Influence of home and away-from-home food environments on diets in urban and peri-urban Kenya: Insights from the Global Diet Quality Score

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Abstract

This paper analyzes the socio-economic, demographic, and food environmental factors influencing diet quality across urban and peri-urban Nairobi and Kisumu. Utilizing 2022 survey data from upto 4 days of consumption across 2,150 individuals, the study employs a novel approach to measure food environment (FE) by including the quality of FEs both around individuals' home and away-from-home (i.e., work/school/other) commuting destinations. We measure diet quality using the Global Diet Quality Score (GDQS), a nutritional tool that assesses diet quality using a 0-49-point scale based on consumption of 25 food groups, with higher scores indicating healthier diets and lower diet-related non-communicable disease risk. Notably, we find that diets are characterized by a heavy emphasis on refined grains, high-fat dairy, and sweets. The likelihood of eating food away from home, including ready-to-eat fast-foods, is higher among individuals who commute, suggesting that commuting behaviors may influence food choices. Econometric analyses reveal that the availability and diversity of healthy food offerings positively influence diet quality, while an abundance of unhealthy food options has the opposite effect. Economic factors, such as income and poverty probability, are robust predictors of diet quality. The study emphasizes the need to consider individual-level factors for a nuanced understanding of the FE and diet quality link. The results underscore the need for targeted policy interventions that enhance food environments, particularly in economically challenged regions. Effective policies should focus on increasing the availability of healthy foods, reducing economic barriers to accessing these foods, and considering gender-specific challenges. This multi-faceted approach aims to address the double burden of malnutrition and promote healthier dietary practices across different populations.

Key words
Food environment, diet quality, consumer food choices, urban nutrition, individual dietary data, Kenya

JEL codes
D12 - Consumer Economics: Empirical Analysis
Q18 - Agricultural Policy; Food Policy
O18 - Urban, Rural, Regional, and Transportation Analysis; Housing; Infrastructure
R23 - Regional Migration; Regional Labor Markets; Population; Neighborhood Characteristics
I12 - Health Behaviour

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1. Introduction

The nutrition transition sweeping across Africa signals a dramatic shift in dietary patterns, with significant health implications for the continent. As populations increasingly embrace diets rich in sugars, unhealthy fats, and salt—departing from their traditionally minimally processed foods—the risks of non-communicable diseases such as obesity, diabetes, and heart disease escalate (Rousham et al. 2020; Laar et al. 2022). This is prompting urgent calls for policy interventions to manage the food environment and curb the negative health impacts of this transition (Laar et al. 2020; Haggblade et al. 2016). This dietary evolution is closely tied to the forces of urbanization and industrialization, manifesting in a higher intake of fast foods and snacks from convenience stores and street vendors instead of home-cooked meals (Popkin, Adair, and Ng 2012; Reardon et al. 2021). Furthermore, the rising middle class in rural and urban regions of East and Southern Africa is driving an increased demand for processed foods, compounding these challenges (Tschirley et al. 2015). As the nutrition transition advances, strategic efforts to modify food consumption behaviors remain vital to mitigating its adverse health consequences.

Amidst this backdrop, an emerging body of research has begun to explore the impact of food environments (FEs) on dietary and nutritional outcomes, particularly in low- and middle-income countries. These studies, diverse in their methods and scope, seek to link the availability and type of food in various environments—ranging from homes to workplaces—with broader health metrics, including the Global Diet Quality Score (GDQS) (Bromage et al. 2021) and others catalogued by Trijsburg et al. (2019). Research investigating the impact of FEs employs various metrics to examine if the availability of specific food types—ranging from nutritious options to high-calorie “junk food”—affects health outcomes and dietary quality. Despite these efforts, the debate over the link between FEs and health continues, fueled by mixed and sometimes contradictory findings reported in the literature (Glass and Bilal 2016; Cooksey-Stowers, Schwartz, and Brownell 2017; Cobb et al. 2015; Ambikapathi et al. 2021).

The existing literature on FEs has several notable limitations. First, much of the research focuses on the FE within residential areas, directly linking the quality of these local FEs to household consumption patterns (Ambikapathi et al. 2021; Busse et al. 2023; Downs et al. 2022; Laska et al. 2010). This focus is driven by the assumption that the physical and social attributes of residential neighborhoods significantly influence food choices and attitudes (Diez Roux and Mair 2010). Commonly, these studies define an area around the home, measuring FE quality by the density of 'healthy' food outlets or their proximity (Duran et al. 2016; Spence et al. 2009). While some research finds statistical links between these local FE metrics and eating habits (Babey et al. 2008; Bodor et al. 2008), the tools used to assess FE quality often lead to inconclusive results regarding the broader impact on health outcomes (Turner et al. 2020). Furthermore, the omission of FEs related to workplaces and schools in many studies limits their ability to explain broader variations in consumption behaviors (Tschirley et al. 2022).

Secondly, the assessment of FE quality frequently relies on quantifying the types of food outlets present or the diversity of food categories available (Turner et al. 2020). Glanz et al. (2005)

introduced a conceptual framework that includes various FEs—such as those at home, school, work, and other locations—that influence household eating behaviors. Commonly, studies in this field explore the relationship between the location of food products on shelves, and the total amount of shelf space dedicated to different food products, and consumption or health outcomes, particularly in developed countries (Bodor et al. 2008; Cameron 2018; Farley et al. 2009; Rose et al. 2009; Vandevijvere, Mackenzie, and Mhurchu 2017; Cobb et al. 2015; Schultz et al. 2021). Although research on FEs in low-income countries is growing, detailed data on shelf space remains sparse (Tschirley et al. 2022), despite evidence from the US that quantitative measures of shelf space are highly predictive of dietary outcomes, and the strong focus of marketing research on shelf space. Recent studies, such as those by Souza Oliveira et al. (2022) and Borges and Jaime (2019), have utilized the AUDITNOVA tool, which assesses the availability, pricing patterns, and brand diversity within stores, thereby providing insights into in-store food availability. Another common measure involves counting food outlets to gauge their density within a specific area (Spence et al. 2009; Kruger et al. 2014). Research like Tschirley et al. (2022) aims to refine these metrics to better capture subtle variation in FEs. Despite these efforts, existing measures often fall short in fully capturing the nuanced variations in exposure to diverse foods.

Furthermore, much of the research on diets in Africa has traditionally focused on household-level purchase and consumption data (Russell et al. 2018), neglecting to account for individual behaviors such as discretionary snacking or meals eaten outside the home (Rousham et al. 2020). As food consumption patterns become more dynamic with increased urbanization and mobility, reliance on household data proves increasingly insufficient for capturing the full spectrum of eating habits (Sauer et al. 2021; Tschirley et al. 2015). Additionally, such approaches fail to address the human-centered elements of the food environment, which are significantly influenced by an individual's perceptions and interactions with food sources (Lytle and Myers 2017; Giskes et al. 2007).

Recognizing these limitations, this study applies a novel approach to FEs in urban and peri-urban Nairobi and Kisumu, Kenya. Our research makes several contributions to the literature. First, we refine the understanding of diet quality by measuring consumption not at the household level but at the individual level, and including detailed assessments of all meals, snacks, and food procurement methods. Second, we integrate data on individual commuting behaviors and geographic details of commuting routes to better evaluate the influence of both home-based and work-related FEs on dietary habits. Third, our detailed quantification of retail shelf space and food service offerings in both home- and work FEs aligns with recent calls in the literature for more precise and contextualized measures of FE quality (Laar et al. 2022; Tschirley et al. 2022). By addressing the gaps in traditional FE research, we aim to offer new insights into the complex interplay between food environments and diet quality in the dynamic urban contexts of Africa.

The study explores two key research questions: 1) What food choices do consumers make in urban and peri-urban Nairobi and Kisumu? 2) How do food environments at home and away from home influence these choices? We utilize multiple day, individual-level food choice data collected from surveys in these two major urban areas of Kenya, converting this data into a diet quality metric through the Global Diet Quality Score (GDQS). Developed by Bromage et al. in 2021, the GDQS is a universally applicable method designed to measure diet quality. This scoring system evaluates both healthy and unhealthy food consumption, addressing the double burden of malnutrition. A novel aspect of this paper is the application of the same GDQS food categories to our quantification of shelf space in food environments, reflecting the measure of diet quality at the consumer level.

The rest of the paper is organized as follows. Section 2 describes the data used for this study, including sampling, data collection approach, and metrics to measure diet quality and food environments. Section 3 describes the method and empirical strategy to understand the influence of home and away-from-home food environments on individual diets. Section 4 presents the results, followed by a discussion of key takeaways from the findings in Section 5 and the conclusion in Section 6.

2. Data

Study area and household sample design

Our study covered four geographic areas within two Kenyan cities: urban and peri-urban Nairobi, and urban and peri-urban Kisumu (see Appendix A for more details on our sampling frame).[1] We employed a multi-stage sampling strategy, beginning with the use of the latest population census data (2019) to construct an index of neighborhood wealth for each administrative "location" (a "location" in this context is similar to a ward). This index included factors such as asset holdings, dwelling characteristics, access to communication tools, and the education and employment status of household heads.

Using this index, we divided each area into wealth quartiles. In urban Nairobi, we excluded the highest wealth quartile due to anticipated low response rates and lack of comparability with other neighborhoods. The remaining neighborhoods were reorganized into new quartiles. For each quartile in both urban and peri-urban Nairobi, we randomly selected two locations, totaling eight locations per urban setting. In Kisumu, both urban and peri-urban areas consisted of eight and seven locations respectively, spanning four quartiles, with all locations being included.

From each chosen location, we randomly selected two enumeration areas (EAs).[2] This process resulted in 16 EAs each in urban Nairobi and peri-urban Nairobi, and 16 and 14 EAs in urban and peri-urban Kisumu, respectively.

After identifying the enumeration areas (EAs), we listed all households within each. Our goal was to sample 375 households per region, evenly distributed across the selected EAs. In the three regions with 16 EAs each, we randomly chose approximately 24 households per EA. In the region with 14 EAs, about 27 households per EA were selected. Attrition among the listed households by the time we conducted the surveys led to slight variations in the number of households per EA. Figure 1 illustrates the distribution of sampled households across Kisumu and Nairobi.

[1] In our study, peri-urban areas are defined as transitional zones bridging urban and rural settings. These areas exhibit a combination of urban and rural characteristics and typically depend more heavily on agricultural activities for income.

[2] The Kenya National Bureau of Statistics (KNBS) delineates the EAs using a cartographic mapping exercise by dividing the whole country into small geographical units. An EA is an area with an average of 100 households in a village, group of villages, or part of a village/town/city. The number of households in each EA varies depending on the population density and size of the area (Kenya National Bureau of Statistics (KNBS) 2019).

The household surveys were primarily conducted with the main shopper of each household, who provided the household-level data. For individual-level data, we selected adults aged 18 and above (including the main shopper) as follows: in single-adult households, the sole adult was included; in households with two adults, both were selected; in households with more than two adults, we randomly chose more than two.

We constructed sampling weights based on the probability of being selected at each stage of our sampling process (i.e., EA, household, and individual). These weights are applied in all analyses to ensure representativeness. Additionally, we adjusted for any gender imbalance in the individual-level sample to align with the overall gender distribution recorded in the household rosters. Consequently, our household and individual sample represents the populations of urban and peri-urban Kisumu and Nairobi, excluding Nairobi's wealthiest neighborhoods. Given Nairobi's larger population compared to Kisumu, pooled data tend to reflect Nairobi's demographics more strongly, so we report results alsoby region and other categorizations.

Data collection

Data collection occurred from April 19 to May 14, 2022, in Nairobi and from May 14 to June 6, 2022, in Kisumu. The distribution of the interviewed households and individuals across the different regions is detailed in Table 1, with the sample slightly skewed in favor of Kisumu urban and peri-urban.

Household survey data was collected using a structured questionnaire that included modules targeting two types of household members: (i) the main shopper, who responded to the household survey, and (ii) individual household members. The main shopper is defined as the adult member responsible for making the household's food purchasing decisions. In cases where shopping duties were shared, one of the main shoppers completed the household survey. Both the individual- and household-level modules collected data on demographics, socio-economic status, and geographic locations. The individual-level survey also gathered detailed information on ethnic and regional identities, commuting habits, income activities, household roles, personal food purchases, food-related values, and detailed food consumption recall over up top four non-consecutive days within a week. For the main shopper at the household level, the survey recorded details such as a household roster, food shopping behavior over the previous day, week, and month, and the main shopper’s food values. Additionally, GPS coordinates for households and their frequented shopping and individual commuting sites were collected.

Methodology for measuring diet quality

In the individual-level survey, we gathered detailed information on the consumption of breakfast, lunch, dinner, and snacks, both within and outside the home. This involved recording the types and portion sizes of food items consumed using a 24-hour recall method over up to four non-consecutive days within a one-week data collection period. The initial day's data was collected in-person alongside the household-level survey, while the remaining data were obtained via telephone on alternating days from a subset of participants.[3] In total, detailed consumption data were collected for 5,940 individual-days.

[3] Owing mostly to a technology error, we experienced some attrition between the in-person interview and the follow-up phone calls. The number of days of consumption data therefore varies from one to four, with over 60% of

Food items were classified into one of 25 categories defined by the Global Diet Quality Score (GDQS, Bromage et al. 2021). In the GDQS, foods are scored with more points awarded for the consumption of larger quantities of healthy foods, and fewer points for higher consumption of unhealthy foods. The GDQS identifies 16 healthy, 7 unhealthy, and 2 conditionally unhealthy (or unhealthy in excessive amounts) food groups. The classification of these food groups is detailed in Appendix B.

To compute the GDQS, we first categorized 290 distinct food items. We then converted the reported quantities into grams, using measurement units familiar to the respondents, such as serving spoons, plates, cups, or handfuls. This conversion utilized both resources tailored to the Kenyan culinary context (Fongar, Gödecke, and Qaim 2019; Fongar et al. 2019) and standard unit conversion tools (e.g., Aqua-Calc.com). For mixed dishes, we dissected the recipes into their constituent ingredients, considering the water absorption characteristics of each component. For instance, in a recipe containing *managu*, *terere*, and *kunde*, we apportioned the water content based on the water-absorbing capacity of each ingredient, as outlined by the FAO/Government of Kenya (2018). This meticulous analysis allowed us to accurately assess the grams of each food category consumed daily, enabling the construction of a daily GDQS for each participant, as well as an average score reflecting their intake over multiple days. The GDQS ranges in value from 0 to 49. A score of 0–15 indicates high risk of diet-related non-communicable disease (NCD), 15–23 indicates moderate risk, and 23–49 indicates low risk.

Methodology for collecting data for food environments

After the completion of household surveys, we gathered outlet-level data to delineate the characteristics of the food environment. The conceptual framework for our study posits that an individual's food consumption is influenced by the quantity, quality, and diversity of available food within their surrounding food environment. This encompasses the food environment at their place of residence (referred to as 'home FE') and the food environment at locations where they regularly spend significant amounts of time for work, education, or other activities ('work FE').

Utilizing the GPS coordinates collected from the consumer surveys, which indicated both residential locations and (as applicable) regular commuting destinations for work, school, or other purposes, we were able to precisely define the home and work FEs for each participant as described below. This approach allowed us to systematically analyze how these specific food environments impact individual dietary patterns.

Defining home FE: For each enumeration area, we calculated a mean geographic center point based on where households were located and established a surrounding buffer circle with a radius of 0.4 km for urban Nairobi, peri-urban Nairobi, and urban Kisumu. In the case of peri-urban Kisumu, which has more rural characteristics, the radius was adjusted to 0.6 km. This radius was selected based on actual shopping behaviors observed during the survey, where it was noted that over 50% of household food shopping occurred within these distances from the geographic center point of their respective enumeration areas.

individuals reporting on at least three days over the course of a week, but some individuals reporting on only one day.

This buffer delineates the boundary of the home FE, representing the immediate vicinity around homes where various food outlets are accessible. This approach to defining the home FE aligns with methodologies employed in other studies (e.g., Spence et al. 2009, Mahasin et al. 2008). Using this approach, we identified 61 home FEs, one for each enumeration area in our sample. It is crucial to highlight that the definition of home FE is consistent across all individuals and households within each enumeration area.

Defining work FE: Unlike the home FE, the work FE is specific to each individual and only defined for those who regularly commute to work, school, or other locations. In our study, more than 1,100 individuals reported commuting to different locations and spending significant time outside their homes. Given the resource-intensive nature of collecting food environment data for each unique work location of these individuals, we adopted a practical approach to defining work FEs as outlined below:

1. We mapped the GPS coordinates of each commuting destination (hereafter referred to as 'work dots') on the map of Nairobi and Kisumu (including surrounding counties). Any work dot within an existing home FE was excluded from further analysis.
2. For each remaining work dot, we identified the administrative location and categorized it as urban, peri-urban, or rural, using the same criteria established to define urban and peri-urban Nairobi and Kisumu (see Appendix A).
3. Leveraging the 2019 Kenya National Bureau of Statistics (KNBS) census data, we assigned each work dot location a socio-economic stratum ranging from 1 (low income) to 5 (high income, applicable only in Nairobi).
4. We then characterized each work dot location using Google Maps and local insights, classifying them as either commercial (including proximity to major roads, business districts, markets, shopping malls, and industrial areas) or residential.
5. Based on these classifications, each work dot in Nairobi and Kisumu was categorized into one of 30 possible combinations, considering three dimensions: urbanization level, income stratum, and location type. This resulted in 60 potential work FE categories across both cities.
6. In Nairobi, 19 categories were represented by work dots, and in Kisumu, 15 categories were represented. Across these categories, we randomly selected 30 work dots in Nairobi and 31 in Kisumu.
7. Like the home FE, we defined a buffer circle with a radius of 0.4 km (0.6 km in peri-urban and rural Kisumu) around each sampled work dot to delineate the work FE.

In total, 61 work FEs were sampled across Nairobi and Kisumu, representing 34 distinct categories. For individuals whose work dots fell within the buffer zones of these sampled work FEs or any of the 61 home FEs, the work FE data correspond to that specific environment. For those whose work dots lie outside any of these circles, their work FE is defined as the nearest FE (measured by the distance between the work dot and the mean center of the FE).

Measuring FE quality: Data were collected for 61 'home FEs' and 61 'work FEs' from June to August 2022. In each FE, a complete census of food outlets was conducted, including those offering prepared foods. In food environments that overlapped with a market, we randomly selected 15% of vendors/outlets in the census survey. Following the census, a survey was conducted to measure the shelf space allocated to various foods according to GDQS categories in a sample of outlets. See Appendix C for more details on the methodologies used for the census and shelf-space surveys. We utilize these two sources of data to characterize the quantity and quality of FEs through metrics such as density, diversity, shelf space, and average price of healthy and unhealthy food offerings.

3. Method

Variables

For several of the variables used in this analysis, the variable construction is not obvious and therefore merits explanation. A summary of variable definitions is available in Appendix D.

The household survey data was used to calculate a poverty likelihood score for each household based on Schreiner's (2018) methodology. This score incorporates ten indicators, such as the number of household members, the quality and size of the living space, ownership of a television and mobile phone, disability presence within the household, and details about the household members' employment, literacy, and education levels. The score translates into a probability of living below the $3.20 poverty line, ranging from 0–100, where lower scores suggest a lower likelihood of poverty and higher scores indicate a greater risk. Households are then classified as having a high or low likelihood of poverty based on whether their score is above or below the median poverty likelihood score.

A key characteristic of each food environment is the density of healthy (or unhealthy) food offer sites (No./km^2). The number of healthy (or unhealthy) food offer sites is derived from the census of all food outlets in the FE and is a count of location-categories offering categories of food classified as healthy (or unhealthy); this is *not* simply a count of "healthy" and "unhealthy" food outlets. If a shop offers foods of category A and category B (both healthy), that counts as 2 healthy location-categories for construction of this indicator. The count is then divided by the area of the food environment. Another key characteristic is the density of healthy (or unhealthy) food shelf space (m^3/km^2). Shelf space is captured in the sample of food outlets (excluding prepared food vendors) with consideration of depth, width, and height to produce a measure of m^3. This variable is the sum of shelf space allocated to healthy (or unhealthy) foods, divided by the area of the food environment. Finally, we calculate the diversity of healthy (or unhealthy) foods in a food environment. A lower diversity measure for healthy foods indicates that the area for healthy foods in the food environment is dominated by a small number of GDQS healthy food categories, while a higher value indicates that the space for healthy foods is allocated to more different categories, facilitating greater exposure to a higher number of categories.

Empirical strategy

To understand the relationship between individuals' average diet quality (averaged over multiple days) and the quality of their home food environment, we employ the following equation:

$$Y_{ihcr} = \alpha + \beta[HomeFE_{hcr}] + \delta[Demog_{ihcr}] + \delta[HH_{hcr}] + \theta[Region_r] + \varepsilon_{ihcr} \quad (1)$$

where Y_{ihcr} is the GDQS of individual i in household h in enumeration area c in region r; $HomeFE_{hcr}$ is a characteristic (or vector of characteristics) of the home food environment; $Demog_{ihcr}$ is a vector of characteristics of the individual; HH_{hcr} is a vector of characteristics of the household; $Region_r$ is an indicator of region (city/urban status); and ε_{ihcr} is an error term. Our focus is on β. The models use robust standard errors clustered at the enumeration area level to account for any potential correlation of errors within the same geographic units.

To understand whether certain factors mediate the relationship between diet quality and the quality of the home food environment, we interact a measure of FE quality with several other variables (across different models). The equation is as follows:

$$Y_{ihcr} = \alpha + \beta[HomeFE_{hcr}] + \psi[HomeFE_{hcr} * Mediator_{ihcr}] + \delta[Demog_{ihcr}] + \delta[HH_{hcr}] + \theta[Region_r] + \varepsilon_{ihcr} \quad (2)$$

The $Mediator_{ihcr}$ is alternately an indicator of gender, a measure the individual's consumption of food away from home, and a set of indicators of region. Our focus here is on ψ, which captures whether the $HomeFE_{hcr}$ has a differential influence on different individuals or populations.

To understand the relationship between individuals' diet quality on a given day and the quality of the food environment to which they were exposed on that day, we apply an individual-day-level regression as follows:

$$Y_{id} = \alpha + \beta[Day_d] + \delta[Home/WorkFE_{id}] + \omega_i + \varepsilon_{id} \quad (3)$$

where Y_{id} is the day-level GDQS of individual i on day d; Day_d is an indicator variable (=1 if it is a work-day; =0 if it is weekend); $Home/WorkFE_{id}$ is a weighted measure of the quality of the food environment on day d; ω_i is an individual fixed effect; and ε_{id} is an error term. The measure of $Home/WorkFE_{id}$ is constructed as a weighted average of the FE quality measures for the home and work FEs, weighted by the % of a 16-hour day that was spent in either location on a given day. This is defined only for individuals with work FEs (i.e., commuters) and is intended to capture the intensity with which the individual was exposed to each of their two FEs on each day. The individual fixed effect, ω_i, controls for all time-invariant characteristics of the individual, including those that are observed in the data (such as income level) and those that are not observed (such as taste preferences or cultural affinity). Our focus is on δ, which captures the relationship between within-individual variation in FE quality and within-individual variation in diet quality from day to day. Standard errors are clustered at the enumeration level.

4. Results

4.1 Descriptive results

Demographic and economic characteristics

Table 2 provides an overview of the demographic and socio-economic attributes of 2,150 individuals across four study regions, highlighting both variations and commonalities. The average age varies minimally across regions, with the oldest average in Kisumu urban and the youngest in Kisumu peri-urban. Education levels beyond primary school are highest in Kisumu urban (~71%) and lowest in Kisumu peri-urban (~59%). Household sizes differ significantly, with Kisumu peri-urban having the largest households on average (4.9 members). Economic activity varies, with the highest engagement in Nairobi urban (83%) and the lowest in Kisumu peri-urban (72%), where crop farming also emerges as a significant income source. Nairobi urban exhibits the highest average daily income at 353 shillings, while Kisumu peri-urban has the lowest at 190 shillings, alongside the highest rates of remittances (~21%) and spending allowance (21%). This region also faces the greatest economic challenges, with the highest probability of poverty at approximately 48%.

The last four columns of Table 2 delve deeper, examining differences based on gender and poverty probability. Males typically have higher education levels and are more involved in income-generating activities compared to females, who generally are part of larger households, suggesting broader family responsibilities, and rely more on spending allowance from other members of the household. Individuals who reside in households with a lower probability of poverty (based on the household's poverty likelihood score (Schreiner 2018)) have achieved higher education and earn more than those facing higher poverty risks. Characteristics like larger household size and more children are correlated with increased poverty likelihood. These insights underscore significant disparities in gender and poverty status which are, in turn, likely to influence food consumption habits and diet quality.

Commuting behavior

Table 3 details commuting behaviors across four study regions, revealing that 64% of participants commute, with the highest incidence in Nairobi urban (68%) and the lowest in Kisumu peri-urban (52%). The primary commuting purpose is work, notably so in Nairobi urban (75%), while school commuting peaks in Kisumu peri-urban (39%). On average, commuters travel five times per week, spending about 5.8 hours in transit weekly, with those in Nairobi urban commuting the longest weekly (6.4 hours). Walking is the predominant mode of transportation, especially in Kisumu peri-urban (67%), with buses and matatus favored in urban settings, and motorcycles and taxis/*boda bodas* more common in Kisumu peri-urban.

Analyzing commuting patterns based on gender and poverty status shows that a higher proportion of males (74%) commute than females (55%), with males also spending more time at destinations and preferring cars and motorcycles. Commuting frequency among those with a high poverty probability (64%) is comparable to those with a lower probability (63%), with the latter group using buses/matatus more and owning more cars.

Table 3 emphasizes gender and economic disparities in commuting behaviors, such as transport choices and commuting duration. It shows how poverty affects transport preferences, with those at higher poverty levels more dependent on walking. This analysis also offers deeper understanding of the socio-economic factors that influence commuting patterns, which in turn could influence their exposure to different types of food environments.

Diet quality

Table 4 offers an in-depth look at eating behaviors, diet quality, and diet-related non-communicable disease (NCD) risks across our four diverse study regions, spotlighting differences in daily calorie consumption, frequency of consuming food away from home (FAFH), and Global Diet Quality Scores (GDQS). Notably, Kisumu peri-urban residents have the highest calorie intake, while those in Nairobi urban consume the least, often opting for more FAFH which seems to significantly impact their total calorie intake. Despite these variations, the overall GDQS remains fairly consistent, on average, albeit slightly better in Nairobi peri-urban. Predominantly, the populations are categorized under moderate risk for NCDs, with minor regional variations.

Table 4 also reveals that males generally consume more calories and FAFH, resulting in lower GDQS scores and higher NCD risks compared to females, who enjoy better diet quality. Additionally, those with a lower probability of poverty not only consume more calories but also maintain better diet quality than their less affluent peers, highlighting how economic advantages influence dietary choices. Notably, while those of low and high poverty likelihood have a similar average score for GDQS– (the score received for avoiding unhealthy foods) (7.7 and 7.8, respectively), individuals of low poverty likelihood have a slightly higher average score for GDQS+ (the score received for consuming healthy foods) (11.2 and 10.5, respectively).

Table 5 further dissects these patterns by detailing daily consumption rates of various food categories defined by the GDQS, distinguishing between healthy, unhealthy, and unhealthy-in-excess foods. Kisumu peri-urban stands out for higher consumption of wholesome foods like whole grains and legumes, whereas Nairobi urban residents tend to have a higher intake of refined grains and sugar-sweetened beverages—factors that may contribute to regional health disparities. High-fat dairy, an important source of calcium and other micronutrients is most consumed in Kisumu urban. Although the Global Diet Quality Score (GDQS) suggests that high-fat dairy and red meat are linked to a higher risk of non-communicable diseases (NCDs) when consumed in large quantities, only 6% of our sample consumed high-fat dairy above the unhealthy threshold and 2% of our sample consumed red meat above the unhealthy threshold, meaning that, as they are consumed in our study, these foods are nearly always "healthy."

The last four columns in Table 5 compare the same food categories across genders and economic statuses. Here, the trends are stark: males significantly indulge in more refined and baked goods, whereas individuals facing poverty consume fewer healthy options.

Collectively, Tables 4 and 5 underscore profound regional, gender, and economic variations in diet, illustrating how these factors collectively shape dietary habits, food quality, and health outcomes. These insights reveal the complex interplay between socio-economic status, geographic location, and gender in influencing dietary choices and subsequent health risks.

Characteristics of home and work food environments

Next, we delve into the characteristics of home and work food environments, presenting a detailed comparison of food availability, shelf space, diversity, and pricing through Tables 6 and 7. Each table offers unique insights into how these environments could plausibly impact dietary choices among commuters and residents.

Table 6 focuses on the characteristics of food environments in both home and work settings. Notably, Nairobi urban stands out with the highest density of healthy food offer sites at both home and work environments, indicating better accessibility to healthier food options. Conversely, Kisumu peri-urban shows the lowest density, highlighting a significant disparity in food access. In terms of shelf space, Nairobi urban also leads with the greatest total shelf space for foods, suggesting a broader availability of dietary options. However, the distribution between healthy and unhealthy foods reveals a higher allocation to unhealthy options across all regions. The price ratio of healthy to unhealthy foods is highest in Nairobi urban. This reflects a cost disparity that may incentivize the consumption of less healthy food options. Another notable pattern is that home environments outpace work environments in terms of total shelf space for food, though work food environments lead in terms of the number of prepared food vendors per km^2. Work environments generally provide a higher percentage of shelf space for healthy foods (especially in Kisumu peri-urban) and greater food diversity. Interestingly, work environments tend to have a higher ratio of healthy to unhealthy food prices, with the most significant price disparities found in Nairobi urban.

Table 7 provides a comparative analysis for commuters, contrasting their home- and work food environment characteristics. It shows that while home environments have a higher density of healthy food sites, work environments offer more total shelf space, more shelf space for healthy foods, and a greater diversity of both healthy and unhealthy foods. Notably, the price of healthy foods is significantly higher at work, potentially influencing commuters to choose cost over nutrition.

Both tables together paint a complex picture of food environments that could plausibly influence dietary behaviors differently at home and work. Nairobi urban, as a common highlight in both tables, appears as a hub of both healthy and unhealthy food availability but also faces the challenge of higher healthy food prices, particularly in work settings. This could potentially discourage healthier eating habits among those with budget constraints.

4.2 Econometric results: Relationship between food environment characteristics and diet quality

To understand whether and how much the home and away-from-home food environments influence diet quality, we turn to an econometric analysis. Table 8 presents the results of an OLS regression model (using equation 1) that explores the relationship between average diet quality scores measured by GDQS and various characteristics of home food environments discussed above. The dependent variable in all models is the average GDQS, and the models adjust for various indicators of food environment quality and individual demographics. Because the dependent variable is a diet quality score, and because the key explanatory variables are often complex, the precise meaning of coefficients can be difficult to interpret; however, we give attention to the sign, statistical significance, and relative magnitudes of these coefficients.

Three key findings emerge from this analysis. First, the number of healthy food offer sites per km² has a significant positive effect on GDQS (0.003, $p<0.01$), indicating that more healthy food availability correlates with better diet quality. Conversely, the density of unhealthy food offer sites per km² negatively affects GDQS (-0.005, $p<0.01$). Second, the ratio of the number of healthy to unhealthy food offer sites shows a positive association with GDQS in model 2 (0.958, $p<0.05$), suggesting that a higher proportion of healthy food sites relative to unhealthy ones is beneficial for diet quality. Third, the diversity of healthy foods within the home food environment has a positive impact on GDQS (0.033, $p<0.01$), whereas the diversity of unhealthy foods does not show a significant effect. Similarly, shelf space devoted to healthy and unhealthy foods does not show a significant impact on GDQS, as indicated by the high standard errors in models 3 and 4.

Among the economic factors, income per day is positively correlated with GDQS across multiple models, signifying that higher daily income is associated with better diet quality. Similarly, the household probability of poverty negatively influences GDQS, indicating that higher poverty likelihood is associated with worse diet quality. Age shows a consistent positive relationship with GDQS across models (approximately 0.017, $p<0.05$), while gender (female) and having education beyond primary school do not show significant impacts in this analysis, once all else is held constant. Individuals that commute also have a consistently higher GDQS compared to those that do not commute.

Surprisingly, individuals with more number of days of consumption data in our sample have higher GDQS. Regional dummies for Nairobi peri-urban, Kisumu urban, and Kisumu peri-urban do not consistently show significant effects, suggesting that regional differences may not be as impactful as individual or household characteristics and the measured characteristics of the FEs.

It is worth noting that the R-squared values across the models range from 0.053 to 0.071, suggesting that while the models explain some variability in GDQS, a significant portion of the variation remains unexplained by the variables included.

In general, these results underscore the importance of the availability and diversity of healthy food options in improving diet quality, as well as the negative impact of poverty and the predominance of unhealthy food options in degrading diet quality. These findings highlight crucial areas for policy intervention aimed at enhancing home food environments to support healthier dietary choices.

In Appendix E, we explore the heterogeneity of this relationship between the average GDQS and various characteristics of home and work food environments for commuters and non-commuters separately. The analysis is divided into three panels, each examining different subpopulations or different ways of measuring FE quality, with results indicating varied influences of food environment qualities on diet quality by commuter status.

Results indicate that for non-commuters, only the diversity of healthy foods in the home food environment has a positive and statistically significant effect on GDQS. None of the other characteristics of the home FE have a significant effect. For commuters, each additional healthy food offer site per km² significantly increases GDQS. The opposite is the case for unhealthy food, as each additional unhealthy food offer site per km² significantly decreases GDQS.

Since commuters spend time away-from-home and are additionally exposed to a 'work' FE, in Panel C, we combine the influence of both home and work food environments, weighted by the time spent in each location. Results are consistent with Panel B, showing the statistically significant impact of healthy and unhealthy food offer sites on GDQS, although the effect is small compared to FE measures that are only based on the home FE. The diversity of healthy foods in the combined FE has a positive and marginally significant impact on GDQS, suggesting a nuanced influence that was not evident in Panel B.

Across all panels, the presence and diversity of healthy food options in both home and combined home/work environments show consistent positive relationships with better diet quality, particularly for commuters. Unhealthy food presence generally correlates with poorer diet outcomes, although the impact is less pronounced in combined home/work environments. The findings underscore the complex interaction between food environment characteristics and dietary quality, highlighting the importance of promoting healthy food availability especially in locations frequented by individuals such as work and home. The results also demonstrate that the impact can differ notably between commuters and non-commuters, with additional variances across different regions.

Next, we explore the mediating factors that influence the relationship between GDQS and the quality of home food environments across three models in Table 9 and disaggregated by commuting status in Appendix F. The focus is particularly on the ratio of the number of healthy to unhealthy food offer sites (a measure of FE quality that was particularly significant in Table 8) and how various factors modify this relationship. Across models, the ratio significantly predicts GDQS, indicating that a higher proportion of healthy food offer sites relative to unhealthy ones leads to better diet quality. The coefficient increases substantially and remains significant when including interaction terms in models 2 and 3. For example, the interaction of the healthy to unhealthy food ratio with being female (model 1) shows a significant positive effect (1.771, $p<0.1$), suggesting that the positive impact of a healthier home food environment is more pronounced for females. We posit that this might be because women are less mobile and therefore more influenced by their home food environments (and by any food environment that is defined as a delimited area around home or work). The interaction with the share of days on which FAFH is consumed is negative (-1.789, $p<0.1$), implying that frequent consumption of FAFH decreases the positive impact of healthy food availability in the home FE. We posit that this might be because individuals who eat more often outside the home are less influenced by the home food environment (which might affect more strongly one's diet inside the home) or might be more mobile than individuals who don't indulge in FAFH. The effects of gender and consumption of FAFH in mediating the influence of home FE are more pronounced for non-commuters and do not exist for commuters (Appendix F). Interactions with regions (Nairobi peri-urban, Kisumu urban, and Kisumu peri-urban) show that the positive impact of a healthier food ratio is less pronounced or negative in these regions compared to the baseline region (Nairobi urban). In other words, the home FE is most important in Nairobi urban. We tentatively posit that this might be because this is the population whose diets are most malleable and influenced by factors apart from culture/tradition. These regional effects are more pronounced for commuters and do not exist among non-commuters (Appendix F).

As an indicator of model fit, the R-squared values are relatively low (ranging from 0.063 to 0.065), indicating that while the models explain some variation in GDQS, most of the variability remains unaccounted for by the factors included in the models, which is consistent with the results in Table 8.

Overall, these results highlight the significant role of food environment quality in influencing diet quality, moderated by demographic factors, personal habits like FAFH consumption, and regional characteristics. They suggest targeted interventions might be necessary to enhance diet quality, considering these interactions.

Finally, Table 10 presents the findings from individual fixed-effects regressions analyzing the relationship between day-level GDQS and various characteristics of food environments. This analysis focuses on how daily exposure to different types of food environments affects diet quality, considering both home and work food environments, and adjusting for individual fixed effects to account for unobserved personal characteristics that could influence diet quality. The models are based on over 3,000 individual-day observations from about 1,150 to 1,172 individuals. The FE quality per day is a weighted average of home FE and work FE which accounts for the number of hours spent at home and at work/school on that day. Note that this analysis excludes individuals that do not commute and are thus not exposed to a 'work' FE.

The findings from this day-level analysis are consistent in both magnitude and statistical significance with the individual level analysis presented in Table 8 for the following three FE variables: number of healthy and unhealthy food offer sites per km^2 (column 1), shelf space (measured in 100s m^3) devoted to healthy and unhealthy foods per km^2 (column 3), and % shelf space that is healthy (column 4). For the ratio of number of healthy to unhealthy food sites, the effect of this metric on GDQS is significantly positive in both individual-level and individual-day-level analysis, underscoring the importance of having more healthy food options relative to unhealthy ones. However, the magnitude of this effect is much larger in the day-level analysis (4.191) compared to individual level analysis (0.958). For the diversity of healthy food offerings, the effect of this metric on GDQS is not significant at the day-level but was significant at the individual level. On the other hand, the opposite is true for the effect of diversity of unhealthy food offerings on diet quality. In the day-level analysis, the diversity of unhealthy food offerings has a significant negative impact on GDQS (-8.133, $p<0.1$), implying that a greater variety of unhealthy food options may lead to poorer diet choices, after controlling for individual's unobservable characteristics.

The values of R-squared are relatively low (ranging from 0% to 3.2%), suggesting that the models explain a small portion of the within-individual variance in GDQS across different days. However, the value of the *rho* statistic (which is comparable to the R-square in a cross-sectional model) indicates that a substantial fraction of the variance in GDQS (ranging from approximately 41% to 45%) is attributable to individual-level effects, which are accounted for in the fixed-effects model.

Overall, these results highlight the significant role that the quality of the food environment plays in influencing daily diet quality. Specifically, having a higher proportion of healthy versus unhealthy food offerings appears beneficial for diet quality, while diversity in unhealthy food options tends to be detrimental. The use of individual fixed effects helps isolate the impact of the food environment from other personal characteristics that might confound these relationships.

5. Discussion of key findings and policy implications

Using individual level food consumption data, we analyze how socio-economic, demographic, and home/work food environmental factors impact diet quality across Nairobi and Kisumu. This approach advances the field by integrating more granular, individual-based FE assessments, compared to the broader FE metrics traditionally used, such as proximity and density of food outlets. Our more granular measurement aligns with the need for refined methodologies in FE research, as highlighted by Turner et al. (2020), and responds to gaps in capturing the complex realities of food choices in urban and peri-urban settings.

The paper highlights significant regional variations in calorie intake and diet quality scores. Notably, Kisumu peri-urban residents consume more calories, while those in Nairobi urban consume less but have more frequent meals away from home. There are stark differences in the availability and diversity of healthy vs. unhealthy food offerings between regions. Urban areas, particularly Nairobi urban, tend to have more healthy food options compared to other regions; but they also tend to have more unhealthy food options. Economic disparities across neighborhoods also affect access to healthy foods, with less impoverished areas having better access to healthy food options and more affordable prices. Across all regions, the shelf space and density of unhealthy foods far exceed those of healthy foods. This pattern echoes findings from the literature that discuss dietary shifts towards more processed foods (Popkin et al., 2012; Reardon et al., 2021).

In peri-urban Nairobi, the population generally enjoys a more varied and healthier diet than those in urban Nairobi. This pattern is not observed in Kisumu, indicating that peri-urban areas surrounding a city the size of Nairobi may sometimes resemble suburban communities more than semi-rural settings.[4] This differentiation supports calls for region-specific strategies to manage the dual burden of malnutrition, as suggested by Haggblade et al. (2016).

Our analysis further reveals that gender and economic status are pivotal in influencing diet quality, with males and lower-income groups exhibiting poorer dietary outcomes. This insight complements the discussions by Laar et al. (2022), advocating for targeted interventions that consider these demographic variables to mitigate poor dietary outcomes effectively.

Moreover, the commuting behaviors analyzed in our study provide a unique lens through which to view dietary choices, particularly the preference for and access to food away from home. This aspect of our study aligns with discussions on the increasing reliance on convenience foods by a growing middle class in East and Southern Africa (Tschirley et al., 2015), highlighting the need for policies that enhance healthy food access both at home and along commuting routes.

Our econometric results show significant associations between various measures of FE quality and GDQS-based measures of individual diet quality. Results suggest that the availability and diversity of healthy food offerings have a positive impact on diet quality, while the presence of

[4] It should be noted that the term "peri-urban" has different connotation in Nairobi (where the selected locations were mostly composed of ‘urban’ EAs) compared to Kisumu (where locations were a combination of both urban and rural EAs).

more unhealthy food options has a negative effect. Economic factors like income and poverty probability are significant predictors of diet quality, indicating that higher income and lower poverty probability are associated with better diet quality. These findings support the literature's call for comprehensive policy actions (Laar et al., 2020) to improve food environments, especially in economically challenged regions.

Individual-day-level analysis of food environment and diet quality confirms that having a higher proportion of healthy versus unhealthy food offerings in one's food environment is beneficial for diet quality on that day. The diversity of unhealthy food options has a detrimental effect on diet quality, emphasizing the need to focus on reducing unhealthy food options in the food environment.

Our cross-sectional regression analysis identifies significant correlations between food environment (FE) quality and Global Diet Quality Score (GDQS) measures. However, the model's explanatory power for variations in diet quality is limited. This observation aligns with findings from a previous study by Tschirley et al. (2022), which focused on a limited number of neighborhoods in Nairobi and reported similar limitations. In this study, we had food consumption data for individuals spanning multiple days, which allowed us to extend the previous work by conducting day-level analysis with individual fixed effects. After accounting for these effects, the model explains approximately 40% of the variation in diet quality, with individual factors having the most substantial impact. This outcome highlights the necessity to further investigate the individual factors influencing the relationship between FE and diet quality, offering a promising avenue for future research that could incorporate advanced analytical techniques like the generalized Random Forest algorithm to explore these individual factors further.

Overall, the findings of this study highlight the crucial need for targeted policy interventions that address both regional and demographic disparities in diet quality, particularly in economically challenged regions. Effective strategies should enhance the availability of healthy foods while tackling economic barriers that restrict access to these options, especially in impoverished neighborhoods. This approach requires a multifaceted policy framework that includes improving the balance of food offerings, particularly by increasing healthy food availability and integrating these enhancements into urban planning to ensure better access and affordability. Moreover, it is essential to develop targeted interventions for lower-income and vulnerable groups, such as women, to improve their economic capabilities and dietary outcomes, while also addressing unique challenges related to economic participation and access to education. Enhancing transportation infrastructure is crucial to facilitate easier access to diverse food markets and support local market development in peri-urban and rural areas. Additionally, launching educational campaigns to raise nutritional awareness and promote healthier diets, alongside ongoing monitoring and research, can adapt policies responsively based on socio-economic trends and leverage technology to track changes in food environment quality and its health impacts. These comprehensive strategies are designed to foster healthier communities through improved food environments and informed public engagement, ensuring that health and economic policies are effectively implemented with consideration for local variations.

6. Conclusion

This study extends the existing literature on food environments and diet quality by incorporating a detailed, individual-level analysis that captures commuting influences. Our findings highlight the critical need for nuanced, locally tailored interventions that address the socio-economic and demographic disparities influencing diet quality in Kenya. By integrating our insights with ongoing policy discussions, we can contribute to more effective strategies aimed at curbing the adverse effects of the nutrition transition in urban and peri-urban Africa. This multi-faceted approach, informed by rigorous empirical evidence and aligned with regional needs, is essential for fostering healthier communities through improved dietary practices.

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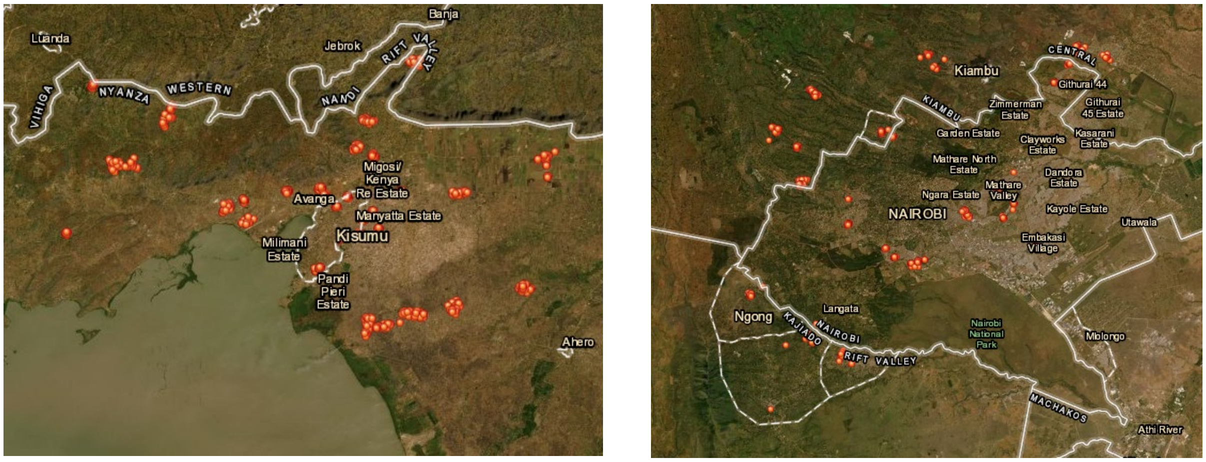
Figure 1. Spatial distribution of sampled households in Kisumu and Nairobi



(a) Kisumu households (b) Nairobi households

Table 1. Sample size of surveyed households and individuals

Region	Household sample		Individual sample	
	Number	Percentage	Number	Percentage
Nairobi urban	375	24.9	505	23.5
Nairobi peri-urban	357	23.7	492	22.9
Kisumu urban	383	25.4	545	25.4
Kisumu peri-urban	392	26.0	608	28.3
Total	1,507	100.00	2,150	100.00

Table 2. Characteristics of individuals

	All	Study-region				Gender		Poverty class	
		Nairobi urban	Nairobi peri-urban	Kisumu urban	Kisumu peri-urban	Female	Male	Low probability of poverty	High probability of poverty
Age (years, mean)	35.6	35.2	36.4	34.3	36.2	35.4	35.9	35.0	36.2
Has some education beyond primary school (%)	67.4	66.5	70.7	61.3	59.2	64.6	70.8	87.8	46.8
Household size (members, mean)	3.9	3.9	3.7	4.9	4.7	4.3	3.4	3.3	4.5
No. adults in household (mean)	2.4	2.4	2.4	2.7	2.7	2.5	2.3	2.3	2.5
No. children in household (mean)	1.5	1.5	1.3	2.2	2.0	1.8	1.2	1.0	1.9
Household probability of poverty at Int$3.20 poverty line (mean)	35.7	35.3	33.4	45.8	47.7	37.4	33.6	13.5	58.1
Engaged in any income-generating activity (%)	81.5	82.6	82.3	72.8	72.2	73.2	91.2	82.4	80.6
Income-generating activities									
Wage work (%)	55.9	60.8	53.5	38.9	33.4	46	67.4	56.3	55.5
Self-employment (%)	26.1	26.2	25	33	23.5	26.4	25.7	27.5	24.6
Crop farm (%)	9.6	3.7	15.2	14.7	33.2	8.6	10.7	10.8	8.4
Livestock farm (%)	8.3	4.3	12.6	9.6	23.4	6.8	10.0	9.7	6.9
Other sources of income									
Spending allowance (%)	16.1	12.6	20	20.8	21.4	21.7	9.6	17.5	14.6
Remittances (%)	13.6	13.5	13.3	11.8	20.5	15.0	12.0	13.4	13.8
Income per day (shillings, mean)	311	353.3	270.6	236.9	190.1	258.1	372.1	408.2	212.8
Observations	2,150	505	492	545	608	1,292	858	921	1,229

Table 3. Commuting behaviors

	All	Study-region				Gender		Poverty class	
		Nairobi urban	Nairobi peri-urban	Kisumu urban	Kisumu peri-urban	Female	Male	Low probability of poverty	High probability of poverty
Commutes anywhere (%)	63.9	67.7	61.3	51.2	51.6	55.2	73.8	63.3	64.4
Among commuters:									
Commute destinations									
Work (%)	69.1	75.3	61.7	64.1	42.9	64.4	73.2	71.9	66.4
School (%)	5.1	3.4	3.6	16.0	38.6	5.7	4.7	6.2	4.0
Irregular (%)	19.1	18.1	21.4	16.8	14.5	17.2	20.6	16.3	21.8
Other (%)	7.6	4.0	14.4	4.1	4.4	13.5	2.5	6.8	8.4
Number of commutes per week (mean)	5	5.1	4.8	5	4.7	4.7	5.2	4.9	5
Time spent commuting (hours/week, mean)	5.8	6.4	4.9	5.1	4.1	5.6	5.9	5.7	5.8
Hours at commuting destination per week (mean)	44.2	46.6	40.9	45.2	35.1	39	48.6	44.7	43.7
Modes of transport:									
Walk (%)	53.8	50.6	58.5	49.9	67	59	49.4	41.8	65.8
Bicycle (%)	1.3	1	0.9	6.6	2	0	2.3	1.2	1.4
Bus/Matatu (%)	34.9	37.2	35.3	15.7	15.6	36.4	33.6	43.3	26.7
Motorcycle (%)	3.1	3	2.1	8.6	9.7	0	5.8	3.6	2.7
Own car (%)	5	6.9	2.7	1.6	1.4	3	6.8	7.5	2.6
Taxi/Boda boda (%)	1.8	1.3	0.5	17.6	4.3	1.5	2.1	2.7	1

Table 4. Eating behaviors, diet quality, and risk of non-communicable diseases

	All	Study-region				Gender		Poverty class	
		Nairobi urban	Nairobi peri-urban	Kisumu urban	Kisumu peri-urban	Female	Male	Low probability of poverty	High probability of poverty
Calories consumed per day (mean)	2,007.5	1,964.4	2,021.3	2,135.9	2,310.5	1,989.6	2,028.1	2,044.7	1,970.0
No. GDQS food categories consumed per day (mean)	7.4	7.2	7.7	7.2	7.2	7.5	7.2	7.7	7.1
Eats any FAFH (%)	40.2	40.6	40.8	36.7	34.5	28.7	53.5	41.8	38.6
% Days on which FAFH is eaten (mean)	34.9	36.4	34.6	30.0	23.7	24.9	46.5	39.3	30.5
% Days on which FAFH is eaten as a meal (mean)	29.5	31.6	27.9	25.7	20.8	19.0	41.7	33.4	25.7
% Days on which FAFH is eaten as a snack (mean)	12.8	11.9	15.5	9.4	6.4	11.6	14.3	14.4	11.2
% Calories consumed as FAFH (mean)	24.7	26.7	22.9	21.7	17.6	20.5	29.6	27.7	21.7
% Value of food consumed as FAFH (mean)	26.1	27.8	24.5	23.8	20.5	19.9	33.2	29.2	23.0
Eats any takeout (%)	67.3	67.5	68.1	65.8	59.0	70.5	63.5	70.6	63.9
Engages in snacking (%)	57.8	55.8	62.1	50.9	55.9	61.2	53.9	64.8	50.8
Consumes FAFH in a social setting (%)	27.6	28.4	27.1	26.6	22.5	20.3	35.9	33.2	21.9
GDQS (overall score, mean)	18.6	18.5	18.8	18.5	18.4	18.7	18.5	18.9	18.3
GDQS+ (score for consuming healthy foods, mean)	10.9	10.7	11.2	10.7	10.7	11.0	10.7	11.2	10.5
GDQS– (score for avoiding unhealthy foods, mean)	7.8	7.8	7.6	7.7	7.7	7.7	7.8	7.7	7.8
Low risk of diet-related NCDs (%)	7.3	7.3	7.0	9.5	7.4	8.2	6.3	9.1	5.4
Moderate risk of diet-related NCDs (%)	81.6	80.6	83.9	77.4	80.9	81.4	81.8	82.3	81.0
High risk of diet-related NCDs (%)	11.1	12.1	9.1	13.2	11.7	10.4	11.9	8.6	13.6

Table 5. Grams consumed of each GDQS category per day (mean values)

	All	Study-region				Gender		Poverty probability class	
		Nairobi urban	Nairobi peri-urban	Kisumu urban	Kisumu peri-urban	Female	Male	Low probability	High probability
Healthy									
Whole grains	175.8	161.6	171.1	248.3	320.2	175.5	176.2	154.5	197.4
Legumes	90.5	87.6	101.5	68.2	60.1	89.8	91.3	98.0	82.8
Dark green leafy vegetables	77.7	70.5	88.4	76.5	81.6	73.6	82.4	76.2	79.2
Other vegetables	54.6	55.8	56.8	37.3	43.1	55.4	53.8	60.4	48.9
Other fruits	71.4	51.8	110.7	41.7	26.6	102.4	35.6	99.3	43.2
Poultry and game meat	24.6	31.1	18.3	11.3	11.5	22.9	26.6	32.3	16.9
Cruciferous vegetables	19.6	21.1	19.6	10.2	11.8	22.9	15.8	21.2	18.0
Liquid oils	17.0	16.8	17.6	15.3	15.8	16.8	17.2	18.5	15.5
Eggs	10.1	8.1	13.0	11.4	9.4	8.9	11.5	13.5	6.7
Fish and shellfish	6.7	7.3	3.2	16.1	16.7	7.4	5.7	6.1	7.2
Deep orange fruits	4.7	4.9	3.7	7.0	6.9	5.8	3.4	6.5	2.8
Deep orange tubers	5.5	6.7	4.3	2.7	3.1	5.2	5.8	5.2	5.7
Citrus	5.6	5.5	6.7	2.4	1.3	8.1	2.7	8.0	3.2
Deep orange vegetables	1.4	0.8	2.5	0.3	0.9	1.7	1.1	1.4	1.5
Nuts and seeds	3.1	4.4	1.2	4.1	2.4	3.2	3.1	5.6	0.7
Low fat dairy	1.8	0.1	4.8	0.5	0.0	0.5	3.3	1.8	1.8
Unhealthy in excessive amounts \a									
High fat dairy	292.7	260.8	362.3	185.3	252.1	289.9	296.0	310.8	274.5
Red meat	3.3	4.0	2.9	1.0	0.9	3.0	3.7	4.1	2.6
Unhealthy									
Refined grains and baked goods	522.5	383.4	788.4	326.6	305.8	382.9	683.5	372.4	674.1
Sweets and ice cream	59.7	56.0	67.5	46.1	58.4	56.1	63.7	67.3	51.9
Purchased deep fried foods	51.8	52.4	48.1	60.1	65.6	52.9	50.5	57.7	45.9
White roots and tubers	28.0	24.6	34.4	21.3	27.0	30.9	24.8	31.1	25.0
Sugar-sweetened beverages	50.5	80.0	13.4	20.9	16.0	73.6	23.7	26.9	74.3
Juice	7.7	1.0	19.8	0.2	1.2	13.4	1.1	13.8	1.5

\a Note that the mean levels observed for the two food groups in this category are within the healthy range of dietary intake.

Table 6. Characteristics of home and work food environments (mean values)

	Home food environments					Work food environments				
	All	Study-region				All	Study-region			
		Nairobi urban	Nairobi peri-urban	Kisumu urban	Kisumu peri-urban		Nairobi urban	Nairobi peri-urban	Kisumu urban	Kisumu peri-urban[a]
Density of healthy food offer sites (No./km^2)	1,061.2	1,369.6	724.9	427	156.2	497.0	835.1	505.8	442.5	123.0
Density of unhealthy food offer sites (No./km^2)	611.2	813.9	375.2	242	85.4	342.2	723.5	296.0	239.0	73.0
No. prepared food vendors per km^2	77.9	107.7	41.1	29.5	10.8	53.9	119.6	45.5	34.0	12.1
Total shelf space for all food types (m^3)	89.0	125.7	41.7	30.7	24.8	71.6	146.4	73.1	49.8	36.2
Total shelf space for GDQS foods (m^3)	82.8	116.8	39.3	28.2	21.7	71.6	135.4	70.0	46.0	33.1
Shelf space for healthy foods (m^3)	28.7	41.2	12.5	8.8	7.1	28.7	50.0	34.1	16.5	14.3
Shelf space for unhealthy foods (m^3)	47.2	65.9	23.5	16.0	13.3	37.4	77.4	28.9	25.4	16.2
Shelf space for unhealthy in excess foods (m^3)	6.9	9.6	3.4	3.4	1.2	5.5	8.0	7.1	4.1	2.6
% Shelf space allocated to healthy foods	36.4	38.8	31.4	37.7	40.9	38.7	39.2	34.3	34.3	53.2
Majority healthy shelf space (%)	19.9	29.9	0.0	31.4	25.7	29.3	21.4	28.6	20.0	60.0
Density of healthy food shelf space (m^3 per km^2)	56.7	82.0	24.8	16.7	6.3	54.1	99.4	67.8	32.5	12.7
Density of unhealthy food shelf space (m^3 per km^2)	93.3	131.1	46.7	30.3	11.8	70.8	154.0	57.4	49.5	14.3
Diversity of healthy foods	81.1	81.1	81.6	80.9	78.9	91.2	97.4	84.5	94.0	86.3
Diversity of unhealthy foods	70.1	70.5	69.7	70.2	65.4	83.1	94.3	78.5	84.5	71.1
Average price healthy foods (KES/gram)	5.7	3.3	10.2	5.9	1.2	9.2	10.0	1.4	18.1	1.2
Average price unhealthy foods (KES/gram)	2.1	2.0	2.2	2.9	0.5	1.8	1.9	0.3	3.5	0.2
Average ratio of prices (healthy:unhealthy)	8.1	7.5	9.6	8.8	3.2	9.5	12.7	5.0	11.8	6.8
Observations	61	16	15	16	14	61	15	15	20	11

Note: For home food environments, enumeration area weights applied to make the sample representative of the population of enumeration areas in these two cities. For work food environments, no weights are applied to generate these statistics.

[a] For the work food environments, the category of Kisumu peri-urban includes 4 food environments that are found in Kisumu rural areas.

Table 7. Characteristics of home and work food environment (FEs) exposed by individuals that commute to work/school/other location

	Home FE	Work FE
Density of healthy food offer sites (No./km^2)	1,028.0	864.9
Density of unhealthy food offer sites (No./km^2)	606.8	618.3
No. prepared food vendors per km^2	80.7	90.0
Total shelf space for food (m^3)	83.6	106.6
Total shelf space for GDQS foods (m^3)	78.3	99.2
Shelf space for healthy foods (m^3)	27.2	35.8
Shelf space for unhealthy foods (m^3)	44.7	56.9
Shelf space for unhealthy in excess foods (m^3)	6.4	6.4
% Shelf space allocated to healthy foods	35.8	35.9
Majority healthy shelf space (%)	17.3	16.1
Density of healthy food shelf space (m^3 per km^2)	53.9	71.0
Density of unhealthy food shelf space (m^3 per km^2)	88.4	112.8
Diversity of healthy foods	80.7	87.0
Diversity of unhealthy foods	70.5	79.6
Average price healthy foods (KES/gram)	5.5	10.2
Average price unhealthy foods (KES/gram)	2.3	2.4
Average ratio of prices (healthy:unhealthy)	9.2	13.1
Observations	1,172	1,172

Table 8. Relationship between average GDQS and home food environment quality (OLS)

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Average GDQS				
Number of healthy food offer sites per km^2	0.003***				
	(0.001)				
Number of unhealthy food offer sites per km^2	-0.005***				
	(0.001)				
Ratio of number of healthy to unhealthy food offer sites		0.958**			
		(0.415)			
Shelf space devoted to healthy foods (100s m^3/km^2)			-0.021		
			(0.419)		
Shelf space devoted to unhealthy foods (100s m^3/km^2)			-0.002		
			(0.234)		
% shelf space in home FE that is healthy				-0.004	
				(0.009)	
Measure of diversity of healthy foods in home FE					0.033***
					(0.012)
Measure of diversity of unhealthy foods in home FE					-0.004
					(0.007)
Average price of healthy foods (KES/gram)	0.011	0.006	0.005	0.004	0.006
	(0.009)	(0.010)	(0.011)	(0.011)	(0.010)
Average price of unhealthy foods (KES/gram)	-0.004	-0.003	0.002	0.003	0.002
	(0.014)	(0.015)	(0.015)	(0.015)	(0.017)
1= Female	0.350	0.381	0.428	0.432	0.396
	(0.271)	(0.303)	(0.321)	(0.332)	(0.306)
Age	0.018**	0.017**	0.017**	0.017**	0.016**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
1= Has some education beyond primary school	0.012	-0.043	-0.043	-0.040	-0.010
	(0.202)	(0.210)	(0.198)	(0.205)	(0.206)
1= Commutes somewhere	0.465*	0.441*	0.442*	0.442*	0.457*
	(0.264)	(0.259)	(0.257)	(0.256)	(0.257)
Income per day (shillings)	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household poverty likelihood (%)	-0.007*	-0.009**	-0.010**	-0.010***	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
No. days with consumption data	0.261***	0.263***	0.269***	0.272***	0.268***
	(0.088)	(0.093)	(0.098)	(0.100)	(0.094)
1= Nairobi peri-urban	-0.161	0.044	0.275	0.272	0.248
	(0.230)	(0.271)	(0.262)	(0.266)	(0.247)
1= Kisumu urban	-0.127	0.033	0.139	0.153	0.095
	(0.295)	(0.284)	(0.287)	(0.277)	(0.266)
1= Kisumu peri-urban	-0.163	-0.042	0.082	0.122	0.050
	(0.267)	(0.274)	(0.251)	(0.212)	(0.233)
Constant	16.897***	15.227***	16.813***	16.905***	14.397***
	(0.563)	(1.083)	(0.619)	(0.655)	(1.354)
Observations	2,150	2,150	2,150	2,150	2,150
R-squared	0.071	0.058	0.053	0.053	0.060

*Robust standard errors in parentheses; standard errors clustered at enumeration area; *** p<0.01, ** p<0.05, * p<0.1*

Table 9. Factors that mediate the relationship between average GDQS and home food environment quality (OLS)

	(1)	(2)	(3)
	Dependent variable: Average GDQS		
Ratio of healthy to unhealthy food offer sites in home FE	0.017	1.598***	1.906***
	(0.542)	(0.579)	(0.631)
Ratio of healthy to unhealthy food offer sites * Female	1.771*		
	(0.932)		
Ratio of healthy to unhealthy food offer sites * Share of days on which FAFH is consumed		-1.789*	
		(1.069)	
Ratio of healthy to unhealthy food offer sites * Nairobi peri-urban			-2.294***
			(0.807)
Ratio of healthy to unhealthy food offer sites * Kisumu urban			-2.762*
			(1.499)
Ratio of healthy to unhealthy food offer sites * Kisumu peri-urban			-1.848***
			(0.666)
Share of days on which FAFH is consumed		3.295*	
		(1.690)	
Average price of healthy foods (KES/gram)	0.005	0.005	0.006
	(0.010)	(0.010)	(0.010)
Average price of unhealthy foods (KES/gram)	-0.000	-0.003	-0.001
	(0.014)	(0.014)	(0.016)
1= Female	-2.756	0.408	0.368
	(1.664)	(0.276)	(0.285)
Age	0.017**	0.017**	0.016**
	(0.007)	(0.007)	(0.007)
1= Has some education beyond primary school	-0.002	-0.047	-0.045
	(0.210)	(0.203)	(0.201)
1= Commutes somewhere	0.403	0.424	0.453*
	(0.253)	(0.275)	(0.261)
Income per day (shillings)	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)
Household poverty likelihood (%)	-0.009**	-0.009**	-0.008**
	(0.004)	(0.004)	(0.004)
No. days with consumption data	0.270***	0.256***	0.250***
	(0.093)	(0.087)	(0.089)
1= Nairobi peri-urban	0.040	0.055	4.208***
	(0.262)	(0.258)	(1.348)
1= Kisumu urban	0.032	0.030	4.833*
	(0.283)	(0.283)	(2.609)
1= Kisumu peri-urban	-0.003	-0.050	3.142***
	(0.259)	(0.292)	(1.079)
Constant	16.844***	14.069***	13.663***
	(1.113)	(1.319)	(1.421)
Observations	2,150	2,150	2,150
R-squared	0.064	0.063	0.065

*Robust standard errors in parentheses; standard errors clustered at enumeration area; *** p<0.01, ** p<0.05, * p<0.1*

Table 10. Relationship between daily diet quality and food environment \a (individual fixed-effects regressions)

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Day-level GDQS				
Number of healthy food offer sites per km^2	0.003*				
	(0.002)				
Number of unhealthy food offer sites per km^2	-0.005**				
	(0.002)				
Ratio of healthy to unhealthy food offer sites		4.191**			
		(1.861)			
Shelf space devoted to healthy foods (100s m^3/km^2)			0.008		
			(1.069)		
Shelf space devoted to unhealthy foods (100s m^3/km^2)			-0.822		
			(0.811)		
% shelf space in home FE that is healthy				-0.006	
				(0.028)	
Measure of diversity of healthy foods					0.006
					(0.052)
Measure of diversity of unhealthy foods					-0.079*
					(0.043)
Average price of healthy foods (KES/gram)	0.014	0.017*	-0.002	-0.011	-0.000
	(0.009)	(0.009)	(0.012)	(0.018)	(0.015)
Average price of unhealthy foods (KES/gram)	-0.106	-0.105	-0.109	-0.083	-0.046
	(0.092)	(0.086)	(0.087)	(0.091)	(0.096)
1= Weekday	-0.128	-0.122	-0.103	-0.104	-0.133
	(0.167)	(0.165)	(0.166)	(0.166)	(0.164)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	19.238***	11.899***	20.029***	19.490***	24.469***
	(0.868)	(3.202)	(0.576)	(1.099)	(3.120)
Observations (Number of individual-days)	3,157	3,157	3,157	3,157	3,157
Number of individuals	1,151	1,151	1,151	1,151	1,151
Rho (fraction of variance due to individual effects)	0.438	0.464	0.438	0.418	0.437
Within r-squared	0.034	0.028	0.014	0.002	0.013

*Robust standard errors in parentheses; standard errors clustered at enumeration area; *** p<0.01, ** p<0.05, * p<0.1*

\a The key explanatory variables that measure the food environment exposure in this model is constructed as an average of the FE quality measures for the home and work FEs, weighted by the % of a 16-hour day that was spent in either location on a given day.

APPENDIX

Appendix A. Sample Frame

The sampling frame for this study includes all the households residing in the urban and peri-urban areas of Nairobi and Kisumu. Administratively, Kenya is divided into counties. Each county is divided into sub-counties, wards, and locations. For sampling purpose, the Kenyan National Bureau of Statistics further divides locations into enumeration areas (EA), and each EA is classified as either urban or rural. We used the 2019 census data at the location level to define the sampling frames for our 4 study areas—Nairobi urban, Nairobi peri-urban, Kisumu urban, and Kisumu peri-urban. Households in peri-urban areas rely relatively more on agricultural activity for their incomes. Peri-urban areas are zones of transition from rural to urban land uses, they are located between the outer limits of urban centres. They can be defined as a mixed zone with characteristics of both urban and rural settings.

To identify, the geographic boundaries of each of our study areas, we used the following approach/definition.

- Nairobi urban: Administratively, this is equivalent to the Nairobi County. It is made up of 73 administrative locations with 100% EAs classified as urban, according to 2019 census data.
- Nairobi peri-urban: To identify peri-urban areas in Nairobi City, we used the definition of Nairobi Metropolis, which includes neighboring counties i.e. Kiambu, Kajiado, and Machakos. Based on the location map obtained from KNBS, we identified 38 locations in these three counties that bordered Nairobi County or were in close proximity to the border of Nairobi County. These 38 locations were made up of both urban and rural EAs. The percentage of urban EAs in a given location ranged from 26-100%.
- Kisumu urban: This is made up of eight locations around Kisumu City CBD (commercial and business district) that had at least 77% of EAs classified as urban in 2019 census data.
- Kisumu peri-urban: We identified 7 locations around (i.e., closer to) Kisumu urban as peri-urban.

Appendix B. GDQS and GDQS sub metric food groups and scoring[1]
[Reproduced version of Table 3 in Bromage et al. (2021)]

Food group	*Categories of consumed amounts (g/d)*				Point values			
	1	2	3	4	1	2	3	4
Healthy								
Citrus fruits	<24	24-69	>69		0	1	2	
Deep orange fruits	<25	25-123	>123		0	1	2	
Other fruits	<27	27-107	>107		0	1	2	
Dark green leafy vegetables	<13	13-37	>37		0	2	4	
Cruciferous vegetables	<13	13-36	>36		0	0.25	0.5	
Deep orange vegetables	<9	9-45	>45		0	0.25	0.5	
Other vegetables	<23	23-114	>114		0	0.25	0.5	
Legumes	<9	9-42	>42		0	2	4	
Deep orange tubers	<12	12-63	>63		0	0.25	0.5	
Nuts and seeds	<7	7-13	>13		0	2	4	
Whole grains	<8	8-13	>13		0	1	2	
Liquid oils	<2	2-7.5	>7.5		0	1	2	
Fish and shellfish	<14	14-71	>71		0	1	2	
Poultry and game meat	<16	16-44	>44		0	1	2	
Low-fat dairy	<33	33-132	>132		0	1	2	
Eggs	<6	6-32	>32		0	1	2	
Unhealthy in excessive amounts								
High-fat dairy (in milk equivalents)[2]	<35	35-142	>142-734	>734	0	1	2	0
Red meat	<9	9-46	>46		0	1	0	
Unhealthy								
Processed meat	<9	9-30	>30		2	1	0	
Refined grains and baked goods	<7	7-33	>33		2	1	0	
Sweets and ice cream	<13	13-37	>37		2	1	0	
Sugar-sweetened beverages	<57	57-180	>180		2	1	0	
Juice	<36	36-144	>144		2	1	0	
White roots and tubers	<27	27-107	>107		2	1	0	
Purchased deep fried foods	<9	9-45	>45		2	1	0	

[1] GDQS, Global Diet Quality Score; GDQS-, GDQS Negative Submetric; GDQS+, GDQS Positive Submetric
[2] Due to the importance of cheese in many food cultures and the significantly different nutrient density of hard cheeses in comparison with other dairy products, we recommend converting consumed masses of hard cheeses to milk equivalents when calculating total consumption of high-fat dairy for the purpose of assigning a GDQS consumption category [using cheddar cheese as a typical example, a conversion factor of 6.1 can be computed as the mass of 1 serving of milk (237 mL °ø 0.95 g/mL = 225 g)
divided by an isocaloric mass of cheddar cheese (37 g)]

Appendix C. Data Collection Methods to Characterize Food Environments

Overall, our study involved collecting data from 61 home food environments (FEs) and 61 work FEs. We executed this data collection in two distinct rounds for each FE. The first round consisted of a comprehensive census of food outlets within these environments. In the second round, we performed a shelf space survey on a subset of these outlets to gather detailed information on the types and quantities of food available, as well as their pricing. The methodologies for each of these survey rounds are outlined below.

Round 1: Census of food outlets

For all the 61 home FE and 61 work FE (total 122), a census of all the food outlets was conducted. To conduct the census, enumerators were supplied with KML maps of the home and work FEs (0.4 km radius for Nairobi urban and Peri urban and Kisumu urban, and 0.6 km for Kisumu peri urban). Using these maps, enumerator walked within the FE and registered outlets using a tool designed to conduct the census. The enumerators used Google Earth and Google Maps to ensure that the outlets covered were within the boundaries of the KML maps provided. In food environments that overlapped with each other, outlets were listed only once, but with a note on the intersecting FEs. In food environments that overlapped with a market, we listed a sample of outlets in the census following a two-step process. In step 1, the enumerator walked across the market and ticked mark each food vendor with a number. In step 2, 15% of vendors/outlets were randomly selected from the total number of tick marked vendors in the market.

A structured questionnaire was used during the census survey to collect the following information for each food outlet—GPS coordinates, type of outlet (see Table C1), categories of food sold, and whether any food sold was fortified. The food categories were defined following Bromage et al. (2021) study. Both unprepared and prepared food outlets were captured in the census. Outlets that sold only alcohol were excluded.

Table C1. Definitions of outlet types

Outlet Type	Description
Small supermarket	Any self-service food outlet with 1-4 cash registers
Large supermarket	Any self-service food outlet with more than 4 cash registers
Duka (e.g., small traditional shop)	traditional (not self-service) food outlets with permanent, constructed quarters from which they operate, typically supplied at least with electricity and perhaps water; not easily movable or removable.
Kiosk	Typically small, free-standing, “semi-movable” with rudimentary or transient structure such as shipping containers located along thoroughfares
Mama mboga	Vegetable seller/vendor specializing in fruits and vegetables usually operating in residential areas
Street vendor	A seller located outside a market on the streets and selling from a mobile structure or from ground (excludes Mama mbogas)
Hawker	Seller that sells items on foot (walking from place to place) may sometimes have a cart
Depot/wholesale	An outlet that primarily sells goods in bulk to either retailers or consumers directly
Milk bar/milk atm	Outlets that primarily sell unpackaged milk and other dairy products. Milk ATMs sell milk that is dispensed through simple mechanized nozzle.
Hotel/restaurant	An outlet selling prepared food for consumption on the premises, featuring permanent construction

Outlet Type	Description
Informal prepared food	Same as street vendor or kiosk—but specialized in selling prepared foods ready to be eaten, rudimentary infrastructure
Cereal shops and posho mills	Specialize in selling dry grains, mainly cereals and pulses. some of them also value add and sell flours from these grains.
Bakery	An outlet that primarily sells baked goods
Butchery	An outlet that primarily sells red or white meat

Round 2: Shelf space survey

After the census was completed, a sub-sample of outlets were randomly selected in each home and work FE for the shelf-space survey. Following sampling procedure was used to select the sub-sample of outlets for this second round of survey. From the list of census outlets, first all supermarkets (large and small format) were identified and added to the shelf space sample. Next, we sampled 15 outlets from the remaining outlets. Where a market was located within the EA, the 15 sampled outlets did not include outlets within the market. Instead, we sampled another 15 outlets from the sample census of the market outlets. Where two EAs intersected, the 15 outlets sampled did not include the outlets in the intersection. Instead, we sampled 15 outlets within the intersection.

The purpose of this second round of sample survey was to collect information on the shelf-space devoted to different categories of foods and their prices. Following procedure was used to collect this data.

Shelf space

1. The store/outlet was divided into N sections, where a section is a contiguous area dedicated primarily to one *sub-category* of food. The store could have more than one section dedicated primarily to the same sub-category, e.g., sugar-sweetened beverages could be located in more than one separate area of the store. In defining the sections, no distinction was made between food items. For example, within sugar-sweetened beverages, no distinction was made between Coke and Fanta; or between types of chips within salty/fatty snack foods.
2. Every section of the store was assigned a sequential number, 1-N. Enumerators then identified the sub-category of food that predominated in each section.
3. Sections of shelf space (a) holding foods not included in the Bromage categories and (b) that were empty were assigned numbers at the end of the sequence.
4. Each section with a sub-category of food, enumerators measured and recorded the length, depth, and height in centimeters.
5. In this exercise, a shelf is defined as any product, whether on a physical shelf, or hanging, or on the floor, that is *immediately available for sale*. Area of the store that was used only for product storage was excluded.
6. For shelves with varying height or depth, measures were taken to the midpoint of the set of product on the shelf
7. Enumerators carried a low-cost metric tape measure. In stores where they can physically reach the shelves, they directly did the measurement. In areas or stores where they cannot reach the shelves, they used the tape measure to visually estimate length and depth.
8. For products that were hanging: Each continuous line of hanging product was considered a shelf and allocated its own section.

Prices

1. Prices of most common food item by food category was collected at the same time as the shelf-space measurement survey.

2. Any item not sold per standard unit of weight (kg, gram) or volume (ml or liter) was weighed and standard units were recorded.
3. If a price (for example of veg or fruit or fish or chicken) is quoted in kg or liters, it was recorded on that basis and not weighed.
4. Examples of price recording: a 750 ml bottle of Coke selling for 80 Ksh was recorded as Unit=4 (ml), quantity=750, shillings=80. Tomatoes selling for 120 Ksh per kg was recorded as Unit=1 (kg), Quantity=1, Shillings=120.

Appendix D. Definitions of key variables

For some variables used in analysis, the definition or construction is less obvious than for others. The table below details the definition or construction of a set of such variables.

Variable	Definition/Construction
Household probability of poverty at Int$3.20 poverty line	A poverty likelihood score for each household, based on Schreiner's (2018) methodology. The value ranges from 0–100, with higher scores indicating a greater likelihood that the household falls below the below the Int$3.20 poverty line.
Low/High probability of poverty	0/1 indicator of whether the household falls below or above the median poverty likelihood score.
Food away from home (FAFH)	Food purchased and consumed away from home *or* prepared (cooked) food purchased away from home and consumed in the home as takeout.
% Value of food consumed as FAFH	To construct this variable, the numerator is the value of food purchased as FAFH, with the value of takeout and the value of communally consumed FAFH captured as the purchase price divided by the number of individuals eating together. The denominator is inclusive of the value of all food, with foods prepared at home valued at the retail price using the median per-gram price observed at the smallest geographic unit (EA, region) for which at least 5 purchase observations are found in the consumption data.
Global Diet Quality Score (GDQS)	The GDQS ranges in value from 0 to 49, with higher scores indicating a healthier diet.
GDQS+ (score for consuming healthy foods)	The sum of points earned towards the overall GDQS that are earned through consumption of the 16 healthy food categories. The GDQS+ ranges from 0 to 32.
GDQS– (score for avoiding unhealthy foods)	The sum of points earned towards the overall GDQS that are earned through consumption of the 7 unhealthy food categories. The GDQS– ranges from 0 to 17.
Density of healthy (or unhealthy) food offer sites (No./km^2)	Within a given food environment, the number of healthy (or unhealthy) food offer sites is the count of location-categories offering categories of food classified as healthy (or unhealthy). If a shop offers foods of category A and category B (both healthy), that counts as 2 healthy location-categories for construction of this indicator. The count is then divided by the area of the food environment. The area of the food environment is 0.5 km^2 except in peri-urban Kisumu where it is 1.1 km^2.
No. prepared food vendors per km^2	Number of food enterprises selling cooked foods, divided by the area of the food environment.
Total shelf space for GDQS foods (m^3)	This value is a bit less than the total shelf space for all foods because some foods are not captured in (excluded from) the GDQS. Examples include coffee, insects, and coconut milk.
% Shelf space allocated to healthy foods	The percent of total shelf space for GDQS foods in the food environment that is taken by foods categorized as healthy.
Majority healthy shelf space (%)	0/1 indicator of whether at least half the shelf space in a food environment is devoted to healthy foods.

Variable	Definition/Construction
Density of healthy (or unhealthy) food shelf space (m^3 per km^2)	Shelf space is captured with consideration of depth, width, and height to produce a measure of m^3. This variable is the sum of shelf space allocated to healthy (or unhealthy) foods, divided by the area of the food environment.
Diversity of healthy (or unhealthy) foods	Diversity of healthy foods = $[1 - \sum_{i=1}^{n} [\frac{Area_i}{Area\_Healthy\_Foods}]^2] * 100$ This is constructed as 1 minus the sum of the squared shares of space allocated to each GDQS category. In this case, a share is in reference to the total area allocated to healthy (or unhealthy) foods. A lower diversity measure indicates that the area for healthy foods in the food environment is dominated by a small number of GDQS healthy food categories, while a higher value indicates that the space for healthy foods is allocated more evenly across different categories.
Average price healthy (or unhealthy) foods (KES/gram)	Each sampled outlet in the food environment identified its most common food item sold in each GDQS category (as applicable) and reported on the price and unit of these items. The average price of healthy foods in a given food environment is the mean value per gram of the food items reported for healthy categories (applying weights that reflect the likelihood of the outlet being sampled). This is a somewhat crude measure of price and may be refined in the future.

Appendix E. Relationship between average GDQS and home/work food environment quality for commuters and non-commuters separately (OLS)

PANEL A: NON-COMMUTERS (Influence of home FE quality)

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Average GDQS				
Number of healthy food offer sites per km^2	0.001				
	(0.001)				
Number of unhealthy food offer sites per km^2	-0.003				
	(0.002)				
Ratio of healthy to unhealthy food offer sites		0.720			
		(0.448)			
Shelf space devoted to healthy foods (100s m^3/km^2)			0.517		
			(0.623)		
Shelf space devoted to unhealthy foods (100s m^3/km^2)			-0.541		
			(0.358)		
% shelf space in home FE that is healthy				0.019	
				(0.011)	
Measure of diversity of healthy foods in home FE					0.052**
					(0.020)
Measure of diversity of unhealthy foods in home FE					-0.011
					(0.012)
All controls	Yes	Yes	Yes	Yes	Yes
Observations	978	978	978	978	978
R-squared	0.074	0.070	0.073	0.072	0.082

PANEL B: COMMUTERS (Influence of home FE quality)

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Average GDQS				
Number of healthy food offer sites per km^2	0.004***				
	(0.001)				
Number of unhealthy food offer sites per km^2	-0.006***				
	(0.002)				
Ratio of healthy to unhealthy food offer sites		1.040			
		(0.690)			
Shelf space devoted to healthy foods (100s m^3/km^2)			-0.395		
			(0.498)		
Shelf space devoted to unhealthy foods (100s m^3/km^2)			0.262		
			(0.287)		
% shelf space in home FE that is healthy				-0.015	
				(0.012)	
Measure of diversity of healthy foods in home FE					0.018
					(0.014)
Measure of diversity of unhealthy foods in home FE					-0.003
					(0.008)
All controls	Yes	Yes	Yes	Yes	Yes
Observations	1,172	1,172	1,172	1,172	1,172
R-squared	0.087	0.067	0.063	0.065	0.063

PANEL C: COMMUTERS (Influence of home + work FE quality weighted by time spent in each environment)\a

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Average GDQS				
Number of healthy food offer sites per km^2	0.001**				
	(0.022)				
Number of unhealthy food offer sites per km^2	-0.001***				
	(0.000)				
Ratio of healthy to unhealthy food offer sites		0.681			
		(0.190)			
Shelf space devoted to healthy foods (100s m^3/km^2)			0.003		
			(0.386)		
Shelf space devoted to unhealthy foods (100s m^3/km^2)			-0.001		
			(0.709)		
% shelf space in home FE that is healthy				-0.003	
				(0.009)	
Measure of diversity of healthy foods in FE					0.027*
					(0.062)
Measure of diversity of unhealthy foods in FE					0.000
					(0.978)
All controls	Yes	Yes	Yes	Yes	Yes
Observations	1,172	1,172	1,172	1,172	1,172
R-squared	0.065	0.065	0.063	0.062	0.066

Robust standard errors in parentheses; standard errors clustered at enumeration area; *** p<0.01, ** p<0.05, * p<0.1

\a The key explanatory variables that measure the food environment exposure in this panel is constructed as a weighted average of the FE quality measures for the home and work FEs, weighted by the % of a 16-hour day that was spent in either location, on average across the days of data collection.

Appendix F. Factors that mediate the relationship between average GDQS and home food environment quality for commuters and non-commuters (OLS)

PANEL A: NON-COMMUTERS (Influence of home FE quality)

	(1)	(2)	(3)
	Dependent variable: Average GDQS		
Ratio of healthy to unhealthy food offer sites in home FE	-0.691	1.873***	1.264*
	(0.692)	(0.595)	(0.736)
Ratio of healthy to unhealthy food offer sites * Female	2.315**		
	(0.994)		
Ratio of healthy to unhealthy food offer sites * Share of days on which FAFH is consumed		-6.143**	
		(2.674)	
Ratio of healthy to unhealthy food offer sites * Nairobi peri-urban			0.000
			(0.000)
Ratio of healthy to unhealthy food offer sites * Kisumu urban			-0.645
			(1.401)
Ratio of healthy to unhealthy food offer sites * Kisumu peri-urban			-1.695
			(2.577)
Share of days on which FAFH is consumed		10.824**	
		(4.116)	
All controls	Yes	Yes	Yes
Observations	978	978	978
R-squared	0.079	0.097	0.071

PANEL B: COMMUTERS (Influence of home FE quality)

	(1)	(2)	(3)
	Dependent variable: Average GDQS		
Ratio of healthy to unhealthy food offer sites in home FE	0.429	1.486**	2.134**
	(0.779)	(0.698)	(0.837)
Ratio of healthy to unhealthy food offer sites * Female	1.270		
	(1.249)		
Ratio of healthy to unhealthy food offer sites * Share of days on which FAFH is consumed		-0.954	
		(1.172)	
Ratio of healthy to unhealthy food offer sites * Nairobi peri-urban			-3.129**
			(1.312)
Ratio of healthy to unhealthy food offer sites * Kisumu urban			-3.127**
			(1.247)
Ratio of healthy to unhealthy food offer sites * Kisumu peri-urban			-2.195**
			(0.890)
Share of days on which FAFH is consumed		1.857	
		(2.004)	
All controls	Yes	Yes	Yes
Observations	1,172	1,172	1,172
R-squared	0.070	0.069	0.079

PANEL C: COMMUTERS (Influence of home <u>and</u> work FE quality weighted by time spent in each environment)\a

	(1)	(2)	(3)
	Dependent variable: Average GDQS		
Ratio of healthy to unhealthy food offer sites in home FE	0.234	1.419*	1.249**
	(0.646)	(0.709)	(0.614)
Ratio of healthy to unhealthy food offer sites * Female	0.956		
	(1.151)		
Ratio of healthy to unhealthy food offer sites * Share of days on which FAFH is consumed		-1.312	
		(0.815)	
Ratio of healthy to unhealthy food offer sites * Nairobi peri-urban			-1.631*
			(0.868)
Ratio of healthy to unhealthy food offer sites * Kisumu urban			-1.891*
			(1.078)
Ratio of healthy to unhealthy food offer sites * Kisumu peri-urban			-1.253*
			(0.651)
Share of days on which FAFH is consumed		2.477*	
		(1.409)	
All controls	Y	Y	Y
Observations	1,172	1,172	1,172
R-squared	0.067	0.068	0.069

Robust standard-errors in parentheses; standard errors clustered at enumeration area; *** p<0.01, ** p<0.05, * p<0.1

\a The key explanatory variables that measure the food environment exposure in this panel is constructed as a weighted average of the FE quality measures for the home and work FEs, weighted by the % of a 16-hour day that was spent in either location, on average across the days of data collection.