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Supermarket Shopping and Nutritional Outcomes: A Panel Data Analysis for Urban Kenya

Kathrin M. Demmler [a], Olivier Ecker [b], Matin Qaim [a]

[a] University of Goettingen, Germany
[b] International Food Policy Research Institute (IFPRI), Washington, D.C., USA

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SUMMARY

Overweight and obesity are growing health problems in many developing countries. Rising obesity rates are the result of changes in people's diets and lifestyles. Income growth and urbanization are factors that contribute to these changes. Modernizing food retail environments may also play a certain role. For instance, the rapid spread of supermarkets in many developing countries could affect consumer food choices and thus nutritional outcomes. However, concrete evidence about the effects of supermarkets on consumer diets and nutrition is thin. A few existing studies have analyzed related linkages with cross-sectional survey data. We add to this literature by using panel data from households and individuals in urban Kenya. Employing panel regression models with individual fixed effects and controlling for other factors we show that shopping in supermarkets significantly increases body mass index (BMI). We also analyze impact pathways. Shopping in supermarkets contributes to higher consumption of processed and highly processed foods and lower consumption of unprocessed foods. These results confirm that the retail environment affects people's food choices and nutrition. However, the effects depend on the types of foods offered. Rather than thwarting modernization in the retail sector, policies that incentivize the sale of more healthy foods—such as fruits and vegetables—in supermarkets may be more promising to promote desirable nutritional outcomes.

1. Introduction

Overweight and obesity are growing health problems worldwide. During1980–2013, the global proportion of overweight or obese adults increased from 29% to 37% in men, and from 30% to 38% in women (Ng *et al.*, 2014). Developing countries are also increasingly affected. The rapid rise in people's body mass index (BMI) strongly contributes to various non-communicable diseases (NCDs), such as diabetes, hypertension, and some forms of cancer (NCD Risk Factor Collaboration, 2016). Obesity and NCDs are associated with morbidity and mortality, lost labor productivity, and high healthcare costs (Bommer *et al.*, 2017; Herman, 2013; IFPRI, 2016; Withrow & Alter, 2011; World Economic Forum, 2011).

Rising rates of obesity are caused by income growth, urbanization, and related changes in people's lifestyles and diets. The "nutrition transition" is particularly characterized by higher consumption of processed foods that are dense in sugar, fat, and salt (Popkin, Adair, & Ng, 2012). Changes in the food retail environment may also play a role. In many developing countries, modern supermarkets are spreading rapidly (Reardon, Timmer, Barrett, & Berdegué, 2003). As supermarkets sometimes offer different types of products than traditional markets and shops, such modernization of the retail sector could possibly contribute to negative nutrition and health outcomes (Hawkes, 2008; Popkin, 2014; Qaim, 2017).

Concrete evidence about the effects of supermarket shopping on people's diets in developing countries is thin. Very few studies analyzed related linkages, with mixed results. Tessier *et al.* (2008) showed that supermarket shopping is associated with improved dietary quality in Tunis, Tunisia. However, average living standards in Tunisia are higher than in most other African countries. Moreover, data from a large city, such as Tunis, may not be representative for other regions. Studies with data from Kenya and Guatemala revealed that supermarkets contribute to higher overall energy consumption and a larger share of energy from processed foods (Asfaw, 2008; Kimenju, Rischke, Klasen, & Qaim, 2015; Rischke, Kimenju, Klasen, & Qaim, 2015). The same studies for Kenya and Guatemala also suggested that supermarket shopping increases adult BMI and the likelihood of being overweight or obese. A study with data from Indonesia found no significant association between supermarket shopping and BMI (Umberger, He, Minot, & Toiba, 2015). These existing studies used cross-sectional survey data,

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partly employing instrumental variable (IV) approaches to draw causal inference. However, finding a valid instrument that is correlated with supermarket shopping but uncorrelated with diets and nutrition is very difficult. Hence, causal inferences based on cross-section observational data remain tentative (Bound, Jaeger, & Baker, 1995).

We contribute to this research direction by using panel data and panel regression models for more robust causal inference. The main aim is to get a better understanding of the effects that the spread of supermarkets in developing countries has on consumers' diets and nutrition. In particular, we use data collected in urban Kenya in 2012 and 2015 to analyze the effects of supermarket shopping on adult BMI and dietary composition. Kenya has one of the most prospering supermarket sectors in sub-Saharan Africa (Neven, Odera, Reardon, & Wang, 2009; Rischke *et al.*, 2015). The share of grocery sales through supermarkets is about 10% at national level, but already much higher in large urban centers (Planet Retail., 2016). A rapid growth of supermarkets is also expected in other parts of Africa. Better understanding the nutrition effects of modernizing retail environments can help to design policies aimed at reducing negative health externalities.

2. Food environment and dietary choices

Food choices are determined by various biological, socioeconomic, and psychological factors (Nestle *et al.*, 1998). Food availability, price, type of display, quality, personal income, attitudes, taste, time constraints, and several other factors play a role when people decide on what to eat (Dover & Lambert, 2016; Ventura & Worobey, 2013). Economic development is typically associated with profound changes in people's diets. Income growth, urbanization, technological change, advances in food preservation, and advertising through mass media, all contribute to higher consumption of relatively energy-dense processed foods and beverages. These dietary shifts are often referred to as the "nutrition transition" (Popkin, 2014; Popkin *et al.*, 2012). In most developed countries, this nutrition transition already occurred several decades ago. In many developing countries, it is now happening at a relatively fast pace.

The nutrition transition can contribute to increases in body weight in two ways. First, consuming energy-dense foods will likely lead to higher overall energy intakes. Second, nutrient composition and processing levels play important roles for the human body's energy usage during food digestion and storage. On average, the human body's energy use for food digestion and storage makes up around 15% of total daily energy expenditures (Barr & Wright, 2010). However, this value varies with dietary composition. For instance, the body requires more energy for digesting proteins than for carbohydrates and fats (Westerterp, 2004). Also, the digestion of fresh and whole foods with higher fiber contents requires more energy than the digestion of processed foods (Barr & Wright, 2010). Higher energy intakes and lower body energy expenditures may have positive nutrition effects in situations where people suffer from energy deficiency. However, for people with sufficient energy consumption, the nutrition transition contributes to overweight and obesity (Popkin *et al.*, 2012).

Changing retail environments may possibly speed up the nutrition transition. In developing countries, supermarkets and other modern retail outlets are spreading rapidly, partly crowding out more traditional markets and small shops (Reardon *et al.*, 2003). Supermarkets tend to be larger than traditional outlets, and they usually offer a bigger range of products under one roof. Another major difference is that supermarkets have self-service character, providing greater freedom of choice for customers. Supermarkets respond to changing consumer preferences and lifestyles, offering the types of foods that customers with rising incomes and appeal for modernity demand. However, it is likely that supermarkets do not only react to changing consumer preferences but, in turn, also shape these preferences to some extent. Influence on consumer food choices can occur through locational factors, the range of products offered, the positioning of items in the shelves, packaging sizes, promotional campaigns, and general shopping atmosphere (Battersby & Peyton, 2014; Hawkes, 2008; Timmer, 2009).

Compared to small traditional shops, supermarkets can better exploit economies-of-scale. Hence, certain foods can be offered at lower prices (Drewnowski, Aggarwal, Hurvitz, Monsivais, & Moudon, 2012; Rischke *et al.*, 2015). This is especially relevant for non-perishable processed food items. In fact, outside of bigger cities, supermarkets in developing countries often concentrate primarily on the sale of processed foods.[1] Cheaper access to processed foods can improve food security and nutrition for very poor population segments (Kimenju & Qaim, 2016; Reardon *et al.*, 2003). However, heavy reliance on processed foods does not necessarily improve dietary quality and can intensify the obesity pandemic. Hence, the spread of supermarkets in developing countries can have both positive and negative nutrition and health effects.

3. Materials and methods

(a) Data

We use data from a survey of households and individuals carried out in two rounds in Central Kenya. The first round was carried out in 2012, the second in 2015. The survey concentrated on small towns (<70 thousand inhabitants), because this is the typical size of towns that supermarket chains currently enter in Kenya. All larger cities in the nation already have one or more supermarkets, whereas in rural areas supermarkets are not yet observed. In 2012, we purposively selected three towns in Central Kenya with differences in the availability of supermarkets.[2] The three towns are Ol Kalou and Njabini in Nyandarua County, and Mwea in Kirinyaga County. Ol Kalou has had a supermarket since 2002. In Mwea, a supermarket was opened in 2011. Njabini had no supermarket, neither in 2012 nor in 2015. This provides a quasi-experimental setting for the analysis of supermarket impacts on diets and nutrition.[3] Except for these differences, the three towns are similar in terms of infrastructure and other economic development indicators (Kenya National Bureau of Statistics, 2010).

Systematic random sampling was used to select households for interview within the urban and peri-urban areas of the three towns. Since recent census data did not exist, we used available population statistics and the help of local administrators. At first, all neighborhoods (residential estates) in each town were listed. Then, household lists were compiled for each neighborhood, from which we randomly selected the required number of households. We selected households from all neighborhoods, in order to avoid clustering and obtain a representative sample at town level.

In each selected household, whenever available one male and one female adult (>18 years) were included in the study for interviews and anthropometric measurements. In 2012, we included 432 randomly selected households and 601 adults. In 2015, we

[1] In big cities, many supermarkets and hypermarkets also have large fresh fruit and vegetable sections, but in smaller cities and towns this is rare up till now, at least in low-income countries of Asia and Africa (Rischke *et al.*, 2015).

[2] The cross-sectional data collected in 2012 were also used by Kimenju *et al.* (2015) and Rischke *et al.* (2015). This study builds up on this earlier research with panel data.

[3] Living in a town with supermarket is not perfectly correlated with supermarket use. Not all households in Ol Kalou and Mwea use supermarkets to buy food, and a few households in Njabini occasionally buy food in supermarkets elsewhere. However, this deliberate choice of towns provides exogenous variation in supermarket use that is very useful for the impact evaluation.

tried to reach the same households and individuals, but were only able to track 219 households and 286 adult individuals of those that were also included in 2012. Unlike in rural areas, where extended families often live in the same place for several generations, in urban areas households are often much smaller and relocate more frequently. Hence, higher attrition rates in urban panels are commonplace. Attrition households were replaced with other randomly selected ones in the same towns and neighborhoods. In total, in 2015 we collected data from 430 households and 598 adult individuals. Thus, the total sample includes 1,199 individual adult observations.

Table 6 in the Appendix compares key variables for individuals that were included in both survey rounds (balanced panel) and those that had to be excluded and newly included in 2015 due to attrition. While small differences occur for age and gender, no significant differences are found for consumption expenditures and other indicators of living standard. Against this background, we use the unbalanced panel in the further analysis, even though we test key results for possible attrition bias.

(b) Statistical methods

Our main objective is to analyze the effects of supermarket shopping on adult nutritional outcomes. For this purpose, we estimate panel data regression models of the following type:

$$N_{it} = \beta_0 + \beta_1 S_{it} + \beta_2 \boldsymbol{X_{it}} + \varepsilon_{it} \qquad (1)$$

where N_{it} is the nutritional outcome variable for individual *i* at time *t*, such as BMI or being overweight or obese. The main explanatory variable of interest is S_{it}, a dummy variable that indicates whether or not the individual (or the household in which individual *i* lives) purchased any food in supermarkets (see below for details of variable definitions). $\boldsymbol{X_{it}}$ is a vector of control variables, and ε_{it} is a random error term. We are particularly interested in the coefficient estimate for β_1. A positive and significant estimate for β_1 would indicate that shopping in supermarkets has a net-increasing effect on BMI, or on the likelihood of being overweight or obese.

One important question is what type of control variables to include in the vector $\boldsymbol{X_{it}}$. Especially relevant are variables that may be jointly correlated with N_{it} and S_{it}, as omitting such variables could lead to biased estimates for β_1. We include a range of factors, such as individual age, gender, marital status, and physical activity levels, as well as household living standard (economic status). In developing countries, living standard is often positively correlated with BMI (Popkin *et al.*, 2012). At the same time, richer households are more likely to buy food in supermarkets, because they can afford a wider range of processed and convenience foods. Moreover, consumers in developing countries often associate supermarkets with western brands and modern lifestyles (Batra, Ramaswamy, Alden, Steenkamp, & Ramachander, 2000; Hawkes, 2008). Hence, not controlling for living standard would likely lead to an overestimated coefficient β_1. Similarly, physical activity levels may also be jointly correlated with supermarket shopping and nutritional outcomes. Finally, we include a time trend as part of vector $\boldsymbol{X_{it}}$, and town dummy variables to control for possible regional differences.

In addition to Eqn. (1) with nutritional outcomes as dependent variables, we estimate models with diet-related dependent variables as follows:

$$D_{it} = \gamma_0 + \gamma_1 S_{it} + \gamma_2 \boldsymbol{X_{it}} + \varepsilon_{it} \qquad (2)$$

where D_{it} is a dietary indicator of individual *i* at time *t*, such as the share of energy consumed from highly processed foods, or the energy consumed from specific food groups. The coefficient γ_1 characterizes the net effects of supermarket shopping on dietary choices and thus helps to better understand the mechanisms for nutritional outcomes.

The models in Eqns. (1) and (2) can be estimated with random effects (RE) panel estimators. However, one potential issue is that the individual decision where to buy food is not random and may be influenced by unobserved factors. If such unobserved factors are also correlated with the nutritional outcomes or the dietary dependent variables, the estimated supermarket effects would be biased. This type of bias due to unobserved heterogeneity is also the main reason why IV approaches are commonly employed in impact evaluations with cross-sectional data. When panel data are available, as in our case, estimators with individual fixed effects (FE) can alternatively be used. FE estimators use differencing techniques, so that time-invariant heterogeneity is canceled out, even if unobserved (Wooldridge, 2010). Time-variant heterogeneity may still bias the results, which is why we control for living standards and levels of physical activity that can change over time. Much more difficult to capture are individual lifestyle factors and attitudes that may also influence the decision where to buy food. However, such unobserved factors are not expected to change within three years (the period in-between our two survey rounds), so that they can be considered as time-invariant in this analysis. Hence, we argue that FE estimators properly control for unobserved heterogeneity in our context without the need for instruments.

FE panel estimators require data variability within individuals over time. Hence, while unbalanced panel data can be used, the FE specifications rely on those individuals that were included in both survey rounds. We run all models with both FE and RE estimators and compare results using the Hausman test (Hausman, 1978). A significant Hausman test statistic means that there is unobserved heterogeneity, so that the FE specification is preferred. For all model estimations, we use standard errors that are cluster-corrected at the household level, which is important because in most households we observed more than one individual. All statistical analyses are conducted using Stata version 13.

(c) Supermarket dummy variable

The main explanatory variable of interest in the regression models is the supermarket dummy variable (S_{it}), which takes a value of one if any food consumed in the household of individual *i* during the 30 days prior to the survey was purchased in a supermarket, and zero if all the food consumed was obtained from traditional sources. Traditional sources include traditional retailers, such as daily markets, small shops, and kiosks, as well as food from own production or obtained through gifts. Table 7 in the Appendix shows characteristics of the different sources of food (retail outlets), including typical food groups obtained from these sources.

Information on food consumption was obtained at the household level through a 30-day recall covering 168 food items. The recall interviews were conducted with the household member that was mainly responsible for food purchases and food preparation. In addition to the quantities consumed, information on sources and monetary expenditures was collected separately for each food item.

In the total sample with 1,199 observations, 668 individuals had consumed food purchased in supermarkets, whereas the other 531 had not. The proportion of supermarket shoppers varies by town. As one could expect, most non-supermarket shoppers live in Njabini, where no supermarket had been opened until 2015. A certain proportion of non-supermarket shoppers is also found in the other two towns, Mwea and Njabini. There is also variation in supermarket shopping over time, which is important for efficient FE estimations. As mentioned, in Mwea a supermarket was only established in 2011, shortly before the first survey round was conducted in

2012. As people first have to get used to this new retail format, some of the households in Mwea that had not yet used the supermarket in 2012 had started to use it by 2015. Some variation in supermarket shopping over time was also observed in the other two towns. Out of those individuals that were included in both survey rounds ($n = 286$), 44 (15%) had switched their supermarket shopping status during 2012–15.

(d) Nutritional outcomes and dietary variables

We use the body mass index (BMI) as the main indicator of nutritional outcomes for adults. BMI is the most common indicator to classify overweight and obesity (Nelms, Sucher, & Lacey, 2011). Anthropometric measurements of individual weight and height were obtained during both rounds of the survey according to international standards (Centers for Disease Control & Prevention, 2007). Using these measurements, we calculated BMI (BMI = body weight in kg/body height in meters squared) for each individual. Using common international thresholds for BMI, we also classified individuals according to their nutritional status (WHO, 2014). Adults with a BMI ≥ 25 kg/m^2 and <30 kg/m^2 are defined as overweight. With a BMI ≥ 30 kg/m^2 individuals are defined as obese. We club the two categories and define individuals with BMI ≥ 25 kg/m^2 as overweight/obese.

For the dietary analysis, we used the food consumption data from the 30-day recall. Quantities of each food item consumed by the household were converted to amounts of energy using national food composition tables for Kenya and other countries in Africa (FAO, 2010, 2012; Sehmi, 1993). Energy consumption from each food item at the household level was divided by 30 to obtain daily values and then converted to individual levels with the help of adult equivalent scales. Adult equivalents (AE) were calculated based on average energy requirements, taking individual age, sex, and body height into account (FAO, 2004).

In addition to total energy consumption per person (expressed in kcal/AE/day), we also look at energy consumption from specific food groups that may be affected by supermarket shopping. As supermarkets in small towns offer very few fresh and unprocessed foods, we are particularly interested in effects on energy from unprocessed staples (grains, pulses, roots, and tubers) and fruits and vegetables. These groups are generally considered as "healthy" foods, because they are high in dietary fiber. Fruits and vegetables are also rich in vitamins and minerals. Other food groups, such as meats and fish, dairy and eggs, and vegetable oils, are more energy-dense and often further processed. High consumption of such energy-dense foods can more easily contribute to overweight and obesity (Swinburn, Caterson, Seidell, & James, 2004). Furthermore, we look at the share of highly processed foods (see Table 8 in the Appendix) in total daily energy consumption, as this may also be influenced by supermarket shopping.

(e) Control variables

In the individual-level regression models to explain nutritional outcomes and diets we control for typical sociodemographic factors such as age, sex, and marital status. In addition, we include a year dummy variable for observations in 2015 and town variables for Ol Kalou and Njabini (Mwea is the reference category). It should be noted that all time-invariant variables drop out in the FE specifications. In all models, we also control for household living standard, measured in terms of per capita consumption expenditures in Kenyan Shillings (KES). These expenditures comprise the value of all food and non-food goods and services consumed over a period of 30 days, including home-produced foods. To make monetary values comparable between survey years, expenditures in 2015 were deflated to 2012 using official consumer price indices (Kenya National Bureau of Statistics., 2016).

Finally, we control for individual physical activity, as this can also influence food consumption and nutritional outcomes. In the survey, respondents were asked for the number of hours of physical activity during leisure time. These data were used to calculate leisure time physical activity ratios (PAR).[4] PAR is a continuous variable taking values larger than 1. Bigger values indicate higher levels of physical activity.

4. Results

(a) Descriptive statistics

Descriptive statistics for key variables used in this analysis are shown in Table 1, for the total sample and also disaggregated for supermarket shoppers and non-shoppers. The upper part of the table shows the nutrition and dietary indicators.

Even though Kenya is still facing problems of undernutrition and child stunting, rates of adult overweight and obesity are high. In our sample, 47% of the adults were overweight or obese. This is higher than the average of 26% found in recent statistics for Kenya (IFPRI, 2016; Kenya National Bureau of Statistics, 2014; WHO, 2015). However, these national statistics refer to all of the country's regions, including poor rural areas where undernutrition is still more widespread. Regionally disaggregated official statistics are only available for women. For Central Kenya, where the three towns included in this study are located, the prevalence of overweight/obesity among female adults was estimated at 47% in 2014 (Kenya National Bureau of Statistics, 2014). Hence, the nutritional outcomes measured in our survey seem to be reasonable for urban areas in Central Kenya.

Looking at the disaggregated groups in Table 1, we see that those shopping in supermarkets have a significantly higher mean BMI and are also more likely to be overweight or obese than those not shopping in supermarkets. Figure 1 breaks these comparisons down by survey year. During 2012–15, BMI of both groups increased considerably, but the increase was more pronounced for those shopping in supermarkets.[5] The data in Table 1 also show that supermarket shoppers have significantly higher total energy consumption than non-supermarket shoppers and a larger share of this energy comes from animal products and highly processed foods. However, these comparisons do not control for other factors that may also influence diets and nutrition. As can be seen in the lower part of Table 1, there are also significant differences in living standard and other sociodemographic variables. Below, we control for such differences through estimation of panel regression models.

(b) Supermarket effects on BMI

Table 2 shows results of panel regression models with BMI as dependent variable. Model (1) refers to the unbalanced panel with all observations included. Two versions are shown, one with FE and the other with RE specifications. The Hausman test statistic, which is shown in the lower part of the table, suggests that the FE specification is preferred. Shopping in supermarkets increases individual BMI by 0.64 kg/m^2. The finding of a net-increasing effect of supermarkets on BMI is consistent with Asfaw (2008) and Kimenju *et al.* (2015), who had used cross-sectional data. However,

[4] PAR is defined as a multiple of the basal metabolic rate. In the nutritional sciences, PAR is often used to calculate physical activity levels (PAL), which are one ingredient in determining individual energy requirements (FAO, 2004).

[5] While the growth rates in BMI and in the prevalence of overweight/obesity during 2012–15 are higher for supermarket shoppers, the growth rate differences between the two groups are not statistically significant.

Table 1
Sample descriptive statistics

Variable	Total	Shopping in supermarkets	Not shopping in supermarkets
Body mass index (kg/m^2)	25.33	25.80***	24.73
	(5.07)	(5.08)	(5.00)
Overweight/obese (1,0)	0.47	0.52***	0.40
	(0.50)	(0.50)	(0.49)
Energy consumption (kcal/AE/day)	3164.61	3300.71*** (1388.74)	2993.41
	(1439.11)		(1483.75)
Energy from unprocessed staples (kcal/AE/day)	408.66	387.46**	435.34
	(386.15)	(421.46)	(335.01)
Energy from fruits and vegetables (kcal/AE/day)	375.32	392.05*** (245.02)	354.26
	(250.35)		(255.58)
Energy from meats and fish (kcal/AE/day)	121.84	148.28*** (123.06)	88.59
	(112.00)		(85.49)
Energy from dairy and egg (kcal/AE/day)	39.75	47.60***	29.89
	(45.90)	(51.67)	(35.02)
Energy from oils (kcal/AE/day)	133.26	187.68*** (208.80)	64.79
	(190.58)		(137.12)
Share of energy from highly processed foods (%)	7.60	8.57***	6.37
	(5.59)	(5.25)	(5.76)
Expenditure per capita (1000 KES)	11.90	14.02***	9.24
	(9.19)	(10.67)	(5.88)
Age (years)	36.54	34.60***	38.99
	(12.20)	(9.92)	(14.21)
Female (1,0)	0.65	0.67	0.63
	(0.48)	(0.47)	(0.48)
Married (1,0)	0.74	0.76**	0.70
	(0.44)	(0.43)	(0.46)
Physical activity ratio (PAR)	2.23	2.21**	2.27
	(0.49)	(0.47)	(0.51)
Ol Kalou (1,0)	0.32	0.50***	0.09
	(0.47)	(0.50)	(0.29)
Mwea (1,0)	0.29	0.41***	0.14
	(0.46)	(0.49)	(0.35)
Njabini (1,0)	0.39	0.08***	0.77
	(0.49)	(0.28)	(0.42)
Share of supermarket purchase (%)	8.39	15.06***	0.00
	(11.24)	(11.25)	(0.00)
Number of observations	1199	668	531

Notes: Mean values are shown with standard deviations in parentheses. **Difference between those shopping and not shopping in supermarkets is significant at 5% level; ***Difference between those shopping and not shopping in supermarkets is significant at 1% level.

our estimate is smaller in magnitude. For instance, Kimenju *et al.* (2015), who used the same data from Central Kenya collected in 2012, estimated that supermarket shopping increases BMI by 1.69 kg/m^2. As argued above, the FE panel estimator used here is more reliable because it does not depend on assumptions about the validity of an instrument. However, in spite of the smaller effect found here, we confirm the hypothesis that supermarkets contribute to BMI increases, even after controlling for unobserved heterogeneity and other confounding factors.

The other results of model (1) in Table 2 show that being married also contributes to higher BMI. Furthermore, the RE specification, which includes the time-invariant characteristics that drop out from the FE specification, suggests that females have a much higher BMI than males. This is consistent with existing statistics from Kenya and elsewhere (Kenya National Bureau of Statistics, 2014; Ng *et al.*, 2014). BMI is also positively associated with age and living standard, as one would expect. Looking at the town variables, we see that people living in Ol Kalou have a higher BMI than those living in Mwea, which is the reference town in this model. As mentioned, Ol Kalou is the town where a supermarket had already opened in 2002. On the other hand, people in Njabini, where no supermarket had been opened until 2015, have a significantly lower BMI. This correlation between the town variables and nutritional status is likely the result of our sampling strategy where we deliberately chose towns with differences in supermarket access. It implies that the town variables may possibly capture some of the effects of supermarket shopping. Indeed, when excluding the town variables from the RE specification of model (1), the supermarket effect on BMI increases to 0.72.

We carry out a few additional tests to check the robustness of the results. A first test relates to the possible effects of sample attrition. Model (2) in Table 2 shows FE and RE specifications of the BMI model with only the observations from the balanced panel included. Except for the constant term, the FE results are identical to those in model (1), which is not surprising. Although all observations were included in model (1), FE estimation of the treatment effect only considers individuals that were included in both survey rounds, as the FE estimator exploits the variation within individuals over time. But also for the RE specifications, results of models (1) and (2) are quite similar, which we take as evidence that sample attrition does not lead to systematic bias.

A second test relates to the relatively small number of supermarket switchers. As mentioned in Section 3, there are only 44 individuals in the sample who were included in both survey rounds and switched their supermarket shopping status during 2012–15 (88 observations). The FE estimates rely on these switchers, so it is important to know how representative they are for the rest of the sample. Table 9 in the Appendix compares key socioeconomic characteristics of these switchers with the total sample. The switchers are more likely to be female. In terms of the other variables, including household living standards, no significant differences are observed. Of course, a larger number of switching observations could lead to more efficient FE estimates. But the similarity of the switchers with the rest of the

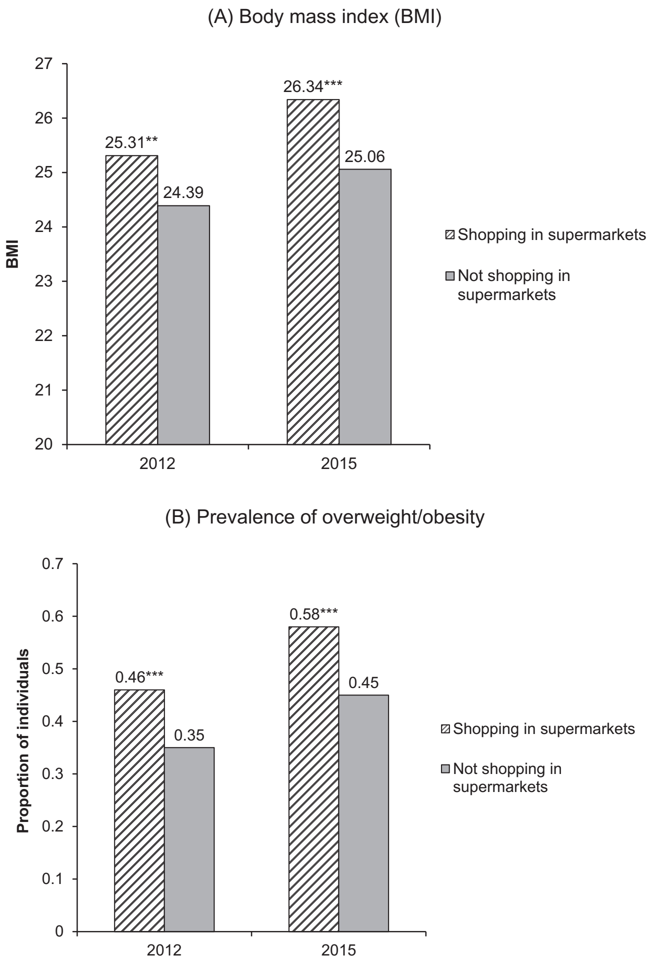

Figure 1. Differences in nutritional outcomes between individuals shopping and not shopping in supermarkets. **Difference between those shopping and not shopping in supermarkets is significant at 5% level; ***Difference between those shopping and not shopping in supermarkets is significant at 1% level.

sample suggests at least that the FE estimates do not suffer from significant selection bias.

A third test relates to the possible role of traditional retail outlets, which are not uniform. As shown in Table 7 in the Appendix, traditional retailers include daily markets, kiosks, and small shops. In terms of some characteristics, small shops are similar to supermarkets: while supermarkets are larger and offer a wider variety of processed foods, some small shops also have a self-service option. To analyze the possible role of small shops, we include an additional dummy variable for shopping in these small shops in the BMI models. Results are shown in Table 10 in the Appendix. Shopping in small shops does not seem to affect individual BMI, neither in the FE nor in the RE specification. At the same time, the supermarket effects remain significant and similar in magnitude to those in Table 2.

(c) Supermarket effects on the prevalence of overweight/obesity

Table 3 shows results of model estimates where being overweight/obese is used as a dummy dependent variable. We use linear probability models for these estimates.[6] The FE and RE specifications of model (1) show positive coefficients for supermarket shopping, but these are not statistically significant. This is surprising because Figure 1 shows that supermarket shoppers are significantly more likely to be overweight/obese than individuals who obtained all of their food from traditional sources. Interesting to see in Table 3, however, is that people in Njabini are significantly less likely to be overweight/obese than people in Mwea, even after controlling for other factors. Njabini is the town where no supermarket had opened until 2015. In model (2) of Table 3, we exclude the town variables and suddenly see a significant positive coefficient for supermarket shopping. According to this model, shopping in supermarkets increases the probability of being overweight/obese by 7 percentage points.[7]

We admit that the evidence of an overweight/obesity increasing net effect of supermarket shopping in our data is not very strong, also because the RE specifications do not control for unobserved heterogeneity. That the supermarket effect is not showing up more clearly is due to the fact that many adults have a BMI around 25 kg/m^2. Of course, supermarkets are not the only factors contributing to BMI increases, so that crossing the overweight/obesity threshold occurs in both groups, supermarket shoppers and non-shoppers (Figure 1). However, the finding that supermarket shopping significantly increases BMI as such already implies that this will also contribute to more overweight/obesity. We presume that this would be more visible with a larger number of switching observations in the balanced panel.

(d) Supermarket effects on dietary choices

To better understand how supermarkets contribute to rising BMI, we analyze effects on consumers' dietary choices. Several studies had used cross-sectional data to show that supermarket shopping contributes to higher total energy consumption (Asfaw, 2008; Kimenju *et al.*, 2015; Rischke *et al.*, 2015; Toiba, Umberger, & Minot, 2015). Rischke *et al.* (2015) showed that the average price of calories purchased in supermarkets is lower than the price per calorie purchased in traditional outlets. This could explain some of the calorie consumption effects. Our descriptive statistics confirm that supermarket shoppers consume significantly more calories than people who obtain all of their food from traditional sources (Table 1). However, panel model estimates that we tried revealed that these differences in total energy consumption cannot be interpreted as a net effect of supermarket shopping. After controlling for other factors, supermarket shopping does not increase total energy consumption significantly.

However, beyond total energy consumption we find significant effects of supermarkets on dietary composition. The FE specification in Table 4 shows that shopping in supermarkets increases the share of energy from highly processed foods in total energy consumption by about 3 percentage points. This increase is plausible given that supermarkets in the small towns considered here primarily sell processed and highly processed foods. Higher consumption of highly processed foods with more sugar, fat, and lower fiber content can contribute to rising BMI even without significant effects on total energy consumption.

A tendency of supermarkets to contribute to dietary shifts toward more processed foods was also found by Asfaw (2008), Kimenju *et al.* (2015), and Rischke *et al.* (2015). Coefficient estimates are not directly comparable across studies, because of differences in the exact specification of the dependent variables and functional forms. Yet, in general, the earlier studies with cross-

[6] Alternatively, one could have estimated probit models. The reason why we prefer linear probability models is that these also allow fixed effects specifications, which is not possible with probit models in most software packages.

[7] This is in line with findings by Asfaw (2008) and Kimenju *et al.* (2015), even though the estimated effects in these earlier cross-sectional studies were larger. For instance, Kimenju *et al.* (2015) estimated that supermarket shopping increases the probability of being overweight/obese by 13 percentage points.

Table 2
Effects of supermarket shopping on body mass index

	Body mass index (kg/m^2)			
	(1)		(2)	
	FE	RE	FE	RE
Shopping in supermarkets (1,0)	0.64^{*} (0.38)	0.61^{**} (0.29)	0.64^{*} (0.38)	0.70^{**} (0.36)
Married (1,0)	1.07^{*} (0.56)	1.06^{***} (0.30)	1.07^{*} (0.56)	0.93^{**} (0.44)
Physical activity ratio	−0.22 (0.18)	−0.25 (0.16)	−0.22 (0.18)	−0.27 (0.17)
Female (1,0)		3.29^{***} (0.28)		3.29^{***} (0.49)
Age (years)	−0.02 (0.04)	0.10^{***} (0.02)	−0.02 (0.04)	0.08^{***} (0.02)
Expenditure per capita (1000 KES)	−0.01 (0.02)	0.06^{***} (0.02)	−0.01 (0.02)	0.03 (0.02)
Ol Kalou (1,0)		-0.84^{**} (0.39)		−0.46 (0.75)
Njabini (1,0)		-0.82^{*} (0.43)		−1.01 (0.76)
Year 2015	0.38^{**} (0.17)	−0.00 (0.13)	0.38^{**} (0.17)	0.03 (0.14)
Constant	25.26^{***} (1.50)	18.63^{***} (0.74)	25.89^{***} (1.62)	20.30^{***} (1.15)
Wald χ^2		236.38^{***}		75.25^{***}
F-value	2.50^{**}		2.48^{**}	
Hausman test χ^2	58.43^{***}		48.39^{***}	
Number of observations	1199	1199	572	572

Notes: Coefficient estimates are shown with standard errors cluster-corrected at household level in parentheses. Model (1) uses the unbalanced panel with all observations. Model (2) only uses observations from the balanced panel. FE, fixed effects; RE, random effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 3
Effects of supermarket shopping on the probability of being overweight/obese

	Being overweight/obese (1,0)		
	(1)		(2)
	FE	RE	RE
Shopping in supermarkets (1,0)	0.01 (0.04)	0.03 (0.03)	0.07^{**} (0.03)
Married (1,0)	0.07 (0.05)	0.09^{***} (0.03)	0.09^{***} (0.03)
Physical activity ratio	−0.04 (0.03)	-0.04^{**} (0.02)	-0.04^{**} (0.02)
Female (1,0)		0.25^{***} (0.03)	0.26^{***} (0.03)
Age (years)	−0.01 (0.01)	0.01^{***} (0.00)	0.01^{***} (0.00)
Expenditure per capita (1000 KES)	−0.00 (0.00)	0.01^{***} (0.00)	0.01^{***} (0.00)
Ol Kalou (1,0)		−0.06 (0.04)	
Njabini (1,0)		-0.10^{**} (0.04)	
Year 2015	0.09^{***} (0.03)	0.04^{**} (0.02)	0.05^{**} (0.02)
Constant	0.80^{***} (0.30)	−0.07 (0.08)	-0.15^{*} (0.08)
Wald χ^2		215.99^{***}	201.00^{***}
F-value	2.17^{**}		
Hausman test χ^2	26.32^{***}		
Number of observations	1199	1199	1199

Notes: Coefficient estimates of linear probability models are shown with standard errors cluster-corrected at household level in parentheses. Being overweight/obese includes individuals with BMI > 25 kg/m^2. FE, fixed effects; RE, random effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 4
Effects of supermarket shopping on the share of energy consumed from highly processed foods

	Share of energy from highly processed foods (%)	
	FE	RE
Shopping in supermarkets (1,0)	3.07^{***} (1.13)	0.45 (0.87)
Married (1,0)	−3.08 (2.62)	-1.61^{**} (0.78)
Physical activity ratio	0.65 (0.57)	−0.20 (0.48)
Female (1,0)		-1.46^{**} (0.59)
Age (years)	0.11 (0.13)	-0.23^{***} (0.02)
Expenditure per capita (1000 KES)	0.06 (0.06)	0.18^{***} (0.04)
Ol Kalou (1,0)		−0.68 (0.80)
Njabini (1,0)		-1.90^{*} (1.07)
Year 2015	2.33^{***} (0.60)	2.76^{***} (0.45)
Constant	4.71 (4.95)	19.77^{***} (2.09)
Wald χ^2		177.89^{***}
F-value	5.96^{***}	
Hausman test χ^2	23.10^{***}	
Number of observations	1199	1199

Notes: Coefficient estimates are shown with standard errors cluster-corrected at household level in parentheses. FE, fixed effects; RE, random effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

sectional data suggested larger effects on dietary composition, underlining again the importance of panel data for identifying reliable net impacts of supermarket shopping.

Table 5 analyzes further details of supermarket effects on people's diets beyond highly processed foods. The models shown have absolute energy consumption from different food groups as dependent variables. In all models, the supermarket dummy variable has significant coefficients, either in the FE or RE specifications. The FE specifications suggest that supermarket shopping reduces energy consumption from unprocessed staples by 112 kcal/AE/day, and from fresh fruits and vegetables by 124 kcal/AE/day. These are substantial effects, accounting for more than one-third of total average energy consumption from these two food groups.

For the other food groups in Table 5, the supermarket dummy variable is only significant in the RE specifications. Yet the Hausman test statistics suggest that unobserved heterogeneity is not an issue in these models, so that the RE estimator produces unbiased estimates.

Supermarket shopping increases the consumption of meats and fish by 24 kcal/AE/day, of dairy and eggs by 9 kcal/AE/day, and of vegetable oils by 60 kcal/AE/day. Together with highly processed foods, these are also the food groups that supermarket shoppers

Table 5
Effects of supermarket shopping on energy consumption from different food groups

	Energy consumption from different food groups (kcal/AE/day)									
	Unprocessed staples		Fruits and vegetables		Meats and fish		Dairy and egg		Vegetable oils	
	FE	RE	FE	RE	FE	RE	FE	RE	FE	RE
Shopping in supermarkets (1,0)	−111.61* (59.27)	−22.43 (30.58)	−124.30** (56.82)	−16.53 (21.34)	5.70 (11.28)	24.17*** (7.30)	7.88 (6.16)	8.94*** (3.45)	9.03 (27.39)	59.81*** (15.31)
Married (1,0)	−56.69 (154.93)	−47.46* (27.56)	−97.29 (93.22)	−28.78* (16.81)	41.23 (32.21)	−5.02 (8.01)	−20.66 (17.11)	−5.34 (4.10)	−37.27 (63.46)	−27.66** (13.26)
Physical activity ratio	21.69 (41.86)	8.07 (17.65)	13.04 (24.79)	31.96** (13.06)	−10.54 (10.84)	−3.80 (6.43)	1.99 (4.17)	−0.86 (3.21)	−5.80 (19.16)	2.82 (11.25)
Female (1,0)		49.31*** (15.59)		24.12** (9.74)		1.13 (4.94)		−3.63 (2.33)		21.06*** (7.39)
Age (years)	3.04 (9.48)	2.83*** (1.04)	−2.99 (4.60)	1.40** (0.62)	0.04 (1.14)	−0.35 (0.26)	0.17 (0.44)	−0.26** (0.13)	−1.16 (2.00)	1.24*** (0.46)
Expenditure per cap. (1000 KES)	15.13*** (5.00)	7.92*** (2.05)	18.92*** (3.07)	11.26*** (1.76)	6.12*** (1.25)	6.23*** (1.48)	1.55*** (0.55)	1.69*** (0.42)	9.70*** (2.42)	7.75*** (1.38)
Ol Kalou (1,0)		80.82** (34.40)		−86.66*** (21.44)		14.06 (9.23)		8.71* (4.60)		−118.73*** (16.97)
Njabini (1,0)		130.68*** (35.16)		−68.36*** (24.85)		3.87 (10.21)		6.20 (3.90)		−112.32*** (17.71)
Year 2015	−199.37*** (53.87)	−170.79*** (24.16)	78.92*** (23.63)	72.35*** (15.38)	5.13 (7.63)	9.10 (5.77)	6.26** (2.93)	6.26*** (2.37)	34.11** (14.10)	35.76*** (9.67)
Constant	272.37 (379.24)	217.03*** (66.29)	331.75* (169.25)	151.57*** (51.71)	34.82 (57.97)	47.73* (28.89)	18.44 (23.67)	24.18** (11.35)	78.65 (117.63)	25.26 (40.36)
Wald-chi2		109.05***		119.49***		94.13***		51.21***		248.89***
F-value	5.40***		9.42***		5.81***		3.25***		54.99***	
Hausman test χ^2	4.23		21.42***		6.41		5.75		8.43	
Number of observations	1199	1199	1199	1199	1199	1199	1199	1199	1199	1199

Notes: Coefficient estimates are shown with standard errors cluster-corrected at household level in parentheses. AE, adult equivalent; FE, fixed effects; RE, random effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

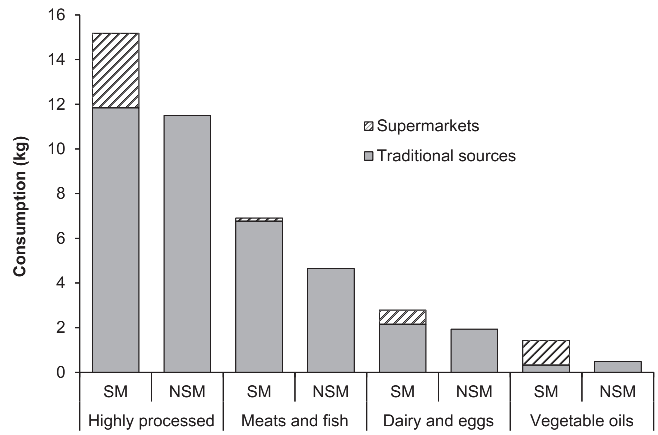

Figure 2. Quantity of food consumed from different food groups and food sources. Notes: Quantities refer to consumption at the household level over a 30-day period. Total quantity consumed per household is split up by quantity purchased in supermarkets and quantity obtained from traditional sources. SM, refers to individuals who purchased some of their food in supermarkets; NSM, refers to individuals who did not use supermarkets at all. Pooled data for 2012 and 2015.

actually purchase most in supermarkets (Figure 2). Table 5 and Figure 2 also reveal a few other interesting phenomena.

Households that use supermarkets purchase only some of their food in supermarkets. Of course, certain foods that are hardly sold in supermarkets but that people still want to consume have to be obtained from traditional sources. Cases in point are unprocessed staples and fresh fruits and vegetables. Results in Table 5 show that supermarket shoppers reduce the consumption of these groups, but they do not abandon them completely. But even for the types of foods that are sold in supermarkets, traditional sources continue to play an important role for all consumers. Interestingly, the quantities of highly processed foods, dairy, and vegetable oils consumed from traditional sources are more or less the same for those shopping and not shopping in supermarkets. Only that supermarket shoppers consume extra quantities of these foods that they purchase in supermarkets (Figure 2). Hence, the quantities of these foods obtained from supermarkets seem to be of additional nature. This may possibly be explained by supermarkets selling popular brands that are not available in traditional outlets. Larger packaging sizes, product placement, pricing, advertising, and the self-service character of supermarkets may also incentivize customers to buy additional quantities.

The establishment of supermarkets in small towns of Kenya is a relatively recent development, and the range of products offered in these supermarkets is still limited, at least when compared to much larger stores in big cities. Our data do not allow us to analyze how dietary behavior of small-town consumers may change when the number of supermarkets, as well as store sizes, continue to grow. However, even at this early stage, the results clearly support the hypothesis that supermarkets contribute to the nutrition transition, rather than only reacting to shifting consumer preferences.

5. Conclusion

Many developing countries currently experience profound transformations in the food retail sector, with modern supermarkets massively gaining in importance. While developments are already more advanced in some parts of Asia and Latin America, the share of supermarkets in food retailing is still relatively low in most sub-Saharan African countries, even though it is increasing rapidly. Possible dietary and nutrition implications are not yet sufficiently understood. We have analyzed effects on food consumers in Kenya, which is among the countries with the fastest growth of supermarkets in Africa. Using panel data from small towns in Central Kenya, we have shown that supermarkets significantly affect nutritional outcomes. After controlling for other relevant factors, our results suggest that shopping food in supermarkets increases adult BMI by 0.64 kg/m^2. That supermarkets tend to increase consumer BMI in developing countries was also shown in a few previous studies (Asfaw, 2008; Kimenju *et al.*, 2015). These previous studies had even suggested larger effects, but they built on cross-section observational data where controlling for possible bias due to unobserved heterogeneity is more difficult. We argue that our estimates with panel data models are more realistic and reliable. However, regardless of the exact magnitude of effects, results confirm that the growth of supermarkets contributes to the nutrition transition in Africa.

To better understand the underlying mechanisms, we have also analyzed effects of supermarkets on consumer dietary choices. Unlike a few previous studies (Asfaw, 2008; Rischke *et al.*, 2015; Toiba *et al.*, 2015), we did not find that supermarkets contribute to net increases in total calorie consumption. However, our panel data models revealed significant shifts in dietary composition. Supermarket shopping contributes to a sizeable decrease in energy consumption from unprocessed staples and from fresh fruits and vegetables. These food groups are hardly sold in the small-town supermarkets in Central Kenya that primarily concentrate on processed foods. Accordingly, we found significant increases of supermarket shopping on energy consumption from dairy, vegetable oil, processed meat products (sausages etc.), and highly processed foods (bread, pasta, snacks, soft drinks etc.). These shifts toward processed and highly processed foods lead to less healthy diets, with higher sugar, fat, and salt contents, and probably lower amounts of micronutrients and dietary fibers. Some of the effects are still relatively small in magnitude, but they may increase with supermarkets further gaining in importance. The observed changes in dietary composition can also explain the increasing effect on BMI, even without a rise in total calorie consumption. The reason is that the human body requires less energy for the digestion of processed and highly processed foods.

These results are alarming from a nutrition and health perspective. Even though we failed to establish a clear effect of supermarket shopping on the likelihood of being overweight or obese, rising BMI will inevitably aggravate nutrition status in situations where many people are already near or above the BMI threshold of 25 kg/m^2, as is the case for adults in Central Kenya. Overweight and obesity are responsible for various non-communicable diseases that cause high economic costs, human suffering, and lost quality of life.

It would be wrong to attribute the obesity pandemic in developing countries to the expansion of supermarkets alone. There are many factors that contribute to the nutrition transition. However, our results suggest that supermarkets are not only a symptom of this transition, but they influence dietary habits to a significant extent. Nevertheless, a modernizing retail sector should not be condemned, because—if properly managed—it can also have important positive nutrition effects. For instance, in a recent study in Kenya, Chege, Andersson, and Qaim (2015) showed that smallholder farmers benefit from marketing contracts with supermarkets in terms of higher incomes that also contribute to better quality diets in these farm households. Depending on initial nutrition status and access to food diversity, the establishment of new supermarkets can also improve the nutrition of consumers. A few studies showed that better access to supermarkets is associated with healthier diets in some regions in the US (Drewnowski *et al.*, 2012; Laraia, Siega-Riz, Kaufman, & Jones, 2004; Morland, Diez Roux, & Wing, 2006). In these situations, supermarkets offer fresh foods that are otherwise more difficult to access, especially for lower income consumers living in so-called "food desert" neighborhoods (Michimi & Wimberly, 2010). This is different from typical situations in Africa, but these examples underline that modern retail is not inevitably associated with negative nutrition and health implications.

The expansion of supermarkets in Africa and other parts of the developing world will likely continue. Hence, from a food policy perspective it is important to understand the diet and nutrition implications and intervene where necessary to avoid undesirable outcomes. Intervening does not imply banning supermarkets. But certain types of regulations and economic incentives may be appropriate in some situations. For instance, supermarkets in small African towns so far hardly sell fresh fruits and vegetables, because this does not yet seem to be profitable. Regulations that incentivize supermarket stores to also offer certain fresh products at reasonable prices could be a possible policy intervention. Alternatively, traditional fruit and vegetable vendors could be encouraged to set up stalls near the supermarket entrances, possibly through contractual arrangements. Other measures to promote dietary diversity and nutrition-sensitive food environments are also worth considering. Apart from regulations, this may also include consumer awareness building for the importance of fruits and vegetables in healthy diets.

Finally, we would like to point out a few limitations of our study. First, while the use of panel data has clear advantages over cross-sectional data, our panel suffered from significant attrition. While we tested for attrition bias to the extent possible, a balanced panel with a larger number of observations would be beneficial to analyze further details. Especially a sample with a larger number of individuals switching their supermarket shopping behavior over time would be useful for more robust causal inference with fixed effects estimators. Second, the geographic range of our data is limited and the time period considered relatively short. More comprehensive and longer term data may help to better understand impact heterogeneity and dynamics. Third, the 30-day food consumption recall at the household level that we used has certain drawbacks in terms of data accuracy (Schoeller, 1995). We chose this relatively long recall period because some of the more durable food items are only purchased once a month. However, shorter and repeated recalls at individual level are preferable when the focus is on analyzing actual food and nutrient intakes (Shim, Oh, & Kim, 2014). Hence, there is clearly scope for follow-up research to better understand the nutrition and health effects of the modernizing retail sector in various developing-country situations.

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Appendix A.

Table 6
Comparison of balanced panel with excluded and newly included observations in 2015

	(1) Total sample	(2) Balanced panel	(3) Excluded and newly included in 2015	(4) Difference between (2) and (3)
Female (1,0)	0.65 (0.48)	0.68 (0.47)	0.63 (0.48)	−0.06** (0.03)
Age, y	36.54 (12.20)	39.44 (12.77)	33.89 (11.02)	−5.55*** (0.69)
Married (1,0)	0.74 (0.44)	0.76 (0.43)	0.72 (0.45)	−0.04* (0.03)
Physical activity ratio	2.23 (0.49)	2.25 (0.50)	2.22 (0.48)	−0.02 (0.03)
Energy availability (kcal/AE/day)	3164.61 (1439.11)	3205.28 (1513.14)	3127.51 (1368.26)	−77.77 (83.60)
Expenditure per capita (1000 KES)	11.90 (9.19)	12.04 (8.28)	11.78 (9.94)	−0.26 (0.53)
Number of observations	1199	572	627	1199

Notes: Mean values are shown with standard deviations in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 7
Different sources of food and their characteristics

Source of food	Characteristics	Main food groups obtained from this source	Average share of total energy consumption (%)	Number of observations using source
Supermarket (modern retail)	Self-service; Large variety of foods and brands; Highly processed foods; Refrigerated and frozen food; Limited offer of fresh foods; Non-food products; No credit possibility	Bread, pasta, cereals, instant noodles, snacks, fats, oils, dairy products, sugar	12.7	668
Small shop (traditional retail)	Semi self-service; Limited variety of foods and brands; Some refrigerated foods; Sometimes credit possibility	Rice, flour, sugar, fats	5.4	485
Market/kiosk (traditional retail)	Over the counter service; Very limited variety of brands; Fresh fruits and vegetables; Unprocessed staples; Credit possibility	Maize, other staple foods, fruits, vegetables, meat, milk	65.7	1199
Own production/gift	Own plot or garden; In a few cases own farms; Gifts from friends	Maize, potatoes, poultry, eggs, milk	16.3	1014

Table 8
Food groups by level of processing

Food groups	Examples
Unprocessed	
Eggs & milk	Eggs, fresh whole milk, natural yoghurt
Fruits & vegetables	Mango, orange, green leafy vegetables, tomatoes, onions
Meats	Beef, pork meat, fresh chicken, fresh fish
Pulses	Lentils, black beans, cowpea etc.
Roots, tuber, plantain	Arrow roots, cassava, yams, potato, cooking bananas
Traditional staples	Amaranth, sorghum, green maize
Medium processed	
Fats & oils	Butter, margarine, vegetable oils
Meats	Frozen fish, frozen chicken, dried fish
Staples	Rice, maize flour, wheat flour, oats
Sugars	Sugar, jiggery
Highly processed	
Bread & pasta	Bread, cornflakes, pasta
Dairy	Flavored yoghurt/milk, tinned baby milk
Fats & oils	Peanut butter
Meats	Sausages, bacon, ham
Miscellaneous	Mandazi, samosa, ketchup
Sugars	Glucose powder
Sweet drinks and snacks	Chips, soft drinks, cake, popcorn

Notes: The food items mentioned are only examples. In total, 168 food items were included in the survey. All of them were classified by level of processing following the same principle.

Table 9
Comparison of total sample with supermarket switchers

Variable	Total sample	Supermarket switchers	Difference
Female (1,0)	0.65 (0.48)	0.77 (0.42)	−0.13*** (0.05)
Age, y	36.54 (12.20)	36.99 (11.02)	−0.48 (1.23)
Married (1,0)	0.74 (0.44)	0.75 (0.44)	−0.01 (0.05)
Physical activity ratio	2.23 (0.49)	2.24 (0.45)	−0.01 (0.05)
Expenditure per capita (1000 KES)	11.90 (9.19)	12.63 (6.02)	−0.78 (0.70)
Number of observations	1199	88	

Notes: Mean values are shown with standard deviations in parentheses (standard errors in the last column). Supermarket switchers are those who changed their supermarket shopping status during 2012–15. ***Difference significant at 1% level.

Table 10
Effects of supermarket shopping on body mass index with additional controls

	Body mass index (kg/m^2)	
	FE	RE
Shopping in supermarkets (1,0)	0.65* (0.38)	0.61** (0.29)
Shopping in small shops (1,0)	−0.14 (0.20)	0.03 (0.19)
Married (1,0)	1.07* (0.56)	1.06*** (0.30)
Physical activity ratio	−0.22 (0.18)	−0.25 (0.16)
Female (1,0)		3.29*** (0.28)
Age (years)	−0.02 (0.04)	0.10*** (0.02)
Expenditure per capita (1000 KES)	−0.01 (0.02)	0.06*** (0.02)
Ol Kalou (1,0)		−0.85** (0.40)
Njabini (1,0)		−0.83* (0.44)
Year 2015	0.38** (0.17)	−0.01 (0.14)
Constant	25.34*** (1.53)	18.63*** (0.74)
Wald χ^2		247.67***
F-value	2.17**	
Hausman test χ^2	59.85***	
Number of observations	1199	1199

Notes: Coefficient estimates are shown with standard errors cluster-corrected at household level in parentheses. FE, fixed effects; RE, random effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

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