices/ income and nutrient consumption in one way or the other. Bouis and Haddad (1992) provide evidence that estimating income elasticities of calorie consumption using calorie availability and household expenditure as proxies for calorie intake and income, respectively, will result in upward biased estimates, especially among rich households. This is in case of random measurement errors in food purchases and because the gap between calorie availability and actual intake tends to increase with higher levels of expenditure. An overestimation of the income-calorie relationship would also lead to overestimating the negative effects of price and income shocks.

3 Baseline Studies and Conceptual Framework

In this chapter we review the baseline studies and provide a conceptual framework that illustrates methodological similarities and differences between methods used. This serves to inform our hypotheses.

While the baseline studies differ in scope, they share a number of limitations which should be kept in mind: all studies investigate short-run effects of food price shocks and consequently exclude second-round effects, for instance via labour markets. Better-off farm households may expand their production in response to higher prices, which could trigger hiring of additional labourers and benefit the landless poor. While long-term effects may mitigate detrimental first round effects, a number or reasons justify a short-run perspective: in order to design timely policy measures (especially in case of emergency situations) short-run effects need to be identified and understood (Harttgen and Klasen, 2012). This is a prerequisite also for deriving more informed hypotheses about the likely direction and magnitude of second-round effects. Consider, for instance, a situation in which there are high rates of poverty and food insecurity: Poor and vulnerable households have a limited capacity to cushion short-run deficits and to count on long-run benefits that may or may not materialize. Short-run food hardships, for example, could result in negative health effects and reduce the capacity of individuals to productively participate in the labour market (Dasgupta, 1997).

All studies under consideration use household food consumption data and exploit a rich source of information, but a number of data limitations shall be reiterated here: First, reported levels of household food consumption, a measure of food availability for that household, are treated as being equivalent to food intake; food wastage, the hosting of guests, and eating meals outside home are not accounted for. Second, data recalled over a certain period (seven days in this case) are assumed to be representative for that household's consumption; potential recall biases and unusually high or low levels of consumption are assumed to be non-systematic and negligible. Third, for a lack of further information, assumptions are required concerning the intra-household distribution of calories, which is usually assumed to be non-discriminatory and according to dietary needs. We refer to the underlying studies, as well as Deaton and Zaidi (2002) or Smith *et al.* (2006) for a more in-depth discussion of these limitations.

Before we detail the studies in turn, note that the conceptual framework (Figure 1) differentiates between different effects on the horizontal axis: First, there are effects on the quantity consumed; the starting point in all simulations. Second, this will affect p.c. calories consumed, the main outcome variable for HK, EQ, and this comparative assessment. Finally, income, an outcome in itself as well as an important intermediate variable will be affected. On the vertical axis, we differentiate between consumer and producer effects, the latter being relevant only for the Compensating Variation approach used by RR.

3.1 Harttgen & Klasen (2012)

In their paper, HK propose a simulation strategy that is based on a reduced-form relationship between income and calorie consumption and that stands out by its 'simple' and straightforward nature. Since no demand system is estimated, the method is less computationally and conceptually demanding than those used by EQ and RR. The empirical set-up is motivated by Sen's entitlement approach which takes an explicit focus on the ability of households to attain food (Sen, 1981). This ability can be reduced because households either lose endowments (e.g. loss of income or assets) or because food price increases alter relative prices (e.g. between food and labour). The authors argue that the method can be applied in a timely fashion and is suitable for consistent cross-country comparisons. From a policy perspective, the model's simplicity is its main advantage but also its main weakness: Indeed, the authors themselves expect their method to yield less precise estimates of food hardships than full blown demand system models that take into account behavioural responses to price and income changes. At the same time, keeping in mind their short-term perspective, they argue that the method provides sufficiently precise predictions of calorie deficiencies to provide valuable information to policy makers, which are complementary to rather than substituting in-depth studies that take a broader perspective.

The main idea is to understand price changes as equivalent changes in income. The estimation proceeds in three steps: First, calorie availability per capita and day is regressed on log per capita income (proxied by total household expenditure). Second, the price change of interest is expressed as income equivalent: The income shock equivalent of a price change is calculated by multiplying the quantity purchased with the change in price. This is equivalent to the additional income necessary to offset such change in price or, to put it differently, can be thought of as drop in real income if consumption patterns are not allowed to change. Based on this income change, in a last step, the effect on calories can be predicted using the estimated calorie-income relationship (Figure 1, method: HK*inc. equiv.*). The latter also serves to predict effects of income changes directly. Behavioural changes are not explicitly taken into account. However, since calorie compositions differ across income levels, consumption patterns are implicitly allowed to change when applying the parametric estimate to make predictions.

Once the estimates are produced, the authors analyse food security mainly in terms of Foster-Greer-Thorbecke indicators originally developed to measure poverty. Calorie deficiencies are thus captured in terms of their prevalence, gap, and severity, which the authors analyse by population subgroups (e.g. rural/urban, income quintiles). The authors find calorie deficiency to be very prevalent in the Malawian population. They establish that both income as well as price shocks have significant effects on food security. The predicted effects of their preferred specification (using income shock equivalents of price shocks), are shown to be less detrimental than making the extreme assumption that households have fixed budgets for specific items which would half the quantity of maize purchased, for example, if maize prices double. The latter estimate (Figure 1, method: KH*no beh.*) is treated as upper bound estimate of price shocks. In general, the authors find that urban as well as poor households are disproportionally hard hit by food price shocks, and that inequality in calorie availability is high.

3.2 Ecker & Qaim (2011)

Motivated by comprehensively assessing nutritional impacts of different policies that reduce prices or boost incomes, EQ go beyond analysing calorie deficiencies and also investigate micronutrient consumption. To do so, the authors estimate and apply income and price elasticities of calorie and micronutrient consumption for different population groups (e.g. rural/urban). The relevance of jointly assessing calories and micronutrients stems from recognizing that substitution effects following price shocks can potentially decrease micronutrient consumption at constant levels of calorie intake. The concern with price regulations, which are a common policy tool in the Malawian context, is that price reductions of staple foods are suspected to crowd out the consumption of more nutritious, yet less calorie dense foods. The authors therefore expect cash-transfers or other income enhancing programmes to have less-distortionary effects on consumption patterns and positive effects on micronutrient consumption.

EQ first estimate expenditure and price elasticities of food demand for 23 food groups using a quadratic almost ideal demand system (QUAIDS) which allows for interdependencies in food demand. While food demand in terms of expenditure shares is estimated directly, the consumption of nutrients is treated as a latent variable that can be retrieved from these expenditure shares. Thus, expenditure and price elasticities of food demand are estimated first and used to derive elasticities of micronutrient demand in a second step. The authors assume three-stage budgeting (between food and non-food in the first, between food groups in the second, and items within food groups in the third stage) and account for censoring in dependent variables (i.e. food budget shares of zero) by using a two-stage Heckman procedure. A price approximation technique is applied to account for quality information embodied in unit values: unit values (i.e. how much money a household pays for a certain quantity of a purchased good) can vary between households either because they face different prices or because they chose different shades of qualities. Cross-price elasticities are not estimated directly. However, when estimating the demand model from which own-price elasticities are derived, relative price for other goods are controlled for.

The authors find that households in Malawi focus on avoiding calorie shortages rather than diversifying their diet and micronutrient consumption. In consequence, many households are vulnerable to multiple nutrient deficiencies. For the majority of goods, nutrient consumption is found to be price-inelastic suggesting that households are able to smooth micronutrient consumption through substitution. However, in case of maize, the main staple food in Malawi, both calorie as well as micronutrient consumption decrease strongly in response to maize price increases. In accordance with their hypotheses, EQ predict income changes to be less detrimental (or more beneficial in case of income enhancing policies) than item specific price shocks (or price subsidies). Indeed, EQ show that price subsidies for maize, for example, could have negative effects on the consumption of some micronutrients. Showing the potential diversity of nutritional impacts that further vary by population subgroups (e.g. rural/urban) the authors illustrate benefits and pitfalls when designing broader nutritional policies.

3.3 Rischke (2010, unpublished)

Starting from the notion that the majority of rural and many urban households in developing countries derive at least some income from agricultural activities, RR uses a farm household model to explicitly account for higher prices received for agricultural sales in a situation of price shocks. Farm households can simultaneously be producers and consumers of food and comprise wage labourers. Thus, rising prices and wages can either represent net benefits or net costs to households (Sadoulet and de Janvry, 1995).

Behavioural changes in consumption are accounted for using own- and cross price elasticities of food demand in terms of food expenditure shares. Elasticities are calculated following Deaton (e.g. 1989; 1997), who exploits price variations within clusters and across regions to estimate price as well as quality elasticities in cross sectional surveys and who deals with potential measurement errors. The identification of quality effects is particularly useful since a number of reasons can prevent households from substituting between goods (e.g. local availability, already low levels of consumption), while substituting high quality with lower quality of the same good might be more relevant in the short-run, especially for poor households. Deaton exploits variation in unit values to estimate quality effects: assuming that prices do not vary within clusters (usually villages interviewed in a short timeframe), within-cluster variation in unit values can be interpreted as reflecting differences in quality. This allows him to deduct quality effects from unit values and to identify "pure" price elasticities. For the reasons of high levels of uncertainty when estimating elasticities (Minot, 2010), RR uses bootstrapping techniques to estimate confidence intervals. For the estimation of behavioural responses RR only uses elasticities that are not found to be outliers and that are statistically significant at a 5% level.

Expressing welfare change in terms of the compensating variation allows for a considerable amount of flexibility since differential changes in both consumer and producer prices can be analysed for single or multiple goods, optionally subject to behavioural changes, e.g. substitution effects. For detailed formulas and derivations, see Minot and Goletti (2000) and Friedman and Levinsohn (2001). In a nutshell, rising producer prices enhance income on the producer side while rising consumer prices result in real income losses on the consumer side. In the short-run, the net effect depends on a household's economic net position, which is in turn affected by differences between consumer and producer prices, the quantity sold, and possible behavioural changes that we consider on the consumer side[3]. Note, however, that when accounting for behavioural changes, cross-price effects drop out if the price is changing only for one good *i* instead of goods *i and j* simultaneously. In case of consumer price increases of good *i*, this is likely associated with a higher CV (i.e. more need to compensate) compared to incorporating cross-price effects of good *i* on other goods, since substitution effects across goods would compensate for part of the welfare loss. Since substitution itself is not considered welfare deteriorating, the results when accounting for it should be thought of as a lower bound estimate of the actual welfare loss. When assuming no behavioural change at all, on the other hand, the resulting welfare effects should be considered as upper bound estimate.

Further note that if consumer and producer prices are assumed to be the same (which is done here), "self-sufficiency production", i.e. food items produced by the household and used for own consumption, are netted out when it comes to welfare changes. In this case, welfare changes are related to a household's initial market surplus (via the profit effect) and to purchased food (via a reduction in real income).

Analysing a food price increase of 38%, which was the average rural price change between 2004 & 2007, RR shows that behavioural changes matter in cushioning shocks, especially for the poor. Significant differences are also found between scenarios that consider a full demand system, rather than restricting the analysis to a particular good, the latter of which requires careful justification. Further, the CV needs to be interpreted with care: behavioural responses tend to be higher among poor households out of a necessity. Accounting for behavioural changes can thus reduce the CV of poor households relatively more than that of better-off households. This would then suggest that richer households are hit harder by a price shock while they are likely to remain with a higher quality diet.

On a methodological note, recent studies have cast doubt on the adequacy of assuming equal changes of producer and consumer prices within the CV framework (Dawe and Maltsoglou, 2014; Minot and Dewina, 2013). Instead the authors argue for a fixed 'marketing margin'. The latter would imply higher benefits to (current) net producers and point to an overestimation of negative welfare effects under current assumptions. However, food price shocks that motivate the type of simulation studies examined here, tend to be grave and accompanied by prices increases among non-food items, most notably fuel, so that marketing costs likely increase as well.

For a brief summary of the methods under consideration, all methods start from a household's food consumption but differ in the way they consider price changes, behavioural responses and in their outcome variable. Only HK and EQ were originally intended to estimate calorie deficiencies, while RR's main outcome variable is the CV. The CV can, however, be used as an intermediate variable in HKs estimation. Both RR and EQ allow for behavioural changes while only RR incorporates the producer side of farm households. However, considering only purchases rather than overall consumption can be thought of as HKs strategy to account for farm households.

3.4 Hypotheses

In accordance with HK, we assume the scenario of directly translating price into consumption changes to provide an upper bound estimate (Figure 1, HK*no beh.*). We will treat this as 'baseline scenario' to compare other specifications and models to. Calculating the income equivalent of a price shock (Figure 1, HK*inc. equiv.*) is conceptually closely related to the consumption side of the CV (Figure 1, RR on the consumer panel), except that RR uses the net quantity consumed rather than purchased, and the CV is expressed as a proportion of initial income, i.e. total expenditure levels.

In case of HK*inc. equiv.*, again, the income shock is used to estimate changes in calorie consumption based on previously estimated calorie - log income relationship. Thus, the results can directly be compared to using the same income shock but explicitly allowing for behavioural change by applying income elasticities provided by EQ (Figure 1: EQ*inc. el.*/HK). For this comparison, we do not expect to see large differences in outcome variables. One source of divergence comes from EQ using income elasticities by rural/urban residence, while HK do not control for other factors apart from income, when generating their parametric estimate.

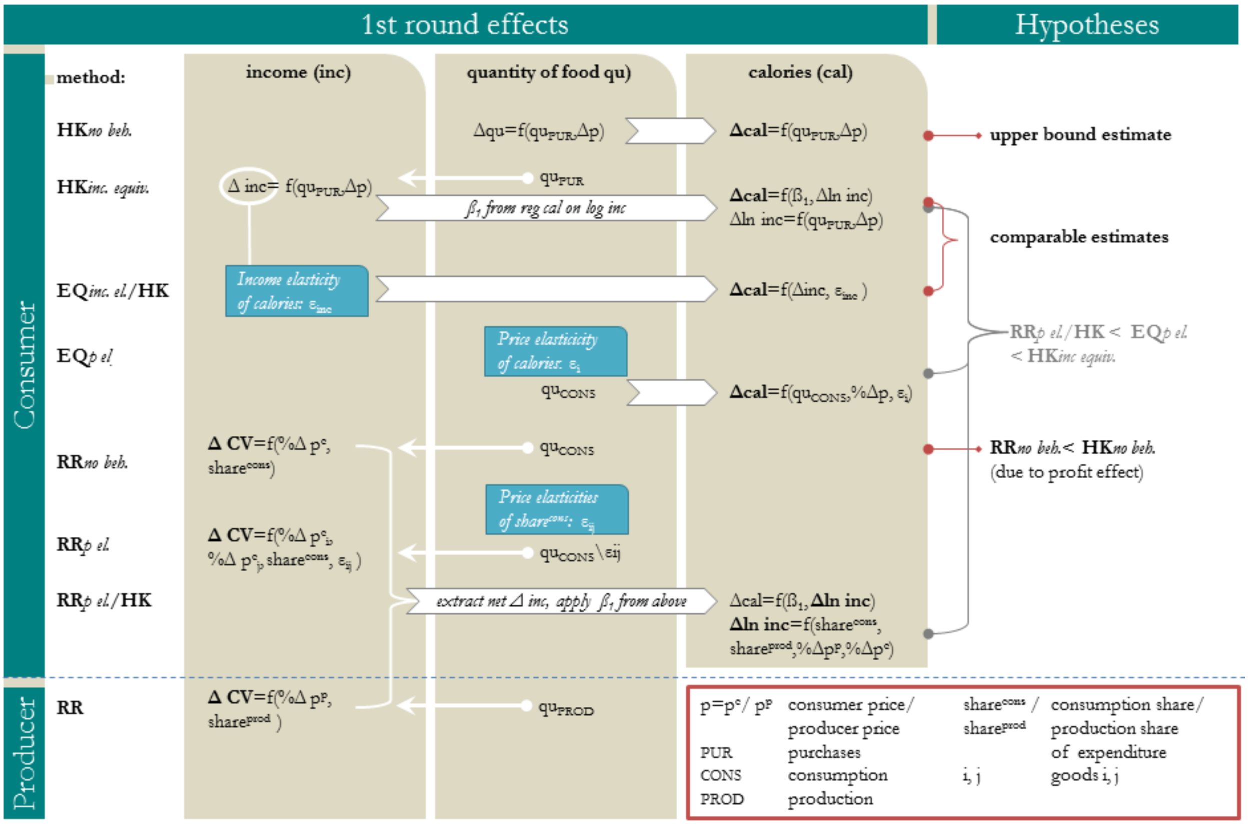
Predictions get more complex when behavioural changes are considered in the form of price elasticities of demand. Both EQ as well as RR derive such elasticities (in terms of calorie and expenditures shares, and just expenditures shares respectively). While the underlying methodologies differ (e.g. different demand systems, Marshallian vs. Hicksian elasticities), they both address issues of using unit values to estimate price elasticities, zero consumption of some items and measurement errors. Thus the elasticities are expected to paint a similar picture of consumption patterns, even though there are a number of sources

[3] RR does not consider behavioural changes on the producer side, since agricultural output is unlikely to change in the short-run analysed here. We assume, however, that the quantity sold remains constant, which is restrictive in that household could chose to forego own consumption of an item in order to sell it instead.

for potential differences: for instance, in addition to own-price elasticities used by EQ, RR explicitly uses cross-price elasticities.

Note that there are different specifications of the CV approach in the framework, which differ on the consumer side but share the producer part of the CV, where the initial market surplus is sold at higher prices (Figure 1, RR). The overall change in CV is the sum of both consumer and producer effects. When behavioural changes are disregarded (Figure 1, RR*no beh.*) initial net consumers inevitably lose while net producers win. Only when demand elasticities are applied (or if differential consumer and producer price changes are analysed), does the picture become more dynamic, since initial net positions can change and price effects can be cushioned from a consumer's perspective (Figure 1, RR*p el.*). In any case, the resulting CV can be expressed as income change and subsequently be combined with HK's parametric estimate in order to generate a prediction on calorie changes. This will prepare our most interesting comparison, since we are now equipped to compare the same outcome variable using the specifications most preferred by the respective authors, which we think of as most credible specifications in each case: Here, estimated welfare changes are expected to be smallest for RR*p el.* (due to producer effects), followed by EQ*p el.* (due to substitution effects) and HK*inc. equiv.* (Figure 1, hypothesis in grey writing).[4]

Figure 1: Conceptual framework and hypotheses



Source: Own illustration.

Note that differences between the methodologies discussed are expected to be more pronounced if non-uniform price changes are looked at since substitution effects will be more pronounced and more diverse. Even allowing for regionally different price changes is expected to increase prediction divergence since the methodologies chosen behave differently to smaller/larger price changes.

4 Data and Methodology

The consumption data used for this paper comes from the Second Integrated Household Budget Survey of Malawi conducted by the National Statistical Office in collaboration with the World Bank. The survey is nationally representative and covers 11.280 households. Data collection was systematically spread over the course of one year (March 2004 to March 2005), which holds true not only for the national sample but for district sub-samples as well so that seasonality effects are captured on various geographical levels (MNSO, 2005).

Analysing consumption data for our purpose requires prior and extensive data preparation, such as converting local non-metric units (e.g. bunches, heaps) into metric units (e.g. kg) and later into calories[5], imputing prices or unit values for non-purchased goods for generating expenditure aggregates etc. While there are some general guidelines, there are no strict rules or uniform conversion factors for the various transformations and the associated data cleaning, which is consequently done differently by different people. In order to rule out data handling by the authors as one source for differences in the findings discussed here, we recalculate all simulations based on the same dataset: Household consumption data in physical units and calories were kindly provided by Olivier Ecker from IFPRI[6], and further data cleaning was kept to a minimum. Table 1 illustrates the relevance of this approach, showing the differences between datasets used across studies in terms of calorie availability per capita and day. Differences in the mean household size between the raw dataset and the others point to selection effects introduced when cleaning data and dropping outliers since both household size and expenditure refer to the values as originally provided in the raw data. In the dataset provided by IFPRI and the one used by HK, the average household size is notably larger and the average p.c. expenditure smaller than in the original dataset. This might result from higher outlier values found among richer households, as discussed before (Bouis and Haddad, 1992) that have been dropped from the sample.

Table 1: Summary statistics of sample by data source

Data Source	IFPRI	HK[1]	EQ[2]	RR	RAW
Calories p.c. per day					
Mean	2261	2349	2171		
Sd	949.64	989.67	928		
Min	351	503			
Max	4998	5000			
Calorie deficiency ratio	0.31	0.28	0.35		
Household size[3]	4.71	4.72		4.54	4.55
Sd	2.26	2.26		2.34	2.34
Expenditure p.c. per day[3]	59.64	59.63		66.84	67.69
Sd	54.94	54.94		71.46	75.85
Number of obs.	10370	10370	10370	10793	11280

[1]Original dataset kindly provided by Harttgen and Klasen. [2]Numbers for EQ extracted from Ecker and Qaim (2011), sampling weights used. [3]Values as provided in the raw data. **Source:** own calculation unless stated otherwise

[4] For the sake of completeness: due to profit effects, we would expect the upper bound of RR estimates (without behavioural change) to produce simulation outcomes below those of HK, yet this comparison is of methodological interest to us only.
[5] The unit we use for measuring calories is kilocalories (kcal).
[6] Also see Ecker, Pauw, and Verduzco-Gallo (2014) *Malawi's Farm Input Subsidy Program: Did Food and Nutrition Security Really Improve?* Draft MaSSP Working Paper, mimeo.

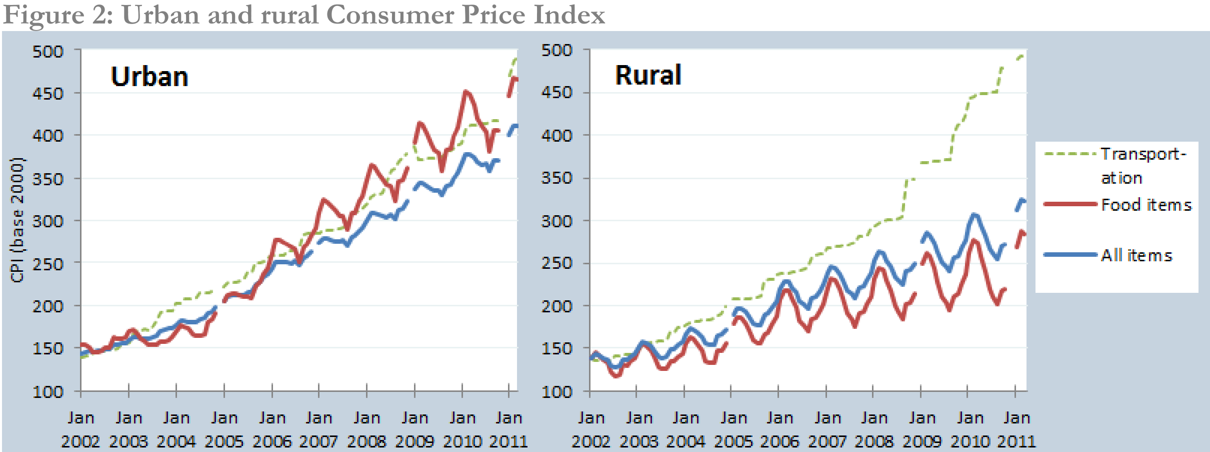
In addition to using the same dataset, for re-estimating the demand system and elasticities used by RR, we harmonise the classification of food groups with those used by EQ and use 22 food groups that fall in the broader categories of staple food, pulses, fresh fruits and vegetables, animal products and meal complements (see Appendix Table A1). EQ and HK already use the same food group classification. For EQ simulations, we use their full set of original elasticities, which they kindly provided. Note that information on beverage consumption is not included in the cleaned IFPRI data. For beverages, Ecker and Qaim (2011) estimate a men per capita consumption of 26 calories per day, the equivalent to 1% of daily food availability.

4.1 Price Data

When the world food price shock was striking, between June 2007 and June 2008, in Malawi, prices for several food items including the main staple maize rose by more than 150% (in US$ terms) and even exceeded the concurrent increase in the world market price (Minot, 2010). Figure 2 shows Malawi's Consumer Price Index by rural and urban residence over the period of 2002-2012. We can see that prices have been rising sharply over the whole period, with strong seasonal patterns and more strongly in urban compared to rural areas. By 2002 already, general living costs as well as food prices have been around 50% higher than in 2000. Transportation costs quintupled from 2000 to 2011 in both urban and rural areas (even though they have a much smaller weight in rural CPI) and were not subject to the same seasonality patterns than the CPI. Thus the assumption of equal increases in prices for consumers and producers might not be too far-fetched for the case of Malawi.

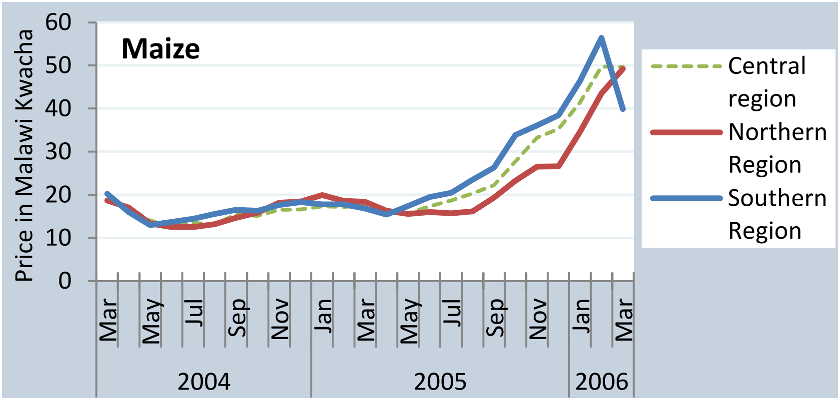
For our analysis, rather than using world food price movements and making assumption about the pass through from world to local markets, we use two main sets of price scenarios: First, an arbitrary general and maize price increase of 10%, which we chose because it is in the price range considered relevant by all studies (and thus the underlying methodologies were expected to capture the effects well). Second, we use locally observed maize price increases provided by the World Food Programme (WFP, 2014) and food CPI data available from the National Statistical Office (MNSO, 2014) which allow us to construct a location and date of interview specific (i.e. household specific) monthly food price index. We use this index to look at price changes over a period of one to twelve consecutive months following the interview. Figure 3 illustrates the advantage of this approach: households interviewed at different months experienced different price changes over a given period, partly of opposite sign, and regional differences increased over time thus introducing considerable variation that we can account for.

Figure 2: Urban and rural Consumer Price Index



Base year: 2000, CPI weights for: Food items urban: 35.2%, rural: 68%, transportation urban: 11%, rural: 2.5%.
Source: Data from National Statistical Office (MNSO, 2014), own illustration.

Figure 3: Regional monthly maize prices from March 2004 to March 2006



Source: World Food Programme (WFP, 2014), own illustration.

4.2 Variables of Interest and Empirical Strategy

Following EQ as well as HK and other relevant literature (e.g. Smith *et al.*, 2006), a household is classified as calorie deficient if their daily calorie availability falls below a threshold of mean recommended energy intakes. These thresholds are household specific, i.e. sensitive to the age and sex composition of household's. For simplicity, however, uniform physical activity levels and body statures are assumed. The intra-household distribution of calories is further assumed to be non-discriminatory and according to dietary needs. See the original articles for a more detailed discussion.

Calorie deficiencies can be analysed from different viewpoints. Using Foster-Greer-Thorbecke indicators as HK did, for example, it can be expressed in terms of absolute numbers of calorie deficient households or individuals, their prevalence, absolute or relative shortfall (of the recommended threshold) or severity (i.e. putting more weight on households with higher calorie shortfall) (Harttgen and Klasen, 2012). All of these indicators, and others such as inequality in distribution, are relevant from a policy and targeting perspective and yield different pieces information to identify preferential focus areas or to estimate total calories required to lift different proportions of households out of food poverty. For the sake of brevity, when comparing simulation outcomes across methods, we will mainly be concerned with the prevalence of calorie deficiency on the level of districts, but provide descriptive statistics on various other indicators as well.

The comparison of simulation outcomes will be done in different steps. First, we will use descriptive poverty maps on the level of districts for our exemplary scenario of a 10% price increase, and study descriptive graphs that repeat the analysis over a whole range of price increases. When systematically varying price scenarios over a range of price increases or a period of twelve months, we also run regressions of the following type:

$$\begin{aligned} calorie\ deficiency\ prevalence_i &= \beta_0 + \beta_i scenario + \boldsymbol{\gamma_i method} + \boldsymbol{\varepsilon_i scenario * method} + \boldsymbol{\theta_i X_i} \\ &+ \boldsymbol{\vartheta_i district} + u_i \end{aligned} \tag{1}$$

where $calorie\ deficiency\ prevalence_i$ is the prevalence of calorie deficiency among individuals in district *i*. Scenario is a continuous variable for the proportional price change or the number of consecutive months over which price changes are considered (ranging from 1 to 80% price increases or 1 to 12 months), $\boldsymbol{method}$ is vector with indicator variables for the methods used to produce the simulations (HK, EQ, and RR) and $\boldsymbol{scenario} * \boldsymbol{method}$ are interaction effects between the scenario and methods. The reason for anticipating interaction effects to play a role is that we expect simulation outcomes to depend on the degree of price changes (that increase with the scenario variable) under consideration. Price elasticities used by EQ as well as RR, for example, are constructed to be valid for small proportional changes in prices, but we partly consider fairly large changes. $\boldsymbol{X_i}$ is a vector of strata level control variables such as initial levels of food poverty, and $\boldsymbol{district}$ is a vector with district dummys to control for all other district fixed effects. u_i is an error term. Note, however, that this is not to establish causality between the simulation methods and simulation outcomes but rather to understand their association.

Finally and again for an exemplary price scenario, we will analyse predictions on the level of households to shed light on the question if the different methods, independent of how they compare in producing absolute food poverty estimates, identify similar household characteristics as indicators for vulnerability towards food insecurity. For this, we analyse linear probability models of the kind:

$$Calorie\ deficient_{jk} = \alpha_0 + \boldsymbol{\beta_j X} + \boldsymbol{\varepsilon_j district} + u_j \tag{2}$$

where $calorie\ deficient_{jk}$ is a dummy variable and refers to household *j* being classified as calorie deficient by method *k*. $\boldsymbol{X}$ is a vector of household level control variables, again, we control for different districts and u_j is an error term. For the selection of control variables, we closely follow Klasen and Lange (2012) who analyse the suitability of different sets of variables for targeting purposes, which is exactly what we are interested in here. Using Proxy Means Test to identify poor households in Bolivia, the authors identify variables suitable for identifying eligible households while limiting associated monitoring costs. They argue that good proxies can be monitored at low costs, are immune to manipulation, and find a simple set of proxies to perform relatively well. This set of variables includes variables such as geographical regions, household size and composition, and dwelling characteristics.

In addition to such proxies, we analyse socioeconomic variables that have been identified to be associated with a household's vulnerability towards price shocks, such as education and gender of the household head, expenditure quintiles, seasonality effects (e.g. Ecker and Qaim, 2011; Harttgen and Klasen, 2012), and the net consumer/producer position of a household (Aksoy and Isik-Dikmelik, 2008) in order to understand their relevance vis-à-vis the simple set of potential proxies.

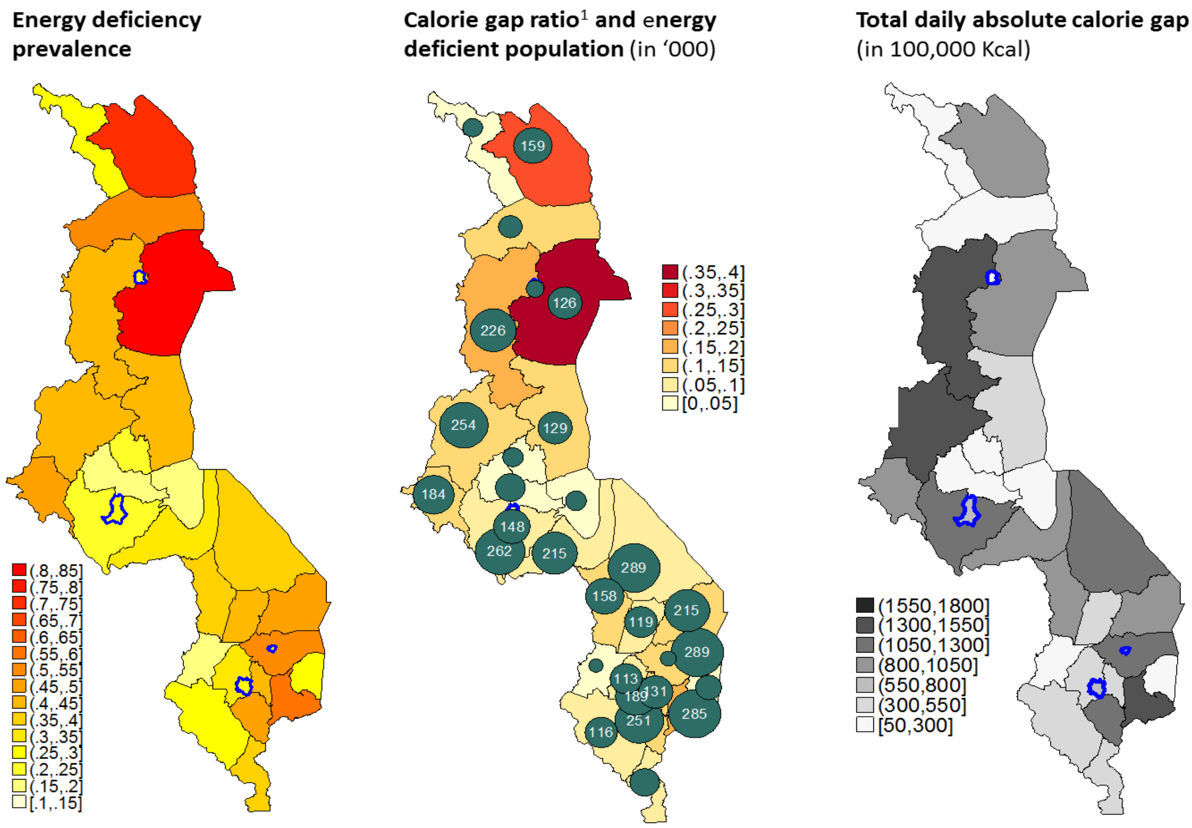
5 Empirical Results

5.1 Descriptive Statistics at the Baseline

Malawi, a small, landlocked and densely populated country heavily relies on agriculture as a livelihood source, yet is a net importer of food that "has always been vulnerable to food insecurity" (Pauw and Thurlow, 2014, p. 1). Main export and import crops have been changing over time: while maize, for example, was imported during the time of the survey and the following years, a heavy input subsidy programme was initiated in 2005 and total cereal exports outweighed cereal imports in 2011 (FAO, 2014a; FAO, 2014b; Pauw and Thurlow, 2014). Malawi ranks very low in the Human Development Index (HDI, 174 out of 187) and is characterised by high levels of inequality within the country. Life expectancy in 2012 was as low as 55 years (it was below age 50 in 2004/05) (UNDP, 2014; WDI, 2014).

Our data reveal that in 2004/05, 87% of the population lived in rural areas, around the same percentage of households produced food, and around 60% sold some food. In rural areas, almost half of the food consumed by households came from own production, urban households produced 13% of the food they consumed. Figure 4 shows different energy deficiency indicators relevant from a policy perspective. Several findings stand out: first, calorie deficiency is very widespread and severe, especially in rural areas: around 38% of the population is calorie deficient, prevalence rates by districts reach a maximum of 83% and tend to be higher in rural compared to urban areas.

Figure 4: Food security indicators Malawi 2004/05



[1]Ratios relative to household specific mean recommended calorie intake, population in circles. Individual sampling weights used. Urban districts/ cities outlined in blue. **Source:** Own calculation.

Energy deficient individuals, on average, fall short about a quarter of their mean recommended energy intake. Second, the geographical distribution somewhat varies between these indicators indicating that they would result in different rankings and targeting if considered on their own. This becomes more evident if we upscale the daily energy gaps by the number of energy deficient individuals to arrive at the total estimated daily calorie shortfall by districts (far right graph): here, we find the most severely food insecure district, in terms of calorie deficiencies at the level of individuals, to have a smaller cumulative burden than others, as they have lower populations. Consequently, we are reminded to evaluate the information at hand from different viewpoints.

5.2 Simulation of Price Shocks – District Level

Figure 5 and Figure 6 show the district-level predictions of a 10% general food price shock. Here, in an interval of five percentage points from one shade of colour to the next, we can only see very few regional differences across simulation methods, both in terms of absolute prevalence categories and consequently relative rankings over districts. At the same time, our 'pseudo benchmark' scenario, which assumes fixed item specific food budgets and thus a direct translation of price into consumption changes (far left graph, HK*no beh* in Figure 1) indicates that calorie deficiency rates as well as calorie gap ratios are not strongly affected over this price range since the graph largely resembles the initial one.

Given that calorie deficiencies are already widespread at the baseline, and that maize consumption covers two thirds and 55% of calories available to households in rural and urban areas respectively (Figure A2), we expected food security indicators to be highly sensitive towards food and maize price shocks and find these results surprising. Their explanation largely seems to lie in the sources of food consumption: on average, only 35% of food (in terms of their quantity) is purchased in rural areas, in urban areas this share is 83%. Rural areas also receive 10% of food as gifts and from other sources (4% in urban), a considerable amount that likely includes food aid and food for work programmes[7].

Since the income shock used to for HK and HK/EQ simulations is based on the share of food or maize that is purchased rather than consumed, the income shock equivalent of the price shock becomes quite small. Consider again the case of an average rural household (Table 2): a 10% price increase of food purchases affects 35% of the 61% food budget, thus around 2% of total household expenditure. For the same household, even a doubling of maize prices would affect only 5% of total expenditure (25% of the 20% maize budget. For urban households, 8% of total expenditure would be affected (69% of 12% maize budget). For the RR simulation, the effects are similar because, as mentioned earlier, own produced consumption also cancels out since similar consumer and producer price changes are assumed. EQ, on the other hand, consider not only purchased items but apply price increases to the full quantity consumed of the item in question. As a result, we find EQ to predict somewhat stronger effects in the 10% scenario, and differences to HK as well as RR become more pronounced when we look at a fuller range of price changes.

To that effect, Figure 7 shows simulations of general food price as well as maize price changes over the range of 1 to 80% and across methods. The latter corresponds to the maximal maize price increase that has been observed for some survey districts over the period of twelve months (WFP, 2014). The maximum general food price increase over the same period (food CPI), was 30% (MNSO, 2014). The grey shaded area depicts the maximum and minimum range of average district level energy deficiency rates, the red dashed line refers to the estimated population mean. We find that first, for HK and RR related methods, minimum and maximum district level deficiency rates only change slowly over the price range under consideration, which is the same for the population mean. Looking at maize price shocks, energy deficiency rates in the preferred HK specification (applying the parametric estimate to the income equivalent of the price shock), and in the HK/EQ specification (applying calorie income elasticities of EQ to HK's income shock), we find estimated population calorie deficiency rates to hardly increase. For a better understanding of these predictions, we add the range of predicted income shocks to the graphs and find that, for a 80% maize price shock, the predicted income shock of the 75th percentile is below 10%.

[7] 30% of rural and 5% of urban households received food aid within the last 3 years, 6% of households participated in food for work programmes.

Figure 5: Prediction calorie deficiency ratio - 10% general price increase

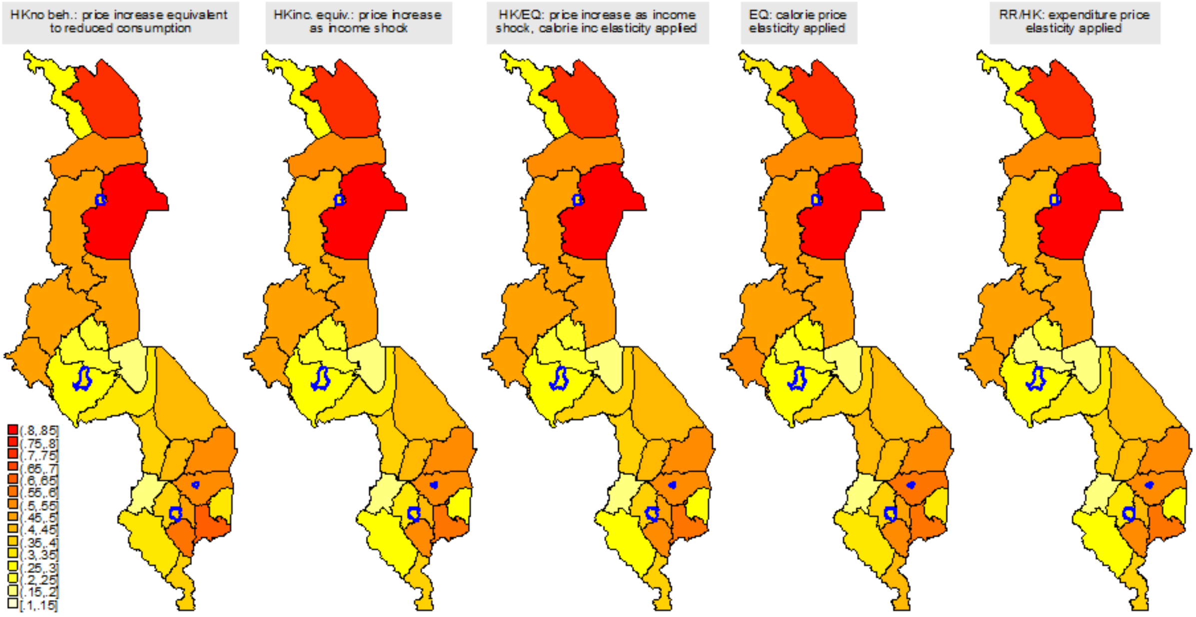
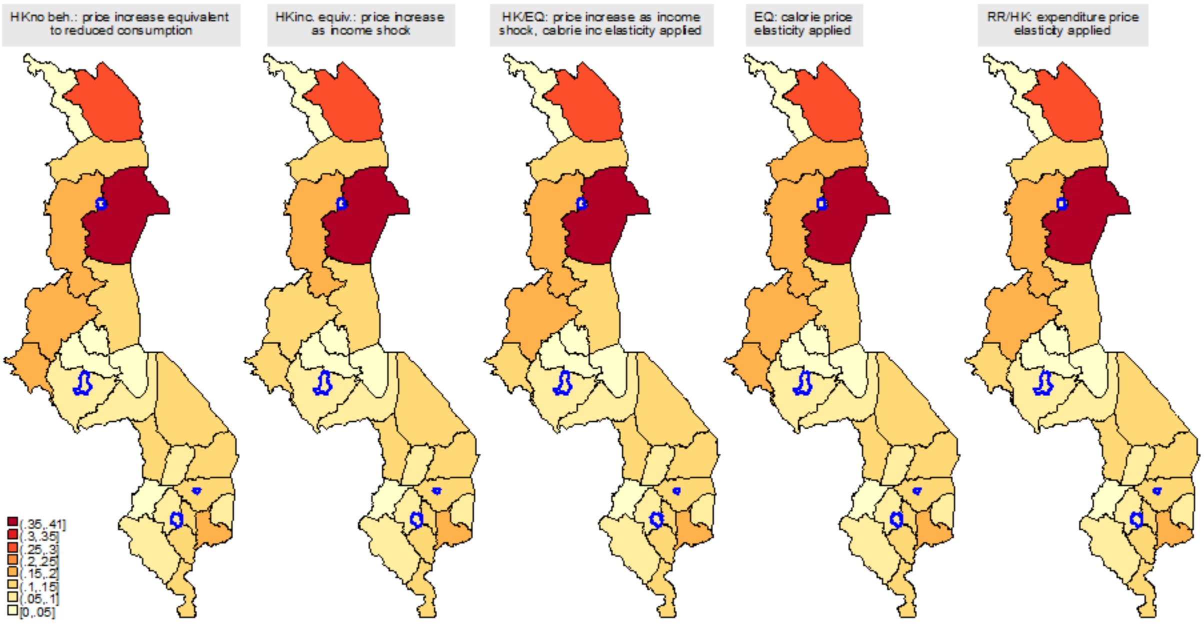


Figure 6: Prediction energy gap ratio – 10% general price increase



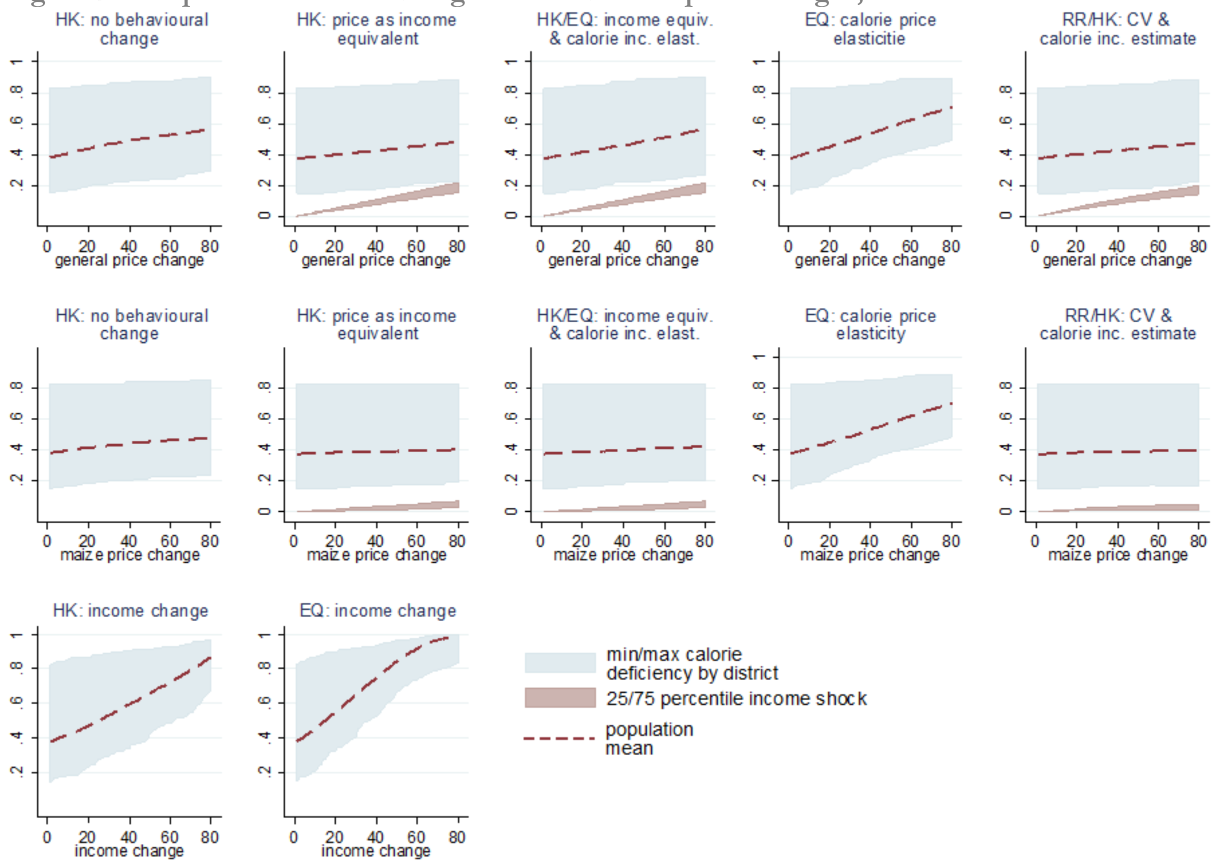
Individual sampling weights used. Urban districts/ cities in blue. **Source:** Own calculation.

Table 2: Food expenditure and purchases by socioeconomic groups

Socio-economic group	Rural: *P.c. expen-diture per day*	Rural: *Food expen-diture share*	Rural: *Maize expen-diture share*[1]	Rural: *Share: maize quan-tity pur-chased*	Rural: *Share: food quan-tity pur-chased*	Urban: *P.c. expen-diture per day*	Urban: *Food expe-nditure share*	Urban: *Maize expen-diture share*[1]	Urban: *Share: maize quan-tity pur-chased*	Urban: *Share: food quan-tity pur-chased*
Total expenditure										
low income	30.41	0.63	0.25	0.32	0.36	39.29	0.62	0.25	0.75	0.79
	(15.65)	(0.12)	(0.13)	(0.43)	(0.31)	(22.62)	(0.10)	(0.13)	(0.38)	(0.27)
middle income	44.08	0.62	0.21	0.25	0.34	54.67	0.61	0.17	0.74	0.82
	(18.91)	(0.12)	(0.12)	(0.40)	(0.29)	(25.60)	(0.10)	(0.10)	(0.41)	(0.26)
high income	83.49	0.58	0.15	0.17	0.34	177.05	0.49	0.09	0.65	0.83
	(59.12)	(0.15)	(0.11)	(0.35)	(0.27)	(196.58)	(0.15)	(0.08)	(0.45)	(0.21)
Owns land	53.03	0.61	0.20	0.23	0.32	125.43	0.53	0.15	0.48	0.70
	(42.60)	(0.13)	(0.13)	(0.39)	(0.27)	(161.25)	(0.16)	(0.12)	(0.46)	(0.25)
Landless	77.43	0.58	0.16	0.50	0.62	140.14	0.53	0.11	0.84	0.91
	(61.68)	(0.13)	(0.11)	(0.47)	(0.32)	(177.38)	(0.14)	(0.08)	(0.34)	(0.16)
All	54.81	0.61	0.20	0.25	0.35	134.34	0.53	0.12	0.69	0.83
	(44.73)	(0.13)	(0.13)	(0.40)	(0.29)	(171.35)	(0.15)	(0.10)	(0.43)	(0.23)

[1] Includes values for own-produced items. **Source:** own calculation.

Figure 7: Comparison of methods – general and maize price changes, income shocks



Individual sampling weights used. **Source:** Own calculation.

For EQ, whose price simulations are not subject to equivalent income shocks, we see that they predict significant increases in energy deficiency rates following food price shocks: mean population prevalence rates rise to 70% following a 80% maize price shock. However, the assumption of constant elasticities across a wide range of price increases might be too restrictive, a criticism that equally applies to RR estimations. When we compare a 20% maize price scenario, which is equivalent to the average maize price increase observed over a 7 month period, and a scenario that is discussed in EQ's original paper, we find the following differences between methods: HK predict an increase of energy deficiency rates of 0.7% points, EQ predict increases of 7.3% points and RR predict a plus of 0.6% points.

For understanding RR's predictions, which use the same parametric calorie – log income estimate as HK, the relevant feature, as well, is the estimated income shock, i.e. in this case the Compensating Variation. Remember that the CV was driven by a household's net position as a buyer or seller of food, subject to behavioural responses to price shocks in consumption. For the 80% maize price scenario, the CV on average was 8% of initial expenditure in urban, and only 2.5% in rural areas, thus smaller than in case of HK. Up to this point, we can thus conclude that, due to relatively low levels of food purchases (and net food sales), particularly in rural areas, price related income shocks are certainly predicted to be smaller than hypothesised, which leads to low predicted increases in food insecurity using HK and RR simulation methods.

However, so far we have only considered uniform price shocks. Since the geographical distribution might change if we allow for differential price changes across regions and items, we apply a local and interview date specific food price index as outlined in chapter 4.1. Exemplary, we have done so for a five month price increase, which we consider comparable to our 10% price increase scenario (maize prices have increased by 11% on average, food prices more generally by 7%), and a twelve month increase, as a maximum price increase scenario (see Appendix Figure A1 and Figure A2). For the 5 month scenario, indeed we do not find strong distributional differences across dicstricts, implying that targeting efforts would not be affected by the choice of methods. This changes in case of the 12 month scenario where we find EQ to provide a considerably different distributional picture than HK and RR, with very high rates of predicted energy deficiency across the country. However, we need to keep in mind also, that the methodologies in questions aim at predicting short-term effects of food price shock. Over the period of 12 months, other relevant factors (general equilibrium effects and coping mechanisms as the case may be), are likely to play a role and income and consumption choices might be affected through more indirect channels.

We formalize the analysis of district level differences in simulation outcomes and provide the results of district level regressions of energy deficiency rates on price change scenarios and methodologies as proposed in Chapter 4.2, equation (1) in the Appendix (see Table A2). We run the regression separately for general price, maize price and monthly price change scenarios. Our findings confirm the visual examination: There are statistically significant, yet (at small price changes) relatively small differences in prediction outcomes between methods. These vary with the degree of price changes under consideration. For small general price changes, for example, EQ predicts lower deficiency rates, but the partial effect becomes positive (compared to HK without behavioural change) at a price change of around 10%, and the estimated gap between EQ and HK*no beh*. grows to an average of 3,5% points for the 30% general price change scenario, for example. Further, and since predicted changes in calorie deficiencies are fairly small for a considerable range of price changes, initial levels of calorie deficiency explain a large share of the variation, which is illustrated by the large jump in R^2 between models including and excluding initial deficiency rates.

Since both HK and EQ methods are suitable for analysing the effects of income shocks also, we provide simulations for a range of uniform income shocks in Figure 7 (bottom panel). We find income shocks to have much stronger effects on calorie deficiency rates than price shocks and both methods predict strong increases. Again, EQ's method predicts stronger effects, which we confirm in simple OLS analysis (not shown): For the income shock range of 1 to 20 % of original income, for example, EQ is on average associated with a 4% points higher prediction of district level deficiency rates as compared to HK.

5.3 Simulation of Price Shocks – Household Level

We conclude our empirical analysis by considering household rather than district level predictions and investigate the extent to which household characteristics that might serve as proxies for identifying energy deficient households in targeting efforts, show similar associations with predicted energy deficiency rates across methods. This corresponds to the analysis proposed in Chapter 4.2, equation (2). Figure A3 shows kernel densities of per capita calorie availabilities for a 10% and 30% general price scenario. As substantiated before, simulation outcomes do not vary substantially in a 10% general price scenario so that we do not expect to find strong differences here. For this reason, we extend the analysis to the 30% price change scenario also. Table A3 shows our results. In general, most of our control variables show the expected signs and, if significant, effect sizes lie within the same range across methods and are very close to those for our baseline data in the 10% scenario, and fairly close still in the 30% scenario. Controlling for households agricultural land ownership shows no robust effect across methods: this variable is not significant in the baseline data. Across HK and RR methods, which are directly influenced by household's agricultural production, we do not find uniform effects. Using the models as specified explains around 20% of the variation in the energy deficiency status of our sample households.

Table A4 introduces additional control variables, which are unlikely appropriate targeting indicators, yet expected to be associated with a household's food security, such as log expenditure, and the education of household heads. Following Aksoy and Isik-Dikmelik (2008), we further generate dummies to indicate if household are 'marginal net buyers', defined as households whose (net) food purchases are worth less than 10% of their total expenditure, and 'vulnerable net buyers' whose (net) food purchases are worth more than 30% of total expenditure. The authors argue that the first group is likely to be only marginally affected by food price changes, while food security of the latter type of households is vulnerable to food price shocks. While we find marginal food buying households to be significantly less likely to be classified as calorie deficient (as compared to the intermediate group), we do not find the group of 'vulnerable net buyers' to be significantly more likely to be so. In fact, across methods, the coefficient is neither robust in terms of sign nor size or significance. While effect sizes and significance levels change across the set of limited and extended control variables used, again, across methods, for significant coefficients, effect sizes lie within in the same range across methods and in the baseline data. Adding socioeconomic controls has increased the predictive power of these models to around 30 to 35%.

6 Discussion and Limitations

Contrary to our initial hypotheses, our main findings may be summarized as follows: First, despite high levels of calorie deficiency in Malawi in 2004/2005 and a high dependency of maize in the average household's diet, we find the predicted effects of general price and maize price shocks on district level and mean population calorie deficiency rates to be moderate. This is within price ranges that have been observed over the course of twelve months following the survey. Second, in the setting at hand, the main differences between simulation outcomes are driven by the consideration of purchases vis-à-vis overall consumption levels of food or specific goods when evaluating the effect of price changes. This can be linked to the debate about direct income effects vs. opportunity costs in the form of foregone earnings. While price shocks immediately and most directly affect the consumption of goods purchased, producing households could decide to reduce their own consumption of high-prices foods in order to sell that quantity on the market (and buy other goods from the profit).

Along these lines, the method used by EQ tends to produce significantly stronger effects of price changes on calorie deficiency rates that the other methods, and particularly stronger effects than HK*no beh.* (i.e. assuming no behavioural adjustments and item specific budgets), which we originally hypothesises to provide upper bound estimates. Driven by using the same estimated income shock for their calculation HK's preferred strategy (i.e. HK*inc. equiv,* applying a parametric estimate to the income equivalent of a price shock) as well as HK/EQ*inc. el.* (i.e. applying EQ's calorie-income elasticity to HK's income shock), indeed produce comparable findings, which could be interpreted as evidence that HK's parametric estimate is able to approximate behavioural responses as captured in EQ's more complex demand system models over a relevant range of price changes. However, for the reason that estimated price related income shocks did not vary as much as expected, we cannot rule out that this picture would change in other settings. Also somewhat contrary to our hypothesis, the preferred models of HK as well as RR produce findings that are very close to one another, both in general price as well as maize price changes. The reason here is twofold: first, when calculating the CV that served as approximation of the income shock, own produced items cancel out as well. Second, we expected RR to produce lower bound estimates smaller than those of HK for the reason that RR allows for positive profit effects from selling market surplus at higher prices. However, there are only few net producing households and market surpluses tend to be very low for items sold, which is why they don't significantly alter the picture in the setting at hand.

The discussion before points to caution required when evaluating the external validity of our results: the study context was characterised by high levels of food insecurity in terms of calorie deficiencies, low levels of food purchases, particularly in rural areas, and high levels of income poverty. Rural households produce large shares of their food consumption, likely aiming at high levels of self-sufficiency, which might already be one important coping mechanism against high food prices: Malawi was suffering from a famine in 2002 and severe food shortages in 2005 also (Ecker and Qaim, 2011). Park (2006), for example, develops a dynamic model to capture decision making of (farm) households and shows that households face trade-offs between maximising their profits and building grain stocks, for example, to insure themselves against risk and uncertainty and for savings. In any case, differences between simulation methods are likely to be stronger, and potentially of different nature in a situation that is less driven by self-sufficiency production.

Methodologically, it remains unclear at which level of price changes or for which timeframe the methods reach their limits: while they share a short-term focus, assumptions about the non-responsiveness of consumption patterns or constant marginal responsiveness of consumption patterns eventually become too strong. Related to this, some price and income scenarios lead to unrealistic calorie estimates, in our case predicted calorie intakes below a threshold ensuring survival and they even can fall below zero[8]. One needs to decide how to treat these cases, which is more relevant when it comes to estimating calorie gap ratios rather than calorie headcounts.

Another limitation shared by all methods and touched upon before is the estimation of the baseline consumption aggregate. Ideally, market prices should be used to value own produced food items instead of median prices reported in the same neighbourhood as we do here (Deaton and Zaidi, 2002; Sadoulet and de Janvry, 1995). Especially in case of high levels of own production, this can lead to a systematic overestimation of total household expenditure with unclear consequences for estimating calorie – (log) income relationships and demand elasticities. At the same time, the net production position might be underestimated since reported sales (potentially at farm gate prices) are added to the imputed value of own produced and self-consumed items to derive the value of total food production, which creates a bias in the opposite direction. A different, yet related issue arises from lumping together information from production and consumption sections of the survey and applies to the method used by RR only: different recall periods for agricultural sales and food consumption likely create biases and production sections of each household further capture seasonality effects, while consumption data of individual households don't. Headey and Fan (2010) point out that Living Standard Measurement Survey more generally capture consumption better than production which would likely result in an underestimation of net production. These issues require further research.

Concerning the differences that we do find between methods, we lack suitable follow up data to compare our predictions to. Only this would allow us to draw conclusions about the predictive power of individual methods and the extent to which the approximations would result in different misidentifications of energy deficient and vulnerable households and misallocation of resources as the case may be. Consequently, we cannot rule out the extreme case that all methods are equally poor in predicting calorie deficiencies at district and households levels, even if they produce coherent and consistent results. Thus, we are restricted to pointing out that they are based on different concepts, which explain large parts of differences in predictions, and that they would identify different preferential targeting areas at high levels of price changes. At the same time, on the level of households, we find similar association between household characteristics and predicted energy deficiencies.

Finally, we need to keep in mind that we use these methods to analyse food security only in terms of calorie deficiencies (in contrast to Ecker and Qaim's original article (2011)). We acknowledge that food security is a complex matter and malnutrition goes beyond calorie adequacy. Policy efforts should build on a more comprehensive framework and take into consideration potential interactions between policies and various aspects of malnutrition in the short- as well as long-run. Furthermore, instead of concentrating on general overlaps between methods, the analysis done here could easily be extended, or adjusted, to analyse overlaps in predicting energy deficiencies for certain population groups of interest, which might be more appropriate with a specific policy intervention or pre-defined target group in mind (e.g. female headed households).

[8] For our 10% maize/general price and 30% general price increase scenarios, few predictions created values below 500 calories p.c. per day (less than 1%). For our 80% maize price scenario, this holds for all methods but EQ, which produces 2% of such values.

7 Conclusions

Our study was motivated by the literature on welfare effects of food price shocks, and the emergence of simulation studies that predict related effects based on pre-shock household survey data in order to guide policies. We have conducted a comparative assessment of different simulation studies that set out to explore the effect of food price shocks on food insecurity in terms of calorie deficiencies and income losses. While methodological setups are usually telling and the scope and limitations of individual studies are acknowledged, the basic question and important research gap that we are addressing is: do different simulation studies on the same subject lead to similar policy conclusions?

In particular, we draw on three different studies of different complexity, that all use the same Living Standard Monitoring Survey in Malawi (IHS II, 2004/2005). Rischke (2010, unpublished) builds on a farm household model, and welfare effects are largely driven by the net position of households, subject to behavioural changes. Harttgen and Klasen (2012) estimate a simple relationship between calorie consumption and log income, which they can use for their predictions once food price changes are expressed in terms of income shocks. Finally, Ecker and Qaim (2011) build on a demand system model that captures behavioural changes to price shocks and is designed to analyse effects of price shocks not only on calorie deficiencies but on micronutrients also.

Generally, and apart from underlying methodologies and concepts, differences in simulation outcomes can result from various factors ranging from study contexts, to data sources and simulation scenarios, to specific estimation techniques. We conveniently rule out the first source of divergence by design. In order to rule out data handling or simulation scenarios as another source for divergence, we further re-estimate all simulations using the same cleaned data and systematically vary simulation scenarios and a general price and maize price changes of varying degree. As far as estimation techniques are concerned, we harmonize underlying parameters to the extent possible. Nonetheless, we note that data inconsistency and poor data quality are one limiting factor in our analysis and we cannot fully exploit the flexibility of the simulation methods as a consequence. As a consequence of data inconsistencies that have been noted in our case by other authors as well (e.g. Dorward *et al.*, 2008), individual data cleaning efforts are extensive and increase differences in data handling across studies. This partly causes large differences in estimation results and generally reduces comparability across studies.

Related to the comparative assessment, several findings stand out in particular: first and generally speaking, estimated effects of food price and maize price shocks are found to be weaker than initially expected. Second, differences between methods depend on the degree of price change under consideration and grow with increasing rates of price changes. For a relevant set of price changes, differences between methods are fairly moderate. Third, still, on average, EQ produce significantly higher predictions of calorie deficiency rates. Fourth, for small price changes in particular, our simulations hardly affect the order of energy deficiency rates across districts, implying that preferential targeting areas would not be affected by the choice of method. This is different for higher degrees of price changes. Lastly, household characteristics are largely similarly associated with energy deficiency rates across methods, suggesting that they would be non-discriminatory across methods.

We have established that prevailing differences largely result from different conceptualisations of price and equivalent income shocks: While EQ focus on overall consumption, RR and HK focus on net consumption and food purchases respectively. Note that these methods are more flexible than the preferred choices of their authors, yet both viewpoints have their own right. With respect to predicting immediate effects of price shocks on calorie deficiencies (rather than more general welfare effects), however, we believe that the consideration of purchases or net production is more appropriate since an immediate real income loss is suffered only to the extent that items are bought (Van Campenhout *et al.*, 2013). Thus, a relevant and interesting extension to the current analysis would be to apply EQ's calorie price elasticities only to purchased items and compare the results.

Our findings suggest that the comparative consistency between simulation methods is context specific in nature. In case of Malawi, we study a country characterised by high levels of income poverty and food insecurity. The nature of agricultural activity, with higher poverty rates among land owing and land cultivating households, and relatively high levels of self-sufficiency in food production at low levels of agricultural sales, points to a situation of structural food insecurity. Self-sufficiency agriculture has likely established in response to past food price shocks and other food crises. For the time being, this shields especially rural households from adverse effects of high food prices, yet they remain highly vulnerable to income as well as idiosyncratic or covariate shocks that affect their harvest, including weather shocks.

Ideally, one would like to extent such analysis by evaluating predictions against follow-up data. After all, all models might be wrong, even if they arrived at similar conclusions. A number of issues, however, impede this undertaking. The first is a lack of available data, which is also linked to the time horizon under consideration. The time gap between the data used to produce predictions and follow-up data might be too long to serve as a benchmark scenario for short-term predictions. Related to this, even if longer-term, general equilibrium effects would be accounted for in the simulations (which usually require more assumptions) confounding effects likely grow stronger over time. This holds especially in the aftermath of shocks, where we hopefully find policy interventions. A lack of congruence between predictions and observed data might result, for instance, from inadequate model assumptions or from particularly successful policy making that relieved the burden for the most troubled. In our opinion, these questions point to highly relevant research gaps in the field of simulating welfare effects and targeting policies that should be systematically investigated in the future.

8 Appendix

Table A1: Summary statistics of calorie consumption by place of residence

Food group	Rural				Urban			
	Calories p.c. per day	*Share of consumpt. produced by HH*[1]	*Expen-diture share of consmpt.*[2]	*Net produc-tion (exp. share)*[3]	*Calories p.c. per day*	*Share of consumpt. produced by HH*[1]	*Expen-diture share of consmpt.*[2]	*Net produc-tion (exp. share)*[3]
Maize	1494	0.647	0.217	-0.069	1362	0.215	0.145	-0.106
	(762)	(0.433)	(0.134)	(0.136)	(619)	(0.377)	(0.111)	(0.098)
Rice	232	0.205	0.011	-0.003	221	0.003	0.025	-0.025
	(226)	(0.403)	(0.031)	(0.038)	(216)	(0.051)	(0.033)	(0.033)
Other cereals	155	0.132	0.017	-0.013	168	0.003	0.044	-0.044
	(260)	(0.306)	(0.034)	(0.028)	(208)	(0.034)	(0.043)	(0.043)
Cassava/cocoyam	235	0.424	0.024	-0.006	138	0.064	0.011	-0.009
	(351)	(0.486)	(0.055)	(0.056)	(244)	(0.244)	(0.022)	(0.018)
Potato	109	0.372	0.014	-0.005	123	0.045	0.017	-0.016
	(119)	(0.469)	(0.031)	(0.023)	(145)	(0.201)	(0.025)	(0.025)
Phaseolus beans	160	0.332	0.026	-0.013	116	0.079	0.027	-0.021
	(164)	(0.468)	(0.043)	(0.033)	(109)	(0.269)	(0.041)	(0.026)
Pigeonpea/cow-	201	0.514	0.018	-0.005	110	0.110	0.005	-0.004
pea/soybean	(215)	(0.490)	(0.038)	(0.040)	(116)	(0.312)	(0.015)	(0.014)
Peanut/bambara	223	0.544	0.027	-0.003	89	0.059	0.010	-0.008
groundnut	(266)	(0.487)	(0.056)	(0.027)	(103)	(0.228)	(0.021)	(0.023)
Tomato	6	0.134	0.016	-0.011	8	0.011	0.033	-0.033
	(6)	(0.340)	(0.019)	(0.036)	(6)	(0.103)	(0.025)	(0.026)
Pumpkin	33	0.758	0.012	-0.002	17	0.256	0.004	-0.003
	(36)	(0.425)	(0.032)	(0.010)	(15)	(0.434)	(0.013)	(0.010)
Green leafy	11	0.550	0.044	-0.012	14	0.141	0.027	-0.019
vegetables	(16)	(0.430)	(0.052)	(0.031)	(15)	(0.314)	(0.029)	(0.022)
Other vegetables	8	0.392	0.009	-0.004	5	0.071	0.012	-0.008
	(14)	(0.462)	(0.020)	(0.014)	(12)	(0.247)	(0.025)	(0.009)
Banana/plantain	43	0.306	0.006	-0.002	28	0.062	0.007	-0.006
	(124)	(0.452)	(0.016)	(0.013)	(52)	(0.237)	(0.017)	(0.012)
Other fruits	58	0.400	0.017	-0.006	45	0.079	0.010	-0.009
	(101)	(0.467)	(0.046)	(0.031)	(77)	(0.253)	(0.018)	(0.016)
Eggs	19	0.584	0.007	-0.003	27	0.019	0.016	-0.015
	(20)	(0.491)	(0.018)	(0.011)	(26)	(0.137)	(0.022)	(0.022)
Fish	65	0.035	0.040	-0.036	74	0.000	0.048	-0.048
	(113)	(0.177)	(0.052)	(0.046)	(78)	(0.015)	(0.042)	(0.042)
Red meat	60	0.032	0.015	-0.003	83	0.003	0.032	-0.030
	(72)	(0.173)	(0.041)	(0.075)	(73)	(0.048)	(0.051)	(0.054)
White meat	46	0.603	0.023	-0.004	54	0.088	0.024	-0.020
	(62)	(0.475)	(0.060)	(0.035)	(59)	(0.282)	(0.047)	(0.043)
Milk and milk	37	0.138	0.004	-0.003	46	0.006	0.013	-0.013
products	(46)	(0.345)	(0.021)	(0.015)	(68)	(0.072)	(0.028)	(0.028)
Fats/oils	84	0.003	0.012	-0.012	173	0.001	0.040	-0.040
	(92)	(0.057)	(0.024)	(0.024)	(156)	(0.030)	(0.033)	(0.033)
Sugar/sweets	101	0.092	0.028	-0.025	184	0.018	0.039	-0.038
	(109)	(0.259)	(0.034)	(0.032)	(120)	(0.106)	(0.027)	(0.026)
Spices	4	0.008	0.011	-0.011	4	0.001	0.011	-0.011
	(14)	(0.062)	(0.011)	(0.011)	(14)	(0.033)	(0.013)	(0.013)

Standard deviations in parentheses. [1]Consumption share in terms of quantity consumes. [2]Own produced items valued with median local specific unit values. [3]Equivalent to consumption expenditure share less production expenditure share. Note that the value of agricultural sales is not included in expenditure aggregate. **Source:** Own calculation.

Figure A1: Prediction general food price increase – 5 month regional price changes

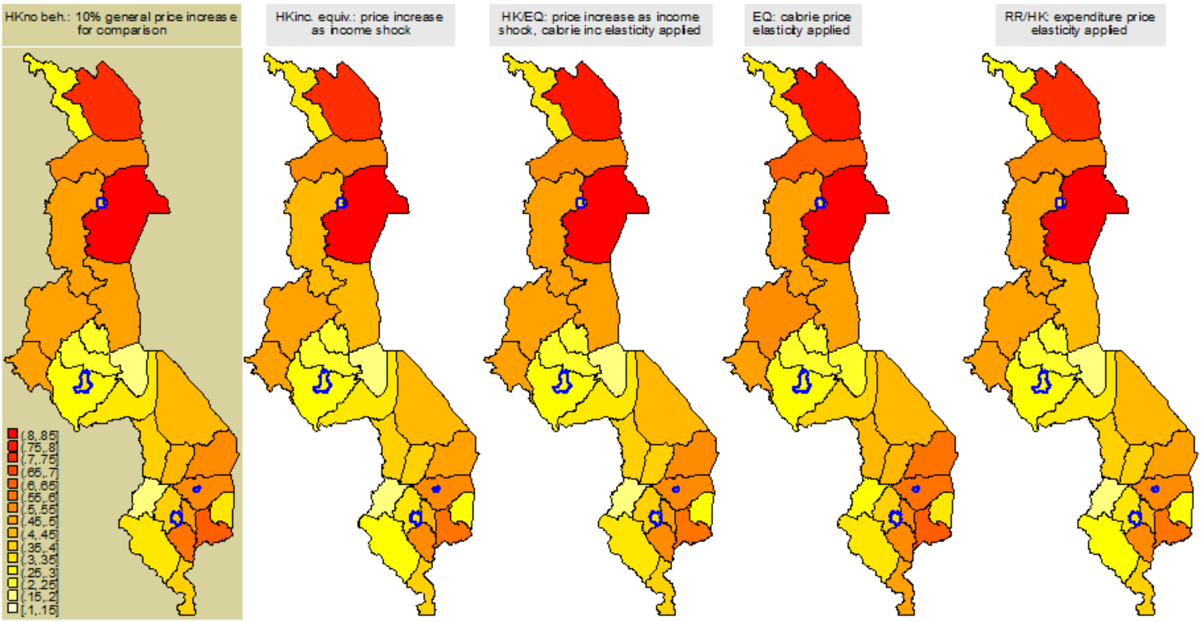
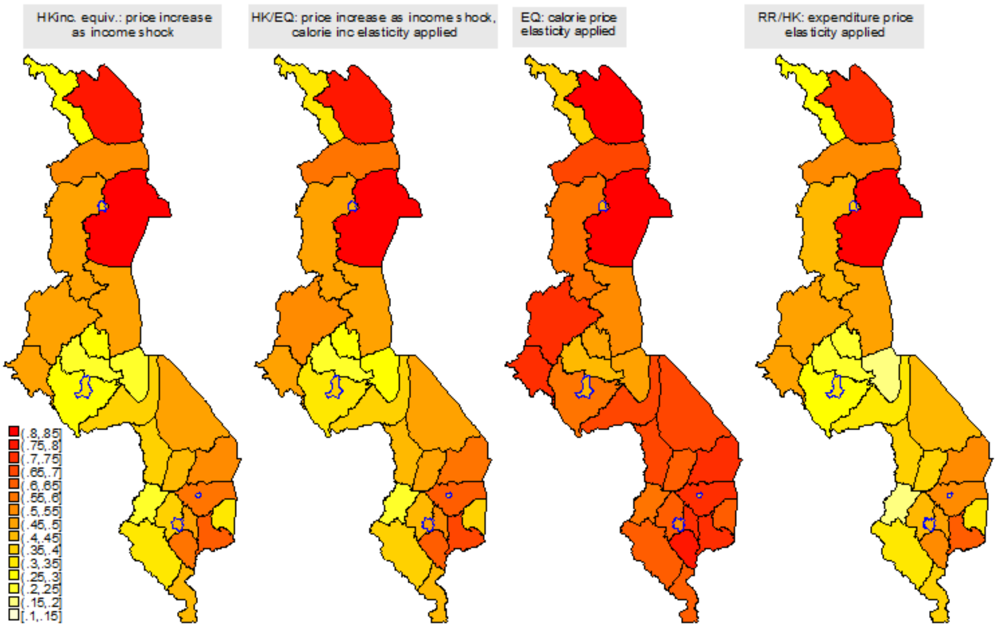


Figure A2: Prediction general food price increase – 12 month regional price changes



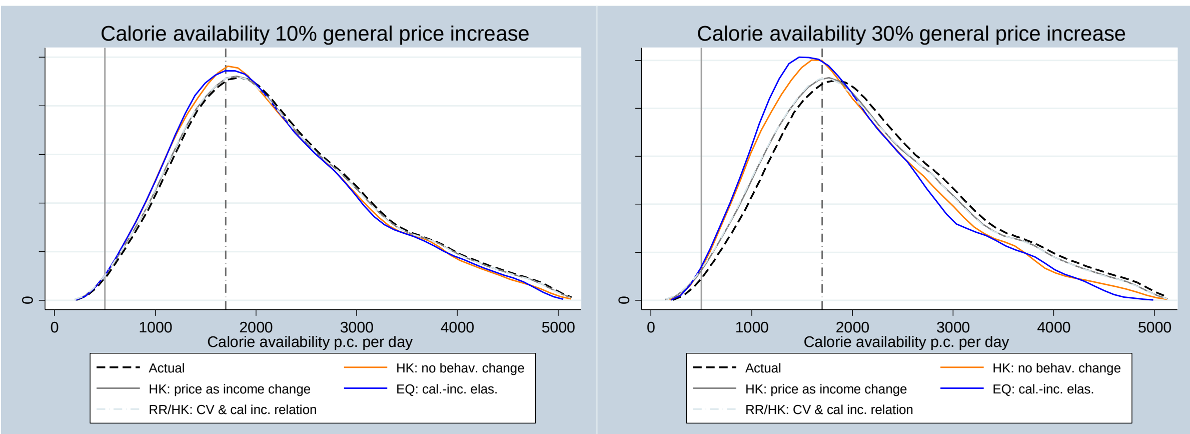
Individual sampling weights used. Urban districts/ cities in blue. **Source:** Own calculation.

Table A2: OLS regressions – district level energy deficiency on methods and scenarios

Dep. variable: Calorie deficiency	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	General price increase			**Maize price increase**			**Monthly price change**		
Method=HK no beh.	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted			
Method=EQ	-0.0250***	-0.0250***	-0.0250***	-0.0198***	-0.0198***	-0.0198***	Omitted	Omitted	Omitted
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)			
Method=HK/EQ	-0.0231***	-0.0231***	-0.0231***	-0.0101***	-0.0101***	-0.0101***	0.0314***	0.0314***	0.0314***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)	(0.005)	(0.005)
Method= HK	-0.0195***	-0.0195***	-0.0195***	-0.0107***	-0.0107***	-0.0107***	0.0342***	0.0342***	0.0342***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)	(0.005)	(0.005)
Method=RR/HK	-0.0154***	-0.0154***	-0.0154***	-0.0087***	-0.0087***	-0.0087***	0.0378***	0.0378***	0.0378***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)	(0.005)	(0.005)
Price change[1]	0.0023***	0.0023***	0.0023***	0.0012***	0.0012***	0.0012***	0.0202***	0.0202***	0.0202***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)
EQ*price change	0.0020***	0.0020***	0.0020***	0.0030***	0.0030***	0.0030***	Omitted	Omitted	Omitted
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
HK/EQ*price change	0.0001	0.0001	0.0001**	-0.0007***	-0.0007***	-0.0007***	-0.0138***	-0.0138***	-0.0138***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)
HK*price change	-0.0009***	-0.0009***	-0.0009***	-0.0009***	-0.0009***	-0.0009***	-0.0161***	-0.0161***	-0.0161***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)
RR/HK*price change	-0.0010***	-0.0010***	-0.0010***	-0.0010***	-0.0010***	-0.0010***	-0.0172***	-0.0172***	-0.0172***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)
District mean: Household size	0.0176	-0.0117**	-0.0303***	0.0248	-0.0052*	-0.0227***	0.0225	-0.0084***	-0.0236***
	(0.039)	(0.005)	(0.001)	(0.039)	(0.003)	(0.000)	(0.040)	(0.002)	(0.001)
District mean: Log daily HH exp.	-0.1383	0.0014	-0.1516***	-0.1409	0.0024	-0.2025***	-0.1383	0.0089	-0.1993***
	(0.168)	(0.016)	(0.004)	(0.175)	(0.011)	(0.002)	(0.183)	(0.007)	(0.004)
District share landless HH	-0.4707	0.1858*	Omitted	-0.6176	0.0555	Omitted	-0.5878	0.1034	Omitted
	(0.771)	(0.106)		(0.775)	(0.078)		(0.788)	(0.079)	
District share HH cultivate land	-0.6511	0.0470	Omitted	-0.6795	0.0362	Omitted	-0.6388	0.0961	Omitted
	(0.884)	(0.117)		(0.890)	(0.075)		(0.909)	(0.076)	
District mean: t0 calorie deficiency		0.9123***	Omitted		0.9353***	Omitted		0.9605***	Omitted
		(0.026)			(0.015)			(0.010)	
Region dummies	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
District dummies	No	No	Yes	No	No	Yes	No	No	Yes
Constant	1.7894	0.0475	1.4147***	1.7930	0.0072	1.6317***	1.7022	-0.1318*	1.5644***
	(1.292)	(0.149)	(0.018)	(1.344)	(0.084)	(0.009)	(1.400)	(0.074)	(0.021)
Observations	12000	12000	12000	12000	12000	12000	1440	1440	1440
R^2	0.423	0.928	0.936	0.424	0.964	0.967	0.342	0.965	0.968

Cluster robust standard errors (level of districts) or robust standard errors (if districts are included) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [1]Models (1)-(6), price change in percent ranging from 1-80, models (7)-(9) use observed price change of 1 – 12 consecutive months. **Source**: Own calculation.

Figure A3: Household p.c. calorie densities – 10% 30% general price increase



Vertical, dotted line refers to mean recommended minimum energy intake p.c. per day. **Source**: Own calculation

Table A3: Household level determinants of calorie deficiency across methods - linear probability models for 10% and 30% general price increase

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. var.		**10% general price shock**				**30% general price shock**			
=1 if HH is calorie deficient	Baseline	HK: no beh.	HK: inc. equival.	EQ: cal. price elast.	RR/HK: CV as inc. shock	HK: no beh.	HK: inc. equival.	EQ: cal. price elast.	RR/HK: CV as inc. shock
Female HH head	0.0472***	0.0514***	0.0487***	0.0506***	0.0510***	0.0393***	0.0460***	0.0525***	0.0549***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)
Age of HH head	0.0064***	0.0061***	0.0060***	0.0059***	0.0058***	0.0060***	0.0055***	0.0066***	0.0050***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Square age of HH head	-0.0000**	-0.0000**	-0.0000**	-0.0000*	-0.0000*	-0.0000**	-0.0000*	-0.0000**	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nb children (0-14)	0.0772***	0.0815***	0.0794***	0.0810***	0.0795***	0.0827***	0.0831***	0.0883***	0.0832***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Nb male adults (15-64)	0.0925***	0.0972***	0.0941***	0.0982***	0.0945***	0.0974***	0.0946***	0.0976***	0.0952***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Nb female adults (15-64)	0.0498***	0.0512***	0.0480***	0.0484***	0.0467***	0.0579***	0.0515***	0.0591***	0.0518***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Nb elderly (65+)	0.0582***	0.0636***	0.0579***	0.0650***	0.0556***	0.0633***	0.0614***	0.0666***	0.0582***
	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)	(0.016)
HH owns house	-0.0077	-0.0123	-0.0114	-0.0130	-0.0127	-0.0208	-0.0073	-0.0021	-0.0116
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Nb of rooms	-0.0203***	-0.0201***	-0.0195***	-0.0205***	-0.0195***	-0.0222***	-0.0205***	-0.0246***	-0.0234***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
HH has improved roof	-0.0711***	-0.0666***	-0.0693***	-0.0729***	-0.0715***	-0.0627***	-0.0697***	-0.0659***	-0.0734***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.016)	(0.015)	(0.015)	(0.015)
HH has improved floor	-0.0543***	-0.0525***	-0.0608***	-0.0678***	-0.0607***	-0.0435***	-0.0537***	-0.0803***	-0.0510***
	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
season=I2004	0.0055	-0.0026	-0.0022	-0.0072	-0.0021	-0.0058	-0.0062	-0.0205	-0.0115
	(0.027)	(0.028)	(0.028)	(0.027)	(0.028)	(0.029)	(0.028)	(0.029)	(0.028)
season=II2004	0.0211	0.0113	0.0181	0.0225	0.0183	-0.0037	0.0124	0.0165	0.0111
	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
season=IV2004	0.0499***	0.0657***	0.0515***	0.0595***	0.0545***	0.0800***	0.0611***	0.0793***	0.0597***
	(0.019)	(0.020)	(0.019)	(0.020)	(0.019)	(0.021)	(0.020)	(0.021)	(0.020)
season=I2005	0.1023***	0.1185***	0.1076***	0.1171***	0.1088***	0.1420***	0.1134***	0.1365***	0.1156***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
HH is landless	0.0168	0.0346**	0.0218	0.0146	0.0253	0.0679***	0.0351**	0.0154	0.0394**
	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)	(0.017)
Observations	10354	10354	10354	10354	10354	10354	10354	10354	10354
R^2	0.208	0.207	0.208	0.207	0.208	0.207	0.208	0.211	0.208

Left out season: III2004. Cluster robust standard errors in parentheses (level of primary sampling units). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. **Source**: Own calculation

Table A4: Household level determinants of calorie deficiency across methods - linear probability models for 10% and 30% general price increase, extended models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		10% general price shock				**30% general price shock**			
	Baseline	HK: no beh.	HK: inc. equiv.	EQ: cal. price elas.	RR/HK: CV as inc. shock	HK: no beh.	HK: inc. equiv.	EQ: cal. price elas.	RR/HK: CV as inc. shock
Female HH head	0.0156	0.0205*	0.0172	0.0185	0.0193*	0.0075	0.0143	0.0150	0.0225**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Age of HH head	0.0062***	0.0059***	0.0058***	0.0058***	0.0056***	0.0058***	0.0052***	0.0064***	0.0047***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Square age of HH head	-0.0001***	-0.0000**	-0.0000***	-0.0000**	-0.0000**	-0.0001***	-0.0000**	-0.0001***	-0.0000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nb children (0-14)	0.0242***	0.0248***	0.0250***	0.0231***	0.0247***	0.0229***	0.0262***	0.0226***	0.0253***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Nb male adults (15-64)	0.0709***	0.0739***	0.0720***	0.0746***	0.0721***	0.0724***	0.0714***	0.0708***	0.0716***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Nb female adults (15-64)	0.0246***	0.0240***	0.0220***	0.0205***	0.0204***	0.0292***	0.0242***	0.0274***	0.0240***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Nb elderly (65+)	0.0185	0.0219	0.0173	0.0216	0.0146	0.0208	0.0193	0.0169	0.0152
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
HH owns house	-0.0144	-0.0155	-0.0169	-0.0190	-0.0188	-0.0132	-0.0129	-0.0104	-0.0182
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)
Nb of rooms	0.0096**	0.0124**	0.0113**	0.0118**	0.0116**	0.0140***	0.0121**	0.0121**	0.0096**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
HH has improved roof	-0.0093	-0.0026	-0.0066	-0.0061	-0.0080	0.0021	-0.0047	0.0110	-0.0072
	(0.014)	(0.013)	(0.013)	(0.014)	(0.013)	(0.015)	(0.014)	(0.014)	(0.014)
HH has improved floor	0.0517***	0.0576***	0.0468***	0.0464***	0.0480***	0.0677***	0.0581***	0.0510***	0.0628***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)
season==I2004	0.0014	-0.0093	-0.0071	-0.0115	-0.0071	-0.0188	-0.0124	-0.0249	-0.0176
	(0.025)	(0.026)	(0.025)	(0.024)	(0.025)	(0.025)	(0.026)	(0.025)	(0.026)
season==II2004	0.0177	0.0124	0.0159	0.0184	0.0157	0.0069	0.0125	0.0104	0.0108
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
season==IV2004	0.0137	0.0222	0.0130	0.0206	0.0159	0.0223	0.0187	0.0360*	0.0169
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)
season==I2005	0.0141	0.0212	0.0164	0.0217	0.0169	0.0304	0.0168	0.0282	0.0175
	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)
HH is 'marginal net buyer'	-0.0349***	-0.0562***	-0.0398***	-0.0374***	-0.0393***	-0.0838***	-0.0563***	-0.0290**	-0.0571***
	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
HH is 'vulnerable net buyer'	-0.0201*	0.0080	-0.0115	-0.0258**	-0.0128	0.0884***	-0.0033	-0.0293**	-0.0063
	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
Log of daily HH exp.	-0.3208***	-0.3414***	-0.3284***	-0.3509***	-0.3315***	-0.3572***	-0.3434***	-0.3985***	-0.3493***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
HH grows tobacco	-0.0085	-0.0109	-0.0108	-0.0172	-0.0137	-0.0134	-0.0136	-0.0124	-0.0147
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
HH head: primary educ.	-0.0156	-0.0055	-0.0118	-0.0045	-0.0106	-0.0044	-0.0066	-0.0109	-0.0074
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
HH head: second. or higher	-0.0101	0.0010	-0.0054	0.0036	-0.0038	0.0091	-0.0035	-0.0008	-0.0023
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10353	10353	10353	10353	10353	10353	10353	10353	10353
R^2	0.306	0.314	0.310	0.318	0.311	0.330	0.316	0.343	0.318

[1]Defined as: value of food purchases below 10% of total expenditure [2]Defined as: value of food purchases exceeding 30% of total expenditure. Left out categories: season III20004, no formal education of household head. Cluster robust standard errors in parentheses (level of primary sampling unit). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. **Source**: own calculation.

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