Essays on Food Security and the Nutrition Transition in Developing Countries

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Essays on Food Security and the Nutrition Transition in Developing Countries

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Nutrition

nu|tri|tion / njʊˈtrɪʃ(ə)n

"The process of providing or obtaining the food necessary for health and growth"

Oxford Dictionary[1]

1 General Introduction

The nature of food insecurity has been changing in the world, yet the one aspect that all forms of malnutrition share is an inadequate diet, i.e. a diet that is not providing or restricted to "the food necessary for health and growth", as the Oxford Dictionary would put it (FAO, 2013). The definition of Food Security as it is widely used today was endorsed by representatives of around 190 governments at the World Food Summit in 1996:

> "Food security exists when all people, at all times, have physical and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences."(FAO, 1996b, paragraph 1)

In this meeting, the government representatives adopted the Rome Declaration on World Food Security and a Plan of Action, both to acknowledge the fundamental human right of being free from hunger and to ascertain their commitment to eradicate food insecurity, poverty and inequality (FAO, 1996a; FAO, 1996b). This underscores the relevance of understanding the nature of food security, particularly in developing countries, associated trends and dynamics.

The definition above goes well beyond earlier concepts that were solely based on the experience of hunger, and most notably incorporates issues of economic access, dietary quality, which can differ across individuals and population groups, stability, and even social aspects to the extent that individual food preferences are to be respected. It is worthwhile to shed some light on this development. We will exemplary trace the changing use of the term food security in the annual report series *The State of Food and Agriculture* by the FAO. The FAO, the Food and Agricultural Organization of the United Nations, was established in 1945 with the mandate to "collect, analyze, interpret and disseminate information relating to nutrition, food and agriculture" (FAO, 1997, Box 2, Article I). Consequently, their annual reports are uniquely suitable to trace the changing nature of food insecurity in the world and related debates in the political arena.

In their first report in 1947, the word was 'scarcity' and the concerns were related to post-war recovery. Further, it was recognized that a return to pre-war levels of agricultural production would not suffice to reach the goal of 'providing all people with enough to eat' due to increasing population growth. Yet, anxieties about future markets and associated price risks were debilitating efforts to increase agricultural production. Geopolitically motivated striving for high levels of self-sufficiency in food production would shape agricultural policies for many years to come. It was only in the mid-1950s that growth in world production exceeded population growth and the FAO members agreed that an increase in agricultural output was not their highest priority anymore. Yet, due to an unequal distribution of demand and supply around the globe, diets were improving and diversifying only for parts of the world population. The

[1] http://www.oxforddictionaries.com, Date accessed: 24.09.2014

majority of people did not benefit from these trends and the gap between industrialized and developing countries was widening. In fact, industrialized countries were now concerned with the disposal of excess production that would not distort food prices and incentives for domestic producers or create new surpluses. At the same time, developing countries did not produce enough food to meet their demand and 'food shortages and other deficiencies' were widespread, particularly in Asian countries. For reasons of very simple production technologies used in developing countries and a huge technology advance elsewhere, there was a large and idle scope to increase agricultural productivity at low costs. For developing countries, the situation deteriorated since they relied on agricultural exports for foreign exchange earnings which were vital to import capital goods. Instead, some countries started to rely on food imports (FAO, 1947; 1949; 1954; 1955; 1958; 1959).

By the 1960s, industrialized countries were able to provide their population with a 'nutritionally adequate' diet, and food aid was becoming a popular tool to help overcome the 'lack of quantity and dietary value' prevalent across developing countries (for the food aid distribution, The World Food Programme was founded by the FAO and the UN). At the same time it was acknowledged that recipient countries must strengthen their domestic agricultural productivity, and organizational as well as institutional aspects were called on the political agenda. In the light of severe food shortages, 'man's right to food' was accepted alongside the responsibility to safeguard this right. Towards the end of the 1960s, a lot of hope was pinned on high-yielding varieties of wheat and rice, introduced in some Asian countries, to overcome 'calorie deficiencies' and 'substandard diets'. In the early 1970s, famine conditions were found in Sahel zone countries of West Africa, and famine struck Bangladesh in 1974. The World Food Congress of the same year led to a resolution calling for all governments to "accept the goal that no child will go to bed hungry, that no family will fear for its next day's bread and that no human being's future and capacities will be stunted by malnutrition" (FAO, 1974, p. viii). The early 1980s saw yet another increase in food insecurity in the developing world. 1984 in particular was a year characterised by the absurdity of record high harvests and surpluses in some countries, and drought related famines in southern and eastern African countries. This episode has most clearly illustrated what was partly recognized earlier, namely that increasing agricultural output would not automatically translate into improved access to those in need for the reason of poverty and income constraints. This is also at the core of Sen's 'entitlement approach', a framework to explain the occurrence of famines (Sen, 1981). The FAO has broadened their definition of world food security as a response and introduced the notion of 'stabilities of supplies and access' to that of general 'food availability' (FAO, 1959; 1962; 1965; 1968; 1970; 1971; 1973; 1974; 1980; 1984).

A decade of political change and trade liberalisations followed in the 1990s and, in a nutshell, has intensified some and set in motion other profound transformations of agri-food chains and systems that have been adding complexity to the topic of food security and malnutrition. These transformations concern the processing, wholesale and retail sector and have interacted with rising income and changing preferences on the consumer side (Reardon *et al.*, 2009; Reardon *et al.*, 2004; Timmer, 2009). One new development in this context, was the so-called 'supermarket revolution' and the spread of fast-food chains in developing countries (Reardon *et al.*, 2009).

Popkin *et al* (2012) describe dietary changes towards more processed, energy-dense, and animal source foods alongside changes toward more sedentary lifestyle in the 1970s already. The consequences of what later became known as the 'nutrition transition', however, were felt among low- and middle income populations of industrialized and in some developing countries only from the 1990s onwards. These consequences refer to rising rates of overweight, obesity, and related health conditions. Among the factors that have played a role for this development were urbanization processes, since they were reinforcing the trend towards more sedentary lifestyles, an increased consumption of purchased and processed foods, and the exposure to mass media. An increasing female labour force participation is argued to have added to the demand for convenience foods, and technological advances in the production of processed, energy dense foods, such as edible oils, and slowly rising level of income made these foods accessible across socioeconomic groups (Popkin, 2004; Reardon and Timmer, 2012). Popkin *et al.* (2012) further describe the clashes between these food consumption patterns and human biology. The preference for fatty foods, for instance, has increasingly clashed with the relatively cheap provision of edible oils, while the preference for sweet foods and the lack of a connection between thirst and satiety mechanism clashed with the emergence of sugary beverages that consequently flush 'empty calories' in the body system (Ibid).

The situation that has emerged in many developing countries as a result is (at least) a 'double burden of malnutrition', with high rates of undernourishment alongside overweight, obesity and non-communicable diseases[2]: Despite considerable successes in reducing child and maternal malnutrition in the past, according to FAOs most recent estimates, 12.5% of the world population, i.e. more than 850 million individuals, are calorie deficient, slightly more than every fourth child in the world is stunted, 2 billion people suffer from micronutrient deficiencies and 1.4 billon people are overweight, half a million of them are obese (FAO, 2013). While the pinning down of exact numbers is a difficult exercise and associated with some degree of uncertainty, the problems of malnutrition in any account are of massive proportions (de Haen *et al.*, 2011; Pangaribowo *et al.*, 2013). Equally concerning are those instances of pre-mature deaths, i.e. deaths that may have been prevented in the presence of appropriate treatment and well-functioning health care systems. Since these are often lacking in developing countries and further over-burdened with issues of communicable diseases and 'traditional health concerns', they are not prepared for the large-scale treatment of nutrition related non-communicable diseases (NCDs) such as diabetes, cardiovascular diseases, and certain cancers (WHO, 2010). The burden of these NCDs is rising fastest in low- and middle-income countries, where an estimated 80% of NCD related deaths occur. In developing countries, around one third of these deaths occur below the age of 60 (in high-income countries, this number is 13%). Issues of inequality within countries further aggravate the situation, since individuals of lower socioeconomic status are less likely to be treated when affected and they die sooner as a consequence (Ibid). In economic terms, hunger and malnutrition, as a result of direct health costs and indirect costs from losses in productivity are estimated to cost the global economy the equivalent of 5% of GDP per year, or around 500US$ per person per year (FAO, 2013). Thus, the goal to ensure food security for all is not only socially and morally desirable, but also expected to yield high returns of investment (Fan, 2014).

Analogous to the important role food security for social and economic development, for development policies and public debates, research on food security issues has played an important role in the field of development and agricultural economics. It has gained momentum again in the course of the question how to feed 9 billion people by 2050 in a sustainable and healthy way (Charles *et al.*, 2010). This dissertation addresses different research questions in the broad field of food security and comprises three different essays that are organised in chapters. The second and the third chapter of this dissertation are concerned with drivers and consequences of the nutrition transition in developing countries. As we have

[2] Some scholars now talk about a "triple burden of malnutrition" to refer to persistently high rates of undernourishment, micronutrient deficiencies, and increasing rates of overweight, obesity and related non-communicable diseases (Pangaribowo *et al.*, 2013).

outlined above, transformations on the supply side, as well as demand side factors have contributed to the nutrition transition and associated health conditions, and they are further expected to be mutually reinforcing (Hawkes, 2008; 2009; Popkin, 2004; Reardon *et al.*, 2004). The spread of supermarkets in developing countries has attracted considerable attention. A body of literature appeared that seeks to understand challenges and opportunities that emerge for small farmers in different contexts: on the one hand, supermarkets may connect farmers to high-value markets and improve their livelihoods, on the other, due to increasing food quality and food safety standards, they may crowd small farmers out of the market and threaten their main sources of livelihood (Mergenthaler *et al.*, 2009; Reardon *et al.*, 2004; Schipmann and Qaim, 2011). Effects of supermarkets on the nutrition and food security of consumers are less well studied and considerable research gaps remain (Giskes *et al.*, 2011; Timmer, 2009). Since supermarkets are a physical and stable access point to a variety of food products, they may enhance food security in developing countries. For the reason of expanding the availability of new types of goods and particularly foods that have been associated with the nutrition transition, they are expected to influence consumer decisions towards the consumption of these foods and thus they may further contribute to the development of overweight and obesity (e.g. Asfaw, 2008; Hawkes, 2008; Monteiro *et al.*, 2010). Since demand or supply side effects interact, causal effects between what supermarket store and what consumers demand are not well understood. In contribution to this strand of literature, chapter two and three are concerned with the following research questions:

1. Does the spread of supermarkets in developing countries change consumption patterns and contribute to the nutrition transition?
2. Does the spread of supermarkets in developing countries contribute to increasing rates of overweight and obesity?

We will address these research questions building on data that we collected in Kenya in 2012.

Side effects of increasing levels of world trade in food are increasing dependencies on global food markets and on their stability. This is especially true for net food importing countries. Many developing countries fall in this category. Demand for food is increasing from various sources, including population growth, rising levels of income, high-value food demand in middle-income countries such as China and India, and increasing demand for grains as livestock feed, and for biofuels, which boom in times of high prices of crude oils (Headey and Fan, 2010; Popkin and Ng, 2007). At the same time, natural resources are increasingly depleted, and there is a very limited scope to increase agricultural productivity by expanding agricultural land. Climate change and climate shocks such as droughts and floods, which occur with increasing frequency and intensity, are not brightening the picture and have put an additional pressure on scarce resources and prices (World Bank, 2013). Against this background, price shocks and price volatility, as observed after their all-time low at the beginning of the 2000s, have been sources of considerable distress for many developing countries and of general concern (Headey and Fan, 2010; Popkin *et al.*, 2012).

In the fourth chapter of this dissertation, we analyse the effect of price shocks on income and calorie deficiencies in Malawi. In particular, we compare different methodologies that are used to predict effects of price shocks using ex-ante household survey data. Such predictions can be used to inform policy makers who wish to design and target mitigation efforts which motivates our third research question:

3. Do different simulation methods produce similar results?

The remainder of this dissertation is structured as follows: we will continue by providing a brief synopsis of the individual research chapters. In section 1.4, we draw some general conclusions and point to open research questions and policy implications. The individual research chapters follow thereafter.

1.1 Synopsis Chapter 2

In chapter two, we establish the relationship between supermarket purchases and consumption patterns in small towns in Kenya, and we analyse the factors that are driving the choice of a particular outlet. For the reason that the consumption of highly processed foods has been identified in the nutrition transition literature as contributing to the development of overweight, obesity and NCDs, our main outcome of interest is the dietary composition between food groups of different levels of industrial processing.

We build our analysis on comprehensive cross-sectional data that we collected in Kenya in 2012 for this very purpose. We collected detailed information on consumption patterns, lifestyles and shopping behaviour of around 450 households in three small towns in Kenya. To establish causality between shopping behaviour and our outcomes of interest, we designed our sample of towns to be quasi-experimental in nature: We chose three towns differing in supermarket access (ranging from a long established supermarket to a town with no supermarket access), and employ instrumental variable techniques to allow for endogeneity of supermarket purchases.

We find that supermarkets affect the dietary behaviour of consumers: supermarket purchases increase the consumption of processed foods at the expense of unprocessed foods. As opposed to our initial hypothesis, however, this is not significantly driven by highly processed foods such as sugary drinks and salty snacks, but by primary processed foods, which include maize, bread, fats and oils. Furthermore, we find supermarket purchases to increase per capita calorie availability, i.e. households consume more calories, which is supported by lower prices paid per calorie in supermarkets, particularly for processed foods. Our results imply that supermarkets contribute to the nutrition transition, while effects on nutrient adequacy are less clear and require further research. With respect to shopping behaviour, we find households to spend 70% of food expenditure in kiosks, (traditional outlets and the main competitor of supermarkets). Lower prices and convenience (e.g. one-stop shopping) are reported by households as most important reasons for shopping in supermarkets, while close physical access to kiosks is by far the most important reason to shop in kiosks.

1.2 Synopsis Chapter 3

In chapter three, we focus on the effects of supermarket purchases on nutritional outcomes at the level of individuals. For doing so, we use the same data source as in chapter two. In addition to household level data, we collected individual level information for children and adolescents (age 5-19) as well as adults that were randomly selected in each household. Aside from anthropometric measurements, and in contribution to the existing literature, we exploit rich information on food eaten away from home and include information on physical activity at home and during leisure time in our analysis.

We find that buying in a supermarket significantly increases the body mass index of adults and raises the probability of adults of being overweight or obese. For adolescents we do not find a significant impact on the probability of being overweight. Instead, buying in a supermarket tends to decrease undernutrition among children and adolescents in terms of stunting (height-for-age). Impacts of supermarkets depend on many factors, including people's initial nutritional status. Using causal chain models, we show that for both adults and the group of children and adolescents, the nutrition impacts of supermarkets occur through higher calorie consumption and higher calorie shares of processed foods, which is consistent with our findings of chapter two.

1.3 Synopsis Chapter 4

In the fourth chapter, we use secondary household survey data from Malawi to analyse 'one of the other faces of malnutrition'. The world food price crisis of 2007/08 and other global and regional price and income shocks that followed have spurred interest in producing timely predictions on their implications for economic welfare and food security. 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. A critical research gap remains with comparing simulation outcomes of different studies on the same subject. This is to establish if and to what extent they might result in different and potentially conflicting policy recommendations. We address this gap building on three simulation studies set in Malawi, which analyse welfare in terms of food security and income effects and use the same 2004/05 household survey data but resort to methodologies of different complexity.

We find differences between methods to depend on the scenario under consideration and to grow with increasing rates of simulated price changes. The differences we find are driven by differences in conceptualising price changes, and the Malawian context. Malawi 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. At the same time, we find relevant inconsistencies in food security indicators specific to our data that invite further investigation.

1.4 General Conclusion

This dissertation provides new insights into some of the cutting edge topics in the field of food security and malnutrition. Overall this research underscores the context specific nature of central nutrition related questions and the subsequent need to understand underlying mechanisms and to scrutinize general perceptions and hypotheses.

Two studies on the nutrition transition in Kenya provide evidence that the presence of supermarkets affects dietary choices. Supermarkets contribute to the nutrition transition by shifting consumption towards processed and away from unprocessed foods. At the same time, calorie availability increases as calories are sourced at lower prices in supermarkets. Data collection for this research was carried out in small Kenyan towns of the kind that accommodate most of the country's urban population. Kenya's supermarket landscape is dynamic. So far, it followed the 'traditional pattern' of the supermarket revolution. The 'double burden' of malnutrition is well under way, with high rates of stunting among children and adult overweight and obesity. Supermarket purchases were found to add to the prevalence of overweight and obesity among adults. Yet, we also find that the availability of supermarkets has a positive effect on the physiological development of 5-19 year olds who have not yet reached their full physiological potential. These changes are driven by an increase in the consumption of primary processed foods, not by an increase in the consumption of highly processed foods, which do not yet play a major role in the diets of Kenyan small town dwellers. Traditional retailers are still by far the most important source of food, even in the one town that has had a supermarket for more than a decade. Along these lines, we find less detrimental health effects than anticipated, which is promising from a public health perspective. However, rising incomes and a continuing expansion of the product range offered by supermarkets may change this picture in the future. Subsequent research will also have to investigate nutritional effects that go beyond the body status of individuals, for instance, effects on blood sugar and micronutrient deficiencies.

Our work on the simulation of price shocks in Malawi illustrates the scope and relevance of comparative assessments building on large-scale datasets that increasingly become available. We find that despite the fact that Malawi is a net food importer and has high levels of food insecurity, the effects of price shocks on food security in terms of calorie deficiencies are not as severe as previously thought. The main reason for this is the high degree of self-sufficiency among rural households, i.e. they produce large shares of their consumption and purchase relatively little. This, however, points to structural poverty and food insecurity since self-sufficiency is probably a strategy to reduce price risk. While it prevents small farmers from experiencing severe spells of food insecurity or their deterioration during price-hikes, it is unlikely a strategy that yields high returns from agricultural production.

In terms of the comparative assessment between simulation methods, we find differences to be moderate for general price changes that were observed in Malawi over the course of one year. However, it is important to improve our understanding of how changes in the underlying methodologies change results and to analyse the sensitivity of simulation outcomes to different model assumptions.

What can we learn from our results in terms of policy implications and future research?

First, much effort has been devoted to understanding different dimensions of food security and nutrition and to the development and refinement of different indicators to capture these dimensions (e.g. de Haen *et al.*, 2011; Pangaribowo *et al.*, 2013). This is highly relevant, not least because it reflects an interest in evidence-based policies and there is a need to continue such efforts.

The matter is complicated because dietary shifts associated with the nutrition transition are partly desirable. For instance, an increased consumption of animal source foods can reduce protein deficiencies and potentially other micronutrient deficiencies, which is particularly important for children and women of reproductive age. However, the returns of these dietary shifts to health tend to be positive only for narrowly defined ranges and become negative thereafter (Schmidhuber and Shetty, 2005). Considerations along these lines are why the excess consumption of calories that ultimately causes overweight and obesity, is sometimes termed 'over-nutrition'. Yet, this term is misleading in the sense that overweight and obesity can be accompanied by micronutrient deficiencies, which are not over-consumed. Popkin (2012) refers to this as an individual double-burden of malnutrition. Furthermore, while it is established that the 'food environment' plays a crucial role in determining dietary outcomes, the exact dietary mechanisms remain unclear (Giskes *et al.*, 2011). In this context, Giskes *et al* (p. e95, 2011) note that in the literature, "associations between the environment and weight status are more consistent than that seen between the environment and dietary behaviours".

Thus, the central question for those concerned with food security and malnutrition, including researchers, governments, donors and civil societies, is how to ensure food security for all without adding to the burden induced by overweight and obesity. An additional concern of countries that have experienced rapid economic development or that currently suffer from high rates of chronic undernourishment is related to intergenerational dynamics of malnutrition that have raised concerns about the appropriateness of some 'standard nutrition programmes' (Popkin 2012).

In order for evidence-based policies to take effect or to be able to evaluate and incorporate context specific factors, there is a general need for more data and indicators to identify and monitor nutritional landscapes and nutritional outcomes (FAO, 2013). Identifying meaningful indicators will require additional research. For the design and implementation of policies, further collaboration between relevant actors is highly desirable. In particular, we need to understand the nutritional effects of policies (Ecker and Qaim, 2011). In this context, collaborations between researchers, development practitioners and the private sector, including supermarkets, could generate valuable (case study) data and insights. Examples that would make intriguing impact evaluations could include programmes to study the effects of different point-of-sale promotions, or the efficient distribution (and profitability) of fortified foods with increased micronutrient contents (FAO, 2013; Popkin *et al.*, 2012). In research and practice alike, strengthening links between agricultural economists, development economists and nutritionists would be very useful. Longitudinal data will be required to investigate the long-term effects and transitions, while qualitative studies can help a great deal in understanding consumer behaviour in more detail.

"The food system transformations as observed in developing countries was long predicted to be impossible" (Reardon and Timmer, 2012, p. 227). This reminds us of the rapidity of even profound changes, and the caution required in making predictions. It is very difficult to form general expectations about the kind of policies that may successfully tackle food insecurity, deal with 'the negative side' of the nutrition transition, and at the same time avoid other externalities. There are, however, a number of policies and noteworthy global initiatives that are promising for different reasons.

First of all, individuals should be informed about the world in which they are living and about forces that surround and affect them. However, the kind of education and information required for tackling different issues of food security and malnutrition will depend on the context. For instance, people may know that overweight and obesity are harmful and can cause diabetes and stroke, yet they may not know when people start falling into these risk categories. Likewise, they may know that they should follow a specific diet but they lack the knowledge of how to follow these recommendations (or they may have the knowledge, physical and economic access to a healthy and well-balanced diet but freely choose another path). In any case, tailored information campaigns and education can have many positive effects, including better nutrition, and should further be considered as an end in itself (Sen, 1999).

In order to avoid cases of food insecurity and undernourishment, structural poverty is the issue to fight and employment opportunities as well as social safety nets are required to shield the poor and vulnerable from shocks and hardship and improve their livelihoods. In terms of nutrition interventions, that have proven to be very important in these contexts, to the extent possible, they should be aimed at providing a diversified and well-balanced diet instead of certain amounts of calories.

To conclude: "Addressing malnutrition, *therefore*, requires integrated action and complementary interventions in agriculture and the food system in general, in public health and education, as well as in broader policy domains. Because the necessary interventions cut across the portfolios of several government institutions, high-level political support is required to motivate the necessary coordination across sectors" (FAO, 2013, p. ixf.).

2 Supermarkets and Food Consumption Patterns: The Case of Small Towns in Kenya.[3]

Abstract

This paper investigates the effect of supermarkets on food consumption patterns in urban Kenya using cross-sectional household survey data collected in 2012. To establish causality, we use quasi-experimental data, with study sites differing in supermarket access, and employ instrumental variable techniques to allow for endogeneity of supermarket purchases. We find that supermarket purchases increase the consumption of processed foods at the expense of unprocessed foods. Supermarket purchases increase per capita calorie availability, which is linked to lower prices paid per calorie, particularly for processed foods. Our results imply that supermarkets increase the consumption of foods that have been associated with the nutrition transition. The effects on nutrient adequacy are less clear.

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[3] This chapter is co-authored Simon C. Kimenju, Stephan Klasen and Matin Qaim. The author's contributions are as follows: All authors contributed to the design of the research. SCK & RR performed research; RR undertook data analysis; RR wrote the manuscript; all authors reviewed and edited the manuscript.

2.1 Introduction

Many low and middle-income countries are experiencing a nutrition transition, which is understood as a rapid change of diets towards more energy-dense, often (highly) processed and convenience foods and beverages that tend to be rich in fat, caloric sweeteners and salt. This "Westernization" of diets (Pingali, 2007, p. 4) and a concurrent trend towards more sedentary lifestyles were soon being observed with concern, because they were found to contribute to surging rates of overweight and obesity, which are risk factors for nutrition related non-communicable diseases such as diabetes, cardiovascular diseases and certain types of cancer (Popkin *et al.*, 2012). Given still prevailing rates of undernutrition and related nutritional deficiencies, many low-income countries are now facing a double burden of malnutrition where undernutrition and obesity coexist, sometimes even in the same households (Popkin *et al.*, 2012; Roemling and Qaim, 2013).

These nutritional transformations have been associated with changes on both the demand as well as the supply side: changing demand patterns, commonly linked to rising incomes and urbanisation processes coincided with a rapid spread of supermarkets (SMs) in what was termed a 'supermarket revolution' (Reardon and Timmer, 2012). While Mergenthaler et al. (2009) provide case study evidence to suggest demand side factors to predominate, both trends are often believed to be mutually reinforcing (Hawkes, 2008; Popkin *et al.*, 2012; Reardon *et al.*, 2004).

The consumption of processed and highly processed foods and beverages is often singled out as an important factor contributing to unhealthy diets, as this category includes high calorie foods with only poor micronutrient content, such as sugary beverages, sweets, and all kinds of salted snacks (Monteiro *et al.*, 2010). Spreading supermarkets, in turn, are suspected to improve the availability of these products and to increase their desirability even among poor households in remote areas (Asfaw, 2008; Hawkes *et al.*, 2009). On the other hand, supermarkets could provide more stable and affordable access to a greater variety of foods and drinks, which might improve the dietary diversity and overall dietary quality of consumers (Asfaw, 2008; Hawkes, 2008).

In any case, supermarkets have the potential to affect dietary choices for better or worse, and it is important to better understand if and how the presence of supermarkets influences consumer decisions. For this reason, our research questions are how supermarkets affect consumption patterns of households and what factors determine where consumers source their food from.

For our empirical analysis, we rely on cross-sectional survey data collected in Kenya in 2012. While our analysis does not consider nutritional outcomes directly, highly disaggregated food consumption data allow us to focus on goods that have been associated with the nutrition transition, and on different levels of processing in particular.

Our contribution to the literature is threefold: first, we use data on actual food purchases from different retail formats in addition to measures of physical access which the food environment literature is often restricted to (notable exceptions are Asfaw, 2008; Tessier *et al.*, 2008). Secondly, in contrast to most other studies (Asfaw, 2008 being another exception), we account for potential endogeneity of supermarket purchases related to selection effects, using instrumental variable techniques and further improve identification by a quasi-experimental survey design using primary data generated for precisely this analysis. Lastly, given the very few studies on this issue in developing countries, we provide the first case study in Sub-Saharan Africa.

For our quasi-experimental design, we chose comparable survey locations among small towns that differ in terms of when, if at all, a local supermarket was established. While most households in large Kenyan towns have fairly good access to supermarkets, this is not yet true for small towns. Small towns in Kenya (less than 50,000 inhabitants) are of particular relevance also because they comprise 70% of the urban population (KNBS, 2010a; KNBS, 2010b), and manifestations of lifestyle changes are less apparent and less well studied there. Adding to the relevance of our case study, Kenya can be classified a double burden country with 2008/09 Demographic and Health Survey data showing 25% of women of ages 15-49 being overweight or obese and 35% of children below age 5 being stunted (KNBS and ICFMacro, 2010).

In qualitative terms, we also provide a detailed account of the current food environment and different retail formats in Kenya and shed some light on the rationale behind consumer decisions. This is relevant as it creates a reference point in a highly dynamic market (Neven *et al.*, 2006; PlanetRetail, 2013). In order to understand potential interactions between the food environment and consumption patterns, we refine a theoretical framework from the literature for the setting at hand.

This Chapter is structured as follows: section 2.2 introduces the concept of food environments and develops the theoretical framework. Section 2.3 gives a background on the food environment in Kenya. Section 2.4 introduces our methodology and data. We present and discuss our empirical results in sections 2.5 and 2.6. Section 2.7 concludes.

2.2 Theoretical Framework and Literature Review

The term food environment refers to the "[food related] physical and infrastructural features of the area" (Giskes *et al.*, 2011, p. e96) such as access to, and the density of different types of retail outlets, including supermarkets. There are several pathways through which supermarkets can influence consumption patterns that go beyond making goods available. The basic argument for an effect of supermarkets on diets is that the food environment affects where people do their shopping which in turn influences their dietary practice (Asfaw, 2008), and that introducing supermarkets significantly alters the food environment.

Figure 2.1 illustrates potential relationships between food environments, consumption choices and dietary practice (see Figure 2.1, column 3) as developed and refined from the literature. Supermarkets improve physical access to, and increase the availability of, goods throughout the year (Gómez and Ricketts, 2013). By offering more types of goods, brands, flavours, functional foods, and levels of processing supermarkets offer a larger variety of all types: healthy, health-neutral and unhealthy products, regardless of the consumer's dietary needs. This is expected to increase the dietary diversity of consumers. At the same time, changing quantities and substitution within and across food categories could be enhancing as well as deteriorating dietary quality (Asfaw, 2008; Hawkes, 2008). Thus, the expected magnitude of these effects has to be further elaborated on and will closely be linked to likely effects on relative prices.

Reardon *et al.* (2004) argue that supermarkets in low-income countries have a price advantage when it comes to industrially processed goods with long shelf-lives. In this context, the term 'processed foods' refers mainly to highly processed foods. These are predominantly ready-to-eat products, produced for instance by adding spices, preservatives, synthetic vitamins, by frying, cooking or baking (Monteiro *et al.*, 2004). It is highly processed foods for which supermarkets are expected to have the strongest advantage over other retail formats. Even though this classification puts flour enriched with vitamins and potato chips in the same processing category, highly processed foods tend to be high in salt, sugar and saturated fats, are often considered unhealthy and found to contribute to developing non-communicable diseases.[4] The effect of supermarkets on prices, however, is controversial in the empirical literature. General price premiums were detected in some cases (Schipmann and Qaim, 2011) and examples of consistently smaller prices in others (Hawkes, 2008). Gómez and Ricketts (2013) argue that traditional retailers can follow a flexible pricing strategy that makes them cheaper than supermarkets.

Following another line of argument, Chandon and Wansink (2012, p. 572) point out that highly processed foods are highly differentiated and not bound to commodity prices because "with these branded products, marketers can establish their own price depending on which consumer segment they wish to target." As an example to the contrary, Popkin *et al.* (2012) mention production related price reductions in edible oils that had already by the mid 1990's enabled poor households to increase their energy intake. Reviewing evidence on pricing strategies of supermarkets in low-income countries, Hawkes (2008) finds that supermarkets tend to be more expensive upon market entry but become more price-competitive later, and first among processed foods as discussed above. On a related note, supermarkets facilitate bulk shopping by offering large packaging sizes, which is often accompanied by quantity discounts. However, poor consumers have a limited capacity to utilise potential quantity discounts due to liquidity constraints. In fact, for poor consumers one advantage of kiosks is that they often offer credit and small package sizes. In sum, the impact of changes in retail and product systems on both price levels and price volatility remain important research gaps (Reardon and Timmer, 2012).

Apart from influencing relative prices, supermarkets use a variety of marketing strategies to influence what and how much customers are buying, many of them affecting consumers subconsciously (Monteiro *et al.*, 2010). In this context, Hawkes (2008, p. 682) talks about the food industry making food 'desirable'. See Chandon and Wansink (2012) for a comprehensive review of marketing strategies and related outcomes. Interestingly, the authors refer to studies showing that temporary price discounts and offering large packaging sizes, relevant strategies for supermarkets in our survey locations, can increase the consumption of respective goods rather than merely shifting it across brands or time. Following this line of argument, supermarkets are hypothesised to increase overall consumption of all food groups (Hawkes, 2008).

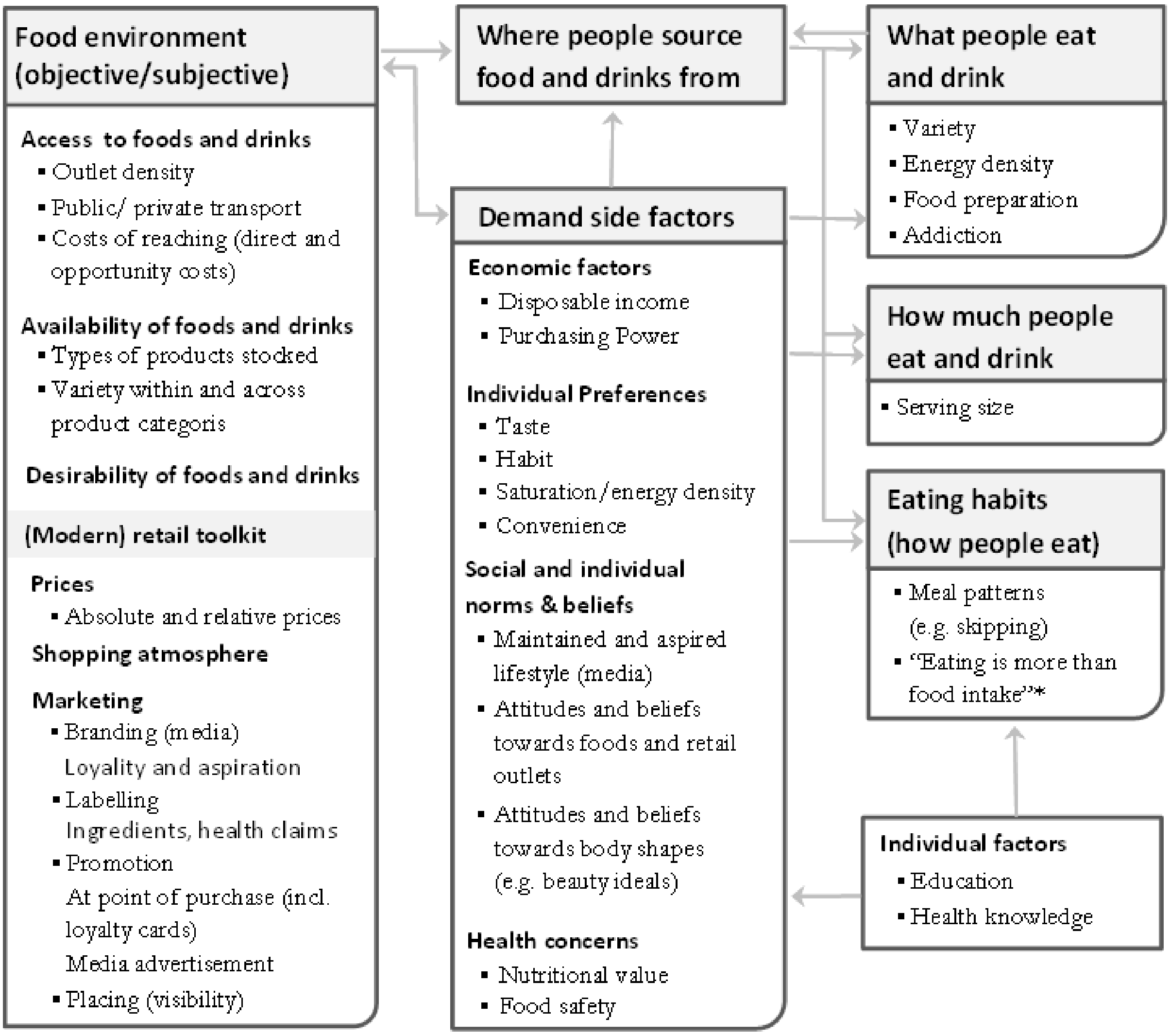
At the same time, a number of demand side factors can directly influence both dietary practices and the place of shopping. These include economic factors (e.g. disposable income), individual and household preferences (e.g. for taste or habits), social and individual norms and beliefs (e.g. attitudes towards modern or traditional foods and outlets, the maintained and aspired lifestyle and beauty ideals) and personal health concerns. We will incorporate proxies for them as control variables in the empirical analysis.

Existing studies confirm that the impact of supermarkets on diets is context-specific in nature and that important research gaps remain with respect to mediating factors: most studies have been carried out in high income countries (e.g. Cummins *et al.*, 2005; Laraia *et al.*, 2004; Moore *et al.*, 2008; Morland *et al.*, 2006b; Pearce *et al.*, 2008; Powell *et al.*, 2007; Wrigley *et al.*, 2003). Two studies were conducted in a developing country context, which further contribute to the literature by considering supermarket

[4] See Monteiro *et al* (2010) and Asfaw (2011) for a discussion of underlying evidence from the medical literature.

purchases rather than supermarket access. Asfaw (2008) finds that supermarket purchases in Guatemala increase the share of partially and highly processed foods at the expense of staple foods and that supermarket purchases are positively associated with BMI. Tessier et al. (2008) in a similarly titled paper conclude that regular users of supermarkets in Tunis have a slightly improved dietary quality. However, only Asfaw addresses issues of endogeneity using IV techniques.

Figure 2.1: Conceptual framework - food environment, consumption and influencing factors



Source: own illustration based on literature review. *(Chandon and Wansink, 2012, p. 583)

Because supermarkets in small towns have a limited catchment area and thus need to target a broad customer base, we assume them to offer a wide range of product qualities and prices. Yet, following the discussion of this section, we hypothesise that their pricing strategy leads to lower prices per calorie. In terms of consumption, as a result of changes to the food environment and supermarkets' expected pricing strategy, we hypothesise that:

H1: Supermarket customers eat differently: supermarket purchases increase consumption shares of processed and highly-processed foods.

H2: Supermarket customers eat more: supermarket purchases increase total per capita calorie consumption.

H3: Supermarket customers eat more types of food: supermarket purchases increase the dietary diversity of consumers.

2.3 Supermarkets and the Food Environment in Kenya

Supermarkets have been spreading rapidly throughout Kenya and the pattern has been similar to the retail revolution described in other low-income countries (Neven *et al.*, 2006; Reardon and Timmer, 2012). In the early 2000s, Kenya's retail sector was already classified as one of the most dynamic in Sub-Sahara Africa (Neven *et al.*, 2006). Today, despite being highly fragmented, it is among the most developed retail sectors in Sub-Sahara Africa (PlanetRetail, 2013). This fragmentation explains why the top three retailers in 2013 only had a market share of around 5% while in 2003 already, supermarkets more generally had an estimated 20% market share of the urban food retail market (Neven and Reardon, 2004; PlanetRetail, 2013). In contrast to the experience of countries with an early supermarket revolution (Reardon *et al.*, 2004), none of today's top five supermarket chains in Kenya[5] are owned by international corporations or foreign firms, but are Kenyan enterprises. It should also be noted that while quite a number of supermarkets do not belong to chains at all or have only a few outlets, they do not qualitatively differ from chain supermarkets.

In Kenya, and typical for a low-income country, common alternatives to supermarkets are smaller self-service stores[6] and, more traditionally, kiosks. Comparing supermarkets and relevant competitors (see Table 2.1 for details), several features stand out: supermarkets are self-service stores, while kiosks are strictly over-the-counter shops. As opposed to kiosks, supermarkets stock large varieties of different kinds of food[7] and non-food products. This is in terms of product ranges and in terms of brands and features of the same product, i.e. different flavours, functionalities (e.g. nutrients added to food) and levels of processing. High-value non-food items (e.g. electronics, furniture) are uniquely offered by supermarkets. The characteristics of small self-service stores are in between those of supermarkets and kiosk.

International and other 'Western style' fast food chains are still restricted to large cities. Only in large cities are supermarkets found that offer fresh fruits and vegetables, have built-in butcheries, restaurants and large bakeries. Western style convenience processing (pre-cut vegetables, prepared salads, frozen or tinned ready-to-heat food) is only available there. Visiting large city supermarkets or hypermarkets ten times larger in size (Neven *et al.*, 2006), it becomes evident that lifestyle and status play a significant role and that 'shopping atmosphere' is not an abstract concept but a strong force. However, Neven *et al.* (2006), who analyse patterns of the retail revolution in Kenya and consumer attitudes in Nairobi, already put forward that the introduction of supermarkets in small towns, from a consumer perspective, is likely to be as impressive and as powerful in influencing consumer choices, as the introduction of hypermarkets in large cities or mini-supermarkets in rural areas. Note that in small towns, product ranges of supermarkets, small self-service stores and kiosks are surprisingly similar (see Appendix Table A2.1 for a detailed account) and the main differences are qualitative in nature.

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[5] Nakumatt, Tuskys, Uchumi, Naivas, and Ukwalla.

[6] In other studies also called small supermarkets, mini-supermarkets or neighbourhood stores (Neven et al., 2006).

[7] For simplicity, we implicitly include beverages unless stated otherwise.

Table 2.1: Defining features of different retail outlets – the case of Kenya

	Supermarket	Small self-service store	Kiosk (traditional retail)
Size indicators	**> 150 m²** (Neven and Reardon, 2004) ▪ Typically >1 floor ▪ Typically >2 modern cash counters	< 150 m², though size in small towns typically **10-30 m²** ▪ Typically 1 floor ▪ Typically 0-2 modern cash counters	▪ **1-10 m²** ▪ No modern cash counter
Service features	▪ **Self-service** ▪ **One-stop shopping** ▪ More sophisticated shopping atmosphere: - Spacious isles - Full shelves - Clean & bright ▪ **No credit**	▪ **Self-service** ▪ Narrow aisles, often little light ▪ **No credit**	▪ **Over-the-counter service** ▪ Direct contact to shop owner ▪ **Gives credit**
Product features	▪ Large variety of different food and non-food products ▪ Large variety of brands and features within product categories ▪ Frozen and refrigerated foods ▪ Small to very large packaging sizes ▪ High-value non-food items, e.g. electronics, furniture, clothes	▪ Large variety of different food products ▪ Limited variety of non-food products, brands and product features ▪ Neither frozen, nor cooled foods ▪ Small to fairly large packaging sizes ▪ No high-value non-food items	▪ Limited but often fair variety of different food products ▪ Only fast-moving non-food products, limited brands and product features ▪ Neither frozen, nor cooled foods ▪ Very small to small packaging sizes ▪ No high-value non-food items

Source: Own observation unless stated otherwise.

2.4 Methodology

2.4.1 Study Design and Data

This study uses data from a household consumption survey conducted in three small towns in Central Province, Kenya. A total of 453 households were interviewed between July and August 2012. Our identification strategy to test for a causal relationship between supermarkets and consumption patterns exploits a quasi-experimental survey design to ensure variation in supermarket shopping behaviour: we selected three towns within the same region that differ in terms of their access to supermarkets while being comparable in other aspects.

1. One with a well-established supermarket (Ol Kalou: one supermarket since 2002),
2. One with a supermarket opened fairly recently but with a sufficient time lag to allow inhabitants to get used to it (Mwea: one supermarket since August 2011) and
3. One town with no supermarket up to that point in time.

Our setting is appealing also in that no Western style fast food outlets but only 'traditional restaurants' and food hawkers are found in our survey towns, thus the defining difference in food environments indeed comes primarily from the presence of supermarkets.

After selecting our survey locations, we identified our area of interest, i.e. the town centres and close peripheries covering the most densely populated parts of town.[8] This area each fell within a radius of about 2.5 km from the town centre. Next, we produced our sampling frame and selected households using systematic random sampling, with a sampling interval chosen as to collect approximately the same number of observations per town.

The survey locations differ quite substantially in terms of size: Njabini is the smallest and least urbanised town with an estimate of 1870 households (estimate based on our sampling frame). Mwea is the largest town with an estimate of 7650 households and Ol Kalou has an estimated 2550 households. Still, in terms is physical and social infrastructure (e.g. main roads being tarmac roads, having access to banks, a hospital, several health centres and other services, having similar administrative structures), all survey locations are comparable. Kikuyu ethnicity and Christian religion are by far the most prevalent in all survey towns, with rates exceeding 80% and 90%, respectively.

2.4.2 Empirical Strategy

In general terms, our model can be specified as proposed by Asfaw (2008):

$$\boldsymbol{D}_i = \boldsymbol{\alpha X_i} + \beta S_i + \varepsilon_i \tag{2.1}$$

$$S_i = \boldsymbol{\gamma X_i} + \delta Z_i + \omega_i \tag{2.2}$$

where $\boldsymbol{D}_i$ refers to dietary indicators of household *i*, $\boldsymbol{X_i}$ to explanatory variables and $\boldsymbol{S_i}$ to the measure of supermarket purchases, our main variable of interest. Because supermarket purchases are likely to be endogenous, we use a two stage least squares instrumental variable approach and thus add equation (2.2) to the model, where $\boldsymbol{Z_i}$ refers to our excluded instrument. ε_i and ω_i are error terms.

Supermarket purchases, i.e. the intensity of supermarket purchases, are conceptualised using the share of supermarket purchases from the overall food basket. Note that this share can be positive for non-supermarket locations due to out-of-town shopping.

Endogeneity of supermarket purchases might result from self-selection on non-observables, i.e. systematic differences between frequent supermarket customers and others. We use distance to the nearest supermarket as an instrument. This reflects our initial hypothesis that supermarket access triggers supermarket shopping, which has been found in the literature (see Gómez & Ricketts (2013) for evidence in low-income countries). At the same time, we claim this variable to be exogenous: while market potential drives the decision to establish a supermarket in a particular town, we argue that this potential boils down to demand side factors, which we control for, and to road infrastructure so as to facilitate logistics. As supermarket managers in our survey towns explained that the location within town was substantially

[8] Due to interview non-participation, we were forced to replace 22% of households initially selected. This was mostly for the reasons of interview partners being busy/ not found at home or having a lack of interest. We replaced households that moved to the survey sites less than 6 months ago reasoning that consumption patterns might still reflect their former food environment. We avoided introducing selection bias to the best of our abilities. Using a dummy for replacement households in robustness checks never turned out significant.

driven by the availability of large plots, we believe that the precise location within a town (and thus the distance to the supermarket for an individual household) is exogenous to equation (2.1).[9]

Distance is measured as physical linear distance between a household and the nearest supermarket based on GPS readings. There is only one supermarket in the two towns with supermarkets, which is located in the town centre and in close proximity to traditional stores and open air markets. Consumers mostly walk to supermarkets in our survey towns, and linear distances approximate walking distances well. For the town without a supermarket, the closest supermarkets can only be reached using public or private transport.

Food consumption was captured with a 30 day recall period because we expect decisions regarding where to shop to vary during a monthly wage cycle (e.g. households might shop in bulk in supermarkets after getting paid while increasingly resorting to smaller portion sizes at kiosks towards the end of the month). In very disaggregated form (e.g. differentiating between fortified and unfortified flour and different types of cooking oil), we first asked if and how much quantity of a particular item was consumed by any household member during the last 30 days. This was for consumption inside the house, since food eaten outside the home is more individual-specific and usually not sourced from supermarkets, but from street hawkers, restaurants and sometimes kiosks. If an item was actually consumed by the household, we asked the respondents to break down the total quantity consumed into quantities consumed from purchases, own production, or other sources (e.g. gifts). Finally, in case of purchases, the respondents additionally indicated 1. how much they spent and 2. what quantity they bought where (supermarkets, smaller self-service stores or traditional, i.e. all other outlets). Because outlets in the latter category only have few overlapping products, we can still and most notably identify the quantity bought in kiosks. Monetary values for non-purchased items (own production and other sources) were imputed in order to include it in the food expenditure aggregate. For this, we use median unit values reported for the same good by neighbouring households. The expenditure share of a particular retail outlet or type of product is from the total food expenditure aggregate of that household, i.e. non-purchased items are included.

Based on the classifications used by Asfaw (2011) and Monteiro et al. (2010), we differentiate products by levels of industrial processing into unprocessed foods (e.g. fresh fruits and vegetables), primary processed foods (e.g. rice, sugar and cooking oils), and highly processes foods (e.g. breakfast cereals, bread and sweets). These categories are mutually exclusive and jointly exhaustive with the exception of alcoholic beverages, which are excluded.[10] We then conceptualise consumption patterns by expenditure shares and calorie shares on different processing categories. Overall consumption is considered in terms of per capita calorie availability per day, and we briefly analyse households' food budget shares also.

Using such a long recall period can increase recall bias. Also, despite asking for actual food consumption, we cannot account for food wastage, for example, so that we do not measure actual intake (e.g. Deaton and Zaidi, 2002). However, the general results of our analysis would only be affected if associated measurement errors differed by the intensity of supermarket purchases, which we consider unlikely.

[9] Regressing log distance on log p.c. expenditure, we find significant effects in the sample of Ol Kalou and Njabini. However, using the same controls as in our main specifications, p.c. expenditure levels are not significantly associated with the distance to supermarkets. Both log distance to supermarkets and log p.c. expenditure enter all first stage regressions.

[10] Alcohol is not commonly consumed at home (only 0.8% expenditure share) and it does not fit well into the categories that we consider here. Robustness checks show that inclusion of alcohol does not change the results.

Our explanatory variables mirror the demand side and individual factors from our conceptual framework presented earlier (see Figure 2.1). Individual level factors, such as education or age, refer to either the household head or to the person responsible for food purchases and preparation. All per capita variables are adjusted by equivalence scales that consider both household size and composition and are thus per household size-adjusted adult equivalent[11].

2.5 Empirical Results

2.5.1 Descriptive Statistics

Table 2.2 summarizes household characteristics by survey locations. The sample size ranges across survey locations from 134 to 161 households[12]. The average household size in Njabini exceeds the other locations by one additional household member. Three quarters of all households in the sample are male headed. Household heads, on average, are 38 years old, with significant differences for Ol Kalou (younger heads) and Njabini (older ones). Despite having older heads, Njabini seems to be lagging behind regarding the share of heads with secondary and tertiary education.

Table 2.2: Household characteristics of sample

	All	**Njabini (no SM)**		**Mwea (SM since 2011)**		**Ol Kalou (SM since 2002)**	
	Mean	Mean	difference to others	mean	difference to others	mean	difference to others
Household size	3.63	4.28	1.01***	3.14	-0.70***	3.38	-0.38**
	(1.93)	(2.38)	(0.18)	(1.44)	(0.20)	(1.57)	(0.19)
Male head (%)	0.74	0.77	0.05	0.69	-0.06	0.74	0.00
Monthly p.c. exp.	9425.15	8105.58	-2059.81***	10415.12	1412.44*	9946.68	792.02
(food + non-food) in KSh	(7995.69)	(8788.48)	(782.13)	(6840.21)	(823.26)	(7923.59)	(796.61)
Age of head	37.51	40.61	4.84***	36.87	-0.91	34.80	-4.11***
	(13.01)	(14.21)	(1.26)	(12.37)	(1.34)	(11.56)	(1.28)
Education of head completed							
No formal educ.	0.03	0.06	0.04**	0.01	-0.02	0.02	-0.02
Primary	0.38	0.48	0.16***	0.32	-0.09*	0.33	-0.08
Secondary	0.38	0.30	-0.11**	0.44	0.09*	0.39	0.03
Tertiary	0.21	0.16	-0.09**	0.22	0.02	0.25	0.07*
Observations	448	161	161	134	134	153	153

For means, standard deviations for rest, standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. **Source**: Own calculation.

Average monthly per capita expenditure across towns is 9,425 KSh, while being significantly and substantially smaller in Njabini. We are not aware of an up-to-date poverty estimate, but based on the latest poverty line (year 2005) and subsequent consumer price statistics publicly available, we extrapolate

[11] We use adult equivalent scales that have previously been used in Malawi as well as Zambia (MNSOb, 2005). The average household size in adult equivalents is 3.21.

today's poverty line to be around 7,500 KSh per capita per month. This would yield a poverty headcount of 47% in our sample. The latest national poverty estimate according to World Bank statistics was 46% in 2005.

Table 2.3 provides an overview of access to different retail outlets and shopping behaviour: in our supermarket locations, the average distance to the local supermarket is below 1 km, while the nearest supermarket is 40 km away from Njabini. Kiosks are very close to most households and can be reached within 5 minutes on average.

Table 2.3: Access to retail outlets and shopping behaviour

	All	**Njabini (no SM)**	**Mwea (SM since 2011)**	**Ol Kalou (SM since 2002)**
	mean/sd	mean/sd	mean/sd	mean/sd
Number of times shopping in [...] last month				
Supermarket	3.05	0.36	2.70	5.77
	(5.36)	(0.98)	(3.27)	(7.46)
Small self-service store	2.50	4.08	0.53	2.71
	(5.73)	(8.44)	(1.91)	(3.66)
Kiosk	25.62	23.84	29.33	24.18
	(16.82)	(17.69)	(15.78)	(16.38)
Distance to SM in km	14.55	39.29	0.67	0.68
	(20.44)	(14.35)	(0.49)	(0.41)
Travelling time to [...] (min. one way)				
Supermarket	47.64	103.68	16.54	15.90
	(47.29)	(33.73)	(9.08)	(10.59)
Kiosk	5.33	8.30	2.95	4.31
	(5.82)	(7.58)	(2.73)	(4.15)
Share of HHs buying in supermarket	0.58	0.14	0.80	0.84
Expenditure shares in [...]				
Supermarket	0.10	0.02	0.11	0.17
	(0.12)	(0.06)	(0.10)	(0.13)
Small self-service store	0.05	0.08	0.02	0.05
	(0.11)	(0.13)	(0.10)	(0.08)
Traditional retail	0.70	0.71	0.75	0.66
	(0.19)	(0.20)	(0.17)	(0.17)
Own production	0.11	0.16	0.08	0.09
	(0.15)	(0.17)	(0.13)	(0.13)
Observations	448	161	134	153

Expenditure shares don't add up to 100% because of left out category 'gift and other sources'.
Source: Own calculation.

Food expenditure shares of different retail outlets are as expected: Ol Kalou has the highest food expenditure share from supermarkets, followed by Mwea and Njabini. In Ol Kalou, the average supermarket share is 17%, in Mwea already 11% of the food expenditure goes to supermarkets. Even in Njabini, the mean supermarket share is positive and 14% of households bought some food in supermarkets the previous month. In Ol Kalou, 84% of households frequented the supermarket, 80% in

[12] Five observations were excluded from the initial sample due to unrealistic consumption figures.

Mwea. Interestingly, in all towns, the frequency of shopping in kiosks is very high, it does not vary much from the overall mean of 25 times last month and traditional retail is by far the most important source for food with expenditure shares ranging from 66% to 75% across towns.

Table 2.4: Reasons for shopping in different retail outlets

	All mean	Njabini (no SM) mean	Mwea (SM 2011) mean	Ol Kalou (SM 2002) mean
Reasons for shopping in supermarket				
Not applicable (doesn't shop there)	0.42	0.85	0.22	0.15
Lower prices or discounts	0.46	0.09	0.69	0.65
More variety/ types of products available	0.18	0.06	0.19	0.31
Convenience (e.g. one-stop shopping)	0.21	0.02	0.31	0.31
Availability of large packaging sizes	0.04	0.02	0.05	0.05
Physical access	0.04	0.06	0.03	0.03
Habit	0.02	0.00	0.00	0.05
Social (e.g. meet people, talk to staff)	0.02	0.00	0.04	0.01
Other	0.09	0.02	0.12	0.14
Reasons for shopping in kiosk				
Not applicable (doesn't shop there)	0.04	0.04	0.06	0.03
Lower prices or discounts	0.04	0.06	0.04	0.03
More variety/ types of products available	0.02	0.04	0.01	0.01
Convenience (e.g. one-stop shopping)	0.02	0.02	0.01	0.03
Get credit	0.20	0.32	0.13	0.14
Availability of small packaging sizes	0.08	0.04	0.18	0.05
Only small number of items needed	0.23	0.22	0.22	0.24
Physical access	0.79	0.70	0.87	0.82
Habit	0.08	0.12	0.01	0.10
Social (e.g. meet people, talk to staff)	0.07	0.11	0.03	0.06
Other	0.06	0.07	0.05	0.06
Observations	448	161	134	153

Source: Own calculation.

Asked for the most important reasons to shop in different retail outlets, around two thirds of the respondents in supermarket locations reported (perceived) lower prices (see Table 2.4). Improved availability, e.g. more variety of food and non-food products, plays a role for around one fifth of our respondents. The possibility for one-stop-shopping and other factors which we attribute to convenience are attracting one third of our respondents in supermarket locations. For shopping in kiosks on the other hand, physical access is by far the most prevalent response in all towns, ranging from 70% in Njabini to 87% in Mwea. 20% of all respondents reported that getting credit was an important reason for shopping in kiosks. We also find that some drivers are more diverse across towns.

2.5.2 Food Consumption Patterns by Processing Levels

Table 2.5 displays our main empirical results regarding expenditure shares by levels of processing using OLS and IV specifications. Summary statistics of variables used are found in the Appendix Table A2.2, for first stage results and robustness checks see Appendix Tables A2.3 and A2.4. Robust standard errors are used in all specifications. We tested each model for cluster effects at the neighbourhood level, our primary sampling unit, and use cluster robust standard errors whenever required. Note that all IV specifications reported in this paper have first stage test statistics, i.e. exclusion and weak instrument criteria meeting or well exceeding conventional thresholds.

The OLS results confirm our initial expectations: supermarket purchases are positively associated with expenditure shares of highly and primary processed foods, while the share of unprocessed foods is declining. In the IV specifications, supermarket purchases lose their significance in case of highly processed foods, and remain significant in all other cases. At the same time, the effect size of supermarket purchases changes in some cases, with the point estimate for all processed foods, for example, increasing from 0.21 to 0.38. In sum, we take this as an indication that endogeneity is a relevant issue here that we correctly account for.

How are these coefficients to be interpreted? If the supermarket expenditure share increased by 1 percentage point (the average share is 9%), the expenditure share on processed foods would increase by 0.21 to 0.38 percentage points, depending on the OLS or the IV specification. However, considering that the average share in our supermarket locations is 14% against 1% where no SM is present, looking at a 10 percentage point increase in purchases seems like a plausible treatment scenario, and would be associated with a 2.1 - 3.8 percentage point increase in expenditure shares on processed food (an increase from 34 to around 36-38% for the average consumer in the non-SM location).

We find positive income effects regarding highly and unprocessed foods, and negative income effects with respect to primary processed food which seems plausible given the basic nature of primary processed food. Note that these effects include quality effects of unknown magnitude. Other variables have the expected signs.[13] Other robustness checks include testing different sets of control variables, and restricting the sample to the supermarket locations only. The most relevant results are shown in the Appendix (see Table A2.4). Generally we find the direction of main effects and their statistical significance to be robust, but effect sizes are sensitive to model specifications. Interestingly, for all expenditure shares, the effects remain stable when excluding our non-supermarket location from the sample. Another interesting finding regards interaction effects that we find between supermarket shares and an indicator variable for households whose kiosk consumption exceeds the town median (see Table A2.5). The idea was that depending on their shopping intensity in traditional outlets, households might frequent supermarkets for different reasons and with different outcomes. Indeed, in the case of primary and all processed foods, controlling for frequent kiosk consumption increases the effect of supermarket purchases, but less among frequent kiosk consumer. It is the other way around for unprocessed foods. Note, however that the interaction effects should be interpreted with care because first, frequent consumers tend to have lower supermarket expenditure shares and second, kiosk purchases might be subject to selection effects also. Other interaction effects, notably with total expenditure, expenditure categories, education or health knowledge proxies, were generally not significant.

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[13] One might be concerned with endogeneity of expenditure so that the size of the coefficient needs to be treated with caution. We are not particularly focusing on this coefficient, but we treat expenditures as an important control variable which is the reason why we include it: robustness checks excluding expenditure show that the main effects remain the same, yet the effect sizes change in the direction of the (former) expenditure effect – this is as expected since higher expenditure households do have a higher share of supermarket purchases. For the reason, however, that expenditure is clearly a strong and important driver of consumption we keep it in our preferred specification.

Table 2.5: OLS and IV regression results – food expenditure shares by levels of industrial processing

	(1) OLS Expenditure share *highly processed* food	**(2) IV** Expenditure share *highly processed* food	**(3) OLS** Expenditure share *primary processed* food	**(4) IV** Expenditure share *primary processed* food	**(5) OLS** Expenditure share *all processed* food	**(6) IV** Expenditure share *all processed* food	**(7) OLS** Expenditure share for *unprocessed* foods	**(8) IV** Expenditure share for *unprocessed* foods
SM expenditure share	0.0766*	0.0712	0.1336***	0.2109**	0.2134***	0.3781***	-0.2127***	-0.3220***
	(0.041)	(0.091)	(0.039)	(0.086)	(0.041)	(0.101)	(0.046)	(0.077)
Ln p.c. expenditure	0.0225***	0.0227**	-0.0829***	-0.0863***	-0.0595***	-0.0668***	0.0313**	0.0361***
	(0.008)	(0.010)	(0.009)	(0.010)	(0.010)	(0.011)	(0.012)	(0.012)
Household size	-0.0009	-0.0009	0.0062	0.0062	0.0045	0.0044	-0.0141***	-0.0141***
	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
=1 if head is married	-0.0228**	-0.0228**	-0.0089	-0.0089	-0.0313***	-0.0314***	0.0412***	0.0413***
	(0.009)	(0.009)	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Education of head in	0.0041***	0.0041***	-0.0009	-0.0014	0.0032**	0.0021	-0.0016	-0.0009
years	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Age of cook	-0.0061***	-0.0061***	0.0002	0.0003	-0.0055***	-0.0053**	0.0055***	0.0054***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age of cook squared	0.0001***	0.0001***	0.0000	0.0000	0.0001**	0.0001**	-0.0001**	-0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
=1 if HH does	-0.0346***	-0.0347***	-0.0243**	-0.0224**	-0.0609***	-0.0569***	0.0702***	0.0675***
farming	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Mwea (SM 2011)			0.0247**	0.0241**				
			(0.010)	(0.009)				
# female adults							0.0371***	0.0376***
							(0.010)	(0.010)
Constant	0.0462	0.0445	0.9562***	0.9810***	0.9955***	1.0487***	0.2164**	0.1812*
	(0.079)	(0.090)	(0.077)	(0.084)	(0.090)	(0.094)	(0.101)	(0.099)
Observations	448	448	448	448	448	448	448	448
R^2	0.256	0.256	0.316	0.310	0.233	0.208	0.240	0.229

Standard errors in parentheses. Robust (1),(2),(5),(6) and cluster robust (3),(4),(7),(8) standard errors used. * p < 0.10, ** p < 0.05, *** p < 0.01.
Source: Own calculation.

Turning to the models on calorie shares from different kinds of food, supermarkets have less pronounced effects than before (see Table A2.6 in Appendix). A positive relationship between supermarket purchases and calorie shares remains significant over both OLS and IV specifications in the case of all processed foods only. The direction of all other effects is as expected but mostly insignificant. In accordance with our previous findings, negative income effects are found for primary processed foods and positive for both highly and unprocessed foods. Considering the robustness checks (see Table A2.7 Appendix), the effect size of supermarket purchases on calorie shares from all processed foods ranges from 1.1 percentage point in OLS to 2.2 percentage points in IV specifications given a 10 percentage point increase in supermarket purchases. The average household in our non-supermarket location consumed 49% of their calories from primary processed food. Again, the effect size rises when we include a dummy for frequent kiosk consumers and an interaction with supermarket purchases but in this case, for high frequency consumers, the effect of supermarket purchases almost cancels out (see Table A2.8 Appendix). To put these finding in perspective, for the case of Guatemala, Asfaw (2011) shows that increasing the calorie share of primary and highly processed foods by 1% point increases BMI by 0.395% and 0.425% respectively, and both increase the probability of being overweight or obese.

What do we take away up to this point? Supermarkets indeed influence consumption patterns in that they are associated with higher consumption shares of processed foods (incl. beverages). This is in terms of expenditure as well as calorie shares of these goods and at the expense of unprocessed foods. These results partly confirm our hypothesis 1 (see section 2.2). The contradicting part concerns highly processed foods, where we expected stronger and significant effects of supermarkets purchases. Given positive income effects we find for highly processed foods, however, we expect a stronger shift towards these goods as income levels are increasing.

2.5.3 Calorie Consumption

In order to address our second hypothesis that supermarket purchases increase overall consumption of calories, we analyse per capita calorie availability per day[14]. Because of a high standard deviation (see Table A2.2 in Appendix), we use the log of p.c. calories in our regressions. This produces more robust results as compared to using absolute values. Table 2.6 presents our main results, robustness checks are shown in Table A2.7. We find supermarkets to be positively and significantly associated with higher p.c. calories so that we cautiously confirm our hypothesis. In the OLS (IV) specification, the semi-elasticities indicate that p.c. calories increase by 0.36% (0.96%) in response to a 1 percentage point increase of supermarket purchases. In case of our example used before, a 10 percentage point increase in supermarket purchases would increase p.c. calories by 3.6% (OLS) to 9.6% (IV) or around 100-250 calories per capita per day in the case of an average consumer in the non-supermarket location. Models (4) and (5) again show a significant interaction between frequent kiosk consumers and supermarket purchases. Above median kiosk purchases are associated with higher p.c. calories while supermarket purchases among frequent kiosk consumers have a negative effect on p.c. calories.[15]

[14] The unit we use for measuring calories is kilocalories (kcal).

[15] As shown, effect sizes of supermarket purchases are higher in the IV as compared to the OLS specifications. This might reflect measurement errors in calories consumed which would bias OLS results towards zero if they are random. IV techniques account for random measurement errors. On the other hand, the validity of the precise point estimate generated by the IV specification depends on supplementary assumptions about the specification of the model so that we think it safe to report both estimates. Rather than emphasizing the precise point estimate, we want to emphasize that both specifications generate significant and quantitatively meaningful estimates.

The finding that supermarket purchases are associated with higher calorie availability is interesting in itself. However, it is worthwhile to investigate further demand effects: since calorie availability is significantly higher holding total expenditure fixed, we expect households either to spend a higher proportion of their expenditure on food, or to source calories at lower prices. Note that this concerns prices paid per calories and not prices per physical unit (kg). We cannot find significant effects of supermarket purchases on the food budget share (controlling for total expenditure, see Table A2.9 in Appendix). Prices per calories, however, are indeed significantly negatively affected by supermarket purchases in the IV specifications, which are much more reliable in this case because of reverse causality between prices and expenditure shares by construction (see Table A2.9 in Appendix). Thus an important reason for the higher calorie consumption resulting from supermarket purchases is their lower price. On average, we find that prices paid per calorie are lowest for primary processed foods, followed by unprocessed and highly processed foods.

To assess the plausibility of these results, one can put together the results from Appendix Table A2.9 and Table 2.6 to show that prices per calorie are some 5-10% lower in supermarkets, leading to the 4-10% increase in calorie consumption. This would imply a price elasticity of food purchases of about -1. Price elasticities for staple foods are usually somewhat lower (e.g. Ecker and Qaim, 2011). Also not that is an average value for heterogeneous food groups and is not derived from a full demand system so that it should be treated with caution. But we take this overall reasonable estimate of a price elasticity as evidence that the price effect can explain the higher caloric intake. The fact that it is a bit higher than values reported in the literature could also suggest that it is not only lower prices but also the shift to cheaper primary processed foods associated with supermarket purchases.

It is not straightforward to assess implications of these findings on nutrient adequacy. One crude proxy of dietary quality is dietary diversity, usually measured by the number of distinct food products or major food categories consumed (Ruel, 2002). We use FAO Guidelines to classify foods into 'micronutrient sensitive' food categories, which distinguish, for example, between green leafy and other vitamin rich vegetables, and exclude other items such as fats and oils, sweets and beverages (Kennedy *et al.*, 2010). While we do not find supermarket purchases to significantly increase the number of food groups consumed within households (see Table A2.10 in Appendix), we find a positive and significant effect on the number of food items that fall in the micronutrient sensitive categories: a 10 percentage point increase in supermarket purchases, adds 2.9 products to the diet (IV), yet barely 1 in case of OLS (0.75). Given that the average number of food groups and food items consumed is fairly high (see Table A2.2 in Appendix), this is still noteworthy suggestive evidence.[16]

[16] However, our measure has several weaknesses. First, measures of dietary diversity typically use shorter recall periods, which also comes with higher variation in food diversity scores. Also, even if we took a positive relationship between dietary diversity and nutrient adequacy as a given, determining the threshold between a high and a low quality diet is a sensitive and context specific issue and requires further research (Ruel, 2002). This is especially true in a nutrition transition context where the nature of products that are added to the diet consumed is crucial.

Table 2.6: OLS and IV regression results – calorie availability at home

	(1) OLS log of *per capita calories* per day	(2) IV log of *per capita calories* per day	(3) 1st stage Dep. Var. SM expenditure share	(4) OLS log of *per capita calories* per day	(5) IV log of *per capita calories* per day
SM expenditure	0.3611*	0.9548*		0.9086***	1.3448*
share	(0.190)	(0.516)		(0.301)	(0.687)
Ln p.c. expenditure	0.3526***	0.3275***	0.0348***	0.3929***	0.3813***
	(0.057)	(0.070)	(0.009)	(0.058)	(0.068)
HH size using adult	0.0074	0.0060	0.0067**	0.0038	0.0022
equivalent scales	(0.024)	(0.025)	(0.003)	(0.023)	(0.023)
=1 for male head	-0.2353***	-0.2272***	-0.0071	-0.2286***	-0.2226***
	(0.062)	(0.062)	(0.011)	(0.059)	(0.060)
Education of head in	-0.0003	-0.0033	0.0033**	0.0003	-0.0013
years	(0.008)	(0.008)	(0.001)	(0.008)	(0.008)
Age of cook	-0.0083	-0.0072	-0.0029	-0.0085	-0.0079
	(0.008)	(0.009)	(0.002)	(0.008)	(0.008)
Age of cook squared	0.0001	0.0001	0.0000	0.0001	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
=1 if HH does	0.2074***	0.2161***	-0.0090	0.2318***	0.2394***
farming	(0.053)	(0.054)	(0.011)	(0.056)	(0.055)
Livelihood: public	-0.1637**	-0.2089***	0.0616***	-0.2106***	-0.2442***
sector employment	(0.070)	(0.075)	(0.019)	(0.075)	(0.084)
Livelihood: private	0.0254	-0.0075	0.0324**	-0.0495	-0.0754
sector employment	(0.066)	(0.075)	(0.013)	(0.065)	(0.079)
Livelihood: self-	-0.0879	-0.1016*	0.0008	-0.1520**	-0.1660***
employment	(0.064)	(0.061)	(0.011)	(0.067)	(0.062)
Livelihood: casual	0.0817	0.0687	0.0067	-0.0029	-0.0252
labour	(0.086)	(0.090)	(0.014)	(0.087)	(0.103)
Ln distance to SM			-0.0250***		
			(0.002)		
= 1 for >median				0.3138***	0.3630***
KIOSK consumpt.				(0.084)	(0.102)
Interaction				-1.1549***	-1.5554**
i.KIOSK*SMsh				(0.386)	(0.689)
Constant	4.8781***	5.0670***	-0.1928**	4.3933***	4.4642***
	(0.501)	(0.590)	(0.096)	(0.540)	(0.595)
Observations	448	448	448	448	448
R^2	0.209	0.195	0.379	0.255	0.250

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculation.

2.6 Discussion

Before discussing the implications of our findings, there are a number of limitations to keep in mind: First, one weakness of our empirical setup regards the lack of town dummies in our main specifications. Inclusion would be appealing in order to capture systematic town differences, such as general price or lifestyle differences. However, including town dummies in the IV specification renders our instrument to work poorly: because we only sampled three towns, town dummies are highly correlated with distance to supermarkets and distance becomes insignificant in our first stage. However, once livelihood sources are controlled for, towns remain significant only in few cases and furthermore, the coefficients of supermarket purchases remain fairly robust (see robustness checks in the Appendix). Furthermore, using expenditure shares rather than absolute expenditures as a measure of consumption should reduce the impact of general price differences across towns.

Second, note again that the food consumption we are analysing here is limited to the food that is consumed or, more precisely, available for consumption at home, which is most relevant for supermarkets and competing outlets. Substitution effects with food consumption outside home are possible but not explicitly addressed. For robustness, we control for food expenditure away from home, which does not alter our main results. The median expenditure shares on food away from home ranges from 6-9% per town (the mean budget share on food inside home is 46%).

Third, self-reported unit values are non-ideal price indicators because different unit prices between households can result either from different prices for homogenous goods or from choosing to buy different shades of quality. Since we cannot measure quality effects directly, our findings are not to be interpreted as conclusive evidence on the pricing strategy of supermarkets in our survey tows. To the extent that lower prices per calorie are paid for homogenous goods of similar product and micronutrient quality, supermarkets could contribute to alleviating food insecurity among calorie poor households. Irrespective of quality effects, lower prices paid have the potential to reduce poverty[17].

Fourth, our sample is restricted to only three towns of small size and with relatively low intensity of supermarket purchases. It is likely that an increase of supermarket purchases on consumption patterns looks different if a higher share of goods would already be sourced from supermarkets. Note, however, that even in Ol Kalou, where the supermarket was established more than a decade ago, the average supermarket share is 17% only. Case studies covering large cities in Kenya, and Zambia find traditional retail outlets to predominate the market and supermarket shares range between 9 and 16% (Tschirley *et al.*, 2010).

Comparing shopping behaviour indicators such as reasons for shopping in different outlets, our findings correspond to what has been reported in the case of Nairobi, implying that consumers in small towns value similar attributes in shopping outlets (Neven *et al.*, 2006). Gómez and Ricketts (2013) point to literature suggesting that resource poor households might shop more often in order to 'cherry pick' the best offers. We cannot find evidence to support this hypothesis in our sample.

2.7 Conclusion

This paper was motivated by the literature about the nutrition transition and negative health consequences in low-income countries. Alongside other lifestyle changes, dietary changes have been linked in the literature to rising rates of nutrition related non-communicable diseases and argued to be demand as well as supply side driven. The rapid spread of supermarkets in low-income countries is suspected to advance the nutrition transition by increasing the availability, affordability and by purposeful marketing associated foods and beverages to consumers. We analyse the effect of supermarkets on consumption patterns using

[17] By naïve calculation: if we keep calories consumed at the household level constant and reduce prices per calorie by 10%, this is equivalent saving 10% of the food budget. Adding these freed resources to total household expenditures would reduce poverty, at our previously extrapolated poverty line, by two percentage points, from 47% to 45%.

very detailed household survey data collected for this purpose in a quasi-experimental setting in Kenya in 2012.

With respect to the affordability of food products, we established that lower (perceived) prices are by far the most important reason for consumer to shop at supermarkets. The strongest incentive to shop at kiosks, the main traditional competitor to supermarkets, is physical access. In sum, drivers of retail outlet choices in small urban towns are similar to the ones that have been reported for large cities (Neven *et al.*, 2006), which suggests that our findings are relevant beyond the important group of small towns that we are looking at.

In terms of consumption patterns, we find that supermarket purchases increase the consumption of processed at the expense of unprocessed foods. This holds in terms of expenditure shares as well as calorie shares and is mainly driven by an increased consumption of primary processed goods. While we had expected a stronger effect on highly processed foods (hypothesis H1), this does nevertheless suggest that supermarkets advance the consumption of foods associated with the nutrition transition, which is further expected to accelerate as income levels rise.

As consumption patterns change towards more processed food, we find a positive effect of supermarket purchases on p.c. calorie availability, which confirms our hypothesis that frequent supermarket consumers consume more (hypothesis H2). We do not find that households increase their food budget share but we confirm that the increase in total calories is supported by a negative effect of supermarket purchases on prices paid per calorie. Particularly with primary processed foods whose expenditure share rises with supermarket purchases, money can buy more calories.

Supermarket purchases also increase the dietary diversity of consumers, confirming our hypothesis (H3). However, it is beyond the scope of this paper to investigate in detail implications for nutrient adequacy. We do find suggestive evidence that supermarket purchases slightly increase the number of food items among micronutrient-sensitive food categories. Also, for the reason that supermarket purchases are not found to significantly increase the consumption of highly processed foods, negative health effects might be less pronounced than initially expected. To the extent that supermarket purchases contribute to a well-balanced diet, beneficial effects might be detected for some parts of the population. Calorie poor and resource poor households could further benefit from lower prices per calorie. It remains unclear how rising income levels will change the picture since we found positive income effects for both, highly processed as well as unprocessed foods, i.e. fresh produce. More research is needed to assess how consumption patterns as well as nutritional outcomes and dynamics associated with supermarket purchases change in the long-run.

Methodologically, our results confirm the adequacy of addressing endogeneity in supermarket purchases, which former studies have often neglected. While our results contribute to causally linking the retail revolution with the consumption of industrially processed foods in developing countries, they lead to further research questions. In particular, future research should investigate what type of supermarket and associated food environment leads to stronger or weaker effects and to which extent structural effects on dietary patterns depend on the initial level of supermarket purchases. Are there saturation effects? The net effect of lower prices per calorie, more diversity, and a higher share of processed foods might have different nutritional implications in different contexts[18]. Lastly, considering the impact of very large supermarkets with a drastically expanded offering (including fresh fruit and vegetables as well as meat) on consumption pattern would also be an important question for future research.

[18] In the context analysed here, we find a positive reduced-form relationship between supermarket purchases and BMI of individuals. This is associated with higher levels of overweight and obesity among adults, and lower levels of stunting among adolescents (see chapter 3).

2.8 Appendix

Table A2.1: Product range of different retail formats in small towns

Typical products categories:	Supermarket	Small self-service store	Traditional kiosk
Non-food items of daily use	Yes	Yes	Yes
Crisps & salted snacks	Yes	Yes	Yes
Milk and yoghurt	Yes, fresh & long life	Yes, long life	**No**
Meat and fish	Yes, cooled sausages, frozen chicken & fish	**No**	**No**
Cooking fat, incl. cholesterol free	Yes	Yes	Yes
Fortified products (e.g. added vitamins)	Yes	Yes	**No**
Tinned products	Yes, but very limited	**No**	**No**
Instant noodles, breakfast cereals	Yes	Yes	Yes
Soft drinks, juices with sugar added, drinking chocolate	Yes	Yes	Yes
Fruit juice without added sugar	Yes	**No**	**No**
Alcoholic Beverages	Yes, but limited	**No**	**No**
Built-in over the counter retail (e.g. bakery, butchery, fast food stall)	**No** (only few cases)	**No**	**No**
Fresh fruits & vegetables	**No** (if yes, only very limited)		

Source: Own observation.

Table A2.2: Summary statistics of main dependent variables

DEPENDENT VARIABLES

	All	**Njabini (no SM)**		**Mwea (SM since 2011)**		**Ol Kalou (SM since 2002)**	
	Mean	Mean	Diff to others	Mean	Diff to others	Mean	Diff to others
Food expenditure shares:							
Unprocessed	0.63	0.65	0.03***	0.62	-0.02	0.62	-0.02
	(0.11)	(0.12)	(0.01)	(0.12)	(0.01)	(0.10)	(0.01)
Primary processed	0.25	0.24	-0.00	0.25	0.01	0.24	-0.00
	(0.11)	(0.12)	(0.01)	(0.10)	(0.01)	(0.09)	(0.01)
Highly processed	0.12	0.10	-0.03***	0.13	0.01	0.13	0.02**
	(0.10)	(0.10)	(0.01)	(0.11)	(0.01)	(0.08)	(0.01)
All processed	0.36	0.34	-0.04***	0.38	0.02*	0.38	0.02*
	(0.11)	(0.12)	(0.01)	(0.12)	(0.01)	(0.10)	(0.01)
Calorie shares:							
Unprocessed	0.48	0.50	0.03**	0.47	-0.02	0.47	-0.01
	(0.12)	(0.13)	(0.01)	(0.12)	(0.01)	(0.11)	(0.01)
Primary processed	0.42	0.42	0.00	0.43	0.01	0.42	-0.01
	(0.13)	(0.14)	(0.01)	(0.12)	(0.01)	(0.12)	(0.01)
Highly processed	0.10	0.08	-0.03***	0.11	0.01	0.11	0.02*
	(0.09)	(0.09)	(0.01)	(0.10)	(0.01)	(0.08)	(0.01)
All processed	0.52	0.50	-0.03**	0.53	0.02	0.52	0.01
	(0.12)	(0.13)	(0.01)	(0.12)	(0.01)	(0.11)	(0.01)
Calories p.c. per day (adult equivalent)	2841.78 (1127.36)	2565.22 (1015.78)	-431.70*** (109.23)	2878.87 (1148.33)	52.91 (116.43)	3100.31 (1161.08)	392.63*** (110.89)

Table A2.2 cont'd	All	Njabini (no SM)		Mwea (SM since 2011)		Ol Kalou (SM since 2002)	
	Mean	Mean	Diff to others	Mean	Mean	Mean	Diff to others
Price per calorie	0.04	0.04	-0.00	0.05	0.00	0.04	-0.00
	(0.02)	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Food budget share (inside home)	0.46	0.49	0.06***	0.42	-0.05***	0.45	-0.01
	(0.15)	(0.15)	(0.01)	(0.15)	(0.02)	(0.13)	(0.01)
Food diversity:							
# of nutrient sensitive food categories consumed	7.74	7.54	-0.31***	7.81	0.09	7.90	0.23**
	(1.19)	(1.37)	(0.12)	(1.20)	(0.12)	(0.94)	(0.12)
# of items (among food categories) consumed	32.54	28.89	-5.68***	36.18	5.20***	33.18	0.97
	(10.29)	(10.12)	(0.98)	(10.03)	(1.03)	(9.45)	(1.02)
Observations	448	161	161	134	134	153	153

For means, standard deviations for rest, standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.
Source**: Own calculation.**

Table A2.3: Expenditure shares 1st stage results of main models

	(1) 1st stage *Highly processed/ all processed food*	**(2) 1st stage** *Primary processed food*	**(3) 1st stage** *Unprocessed food*
	SM expenditure share	SM expenditure share	SM expenditure share
Ln p.c. expenditure	0.0353***	0.0358***	0.0354***
	(0.009)	(0.010)	(0.012)
HH size	0.0043	0.0034	0.0046
	(0.003)	(0.003)	(0.003)
=1 if head is married	0.0010	0.0019	0.0010
	(0.011)	(0.009)	(0.008)
Education of head in years	0.0051***	0.0050***	0.0051***
	(0.001)	(0.002)	(0.001)
Age of cook	-0.0025	-0.0018	-0.0025
	(0.002)	(0.002)	(0.002)
Age of cook squared	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)
Mwea (SM 2011)		-0.0157*	
		(0.008)	
# female adults			-0.0011
			(0.005)
=1 if HH does farming	-0.0135	-0.0532***	-0.0135
	(0.010)	(0.018)	(0.009)
Ln distance to SM	-0.0252***	-0.0305***	-0.0252***
	(0.002)	(0.003)	(0.002)
Constant	-0.2056**	-0.1976*	-0.2058*
	(0.093)	(0.100)	(0.116)
Observations	448	448	448
R^2	0.351	0.384	0.351

(1) Robust and (2) cluster robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ **Source**: Own calculation.

Table A2.4: Selected robustness checks, only main variable of interest shown

Expenditure share highly processed foods

OLS	Standard controls	Including all towns	Additional controls	HH replacement control	SM location sample only
SM expenditure share	0.0766*	0.0736	0.0942**	0.0759*	0.0900*
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
R^2	0.256	0.256	0.259	0.256	0.201
IV	Standard controls	Including all towns	Additional controls	HH replacement control	SM location sample only
SM expenditure share	0.0712	IV invalid	0.0441	0.0690	IV invalid
	(0.09)		(0.09)	(0.09)	
R^2	0.256		0.256	0.256	

Expenditure share primary processed foods

OLS	Standard controls	Including all towns	Additional controls	HH replacement control	SM location sample only
SM expenditure share	0.1336***	0.1095**	0.1628***	0.1363***	0.1014*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
R^2	0.316	0.317	0.348	0.316	0.290
IV	Standard controls	Including all towns	Additional controls	HH replacement control	SM location sample only
SM expenditure share	0.2109**	IV invalid	0.1854**	0.2255***	IV invalid
	(0.09)		(0.08)	(0.08)	
R^2	0.310		0.348	0.308	

Expenditure share all processed foods

OLS	Standard controls	Including all towns	Additional controls	HH replacement control	SM location sample only
SM expenditure share	0.2134***	0.1831***	0.2897***	0.2166***	0.1698***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
R^2	0.233	0.242	0.264	0.234	0.256
IV	Standard controls	Including all towns	Additional controls	HH replacement control	SM location sample only
SM expenditure share	0.3781***	IV invalid	0.3625***	0.3942***	IV invalid
	(0.10)		(0.09)	(0.10)	
R^2	0.208		0.259	0.205	

Expenditure shares unprocessed foods

OLS	Standard controls	Including all towns	Additional controls	HH replacement control	SM location sample only
SM expenditure share	-0.2127***	-0.2048***	-0.2864***	-0.2121***	-0.2968***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
R^2	0.240	0.244	0.234	0.240	0.270
IV	Standard controls	Including all towns	Additional controls	HH replacement control	SM location sample only
SM expenditure share	-0.3220***	IV invalid	-0.3083***	-0.3249***	IV invalid
	(0.08)		(0.08)	(0.10)	
R^2	0.229		0.234	0.229	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard set of controls and correction of standard errors as in main models, see Table 2.5. **Source**: Own calculation.

Table A2.5: Expenditure shares: Interaction effects

	(2) IV P*rimary processed* food	**(4) IV** *All processed* food	**(6) IV** *Unprocessed* foods
SM expenditure share	0.2679***	0.4296***	-0.3635***
	(0.099)	(0.128)	(0.129)
=1 for >median KIOSK conspt.	0.0548***	0.0711***	-0.0607***
	(0.015)	(0.016)	(0.017)
Interaction i.KIOSK*SMshare	-0.2361**	-0.2725**	0.2307*
	(0.104)	(0.107)	(0.128)
Other controls (see Table 2.5)	yes	yes	yes
Constant	0.8695***	0.8929***	0.3146***
	(0.082)	(0.092)	(0.112)
Observations	448	448	448
R^2	0.343	0.258	0.267

Cluster robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source**: Own calculation.**

Table A2.6: Share of calories from different food categories – OLS and IV estimates

	(1) OLS Calorie share *highly processed* foods	**(2) IV** Calorie share *highly processed* foods	**(3) OLS** Calorie share *primary processed* foods	**(4) IV** Calorie share *primary processed* foods	**(5) OLS** Calorie share *all processed* food	**(6) IV** Calorie share *all processed* food	**(7) OLS** Calorie share *unprocessed* foods	**(8) IV** Calorie share *unprocessed* foods
SM expen-diture share	0.0261	0.0381	0.0949*	0.1475	0.1209***	0.1857*	-0.1167***	-0.1787*
	(0.035)	(0.079)	(0.048)	(0.116)	(0.042)	(0.111)	(0.042)	(0.108)
Ln p.c. expenditure	0.0286***	0.0281***	-0.0712***	-0.0735***	-0.0426***	-0.0454***	0.0387***	0.0414***
	(0.007)	(0.008)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.013)
HHsize (ad. equiv.)	-0.0018	-0.0018	0.0016	0.0016	-0.0002	-0.0002	-0.0002	-0.0002
	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Other controls	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-0.0405	-0.0366	1.0224***	1.0393***	0.9819***	1.0027***	0.0495	0.0296
	(0.067)	(0.078)	(0.110)	(0.110)	(0.111)	(0.117)	(0.107)	(0.113)
Observations	448	448	448	448	448	448	448	448
R^2	0.264	0.264	0.141	0.139	0.148	0.145	0.147	0.144

Robust (1)-(4) and cluster robust (5)-(8) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculation.

Table A2.7: Selected robustness checks – only main variable of interest shown

Calorie share all processed food

OLS	Standard controls	Including all towns	Additional controls	HH replace-ment control	SM location sample only
SM expenditure	0.1209***	0.1124**	0.1695***	0.1310***	0.0627
share	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
R^2	0.148	0.151	0.193	0.153	0.159
IV	Standard controls	Including all towns	Additional controls	HH replace-ment control	SM location sample only
SM expenditure	0.1857*	IV not valid	0.1386	0.2177**	IV not valid
share	(0.11)		(0.10)	(0.11)	
R^2	0.145		0.181	0.148	

Cluster robust standard errors in parentheses.

Calorie availability p. c. per day

OLS	Standard controls	Including all towns	Additional controls	HH replace-ment control	SM location sample only
SM expenditure	0.3611*	0.0744	0.4656**	0.3260*	0.3734
share	(0.19)	(0.19)	(0.19)	(0.19)	(0.29)
R^2	0.209	0.223	0.348	0.213	0.330
IV	Standard controls	Including all towns	Additional controls	HH replace-ment control	SM location sample only
SM expenditure	0.9548*	IV invalid	0.7072	0.8648*	IV invalid
share	(0.52)		(0.43)	(0.52)	
R^2	0.195		0.346	0.202	

Robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Standard controls as in model (1), Table 2.6. **Source**: Own calculation.

Table A2.8: Calorie shares: Interaction effects

	(1) OLS *All processed* food	**(2) IV** *All processed* food
SM expenditure	0.2249***	0.2445*
share	(0.054)	(0.140)
=1 for >median	0.0571***	0.0593***
KIOSK conspt.	(0.017)	(0.020)
Interaction	-0.2474***	-0.2653*
i.KIOSK*SMshare	(0.092)	(0.139)
Other controls	yes	yes
Constant	-0.2073**	0.8777***
	(0.092)	(0.112)
Observations	448	448
R^2	0.352	0.176

Cluster robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source**: Own calculation.**

Table A2.9: Food budget shares and prices per calories, OLS and IV estimation

	(1) OLS Food budget share	(2) IV Food budget share	(3) OLS Price per calorie	(4) IV Price per calorie	(5) OLS Price per calorie	(6) IV Price per calorie
SM expenditure	-0.0244	-0.1494	-0.0109*	-0.0534***	-0.0167***	-0.0472***
share	(0.046)	(0.106)	(0.006)	(0.012)	(0.006)	(0.011)
Ln p.c. expenditure	-0.1280***	-0.1220***	0.0138***	0.0157***	0.0123***	0.0133***
	(0.012)	(0.014)	(0.002)	(0.002)	(0.002)	(0.002)
=1 if HH does	0.0150	0.0118	-0.0045***	-0.0054***	-0.0053***	-0.0062***
farming	(0.011)	(0.011)	(0.001)	(0.001)	(0.001)	(0.001)
Exp share on food	-0.3593***	-0.3680***				
away from home	(0.061)	(0.065)				
=1 for >median					-0.0063***	-0.0078***
KIOSK consumpt.					(0.001)	(0.001)
Other controls	yes	yes	yes	yes	yes	yes
Constant	1.8027***	1.7598***	-0.0722***	-0.0859***	-0.0549***	-0.0601***
	(0.117)	(0.132)	(0.016)	(0.017)	(0.015)	(0.017)
Observations	448	448	448	448	448	448
R^2	0.492	0.484	0.437	0.348	0.472	0.428

Cluster robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. **Source**: Own calculation.

Table A2.10: Food diversity indicators, OLS and IV estimation

	(1) OLS # 'nutrient sensitive' food groups consumed	(2) IV # 'nutrient sensitive' food groups consumed	(3) OLS # products consumed from food groups	(4) IV # products consumed from food groups
SM expenditure share	0.2931	0.8399	7.5684**	29.3534***
	(0.341)	(0.720)	(3.012)	(5.342)
Ln p.c. expenditure	0.6443***	0.6201***	6.6460***	5.6803***
	(0.150)	(0.154)	(1.090)	(0.999)
=1 if HH does	0.5228***	0.5350***	4.5043***	4.9876***
farming	(0.117)	(0.111)	(1.034)	(0.934)
=1 for male head	-0.4001***	-0.3935***	-4.4877***	-4.2224***
	(0.112)	(0.113)	(0.979)	(1.028)
Other controls	yes	yes	yes	yes
Constant	2.1851	2.3604*	-33.9562***	-26.9688***
	(1.341)	(1.389)	(9.216)	(8.503)
Observations	448	448	448	448
R^2	0.191	0.189	0.323	0.272

Standard errors in parentheses.* p < 0.10, ** p < 0.05, *** p < 0.01.
Source: Own calculation.

3 Do Supermarkets Contribute to the Obesity Pandemic in Developing Countries?[19]

Abstract

In this chapter, we employ instrumental variable techniques to analyse the impact of supermarket purchases on the nutritional status of adults and of children and adolescents. We use household survey data collected in Kenya in 2012. We also estimate causal chain models to examine the pathways through which supermarkets may affect the nutritional status of individuals. Controlling for other factors, buying in a supermarket increases the body mass index of adults and raises the probability of adult overweight or obesity. For children and adolescents we do not find a significant impact on overweight. Instead, buying in a supermarket tends to decrease child undernutrition in terms of height-for-age z-scores. Impacts of supermarkets depend on many factors, including people's initial nutritional status. Kenya and many other developing countries face a dual burden of malnutrition, where adult overweight coexists with childhood stunting. For both, adults and children, the nutrition impacts of supermarkets occur through higher calorie consumption and changes in their dietary composition.

[19] This chapter is co-authored by Simon C. Kimenju, Stephan Klasen and Matin Qaim. The author's contributions are as follows: All authors contributed to the design of the research. SCK & RR performed research; SCK undertook data analysis; SCK and MQ wrote the manuscript; all authors reviewed the manuscript, RR edited the manuscript to include it in this dissertation.

3.1 Introduction

Based on the same motivation as the previous chapter, that is to understand the drivers and consequences of the nutrition transition in developing countries, in this chapter we follow up on the effects of supermarkets on nutritional outcomes: In chapter two, we have established that supermarket purchases are indeed associated with changing consumption patterns on the level of households. This was in the context of small urban towns in Kenya. Here, we aim to shed light on the consequences on nutritional outcomes for individuals. More explicitly, we aim to understand if supermarket purchases and the changes in consumption patterns they induce contribute to increasing rates of overweight and obesity.

Rising rates of overweight and obesity have been associated with serious negative implications for people's health (Hawkes *et al.*, 2009; Popkin *et al.*, 2012; Rtveladze *et al.*, 2014). In 2008, 34% of all adults in the world were overweight or obese (Finucane *et al.*, 2011). While average overweight rates are still higher in most industrialized countries, many developing countries are rapidly catching up. In chapter 2.2., we discussed the spread of supermarkets in developing countries and mechanisms in which retail formats, and supermarkets in particular, influence the types of products offered, marketing practices including sales prices, the shopping atmosphere, and ultimately consumer food choices. One important question to follow up on is whether supermarkets contribute directly to rising rates of overweight and obesity in developing countries. We address this question building on the same observational data used in chapter 2 and collected in Kenya.

Empirical studies on the impact of supermarkets on the nutritional status of consumers in developing countries are rare. Studies in the context of the US show that access to supermarkets is nowadays often associated with lower obesity rates (Drewnowski *et al.*, 2012; Lear *et al.*, 2013; Michimi and Wimberly, 2010; Morland *et al.*, 2006a), but the situation in developing countries is different. One study for Guatemala found that food purchases in supermarkets increase the BMI of consumers (Asfaw, 2008). However, the research for Guatemala builds on a household living standard survey that was not specifically designed for analysing the nutritional impact of supermarkets. Hence, a few variables of interest, such as item specific food quantities purchased in different retail outlets, were not properly captured. Moreover, the impact on BMI was analysed for all individuals in the sample above 10 years of age, an approach that masks possible differences between adults and children. BMI is a suitable indicator of nutritional status only for individuals who have reached their final body height. For children and adolescents, it is recommended to use indicators such as height-for-age or BMI-for-age Z-scores, which set individual measures in relation to a reference population of the same age (de Onis *et al.*, 2007).

We address these shortcomings in the previous literature by using data from a survey of Kenyan consumers that was specifically designed for this purpose. As we detailed in chapter 2.3, Kenya has recently witnessed a rapid spread of supermarkets and large chain supermarkets now account for about 10% of national grocery sales (PlanetRetail, 2013). This retail share of supermarkets in Kenya is lower than in many middle-income countries, but it is already higher than in most other low-income countries in Sub-Saharan Africa and Asia. Hence, trends observed in Kenya may be helpful to predict future developments in other poor regions. Using household as well as individual specific data, we analyse the impact of supermarket purchases on the nutritional status of individuals. We also examine impact pathways. The analysis is carried out separately for adults and for the group of children and adolescents, because impacts may differ by age cohort.

This chapter is organised as follows: section 3.2 adds relevant information of our study design and describes our empirical strategy. Section 3.3 presents our empirical findings. Section 3.4 discusses our results and concludes.

3.2 Methods

3.2.1 Study Design – Relevant Extensions

Since we use the same survey data as we use for chapter 2, the setting and general study design are identical (see chapter 2.4.1). However, for the reason of using individual level data in addition to household level data used before, some additional aspects need to be mentioned here and other relevant issues will be reiterated.

Data on socioeconomic characteristics, including food consumption and expenditure, were collected at the household level. Details on food consumption at home were collected using a 30-day recall period, which allowed us to also capture purchases that are undertaken by households only once per month. During a questionnaire pre-test we learned that shopping behaviour and places of purchase may differ according to the wage cycle. Data on food consumption quantities, expenditures, and place of purchase were collected in disaggregated form for 170 food items.

In addition to the household-level data, we collected individual-level data for randomly selected household members such as food eaten away from home as well as work and leisure related physical activity. In each household, up to three household members were randomly selected to provide these information and for having anthropometric measurements taken[20]: one male adult, one female adult, and one child or adolescent in the 5-19 years age range. Children below 5 years of age were not chosen for measurement since we hypothesised that supermarkets are more likely to influence the diets of adults and older children. Participation was voluntary. Prior to taking anthropometric measures we obtained written consent from all adults through signatures for themselves and their children. In total, we collected individual data from 615 adults and 216 children and adolescents.

3.2.2 Variables of Interest

Our main nutritional outcome variable for adults is body mass index (BMI), defined as weight in kilograms divided by squared height in meters. Adults with a BMI ≥ 25 kg/m^2 are classified as overweight or obese (WHO, 2000). For children, we use two nutritional outcome variables, namely BMI-for-age Z-scores (BAZ) and height-for age Z-scores (HAZ), which are calculated based on the World Health Organization (WHO) growth reference for school-aged children and adolescents (de Onis *et al.*, 2007). Childhood overweight/obesity is defined as a BAZ > 1 standard deviations (sd) from the median of the reference population. Stunting is defined as HAZ < -2 sd, mild stunting as HAZ < -1 sd, and severe stunting as HAZ < -3 sd from the median reference population (WHO, 2006).

[20] A group of eight local enumerators was involved in the survey; we used the same enumerators in all locations. Prior to data collection, the enumerators were trained thoroughly in all aspects of administering the questionnaire, including anthropometric measurements.

The exposure variable for the impact assessment captures food purchases in supermarkets. Supermarkets in this context are defined as large modern retail formats with at least two cash counters that offer a relatively large variety of food items, including cooled and frozen foods (see chapter 2.3 for details). Supermarket purchases are measured in two different ways, first as a dummy variable that takes a value of one for households that purchased at least some of their food in supermarkets in the reference period, and second as a continuous variable measuring the share of supermarket purchases in total household food expenditure. Households that do not buy in supermarkets (i.e., the dummy and the supermarket share are equal to zero) obtained all of their food from traditional sources.

Other factors that may influence the nutritional status and for which we collected data include age, gender, education, physical activity during work and leisure time, and household expenditure. Furthermore, nutritional knowledge and awareness may play a role. In Kenya, district hospitals are responsible for coordinating nutrition awareness programmes. We use household distance to the nearest district hospital as a proxy for nutritional awareness.

We also analyse the impact of supermarkets on calorie consumption and on calories from processed foods. Quantities of food consumed in the household were converted into calories using food composition tables developed for Kenyan foods (FAO, 2010; Sehmi, 1993). A few foods that could not be found in these local food composition tables were converted into calories using international values (FAO, 2012). For food eaten away from home, survey respondents reported dishes consumed, not ingredients. To determine calories from these dishes, actual cooking was done with the help of restaurant operators who advised on types and quantities of ingredients that went into a particular dish, and on serving portions. The dishes were then converted into calories after adjusting for edible portions and weight changes due to cooking (EuroFIR, 2008). Calories consumed at home at the household level were allocated to individuals based on adult equivalence scales for energy requirements, assuming light physical activity (FAO *et al.*, 2004). We also took into account the number of meals consumed away from home by individual household members. For adults, individual calories consumed away from home were added to those consumed at home. For children and adolescents, we found the data on food eaten away from home to be less accurate and to contain several missing values, so that only calories from foods consumed at home were considered. Since all supermarket purchases fall into this 'consumed at home' category, this limitation should not affect our analysis much. To differentiate between calories from processed and unprocessed foods, we follow common classifications in the literature (Asfaw, 2011; Monteiro *et al.*, 2011). As a rule of thumb, foods are considered processed if any industrial method was used to develop food products from fresh whole foods.

3.2.3 Statistical Analysis

Our main objective is to analyse the impact of supermarket purchases on the nutritional status of adults and of children and adolescents. For this purpose, we estimate models of the following type:

$$\boldsymbol{N}_i = \beta_0 + \beta_1 S_i + \boldsymbol{\beta_2 X_i} + \varepsilon_i \tag{3.1}$$

where $\boldsymbol{N_i}$ refers to the outcome variables characterising the nutritional status of individual *i*, S_i is the variable for supermarket purchases, $\boldsymbol{X}_i$ is a vector of control variables, including individual and household characteristics, and ε_i is a random error term.

In this model, supermarket purchases may potentially be endogenous, since there could be unobserved factors that determine supermarket purchase and nutritional status simultaneously. This could lead to biased impact estimates. To avoid this problem, we use an instrumental variable (IV) approach. Supermarket purchases are instrumented with the household distance to the nearest supermarket (measured through GPS coordinates). For a discussion of this instrument, we refer to chapter 2.4.2. For continuous outcome variables (i.e. BMI or HAZ), we use an IV two-stage least squares estimator. For binary outcome variables (i.e. being overweight/obese or stunted) we use an IV probit estimator. Marginal effects for the IV probit are evaluated at sample means.

In addition to the reduced-form models in equation (3.1), we also analyse possible pathways through which supermarkets affect nutritional outcomes of adults and children/adolescents by estimating structural equation models. Based on previous considerations, on the one hand, supermarket purchases may influence the amount of calories consumed. On the other hand, the dietary composition i.e. the types of calories consumed may also be affected. Both pathways are relevant and the available literature suggests that the share of calories from processed foods may increase BMI even after controlling for the total amount of calories consumed (Asfaw, 2011). We model a causal chain, hypothesizing that supermarket purchases affect total calorie consumption and the share of calories from processed foods, and that these two variables both affect nutritional status. The causal chain is modelled as follows:

$$N_i = \beta_0 + \beta_1 C_i + \beta_2 P_i + \boldsymbol{\beta_3 X}_i + \varepsilon_{i1} \tag{3.2}$$

$$C_i = \alpha_0 + \alpha_1 S_i + \boldsymbol{\alpha_2 U}_i + \varepsilon_{i2} \tag{3.3}$$

$$P_i = \delta_0 + \delta_1 S_i + \boldsymbol{\delta_2 V}_i + \varepsilon_{i3} \tag{3.4}$$

$$S_i = \gamma_0 + \gamma_1 D_i + \boldsymbol{\gamma_2 W}_i + \varepsilon_{i4} \tag{3.5}$$

where N_i is the nutritional status of individual *i*, C_i is calorie consumption of the same individual, P_i is the share of calories from processed foods, S_i are supermarket purchases, and D_i is the distance to the nearest supermarket. $\boldsymbol{X}_i$, $\boldsymbol{U}_i$, $\boldsymbol{V}_i$, and $\boldsymbol{W}_i$ are vectors of individual and household characteristics, while ε_{i1} to ε_{i4} are random error terms. This system of simultaneous equations is estimated using a three-stage least squares estimator. We estimate separate models for adults and for children and adolescents.

3.3 Results

While 41% of the adults in our sample are classified as either overweight or obese, 10% of the children and adolescents fall into this category. On the other hand, 21% of the children in our sample are affected by stunting, a common indicator of child undernutrition (see Tables A3.1 and A3.2 in the Appendix). Table 3.1 compares nutrition related variables between individuals from households that buy and do not buy in supermarkets. Adults in supermarket-buying households have a significantly higher BMI and are more likely to be overweight or obese. They also consume significantly more calories, and a greater share of their calories comes from processed foods. For children and adolescents, the patterns are different. While there is a slight difference in mean BAZ between supermarket buyers and non-buyers, this difference is not statistically significant. Yet we observe significantly higher HAZ among children from households that buy in a supermarket, and a lower prevalence of stunting. This illustrates the appropriateness of modelling adults and children/adolescents separately.

Table 3.1: Comparison of nutrition variables by supermarket purchases

Category	Variable	Household buys in supermarket	Household does not buy in supermarket
Adults	BMI	25.22* (4.73)	24.43 (4.98)
	Overweight or obese (dummy)	0.45* (0.50)	0.36 (0.48)
	Underweight (dummy)	0.04 (0.19)	0.04 (0.20)
	Calorie consumption per day (kcal)	3500.70** (1230.79)	3143.32 (1426.80)
	Share of calories from processed foods (%)	51.52*** (11.25)	44.36 (20.55)
	Food expenditure (KSh per AE and month)	6954.96*** (5351.4)	4916.79 (3016.0)
	Number of observations	357	258
Children/ adolescents	BMI-for-age Z-score	-0.26 (1.09)	-0.36 (0.90)
	Overweight or obese (dummy)	0.10 (0.30)	0.09 (0.30)
	Height-for-age Z-score	-0.76*** (1.09)	-1.35 (1.43)
	Stunted (dummy)	0.14 (0.34)	0.28** (0.45)
	Calorie consumption per day (kcal)	2531.67 (959.88)	2310.54 (1428.13)
	Share of calories from processed foods (%)	52.15*** (10.27)	44.14 (21.66)
	Number of observations	110	106

*, **,***, mean value is significantly higher than that of the other group at the 10%, 5%, and 1% level, respectively. Mean values are shown with standard deviations in parentheses. BMI, body mass index; KSh, Kenyan shillings; AE, adult equivalent. **Source**: Own calculation.

3.3.1 Impact of Supermarket Purchases on the Nutritional Status

The mean differences in Table 3.1 are a first indication that buying food in a supermarket may contribute to an increasing BMI and a higher prevalence of overweight and obesity among adults. To test this hypothesis we regress BMI and the probability of being overweight or obese on supermarket purchases using IV specifications. Estimation results are shown in Table 3.2. Independent of the exact specification, supermarket purchases have significant effects on nutritional outcomes. Buying in a supermarket increases BMI by 1.7 kg/m^2 and the probability of being overweight or obese by 13 percentage points. Similarly, an increase in the share of supermarket purchases by one percentage point increases BMI by 0.08 kg/m^2 and the probability of being overweight or obese by around one percentage point. Most of the control variables have the expected signs, with age and household expenditure contributing to higher BMI, and physical activity to lower BMI.

Table 3.2: Impact of supermarket purchases on adult nutrition - IV regression results

Explanatory variables	BMI	BMI	Overweight/ obese (dummy)	Overweight/ obese (dummy)
Buys in supermarket (dummy)	1.688** (0.72)		0.132* (0.07)	
Supermarket purchase share (%)		0.080* (0.04)		0.008** (0.00)
Age (years)	0.110*** (0.02)	0.112*** (0.02)	0.011*** (0.00)	0.011*** (0.00)
Female (dummy)	0.501 (1.08)	0.590 (1.09)	0.150 (0.12)	0.151 (0.12)
Female-age interaction	0.066** (0.03)	0.066** (0.03)	0.003 (0.00)	0.002 (0.00)
Heavy work (dummy)	-0.892** (0.35)	-0.946*** (0.36)	-0.093** (0.04)	-0.097*** (0.04)
Leisure-time physical activity (hours per week)	-0.047** (0.02)	-0.040* (0.02)	-0.003 (0.00)	-0.002 (0.00)
Household expenditure (1000 KSh per AE and month)	0.077*** (0.03)	0.077** (0.03)	0.005 (0.00)	0.005 (0.00)
Education of person responsible for food (years)	0.168*** (0.05)	0.166*** (0.06)	0.020*** (0.01)	0.018*** (0.01)
Married household head (dummy)	0.915** (0.39)	1.066*** (0.40)	0.100** (0.04)	0.111*** (0.04)
Distance to nearest district hospital (log of km)	0.316** (0.13)	0.386** (0.17)	0.017 (0.01)	0.028* (0.02)
Constant	15.401*** (0.98)	15.280*** (1.01)		
Number of observations	615	615	615	615
Chi-squared test statistic	504.98***		560.46***	339.24***

*, **,***, statistically significant at the 10%, 5%, and 1% level, respectively. Marginal effects are shown with robust standard errors in parentheses. Estimates are based on instrumental variable models with the supermarket purchase variables instrumented. For the last two table columns (overweight/obese), instrumental variable probit models were used. First-stage regression results are shown in the Appendix (Table A3.3). BMI, body mass index; KSh, Kenyan shillings; AE, adult equivalent. **Source**: Own calculation.

Table 3.1 did not reveal significant differences in overweight and obesity between children/adolescents from households that buy and do not buy in supermarkets. The regression results in Table 3.3 confirm that supermarket purchases do not affect BAZ in a statistically significant way. However, supermarket purchases have a positive and significant effect on HAZ. Buying in a supermarket increases HAZ by 0.63. Similarly, an increase in the share of supermarket purchases by one percentage point increases HAZ by 0.03. This is evidence that supermarkets contribute to reducing problems of undernutrition among children and adolescents. The supermarket coefficients in the stunting models are negative, but not statistically significant. This may be related to the relatively small sample size. Moreover, how many individuals can be lifted above a threshold depends on the variable distribution and the magnitude of the threshold. The standard threshold for stunting is HAZ < -2 sd, which is what we used for the estimates in Table 3.2. Using common thresholds for mild stunting (HAZ < -1 sd) and severe stunting (HAZ < -3 sd), we do find significant effects (Table A3.5 in the Appendix). Buying in a supermarket significantly decreases the probability of severe stunting, with a point estimate of minus 23 percentage points at sample means.

Table 3.3: Impact of supermarket purchases on child/adolescent nutrition – IV regression results

Explanatory variables	BAZ	HAZ	HAZ	Stunted (dummy)	Stunted (dummy)
Buys in supermarket (dummy)	0.183 (0.34)	0.634** (0.27)		-0.056 (0.10)	
Supermarket purchase share (%)			0.033*** (0.01)		-0.004 (0.00)
Age (months)	-0.004** (0.00)	-0.007*** (0.00)	-0.008*** (0.00)	0.002*** (0.00)	0.002*** (0.00)
Female (dummy)	0.107 (0.13)	0.082 (0.15)	0.130 (0.15)	-0.022 (0.05)	-0.028 (0.05)
Household expenditure (1000 KSh per AE and month)	0.001 (0.01)	0.029* (0.02)	0.024 (0.02)	-0.013** (0.01)	-0.013** (0.01)
Education of person responsible for food (years)	0.027 (0.02)	0.002 (0.03)	0.003 (0.03)	-0.000 (0.01)	0.000 (0.01)
Married household head (dummy)	-0.115 (0.16)	0.138 (0.20)	0.181 (0.20)	-0.073 (0.05)	-0.081 (0.05)
Malaria or respiratory infection (dummy)		-0.440* (0.26)	-0.430* (0.24)	0.038 (0.09)	0.038 (0.08)
Height of female adult (cm)		0.057*** (0.02)	0.057*** (0.02)	-0.014*** (0.00)	-0.014*** (0.00)
Age of female adult when the child was born (years)		0.025** (0.01)	0.025** (0.01)	-0.000 (0.00)	-0.000 (0.00)
Household treats drinking water (dummy)		0.357** (0.15)	0.345** (0.15)	-0.066 (0.05)	-0.063 (0.05)
Distance to nearest health care centre (log of km)		-0.040 (0.07)	0.025 (0.07)	0.047* (0.03)	0.042 (0.03)
Age of female adult (years)	0.014* (0.01)				
Physical education at school (hours per week)	-0.024 (0.03)				
Leisure-time physical activity (hours per week)	-0.004 (0.01)				
Distance to nearest district hospital (log of km)	0.011 (0.06)				
Constant	-0.607 (0.45)	-10.760*** (2.57)	-10.715*** (2.54)		
Number of observations	216	216	216	216	216
Chi-squared test statistic	169.347***	211.088***	--	156.787***	336.572***

*, **,***, statistically significant at the 10%, 5%, and 1% level, respectively. Marginal effects are shown with robust standard errors in parentheses. Estimates are based on instrumental variable models with the supermarket purchase variables instrumented. For the last two table columns (stunted), instrumental variable probit models were used. First-stage regression results are shown in Appendix A3 (Table A3.4). BAZ, BMI-for-age Z-score; HAZ, height-for-age Z-score; KSh, Kenyan shillings; AE, adult equivalent. **Source**: Own calculation.

Control variables for the child/adolescent models were chosen based on the broad nutrition and health literature (Asfaw, 2011; Black *et al.*, 2013; Jones-Smith *et al.*, 2012; Kanter and Caballero, 2012; Lear *et al.*, 2013; Roemling and Qaim, 2013; Simon *et al.*, 2014). Factors that contribute to overweight and obesity may be somewhat different from factors that contribute to undernutrition, which is why model specifications in Table 3.3 are not uniform. Most of the control variables show the expected signs. Household expenditure, height and age of the mother, and treated drinking water increase HAZ and thus reduce child undernutrition, while recent episodes of infectious diseases have a significantly negative effect on HAZ.

3.3.2 Impact Pathways

We have shown that buying in supermarkets increases BMI and the probability of overweight and obesity among adults. Now we explore possible impact pathways. Estimation results from the causal chain model for adults are summarized in Table 3.4. The results confirm the hypothesis that total calorie consumption and the share of calories from processed foods both play a significant role. An increase in the share of supermarket purchases by one percentage point entails a calorie consumption increase of 15 kcal per day, and an increase in the share of calories from processed foods of 0.33 percentage points. Furthermore, both variables significantly increase adult BMI.

Table 3.4: Impact pathways of supermarket purchases on adult BMI

Pathway	Marginal effect (standard error)
Effect on BMI from	
Calorie consumption per day (kcal)	0.002*** (0.00)
Share of calories from processed foods (%)	0.118*** (0.04)
Effect of supermarket purchase share (%) on calorie consumption per day (kcal)	15.443* (8.53)
Effect of supermarket purchase share (%) on share of calorie from processed food (%)	0.330*** (0.11)
Number of observations	615
Chi-squared test statistic	130.044***

*, ***, statistically significant at the 10% and 1% level, respectively. Estimates are based on causal chain model, full results of which are shown in the Appendix (Table A3.6). BMI, body mass index.
Source: Own calculation.

For children and adolescents, supermarkets do not seem to increase overweight and obesity, but we found that supermarket purchases contribute to reduced undernutrition in terms of higher HAZ. Like overweight and obesity, undernutrition is determined by the quantity and types of foods consumed, among other factors. Hence, we estimate a causal chain model similar to the one used for adults, but with child/adolescent HAZ as nutritional outcome variable. The main results are shown in Table 3.5. While the effect of supermarket purchases on calorie consumption is positive, it is not statistically significant. Yet, supermarket purchases have a significantly positive effect on calories from processed foods, indicating changes in dietary composition. An increase in the share of supermarket purchases by one percentage point increases the share of calories from processed foods by 0.45 percentage points. The amount of calories and the share of calories from processed foods both have positive and significant effects on individual HAZ.

Table 3.5: Impact pathways of supermarket purchases on child/adolescent HAZ

Pathway	Marginal effect (standard error)
Effect on HAZ from	
Calorie consumption per day (kcal)	0.001* (0.00)
Share of calories from processed foods (%)	0.025* (0.01)
Effect of supermarket purchase share (%) on calorie consumption per day (kcal)	17.240 (13.25)
Effect of supermarket purchase share (%) on share of calorie from processed food (%)	0.447** (0.18)
Number of observations	216
Chi-squared test statistic	65.561***

*, ***, statistically significant at the 10%, 5%, and 1% level, respectively. Estimates are based on causal chain model, full results of which are shown in Appendix A3 (Table A3.7). HAZ, height-for-age Z-score. **Source**: Own calculation.

3.4 Discussion and Conclusion

Our results show that buying in supermarkets increases BMI and the probability of being overweight or obese among adults in small towns in Kenya. These effects hold when we control for other factors that influence BMI and that may be correlated with supermarket purchases, such as household expenditure and physical activity. This finding is consistent with the scant literature on the relationship between supermarkets and consumer nutritional outcomes for adults in developing countries (Asfaw, 2008). For children, to the best of our knowledge, the relationship between supermarket purchases and nutritional outcomes has not been analysed previously. Our data suggest that buying in supermarkets does not contribute to higher overweight and obesity in children and adolescents. Rather, supermarket purchases reduce child undernutrition through a positive impact on HAZ. Supermarkets also reduce the probability of severe stunting.

Supermarket purchases increase adult BMI through two pathways, namely through more calories consumed and through a higher share of calories from processed foods, which is consistent with the results we presented in chapter 2. The impact pathways for child HAZ seem to be similar, although the effect of supermarkets on total calorie consumption is not statistically significant, possibly due to the smaller sample size. At this point it is useful to briefly recall why supermarkets may cause consumers to eat more and change their dietary composition (see chapter 2.2. for more details). While some of the supermarkets in larger Kenyan cities offer fresh products, such as fruits and vegetables or whole grains, this is not yet the case for supermarkets in smaller towns, as analysed here. Hence, small town consumers who buy a lot in supermarkets will automatically increase the share of processed foods in their diet. When asked why they buy in supermarkets, 65% of the respondents in our sample reported lower food prices as the most important reason (see Figure A3.1 in the Appendix). Whether prices in supermarkets are really lower may be difficult to judge for consumers, due to differences in exact product choices and packaging sizes. But the perception of lower prices may suffice to increase consumption. Also, as we have established in chapter 2, supermarket purchases indeed have significantly negative effects on prices paid per calorie.

The fact that the same mechanisms lead to nutritional outcomes that differ by age cohort is interesting and underlines the need for disaggregated analysis. For adults who have already reached their final body height, increasing calorie consumption can ceteris paribus only lead to higher BMI. Waistlines will increase especially when levels of physical activity are low, as is the case with more sedentary lifestyles. For children and adolescents, the situation is different, because higher calorie consumption can also lead to gains in body height, as observed in our study. Moreover, children and adolescents in our sample are more physically active than adults (see Tables A3.1 and A3.2 in the Appendix). Concerning effects on body height, it should be mentioned that, beyond calories, certain micronutrients also play a crucial role for child growth (Martorell *et al.*, 1994). While not analysed here, dietary changes through buying in supermarkets may potentially be associated with higher micronutrient consumption, for instance, if they increase dietary diversity and contribute to a well-balanced diet.

Clearly, the impact of expanding supermarkets in developing countries will much depend on people's initial nutritional status. In Kenya, we observe relatively high rates of overweight among adults, while stunting is a more widespread problem among children and adolescents. This dual burden of malnutrition is common in many developing countries (Doak *et al.*, 2005; Roemling and Qaim, 2013), implying that some of our results may also be of relevance for other settings. Reducing child stunting and controlling the global obesity pandemic are both important public health objectives.

Our results suggest that the supermarket revolution in developing countries is not just a business response to the rapid nutrition transition, but that supermarkets also contribute to changing food consumption habits and nutritional outcomes. Yet the types of outcomes can be diverse, depending on many factors. Hence, simple conclusions on whether supermarkets are good or bad for nutrition and health are not justified. It should also be noted that impacts may change over time. Rates of child undernutrition will decrease and childhood obesity may increase when household incomes rise. Furthermore, supermarkets may gradually offer a greater variety of products, including more fresh and healthy foods, which can contribute to nutritional improvements, as shown in the US (Lear *et al.*, 2013; Michimi and Wimberly, 2010). Our analysis should not be seen as the final judgment about supermarket nutritional impacts in developing countries, but as early evidence that can contribute to a better understanding of this complex and emerging theme. To reduce negative health outcomes, the nutrition transition should be accompanied by broader, yet target group specific nutrition education and awareness campaigns. In some cases, specific regulations for supermarkets and other actors in the food industry may be an option.

3.5 Appendix

Table A3.1: Descriptive statistics for variables used in adult nutrition models

Variable	Mean	Standard deviation
BMI	24.893	4.845
Overweight (dummy)	0.270	0.444
Obese (dummy)	0.143	0.350
Underweight (dummy)	0.039	0.194
Calorie consumption per day (kcal)	3350.776	1327.238
Share of calories from processed foods (%)	48.51	16.21
Food expenditure (KSh per AE and month)	6099.922	4628.725
Buys in supermarket (dummy)	0.580	0.494
Supermarket purchase share (% of total food expenditure)	9.671	11.596
Distance to nearest supermarket (km)	15.105	20.478
Age (years)	34.763	11.905
Female (dummy)	0.641	0.480
Heavy work (dummy)	0.460	0.499
Leisure-time physical activity (hours per week)	8.806	7.221
Household expenditure (KSh per AE and month)	12005.460	10041.010
Education of person responsible for food (years)	9.724	3.778
Household size (AE)	2.642	1.233
Married household head (dummy)	0.735	0.442
Household does farming (dummy)	0.654	0.476
Household owns television (dummy)	0.598	0.491
Distance to nearest district hospital (km)	10.426	7.171
Number of observations	615	

BMI, body mass index; KSh, Kenyan shillings; AE, adult equivalent. **Source**: Own calculation.

Table A3.2: Descriptive statistics for variables used in child/adolescent nutrition models

Variable	Mean	Standard deviation
Height-for-age Z-scores (HAZ)	-1.049	1.296
Stunted (dummy)	0.208	0.407
BMI-for-age Z-scores (BAZ)	-0.308	1.000
Overweight/obese (dummy)	0.097	0.297
Calorie consumption per day (kcal)	2423.15	1214.68
Share of calories from processed foods (%)	48.22	17.29
Buys in supermarket (dummy)	0.509	0.501
Supermarket purchase share (% of total food expenditure)	8.480	11.204
Distance to nearest supermarket (km)	15.489	19.763
Age (months)	115.755	43.717
Female (dummy)	0.481	0.501
Physical education at school (hours per week)	1.473	2.076
Leisure-time physical activity (hours per week)	16.589	9.504
Malaria or respiratory infection during last month (dummy)	0.093	0.291
Height of female adult measured in household (cm)	158.126	5.845
Age of female adult measured in the household (years)	35.213	10.513
Age of female adult when the child was born (years)	25.567	9.791
Female adult is the mother (dummy)	0.833	0.374
Household treats drinking water (dummy)	0.477	0.501
Household expenditure (KSh per AE and month)	9223.462	6193.470
Education of person responsible for food (years)	8.769	3.833
Household size (AE)	3.228	1.196
Married household head (dummy)	0.75	0.434
Household does farming (dummy)	0.699	0.460
Household owns television (dummy)	0.537	0.500
Distance to nearest district hospital (km)	9.747	7.050
Distance to nearest health care centre (km)	2.087	2.159
Number of observations	216	

KSh, Kenyan shillings; AE, adult equivalent. **Source**: Own calculation.

Table A3.3: First-stage results of instrumental variable models for impact of supermarket purchases on adult nutrition

Explanatory variables	Buys in supermarket (dummy)	Supermarket purchase share (%)
Distance to nearest supermarket (log of km)	-0.502***	-2.272***
	(0.04)	(0.19)
Age (years)	-0.021**	-0.097**
	(0.01)	(0.04)
Female (dummy)	-0.115	-1.249
	(0.43)	(2.19)
Female-age interaction	0.007	0.033
	(0.01)	(0.05)
Heavy work (dummy)	-0.177	-0.249
	(0.14)	(0.72)
Leisure-time physical activity (hours per week)	0.016*	-0.008
	(0.01)	(0.05)
Household expenditure (1000 KSh per AE and month)	0.072***	0.183***
	(0.01)	(0.04)
Education of person responsible for food (years)	0.048**	0.411***
	(0.02)	(0.11)
Married household head (dummy)	0.676***	0.788
	(0.17)	(0.96)
Distance to nearest district hospital (log of km)	0.004	-1.363***
	(0.05)	(0.33)
Constant	-0.401	11.065***
	(0.44)	(2.34)
Number of observations	615	615
Chi-squared test statistic	242.159***	
F statistic		44.73***

*, **,***, statistically significant at the 10%, 5%, and 1% level, respectively. Coefficient estimates are shown with robust standard errors in parentheses. KSh, Kenyan shillings; AE, adult equivalent. **Source**: Own calculation.

Table A3.4: First-stage results of instrumental variable models for impact of supermarket purchases on child/adolescent nutrition

Explanatory variables	Buys in supermarket (dummy)		Supermarket purchase share (%)
	BAZ model	HAZ/stunted models	
Distance to nearest supermarket (log of km)	-0.547*** (0.07)	-0.567*** (0.07)	-3.092*** (0.28)
Age (months)	-0.007** (0.00)	-0.009*** (0.00)	-0.017 (0.01)
Female (dummy)	0.073 (0.24)	0.044 (0.24)	-1.241 (1.16)
Household expenditure (1000 KSh per AE and month)	0.092*** (0.03)	0.080*** (0.03)	0.347*** (0.11)
Education of person responsible for food (years)	0.024 (0.04)	0.028 (0.04)	0.169 (0.21)
Married household head (dummy)	0.206 (0.28)	0.163 (0.28)	-0.362 (1.49)
Malaria or respiratory infection (dummy)		0.144 (0.40)	-0.675 (2.15)
Height of female adult (cm)		-0.010 (0.02)	-0.024 (0.08)
Age of female adult when child was born (years)		-0.007 (0.01)	0.015 (0.06)
Household treats drinking water (dummy)		0.281 (0.24)	1.464 (1.16)
Distance to nearest health care centre (log of km)		0.052 (0.13)	-1.812** (0.71)
Physical education at school (hours per week)	0.036 (0.05)		
Leisure-time physical activity (hours per week)	0.018 (0.01)		
Age of female adult (years)	-0.006 (0.01)		
Distance to nearest district hospital (log of km)	-0.029 (0.10)		
Constant	0.033 (0.79)	2.219 (3.02)	13.296 (12.68)
Observations	216	216	216
Chi-squared test statistic	96.365***	111.231***	
F statistic			22.2***

*, **,***, statistically significant at the 10%, 5%, and 1% level, respectively. Coefficient estimates are shown with robust standard errors in parentheses. BAZ, BMI-for-age Z-score; HAZ, height-for-age Z-score; KSh, Kenyan shillings; AE, adult equivalent. **Source**: Own calculation.

Table A3.5: Impact of supermarket purchases on child/adolescent mild and severe stunting

	Mildly stunted (HAZ < -1 sd)		Severely stunted (HAZ < -3 sd)	
Buys in supermarket (dummy)	-0.131 (0.09)		-0.231*** (0.05)	
Supermarket purchase share (%)		-0.009** (0.00)		-0.016*** (0.00)
Age (months)	0.003*** (0.00)	0.003*** (0.00)	0.001** (0.00)	0.001*** (0.00)
Female (dummy)	-0.021 (0.06)	-0.032 (0.06)	-0.004 (0.03)	-0.025 (0.03)
Household expenditure (1000 KSh per AE and month)	-0.007 (0.01)	-0.005 (0.01)	0.003 (0.00)	0.004 (0.00)
Education of person responsible for food (years)	-0.006 (0.01)	-0.004 (0.01)	-0.012*** (0.00)	-0.012* (0.01)
Married household head (dummy)	-0.087 (0.07)	-0.099 (0.07)	-0.033 (0.03)	-0.063* (0.03)
Malaria or respiratory infection (dummy)	0.097 (0.10)	0.095 (0.10)	0.177*** (0.04)	0.185*** (0.05)
Height of female adult (cm)	-0.019*** (0.00)	-0.019*** (0.00)	-0.005 (0.00)	-0.005 (0.00)
Age of female when the child was born (years)	-0.010*** (0.00)	-0.010*** (0.00)	-0.003* (0.00)	-0.003* (0.00)
Household treats drinking water	-0.105* (0.06)	-0.096* (0.06)	-0.017 (0.04)	-0.009 (0.03)
Distance to nearest health care centre (log of km)	-0.052* (0.03)	-0.065** (0.03)	0.048** (0.02)	0.037* (0.02)
Number of observations	216	216	216	216

*, **,***, statistically significant at the 10%, 5%, and 1% level, respectively. Marginal effects are shown with robust standard errors in parentheses. Estimates are based on instrumental variable probit models with the supermarket purchase variables instrumented. HAZ, height-for-age Z-score; KSh, Kenyan shillings; AE, adult equivalent.
Source: Own calculation.

Table A3.6: Causal chain model to explain the impact of supermarket purchases on adult BMI

Explanatory variables	BMI (kg/m²)	Calorie consumption per day (kcal)	Share of calories from processed foods (%)	Supermarket purchase share (%)
Calorie consumption per day (kcal)	0.002*** (0.00)			
Share of calories from processed foods (%)	0.118*** (0.04)			
Age (years)	0.112*** (0.02)			
Female (dummy)	1.344 (1.23)			
Female-age interaction	0.040 (0.03)			
Heavy work (dummy)	-0.672* (0.37)			
Leisure-time physical activity (hours per week)	-0.041* (0.02)			
Supermarket purchase share (%)		15.443* (8.53)	0.330*** (0.11)	
Household expenditure (1000 KSh per AE and month)		39.060*** (5.78)	-0.241*** (0.07)	0.144*** (0.04)
Education of person responsible for food (years)		-12.780 (15.06)	0.755*** (0.19)	0.448*** (0.11)
Household size (AE)		-30.612 (41.79)	-0.990* (0.52)	
Household does farming (dummy)		179.862* (108.04)	-4.230*** (1.37)	-2.522*** (0.79)
Household owns television (dummy)			3.075** (1.29)	2.274*** (0.80)
Distance to nearest supermarket (log of km)				-2.564*** (0.18)
Constant	6.996** (2.88)	2820.068*** (199.77)	44.416*** (2.48)	6.420*** (1.22)
Number of observations	615			
Chi-squared	130.044***			

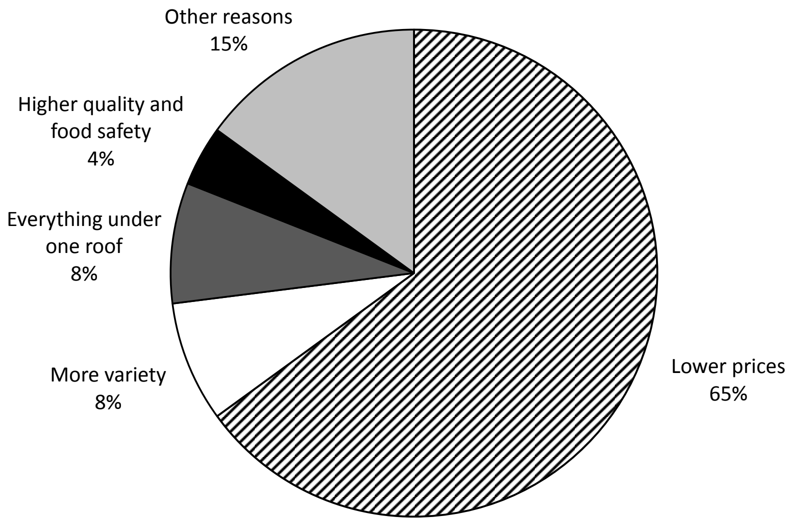
*, **,***, statistically significant at the 10%, 5%, and 1%, level respectively. Coefficient estimates are shown with standard errors in parentheses. The system of simultaneous equations was estimated with three-stage least squares. BMI, body mass index; KSh, Kenyan shillings; AE, adult equivalent. **Source**: Own calculation.

Table A3.7: Causal chain model to explain the impact of supermarket purchases on child/adolescent HAZ

Explanatory variables	HAZ	Calorie consumption per day (kcal)	Share of calories from processed foods (%)	Supermarket purchase share (%)
Calorie consumption per day (kcal)	0.001* (0.00)			
Share of calories from processed foods (%)	0.025* (0.01)			
Age (months)	-0.009*** (0.00)			
Female (dummy)	0.105 (0.15)			
Malaria or respiratory infection (dummy)	-0.436* (0.26)			
Height of female adult (cm)	0.059*** (0.01)			
Age of female adult when the child was born (years)	0.019* (0.01)			
Household treats drinking water (dummy)	0.364** (0.16)			
Supermarket purchase share (%)		17.240 (13.25)	0.447** (0.18)	
Household expenditure (1000 KSh per AE and month)		49.278*** (16.12)	-0.358 (0.23)	0.331*** (0.11)
Education of person responsible for food (years)		-23.578 (30.37)	-2.356** (0.96)	0.201 (0.18)
Household size (AE)		-41.883 (69.42)	0.876*** (0.33)	
Household does farming (dummy)		-41.328 (174.76)	-6.007** (2.42)	-1.456 (1.28)
Education of household head (years)		-32.853 (27.60)		
Age of female adult (years)		3.467 (7.89)		
Household owns television (dummy)			1.918 (2.17)	0.566 (1.28)
Distance to nearest supermarket (log of km)				-2.830*** (0.30)
Constant	-12.428*** (2.40)	2383.898*** (449.13)	50.831*** (4.52)	7.586*** (1.84)
Number of observations	216			
Chi-squared	65.561***			

*, **,***, statistically significant at the 10%, 5%, and 1%, level respectively. Coefficient estimates are shown with standard errors in parentheses. The system of simultaneous equations was estimated with three-stage least squares. HAZ, height-for-age Z-score; KSh, Kenyan shillings; AE, adult equivalent. **Source**: Own calculation.

Figure A3.1: Most important reason for shopping in supermarket.



Based on household survey responses. Only households that buy in a supermarket are included.
Source: Own calculation.

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

Abstract

Following the 2007/08 and subsequent world food price-hikes, a growing number of 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 tool to guide the planning and targeting of mitigation programmes. In this chapter we examine the extent to which differences in simulation methods result in different predicted outcomes and thus in potential targeting efforts. We build on three simulation studies based on 2004/05 LSMS data from Malawi. We find overlaps in simulation outcomes to be context specific and to depend on scenarios and the time horizon under consideration. In the context of Malawi, for a relevant set of price changes, mean outcomes at district levels are fairly robust to underlying methodologies.

4.1 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.[21]

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

[21] 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.

4.2 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[22] 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.

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[22] 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.

4.3 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 4.1) 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.

4.3.1 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 4.1, 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 4.1, 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.

4.3.2 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.

4.3.3 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[23]. 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.

4.3.4 Hypotheses

In accordance with HK, we assume the scenario of directly translating price into consumption changes to provide an upper bound estimate (Figure 4.1, 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 4.1, HK*inc. equiv.*) is conceptually closely related to the consumption side of the CV (Figure 4.1, 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 4.1: 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.

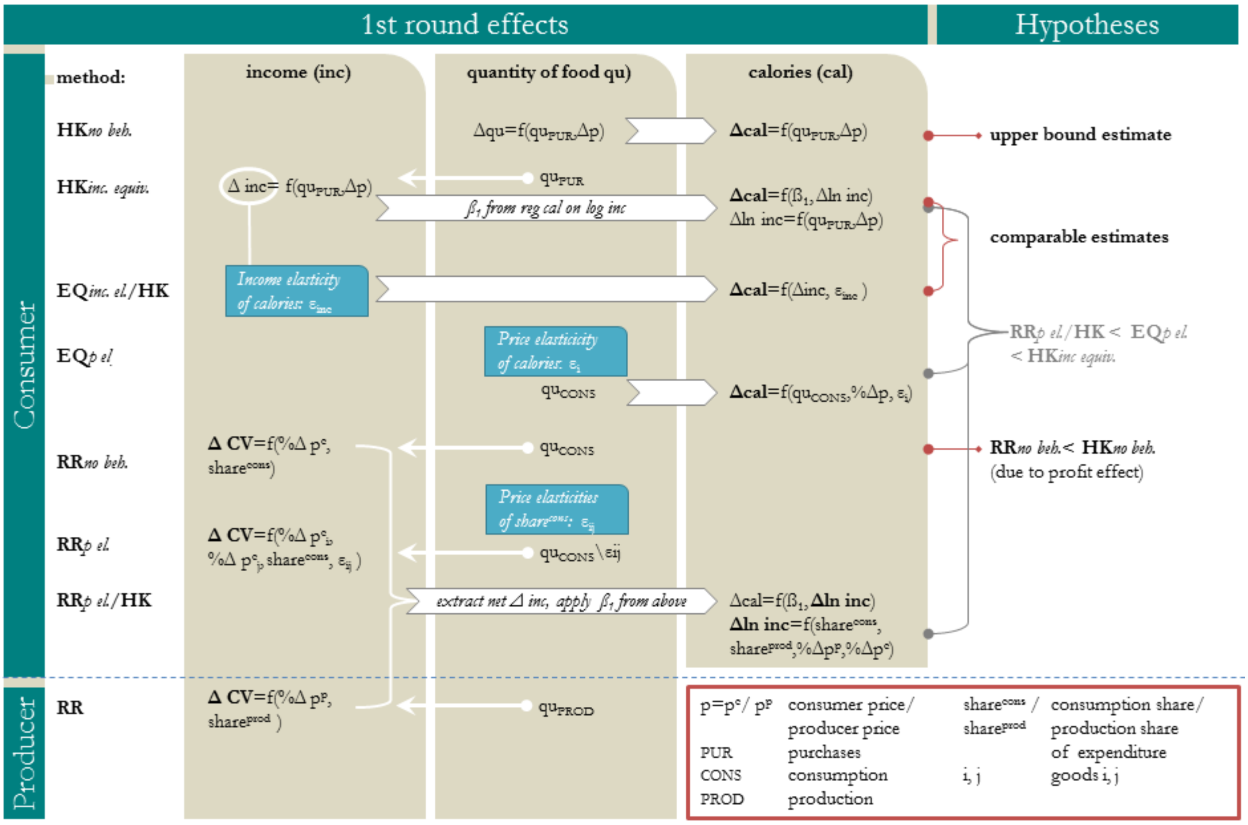
Predictions get more complex when behavioural changes are considered in the form of price elasticities of demand. Both EQ as well as RR derive such elasticities (in terms of calorie and expenditures shares, and just expenditures shares respectively). While the underlying methodologies differ (e.g. different 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

[23] 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 4.1, RR). The overall change in CV is the sum of both consumer and producer effects. When behavioural changes are disregarded (Figure 4.1, 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 4.1, 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 4.1, hypothesis in grey writing).[24]

Figure 4.1: 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.

[24] 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.

Even allowing for regionally different price changes is expected to increase prediction divergence since the methodologies chosen behave differently to smaller/larger price changes.

4.4 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, 2005a).

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[25], 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, and further data cleaning was kept to a minimum. Table 4.1 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 4.1: 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

[25] The unit we use for measuring calories is kilocalories (kcal).

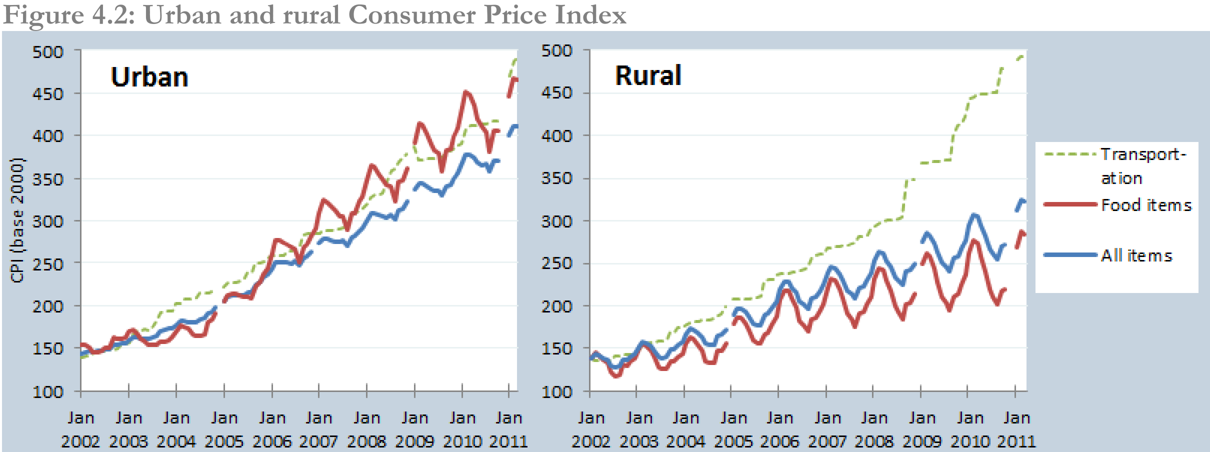
In addition to using the same dataset, for re-estimating the demand system and elasticities used by RR, we harmonise the classification of food groups with those used by EQ and use 22 food groups that fall in the broader categories of staple food, pulses, fresh fruits and vegetables, animal products and meal complements (see Appendix Table A4.1). 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.

4.4.1 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 4.2 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.

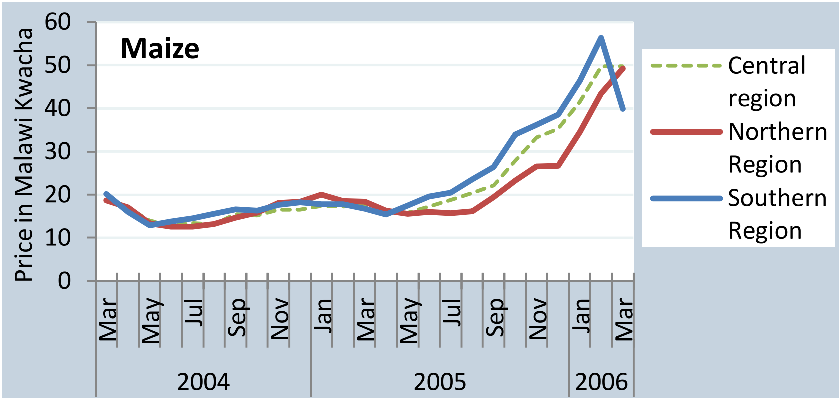
For our analysis, rather than using world food price movements and making assumption about the pass through from world to local markets, we use two main sets of price scenarios: First, an arbitrary general and maize price increase of 10%, which we chose because it is in the price range considered relevant 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 4.3 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 4.2: 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 4.3: Regional monthly maize prices from March 2004 to March 2006



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

4.4.2 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:

$$\begin{aligned} &calorie\ deficiency\ prevalence_i \\ &\quad = \beta_0 + \beta_i scenario + \boldsymbol{\gamma_i method} + \boldsymbol{\varepsilon_i scenario} * \boldsymbol{method} + \boldsymbol{\theta_i X_i} \\ &\quad + \boldsymbol{\vartheta_i district} + u_i \end{aligned} \tag{4.1}$$

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:

$$Calorie\ deficient_{jk} = \alpha_0 + \boldsymbol{\beta_j X} + \boldsymbol{\varepsilon_j district} + u_j \tag{4.2}$$

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.

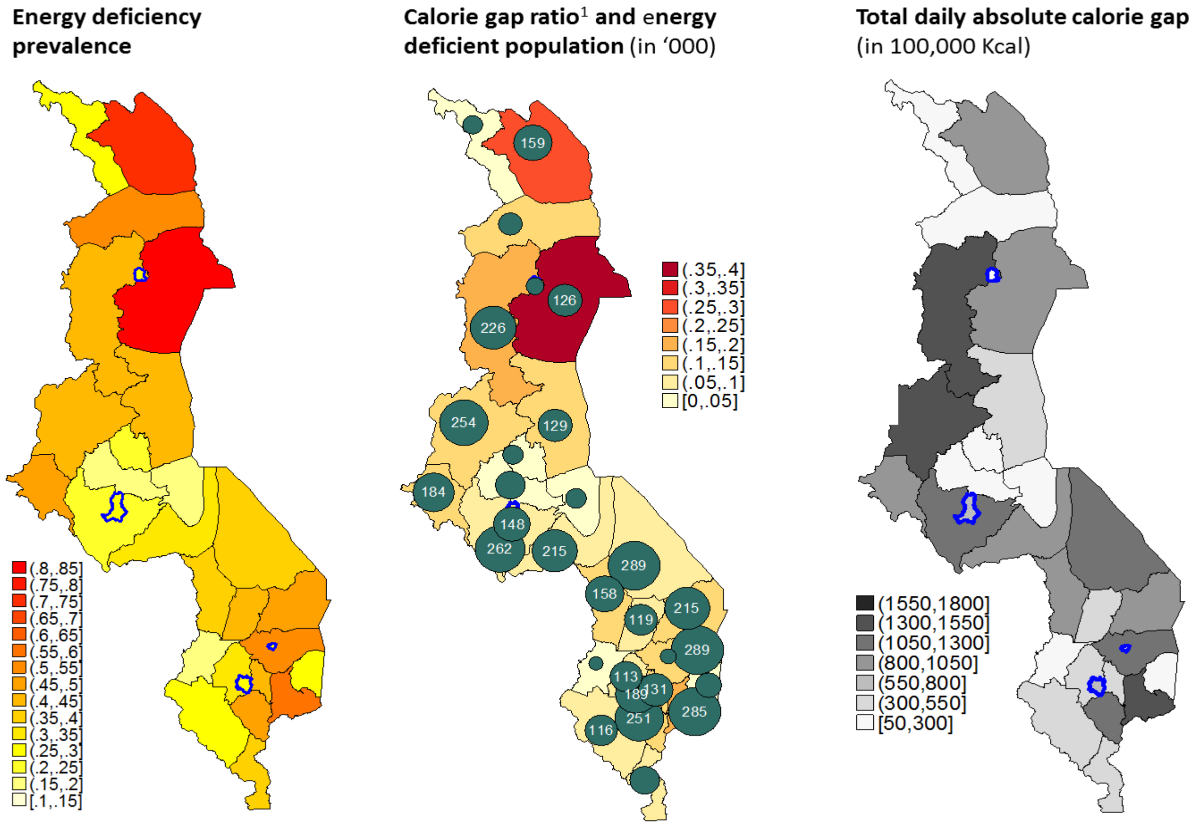
4.5 Empirical Results

4.5.1 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 4.4 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 4.4: 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.

4.5.2 Simulation of Price Shocks – District Level

Figure 4.5 and Figure 4.6 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 4.1*)* 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 A4.2), 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[26].

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 4.2): 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 4.7 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%.

[26] 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 4.5: Prediction calorie deficiency ratio - 10% general price increase

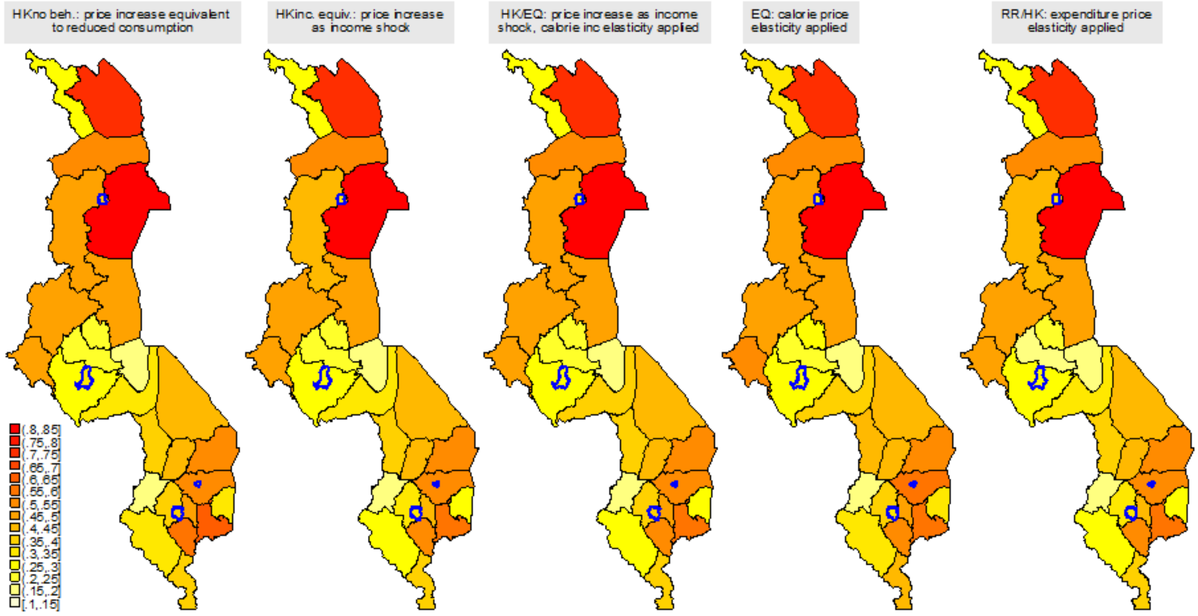
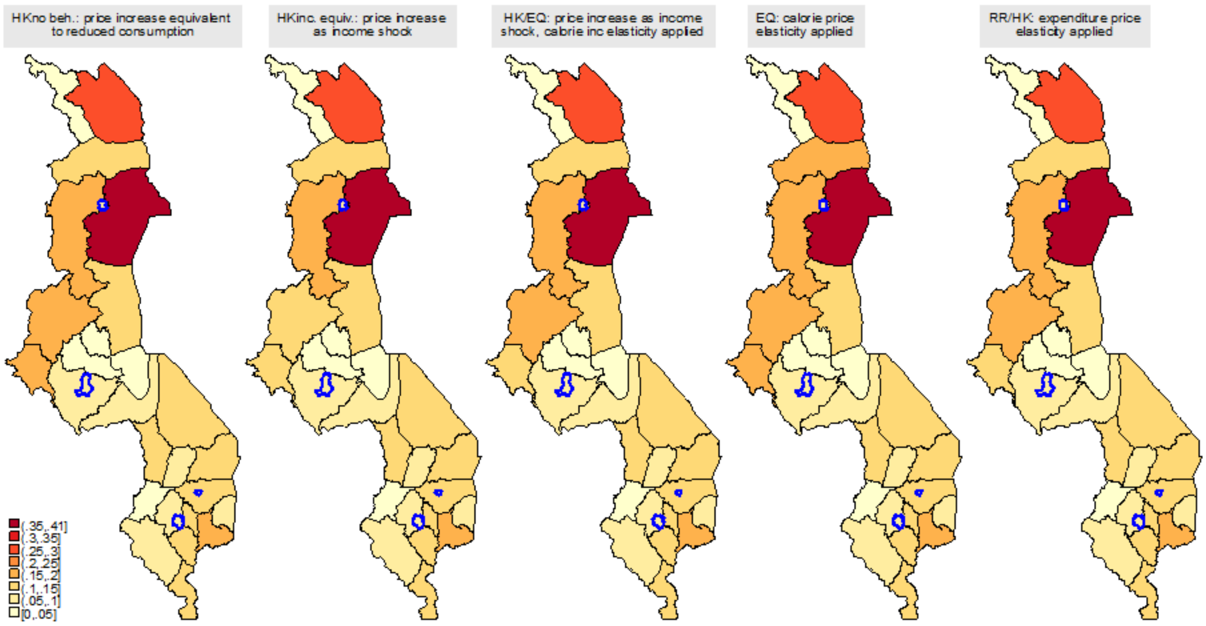


Figure 4.6: Prediction energy gap ratio – 10% general price increase



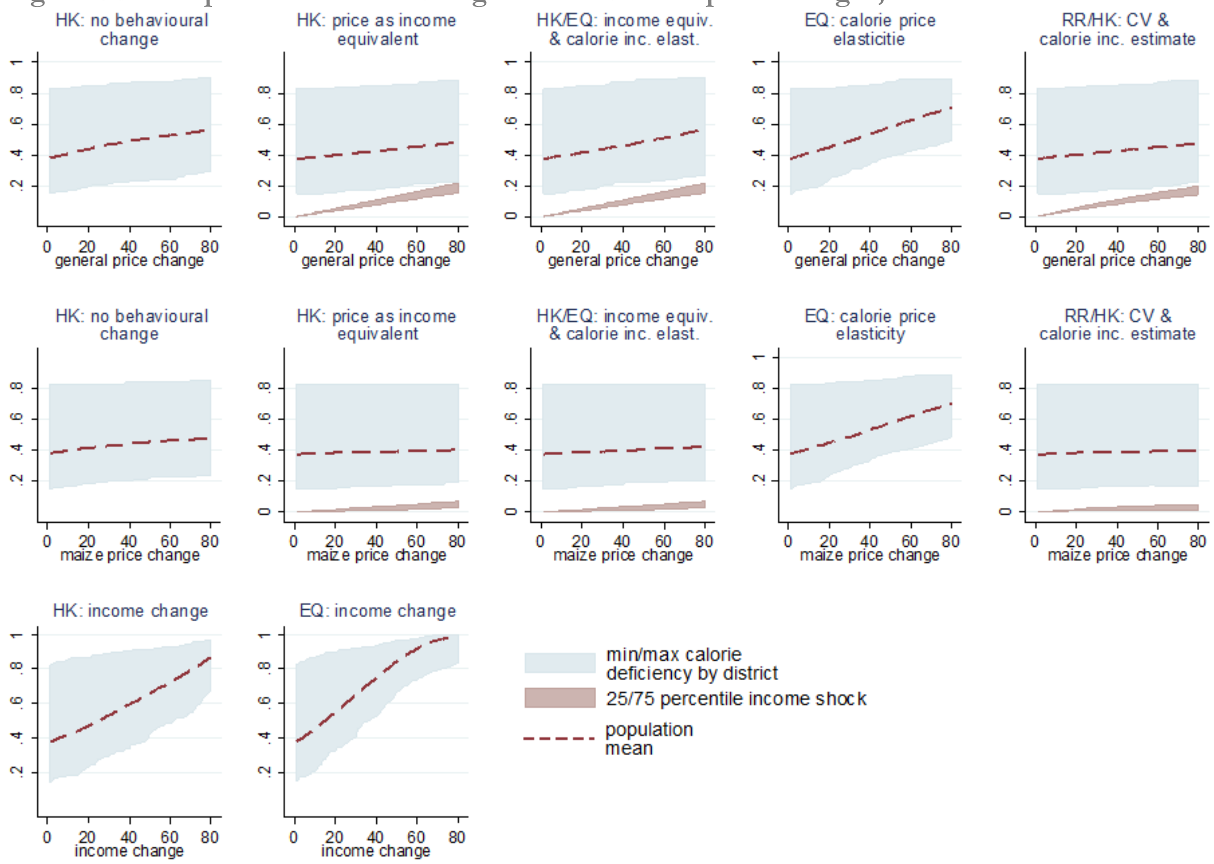
Individual sampling weights used. Urban districts/ cities in blue. **Source:** Own calculation.

Table 4.2: 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 4.7: 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 4.4.1. 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 A4.1 and Figure A4.2). 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 4.4.2, equation (4.1) in the Appendix (see Table A4.2). 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 4.7 (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.

4.5.3 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 4.4.2, equation (4.2). Figure A4.3 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 A4.3 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 A4.4 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%.

4.6 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[27]. 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).

[27] 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.

4.7 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.

4.8 Appendix

Table A4.1: 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-pea/soybean	201	0.514	0.018	-0.005	110	0.110	0.005	-0.004
	(215)	(0.490)	(0.038)	(0.040)	(116)	(0.312)	(0.015)	(0.014)
Peanut/bambara groundnut	223	0.544	0.027	-0.003	89	0.059	0.010	-0.008
	(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 vegetables	11	0.550	0.044	-0.012	14	0.141	0.027	-0.019
	(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 products	37	0.138	0.004	-0.003	46	0.006	0.013	-0.013
	(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 A4.1: Prediction general food price increase – 5 month regional price changes

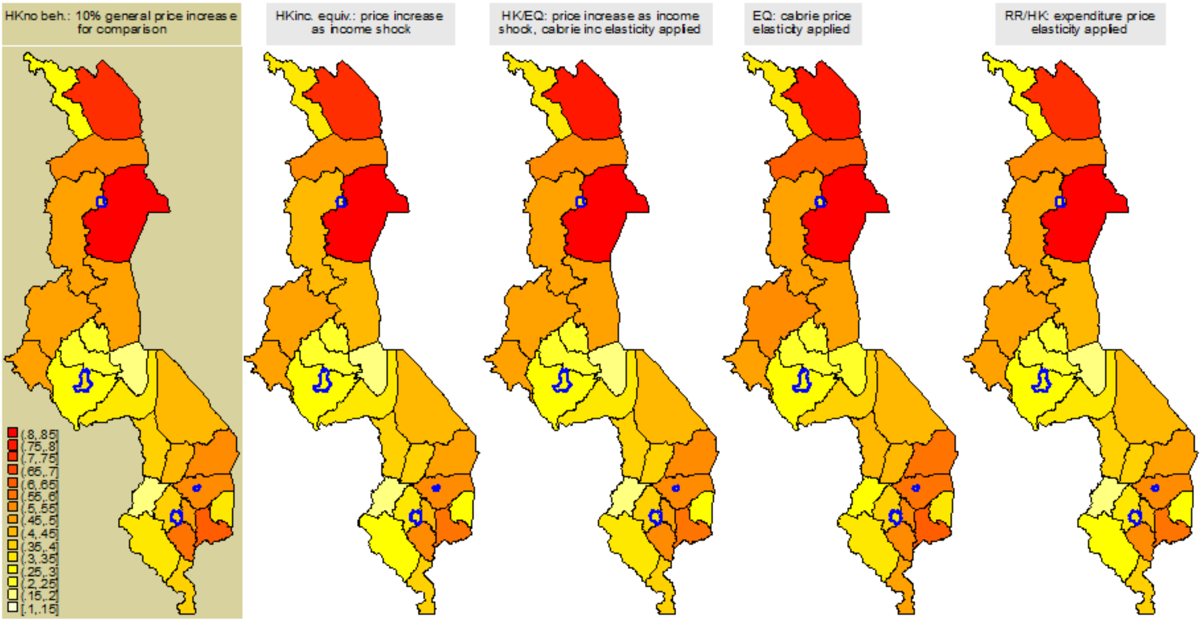
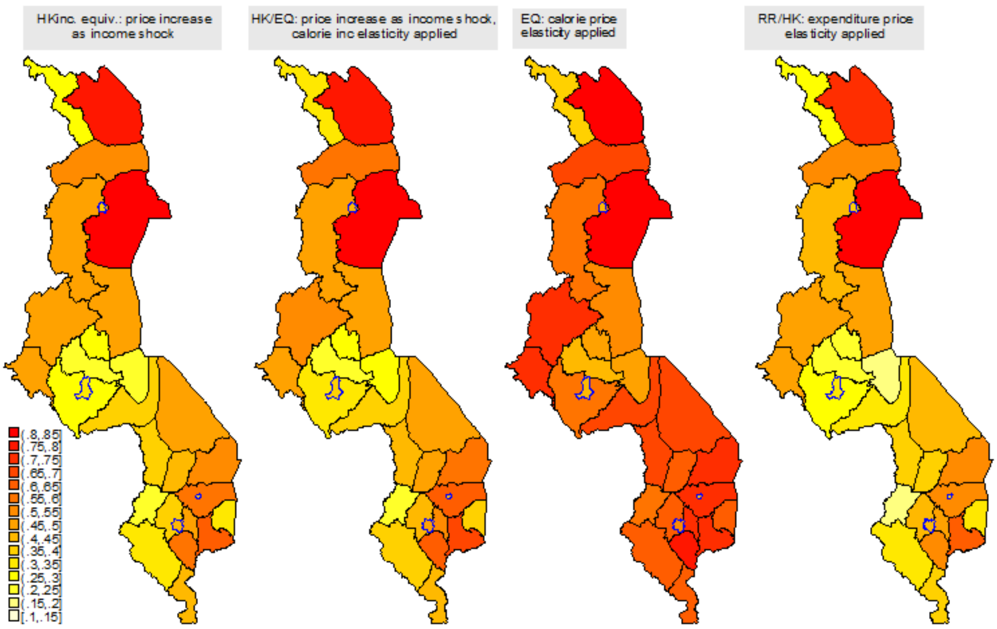


Figure A4.2: Prediction general food price increase – 12 month regional price changes



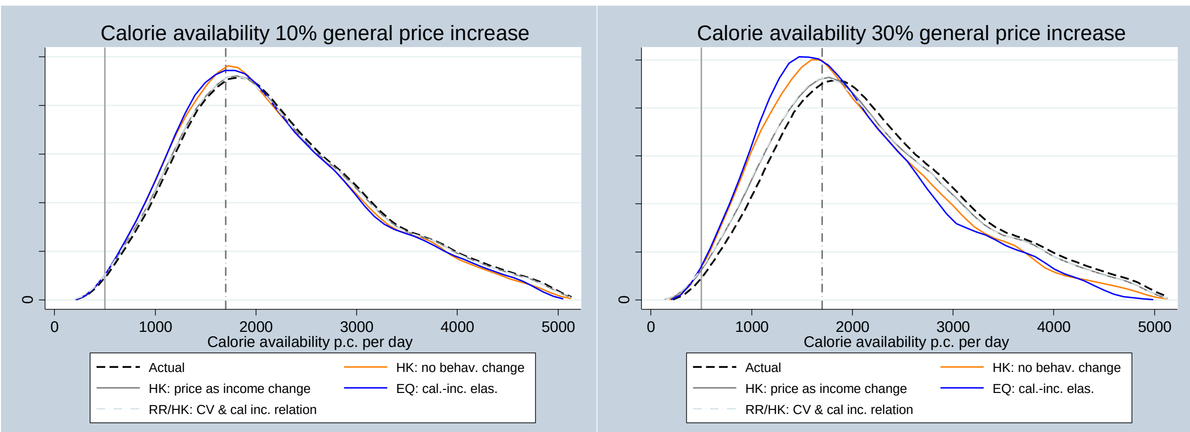
Individual sampling weights used. Urban districts/ cities in blue. **Source:** Own calculation.

Table A4.2: 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 A4.3: 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 A4.3: 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 A4.4: 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	-0.0001***	-0.0000**	-0.0000***	-0.0000**	-0.0000**	-0.0001***	-0.0000**	-0.0001***	-0.0000**
HH head	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nb children (0-	0.0242***	0.0248***	0.0250***	0.0231***	0.0247***	0.0229***	0.0262***	0.0226***	0.0253***
14)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Nb male adults	0.0709***	0.0739***	0.0720***	0.0746***	0.0721***	0.0724***	0.0714***	0.0708***	0.0716***
(15-64)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Nb female adults	0.0246***	0.0240***	0.0220***	0.0205***	0.0204***	0.0292***	0.0242***	0.0274***	0.0240***
(15-64)	(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	-0.0093	-0.0026	-0.0066	-0.0061	-0.0080	0.0021	-0.0047	0.0110	-0.0072
improved roof	(0.014)	(0.013)	(0.013)	(0.014)	(0.013)	(0.015)	(0.014)	(0.014)	(0.014)
HH has	0.0517***	0.0576***	0.0468***	0.0464***	0.0480***	0.0677***	0.0581***	0.0510***	0.0628***
improved floor	(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	-0.0349***	-0.0562***	-0.0398***	-0.0374***	-0.0393***	-0.0838***	-0.0563***	-0.0290**	-0.0571***
net buyer'	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
HH is 'vulnerable	-0.0201*	0.0080	-0.0115	-0.0258**	-0.0128	0.0884***	-0.0033	-0.0293**	-0.0063
net buyer'	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
Log of daily HH	-0.3208***	-0.3414***	-0.3284***	-0.3509***	-0.3315***	-0.3572***	-0.3434***	-0.3985***	-0.3493***
exp.	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
HH grows	-0.0085	-0.0109	-0.0108	-0.0172	-0.0137	-0.0134	-0.0136	-0.0124	-0.0147
tobacco	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
HH head:	-0.0156	-0.0055	-0.0118	-0.0045	-0.0106	-0.0044	-0.0066	-0.0109	-0.0074
primary educ.	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
HH head:	-0.0101	0.0010	-0.0054	0.0036	-0.0038	0.0091	-0.0035	-0.0008	-0.0023
second. or higher	(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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