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Drivers and Cost Implications of Overnutrition in Kenya

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Abstract

Kenya's population is experiencing a rising prevalence of overweight and obesity. This trend poses a significant concern, as overweight and obesity are major risk factors for non-communicable diseases (NCDs), leading to increased human suffering, raised mortality, and substantial private and social costs. This issue coexists with ongoing challenges of undernutrition and infectious diseases, further straining the country's underfunded health system. The increase in overweight and obesity is driven by economic change, urbanization, and technological advancements, which have led to shifts in lifestyles and eating habits, including higher consumption of processed foods and reduced physical activity.

This study first examines how socio-economic differences in food choice motives affect diet diversity and weight outcomes. The findings show notable differences in food choice motives by socio-economic group. High income is associated with higher prioritization of health, mood, sensory appeal, and weight, while higher education is linked to increased health and sensory motivations and reduced familiarity concerns. Results from mediation analysis show that sensory motives account for 29% of the income-BMI relationship and 30% of the education-BMI link. Familiarity concerns negatively mediate the education-BMI association by -4%. Health and sensory motives also positively mediate the education-diet diversity association by contributing 11% and 4%, respectively.

Secondly, the study evaluates the impact of various types of physical activity (PA)—work, leisure, and transport—along with sedentary time on BMI and NCD outcomes, using 2015 and 2022 data with panel fixed effects, probit, and entropy balancing methods. Findings indicate a decline in overall physical activity (measured in metabolic equivalents, or METs), alongside increases in sedentary time, BMI, and the incidence of NCDs. Work-related PA was the largest contributor to total PA, followed by transport and leisure. An additional MET-hour per week of vigorous work, leisure, and transport PA was linked to reductions in BMI by 0.03%, 0.16%, and 0.05%, respectively. Similarly, increases in vigorous work, moderate work, and leisure PA decreased the probability of having an NCD by 0.15%, 0.11%, and 0.53%, respectively. In comparison, sedentary time was associated with a 0.18% increase in NCD risk.

Finally, the study investigates the health costs of Kenya's current food system, focusing on the impact of unhealthy diets using 2022 Kenya Demographic and Health Survey data and two-part and instrumental variable methods. Results show that overweight and obesity increase the likelihood of outpatient and inpatient medical expenditures by 3.3 and 1.4 times, respectively. Overweight and obesity raised outpatient monthly expenditures by KES 445.0 ($3.61) and annual inpatient costs by KES 16,942.8 ($137.33). An increase of one BMI unit raises marginal outpatient monthly healthcare spending by KES 277.8 ($2.25) and annual inpatient spending by KES 5,119.0 ($41.49). The social costs of overweight and obesity among adult women in 2022 amounted to $1.11 billion, or KES 10,557.2 ($85.57) per woman.

This dissertation concludes by highlighting potential cost-effective policies to reduce the prevalence of overweight and obesity, including implementing a 20% sugar-sweetened beverage tax, mandatory kilojoule menu labeling, front-of-pack nutrition labeling, revising public food procurement policies, mass media campaigns for healthier diets, restricting harmful food marketing to children, promoting breastfeeding practices, and community-wide public education campaigns on physical activity.

Treiber und Kostenimplikationen von Überernährung in Kenia

Kurzfassung

Kenias Bevölkerung erlebt eine steigende Prävalenz von Übergewicht und Adipositas. Dieser Trend stellt ein erhebliches Problem dar, da Übergewicht und Adipositas wichtige Risikofaktoren für nicht übertragbare Krankheiten (NCDs) sind, die zu erhöhter Mortalität und menschlichem Leiden und erheblichen privaten sowie sozialen Kosten führen. Dieses Problem besteht neben den anhaltenden Herausforderungen durch Unterernährung und übertragbare Krankheiten, was das unterfinanzierte Gesundheitssystem des Landes zusätzlich belastet. Der Anstieg von Übergewicht und Adipositas wird durch Wirtschaftswachstum, Globalisierung, Urbanisierung und technologische Fortschritte vorangetrieben, die zu Veränderungen in den Lebensstilen und Ernährungsgewohnheiten geführt haben, einschließlich eines höheren Konsums von verarbeiteten Lebensmitteln und geringerer körperlicher Aktivität.

In dieser Studie wird zunächst untersucht, wie sich sozioökonomische Unterschiede bei den Motiven für die Lebensmittelauswahl auf die Ernährungsvielfalt und das Gewicht auswirken. Die Ergebnisse zeigen bemerkenswerte Unterschiede bei den Motiven für die Lebensmittelauswahl je nach sozioökonomischer Gruppe. Ein hohes Einkommen wird mit einer höheren Priorisierung von Gesundheit, Stimmung, sensorischer Attraktivität und Gewicht in Verbindung gebracht, während ein höheres Bildungsniveau mit einer stärkeren gesundheitlichen und sensorischen Motivation und geringeren Bedenken hinsichtlich der Vertrautheit verbunden ist. Die Ergebnisse der Mediationsanalyse zeigen, dass sensorische Motive für 29 % des Zusammenhangs zwischen Einkommen und BMI und für 30 % des Zusammenhangs zwischen Bildung und BMI verantwortlich sind. Vertrautheitsbedenken wirken sich negativ auf den Zusammenhang zwischen Bildung und BMI aus (-4 %). Gesundheits- und Sinnesmotive wirken sich auch positiv auf den Zusammenhang zwischen Bildung und Ernährungsvielfalt aus, indem sie 11 % bzw. 4 % beitragen.

Zweitens bewertet die Studie die Auswirkungen verschiedener Arten körperlicher Aktivität (PA) – arbeitsbezogen, in der Freizeit und bei der Fortbewegung – sowie der sitzenden Tätigkeit auf den BMI und die NCD-Ergebnisse, wobei Daten aus den Jahren 2015 und 2022 mithilfe von Panel-Fixed-Effekten, Probit- und Entropieausgleichsmethoden analysiert werden. Die Ergebnisse zeigen einen Rückgang der gesamten körperlichen Aktivität (gemessen in metabolischen Äquivalenten oder METs) und einen Anstieg der sitzenden Zeit, des BMI und der Inzidenz von NCDs während des Studienzeitraums. Arbeitsbezogene PA trug am meisten zur Gesamt-PA bei, gefolgt von Verkehr und Freizeit. Eine zusätzliche MET-Stunde pro Woche an intensiver Arbeits-, Freizeit- und Verkehrs-PA war mit einer Verringerung des BMI um 0,03 %, 0,16 % bzw. 0,05 % verbunden. In ähnlicher Weise verringerte eine Zunahme intensiver Arbeit, moderater Arbeit und Freizeit-PA die Wahrscheinlichkeit, eine NCD zu entwickeln, um 0,15 %, 0,11 % bzw. 0,53 %, während sitzende Tätigkeiten mit einem um 0,18 % erhöhten NCD-Risiko verbunden waren.

Schließlich untersucht die Studie die Gesundheitskosten des aktuellen kenianischen Ernährungssystems, wobei der Schwerpunkt auf den Auswirkungen ungesunder Ernährung liegt, basierend auf den Daten der Kenya Demographic and Health Survey von 2022 sowie Two-part- und Instrumentenvariablenmethoden. Die Ergebnisse zeigen, dass Übergewicht und Adipositas die Wahrscheinlichkeit ambulanter und stationärer medizinischer Ausgaben um das 3,3- bzw. 1,4-fache erhöhen. Übergewicht und Adipositas erhöhten die monatlichen ambulanten Ausgaben um KES 445,0 ($3,61) und die jährlichen stationären Kosten um KES 16.942,8 ($137,33). Ein Anstieg des BMI um einen Punkt erhöht die marginalen monatlichen ambulanten Gesundheitsausgaben um KES 277,8 ($2,25) und die jährlichen stationären

Ausgaben um KES 5.119,0 ($41,49). Die sozialen Kosten von Übergewicht und Adipositas bei erwachsenen Frauen beliefen sich im Jahr 2022 auf 1,11 Milliarden US-Dollar oder 10.557,2 KES ($85,57) pro Frau.

Abschließend werden mögliche kosteneffiziente Maßnahmen zur Verringerung von Übergewicht und Adipositas aufgezeigt, darunter die Einführung einer 20-prozentigen Steuer auf zuckergesüßte Getränke, die obligatorische Kennzeichnung von Kilojoule-Menüs, die Nährwertkennzeichnung auf der Vorderseite von Verpackungen, die Überarbeitung der öffentlichen Beschaffungspolitik für Lebensmittel, Kampagnen in den Massenmedien für eine gesündere Ernährung, die Einschränkung von schädlichem Lebensmittelmarketing für Kinder, die Förderung des Stillens und gemeinschaftsweite Aufklärungskampagnen über körperliche Bewegung.

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2PM	Two-part model
2SLS	Two-stage least squares
2SRI	Two-stage residual inclusion
ADW	Average daily wage
APE	Average partial effects
ATC	Average transport cost
BMI	Body mass index
COI	Cost of illness
COVID-19	Coronavirus disease 2019
DALY	Disability-adjusted life years
DBM	Double burden of malnutrition
FCQ	Food choice questionnaire
FE	Fixed effects
GHI	Global Hunger Index
GLM	Generalized Linear Model
HALY	Health-adjusted life year
ICG	Informal caregiver
IPAQ	International Physical Activity questionnaire
IV	Instrumental variables
IR	Individual record
KDHS	Kenya Demographic and Health Surveys
KES	Kenyan shillings
KHB	Karlson-Holm-Breen
KNBS	Kenya National Bureau of Statistics
LMICs	Low- and middle-income countries
MEPS	Medical Expenditure Panel Survey
MET	Metabolic equivalent
MoH	Ministry of Health
NACOSTI	Kenya National Commission on Science, Technology, and Innovation
NASSEP V	National Sample Surveys and Evaluation Program
NCDs	Non-communicable diseases
NHIF	National Health Insurance Fund

NLPM	Non-linear probability models
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary least squares
PA	Physical activity
PCA	Principal component analysis
PPP	Purchasing power parity
RE	Random effects
SEP	Socio-economic position
SIA	Sequential ignorability assumptions
SSA	Sub-Saharan Africa
SSB	Sugar-sweetened beverages
STEPS	STEPwise approach to NCD risk factor surveillance
USD	United States dollars
VIFs	Variance Inflation Factors
WHO	World Health Organization

Chapter 1: General introduction

This dissertation examines the growing issue of overnutrition, defined as being overweight or obese, in Kenya. The first two essays examine the main behavioral drivers, dietary choices, and physical inactivity. In the third essay, we investigate the broader implications of overnutrition for both individuals and society. The first essay fills a gap in the literature by analyzing how food choices affect diet diversity and weight outcomes among socioeconomic groups. In the second essay, we utilize panel data to evaluate the effects of different types of physical activity on weight and the risk of non-communicable diseases (NCDs). Finally, the third essay will conclude by estimating the private and social costs of overweight and obesity among Kenyan women of reproductive age to offer insights for policy making.

1.1 Background

Malnutrition is a major global health concern. Undernutrition, micronutrient deficiencies, and overnutrition persist despite global attempts to eradicate them. According to the World Health Organization (WHO), the number of stunted children has dropped by 30 million since 2012, reaching 22.3% in 2022 (World Health Organization, 2023). However, we are still not on track to achieve the target of 13.5% by 2030 set by the World Health Assembly and the WHO. Wasting affects 45 million children, 94% of whom live in low- and middle-income countries (LMICs) (World Health Organization, 2023). Undernutrition is linked to nearly half of all deaths among children under five, and over half of children in this age group are deficient in essential micronutrients such as iron, zinc, and vitamin A (Stevens et al., 2022). Concurrently, 37 million children under five were classified as overweight or obese in 2022, with 77% of them living in LMICs (World Health Organization, 2024a). Malnutrition among adults is equally concerning: an estimated 2.5 billion adults were overweight, 890 million were obese, and 390 million were underweight in 2022 (World Health Organization, 2024b). Additionally, over two-thirds of non-pregnant women of reproductive age lacked sufficient levels of at least one essential micronutrient, such as iron, zinc, or folate (Stevens et al., 2022).

Global shifts towards higher obesity rates mean that overweight and obesity is now on the rise in developing nations. Between 1990 and 2022, obesity surpassed underweight in 177 countries for women and 145 countries for men (Phelps et al., 2024). This change has resulted in the double burden of malnutrition (DBM), in which undernutrition and overnutrition coexist within the same country, community, household, or individual (Shrimpton & Rokx, 2012). High rates of undernutrition (stunting >30%, wasting >15%, female thinness >20%) and overweight

(>20%) are prevalent in more than one-third of 126 LMICs (Seferidi et al., 2022). Household-level DBM varies between 3% and 35% across these countries, with the most common combinations being stunted child–overweight mother pairs and overweight mother–wasted child pairs. This underscores the global trend of rising obesity, even as undernutrition continues to pose challenges in many regions.

Overnutrition is of concern since it is linked to the development of multiple NCDs, such as cancers, cardiovascular diseases, type 2 diabetes, and chronic kidney disease. In Africa, deaths as a result of NCDs are now at 37%, up from 24% in 2000, with the leading cause of death being cardiovascular diseases. The region is disproportionately affected by NCD mortality, and in the next 20 years, cancer deaths are expected to increase by 30% relative to the global average (World Health Organization, 2024d). There are also severe economic repercussions due to overweight and obesity, with medical and social costs expected to climb dramatically by 2060, especially in LMICs, where they could increase by 12–25 times (Okunogbe et al., 2022).

Overweight and obesity is caused by the interaction of social, environmental, genetic, and behavioral factors. Dietary behaviors directly impact weight since they determine the diet's quantity, quality, and diversity (Fanzo et al., 2017). The nutrition transition is a trend in developing countries where traditional diets have been replaced by the increased consumption of ultra-processed, high-fat, high-sugar foods and energy-dense beverages due to economic and social changes (Popkin, 2001). Increased income growth, urbanization, and technological changes have increased the availability and promotion of cheap, unhealthy foods, creating obesogenic food environments. These unhealthy food environments, in turn, impact consumer food choice motives; this is how people consider, obtain, prepare, store, distribute, and consume foods and beverages (Sobal & Bisogni, 2009). Food choice motives are also influenced by various interpersonal and individual factors such as convenience, taste, values, customs, cultural influences, life events, and beliefs (Fanzo et al., 2017). Differences in food choice motives are also a result of socioeconomic factors such as income and education. Income constraints might lead to the consumption of less diverse, cheap foods, while higher education can lead to better food choices that consider health knowledge. However, the relationship between nutrition quality and socioeconomic level might be complex in developing countries. As incomes increase, people end up consuming more calorie-dense, unhealthy foods in addition to diverse nutrient-rich foods (Mayén et al., 2014). Food decisions, made multiple times a day, are dynamic and multifaceted, ultimately influencing what and how much is consumed, shaping health outcomes (Sobal & Bisogni, 2009).

Physical activity (PA) is also an important behavioral determinant of overweight, obesity, and NCDs. When energy intake exceeds energy expenditure, it results in the accumulation of fat in tissues, which then leads to excessive weight gain. PA helps to increase energy expenditure, thereby regulating weight; it also enhances well-being and improves mental health. Despite these advantages, 81% of adolescents and one-third of adults do not reach the recommended amounts of PA (World Health Organization, 2022). Adults need to participate in at least 150 minutes of moderate physical activity or 75 minutes of vigorous physical activity every week in order to achieve health benefits (World Health Organization, 2020). Not meeting this guideline results in being classified as physically inactive, which raises the risk of developing diabetes, hypertension, cardiovascular disease, and cancer. There are differences in PA levels: women are more likely to be physically inactive than men (34% vs. 29%), and older persons, especially those over 60, are more likely to be physically inactive compared to younger age groups (World Health Organization, 2022). The prevalence of physical inactivity also varies by region, with Southeast Asia and the Eastern Mediterranean having the highest rates at over 40%, while Africa has the lowest percentage at 16%. Physical inactivity in LMICs has increased significantly from 22% in 2000 to 38% in 2022. This is higher than the 33% rate of physical inactivity reported in high-income countries (World Health Organization, 2022). Economic development has resulted in more sedentary lifestyles as more people substitute active walking and cycling for motorized transportation and adopt more technology for leisure activities, such as televisions and computers. According to economic models of time allocation and health demand theory, individuals balance immediate utility with future health considerations. Economic factors influence time allocation between work, active leisure, and sedentary activities, impacting physical activity levels and health outcomes. Changes favoring sedentary behaviors within economic transformations increase the marginal utility obtained from these activities contributing to rising rates of overweight, obesity, and associated health issues globally (Cawley, 2004).

Overweight and obesity are consequences of a flawed food system. The current food system is unsustainable, with significant environmental, social, and health costs associated with it. Market prices fail to account for the true costs of harmful foods or the benefits of healthy ones (S. Hendriks et al., 2023; von Braun & Hendriks, 2023). These costs include greenhouse gas emissions, social effects such as poverty among agrifood workers, and health costs from lost productivity due to obesity and NCDs associated with poor diets (Lord, 2023). Due to market externalities, the current food system encourages the production of unhealthy, highly processed foods rich in salt, fats, and sugars that are highly consumed since they are cheaper, heavily marketed, and easily accessible. Consequently, this promotes unsustainable and unhealthy food systems (S. Hendriks et al., 2021; Von Braun et al., 2021; von Braun & Hendriks, 2023). True pricing, in which market prices reflect hidden costs, is necessary to account for these hidden expenses and create a sustainable food system that is inexpensive and healthful for everyone (S. Hendriks et al., 2023). The true cost of the current food system was estimated at $19.8 trillion annually, higher than the $9 trillion market price, with health-related costs resulting from unhealthy diets accounting for $12 trillion (S. Hendriks et al., 2023). Lord (2023) further estimated the true cost of agrifood systems in 2020 at $13.1 trillion, with the most significant costs, $8–10 trillion, attributed to productivity losses due to unhealthy diets (Lord, 2023).

1.2 Main research questions

The main research questions examined in this dissertation are:

1. Which food choice motives mediate the relationship between socioeconomic status and body mass index (BMI)?
2. Which food choice motives mediate the relationship between socioeconomic status and diet diversity?
3. What effect do work, leisure, and transport-related physical activities, as well as sedentary time, have on BMI and NCD outcomes?
4. Does a higher BMI impact inpatient and outpatient medical expenditures among women of reproductive age?
5. What are the social costs associated with overweight and obesity among women of reproductive age?

1.3 Preview of the research problem and contribution of the study

The influence of food choice motives on diet diversity and weight outcomes across socioeconomic groups has not been established in African countries. This is crucial because understanding how people choose foods can help influence consumer preferences and eventually change food systems to meet human and environmental health objectives. Targeted demand-side tactics, such as choice architecture, incentives, educational initiatives, and improved consumer knowledge, can utilize knowledge of food choice motives to help achieve this (Kim et al., 2024). A popular instrument for measuring food choice motives is the Food Choice Questionnaire (FCQ) developed by Steptoe, Pollard, and Wardle in 1995. This scale has been widely validated and used in different countries in North and South America (US, Canada and Brazil), Europe (Ireland, Germany, Italy, Netherlands, the UK, Poland, Croatia, Greece, and Norway), Asia (Japan, China, Malaysia, South Korea and Taiwan) and in Africa (Cape Verde and Malawi) to measure the determinants of food selection. The FCQ includes the following motives: health, sensory, price, convenience, mood, familiarity, natural, and weight control motives (Steptoe et al., 1995). The decision to consume certain foods is greatly influenced by sensory factors such as taste, smell, flavor, and texture. These sensory qualities are enhanced by foods heavy in sugar, salt, and saturated fats, which makes diets more enticing and tasty (Drewnowski, 1989a, 1992). Convenience motives are due to time constraints that affect the time spent buying, preparing, and cooking food. Food choice ranking varies by nation (Asraf Mohd-Any et al., 2014; Buksh, 2024; Dahal et al., 2022; Jalali-Farahani & Amiri, 2023; Milošević et al., 2012). Price was the most significant consideration in five European nations—Spain, Greece, Ireland, Portugal, and the Netherlands. Sensory appeal ranked first in three countries—Norway, Germany, and the UK. In all these countries, familiarity and ethical concern were rated as the least significant motives (Markovina et al., 2015). In Malawi and Cape Verde, sensory variables were ranked lower, and mood and health were ranked higher (Cabral et al., 2017; Gama et al., 2018a). Given the variations in the reasons people choose foods in different nations, it is critical to identify these cultural differences.

Motives for food choices also vary by socioeconomic position (SEP), which is determined by income and education levels. According to research from developed countries, people in higher SEPs (with more income and education) prioritize health-related factors when making food choices, whereas people in lower SEPs are more focused on time, familiarity, and cost (Konttinen et al., 2013; Robinson et al., 2022; Steptoe et al., 1995). Health outcome patterns show that people in higher SEPs typically have lower prevalences of overweight, obesity, and NCDs than people in lower SEPs. However, these findings do not apply in SSA, where individuals in higher SEPs have an inverse health outcome pattern, with a higher prevalence of overweight, obesity, and NCDs. In these countries, people with high socioeconomic status tend to consume more fat, salt, and sugar. It is theorized that individuals in high SEPs are often the first to diversify and adopt diets rich in added sugars and fats (Mayén et al., 2014). We have limited insight into how people choose what they eat, what factors influence their food choices, and if these factors influence the variations in diet diversity and obesity outcomes noted across socioeconomic groups. Therefore, this essay aims to understand how food choice motives impact diet diversity and weight outcomes throughout Kenya's socioeconomic categories. Although SEP, diet diversity, and weight outcomes have been studied independently in SSA, the psychological aspects of these relationships have not been investigated. This study will address this gap in the literature by investigating the behavioral pathways through which SEP influences diet diversity and weight in the region. The chapter will demonstrate why people in higher SEPs diversify their diets and consume more unhealthy foods, which results in higher weight outcomes during the nutrition transition process.

The second research gap relates to the impact of various types of PA (work, leisure, and transport) and sedentary time on BMI and NCD outcomes. The effect of physical activity on health outcomes has been researched in high-income countries using robust econometric methods. Evidence is mixed on whether there is a significant long-term impact or none at all. Some studies have shown a statistically significant negative relationship between PA related to transport, leisure, and work and the probability of obesity and chronic conditions such as diabetes, high blood pressure, and heart disease (Elwood et al., 2013; Koolhaas et al., 2016; Martin et al., 2015; Ng & Popkin, 2012; Petersen et al., 2012; Sarma et al., 2014). However, some estimations have found that leisure PA does not affect the probability of chronic conditions (Ferrario et al., 2018; Gillum et al., 1996; Petersen et al., 2012; Stenehjem et al., 2018), While some have found that only work-related PA results in a reduced probability of both obesity and chronic conditions (Sarma et al., 2015). In SSA, some empirical studies have explored the connections between physical activity and sedentary behaviors, and their impact on weight and NCDs (F. K. Assah et al., 2011; Iyer et al., 2021; I.-M. Lee et al., 2012; Muti et al., 2023; Sobngwi et al., 2002). Most of these studies have primarily focused on various predictors of obesity and NCDs; however, no study has yet conducted a panel or causal analysis on the impact of PA on health outcomes in SSA. Understanding this relationship is crucial because the levels and distribution of PA vary by region. In high-income countries, total PA levels are lower, with leisure PA contributing more to overall activity. In contrast, in the SSA context, total PA levels are higher than in other regions, with work and transport PA making a more significant contribution. This difference is attributed to less developed transportation infrastructures, which lead to a greater reliance on walking and cycling, as well as a workforce primarily engaged in the informal sector with physically demanding jobs. Empirical evidence gathered from this chapter can inform policy design by tracking trends in PA levels over time to determine whether there is a shift toward less physically demanding work, increased use of motorized transportation, and more sedentary lifestyles. This evidence can guide the promotion of activities that have the greatest impact on health, whether by encouraging workplace-based activities or by designing environments that support active transportation and leisure activities to offset declining PA in other areas. We also disentangle work-related PA into moderate and vigorous activity to examine whether the intensity of activity makes a difference in the health outcomes.

The final research chapter will conclude by discussing the health costs of poor diets linked to our existing food system. Since overweight and obesity are linked to several NCDs, cost-of-illness (COI) studies have shown that they have a substantial financial impact. By 2060, the estimated worldwide economic effect is expected to increase to 3.3% of the global gross domestic product (GDP), up from 2.2% at present (Okunogbe et al., 2022). Obese people have greater inpatient and outpatient medical expenses, which results in significant private costs. For example, it is projected that the additional medical costs for overweight and obese people in the United States can reach $2,505 and that these costs increase with obesity class (Cawley et al., 2021). Similar results have been observed in China and Spain (Mora et al., 2015; Qin & Pan, 2016). Our goal in this chapter is to calculate the social and private costs of overweight and obesity among Kenyan women between the ages of 15 and 49. Particularly for vulnerable groups like women of reproductive age, whose incidence has dramatically increased over time, according to health surveys, it is imperative to understand the economic effect of these illnesses. Growing private costs among the overweight or obese might result in catastrophic health expenditures, especially in Kenya, where the majority of medical expenses are paid for out of pocket. We will also estimate the social costs of poor diets in this population, such as caregiver costs, travel costs, and productivity losses. This will aid in prioritizing policies, interventions, and resource allocation initiatives.

1.4 Study area in the broader context

This dissertation focuses on Kenya as the study region for all three essays. We chose Kenya due to its suitability for examining these emerging health issues. With consistent economic growth over the years, it has the most stable economy in East Africa. Before the COVID-19 pandemic, Kenya's GDP grew at a rate averaging 4.8% between 2015 and 2019. Following the pandemic, the nation's agriculture industry helped sustain robust GDP growth of 7.5% in 2021, 4.8% in 2022, and 5.4% in 2023 (World Bank, 2024). Urbanization is also high, with the proportion of people living in cities at 30%, increasing at a pace of 4.3% annually (World Bank, 2024). This rapid urbanization and economic expansion have created a dynamic food system with multiple malnutrition problems, such as rising rates of overnutrition and persistent undernutrition problems. Approximately 27% of the population remains undernourished. According to the 2023 Global Hunger Index (GHI) report, Kenya ranked 90th out of 121 countries, with a GHI score of 22.0, indicating a serious hunger level (Miriam Wiemers et al., 2024). The food system still struggles to provide basic nutritional needs; as many as 945,610 children between the ages of 6 and 59 months need management for acute malnutrition. At the same time, the prevalence of overweight and obesity has been increasing, especially among women aged 20-49 years, the rate has rose from 15% in 1993 to 45% in 2022, as shown in Figure 1.1 (Kenya National Bureau of Statistics et al., 2022). The incidence of overweight and obesity correlates with wealth and education levels; in the lowest wealth quintile, about 20% of women aged 20–49 years are overweight or obese, while this figure increases to 60% in the highest wealth quintile (Kenya National Bureau of Statistics et al., 2022).

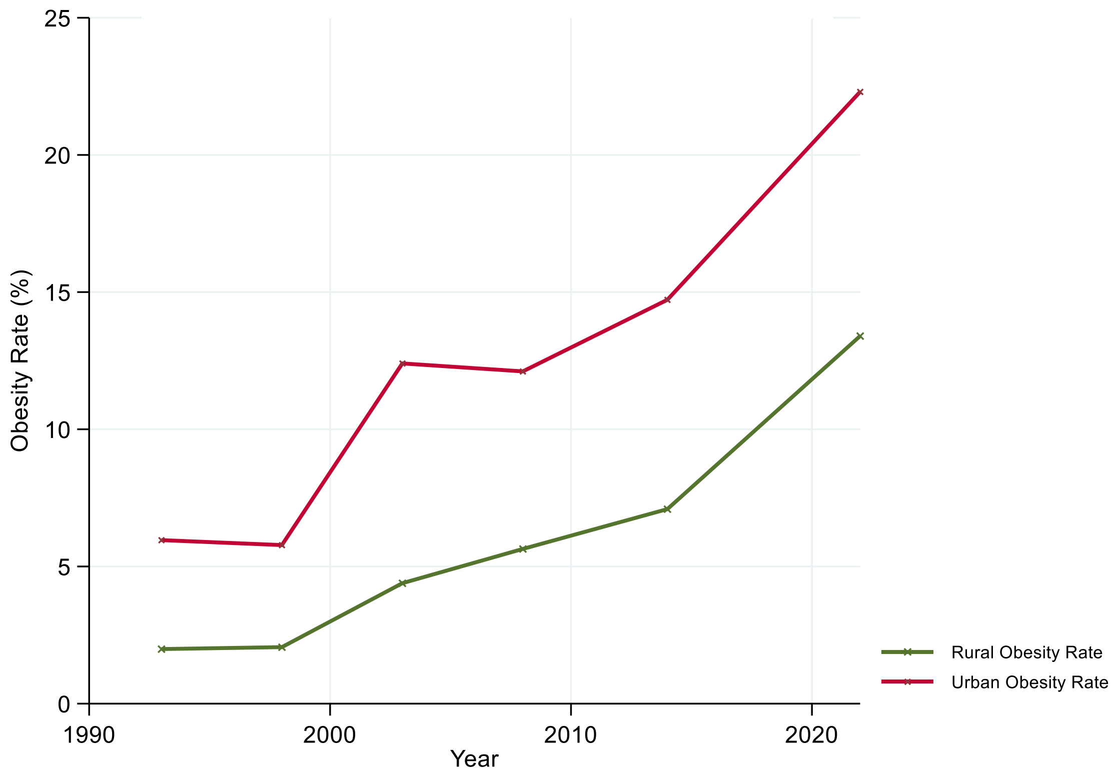

Figure 1.1. Trends in obesity rates of rural and urban women in Kenya

We also selected Kenya due to the observed low physical activity levels, a risk factor for overweight, obesity, and NCDs. In 2022, 85% of boys and 89% of girls did not reach the recommended levels of physical activity (World Health Organization, 2022). Physical inactivity rates among adults were 14% for men and 17% for women (World Health Organization, 2022). Although these rates for adults are lower than those of industrialized nations, future economic expansion and technological developments may increase physical inactivity. Furthermore, the prevalence of NCDs has increased in the country. The proportion of mortality linked to NCDs rose from 20.5% to 41% between 2000 and 2022. The World Bank (2024) reports that the national incidence of hypertension is at 33%, while the prevalence of diabetes rose from 4.3% in 2000 to 6.2% in 2014 (World Bank, 2024). Kenya today ranks eighth among African nations in terms of costs associated with overweight and obesity. In 2019, the total costs were estimated at $742.6 million, which included $131.2 million for direct medical expenses, $65.7 million for absenteeism, $146.6 million for presenteeism, and $393.4 million for premature mortality (Okunogbe et al., 2022). The cost per person was $14.10, projected to rise to $106.80 by 2060 (Okunogbe et al., 2022). This is concerning since out-of-pocket health expenditure is as high as 23% (Kenya National Bureau of Statistics et al., 2022).

Kenya's demographic is similar to that of other countries in SSA, making it an ideal study area. In 2023, the country had a population of 55 million people and an annual population growth rate of 1.9% compared to the regional average of 2.5% (World Bank, 2024). The population is composed of 50.4% women and 49.6% men, with a median age of 19.6 years (Kenya National Bureau of Statistics et al., 2022). The nation has a moderately high degree of income inequality and is ranked 63rd in the world with a GINI value of 38.9. In 2021, a third of the population subsisted on less than $2.15 a day. Over 75% of persons over 25 have at least a primary school diploma, demonstrating educational progress in the country. As a result of all these factors, Kenya makes an interesting case study for a developing nation in SSA that is growing economically and also dealing with new disease areas and risk factors for NCDs, together with persistent issues of infectious diseases and undernutrition. Because of its dynamic population, similar to other SSA countries, the conclusions drawn from these chapters may apply to other countries in the region dealing with nutrition issues.

1.5 Data

Figure 1.2 displays a map of the counties in Kenya where data was collected for the first and second chapters of this study. The four counties included are Kiambu, Murang'a, Uasin Gishu, and Nakuru. The first wave of data collection was conducted in 2015 by the Kenya National Bureau of Statistics (KNBS) as part of the nationally representative WHO STEPs survey that collected data on the determinants and risk factors for NCDs, injuries, and oral health. The second wave of data collection occurred in 2022, as a follow-up to the 2015 WHO STEPS survey, to collect data from participants in these four counties to construct a panel dataset. The team from the Kenya National Bureau of Statistics (KNBS) kindly provided us with participant information to help with the 2022 follow-up data collection. Structured questionnaires were used to gather self-reported information on physical activity, health habits (such as smoking and alcohol consumption), and demographics (such as age, gender, and household size). We also collected new data for the 2022 survey on diet diversity and food choice motives that were not included in the 2015 survey. In addition, trained enumerators measured participants' weight and height. The study received ethical approval from the University of Bonn and a research license from the Kenya National Commission on Science, Technology, and Innovation (NACOSTI). Verbal permission to conduct the interviews was obtained from local authorities, and verbal informed consent was secured from all participants.

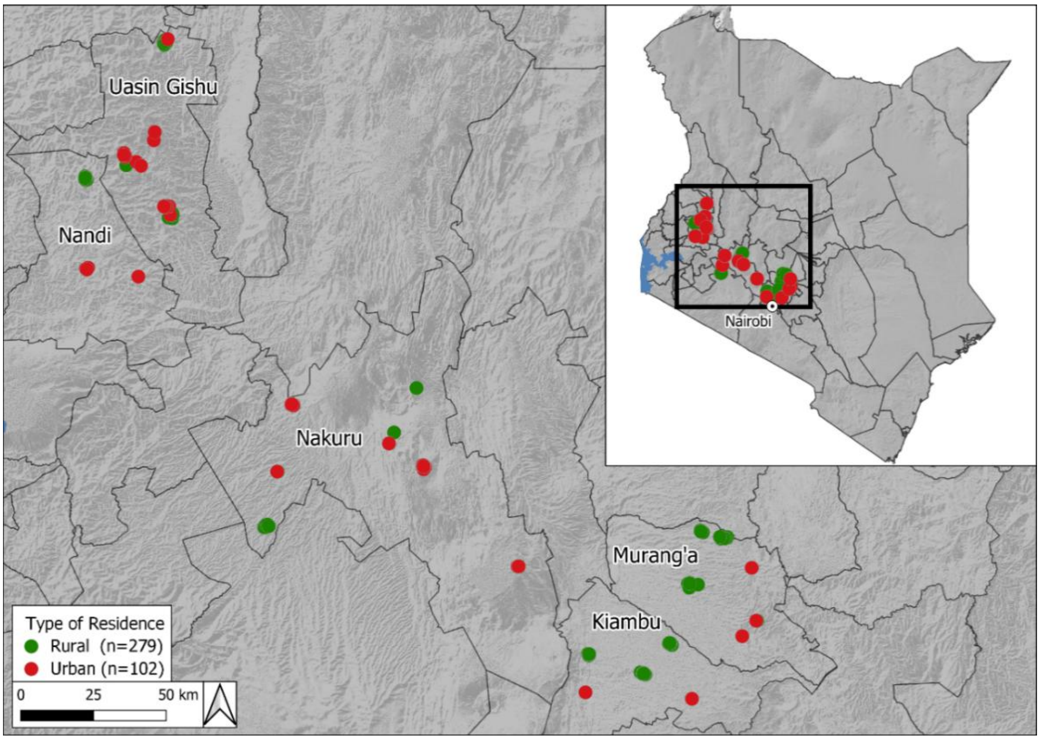

Figure 1.2. The map of Kenya and the location of the survey sampled sites

The first chapter used cross-sectional data from the 2022 wave, with a final sample of 381 adults aged 18 and above, comprising 196 women and 185 men. Of these participants, 279 were from rural areas and 102 from urban areas. For the second chapter, a panel dataset was created by merging some participants from the 2022 dataset with the 2015 WHO STEPs dataset. We were able to merge the participants based on their IDs, names, geo-location, and personal characteristics, ensuring an exact match. The same individuals who had participated in the baseline study conducted in 2015 in the four selected counties were chosen for follow-up interviews. The final sample for the second chapter consisted of 166 respondents, including 101 women and 65 men, with 142 individuals residing in rural settings and 24 in urban areas. The count was lower than the 2022 data due to inaccuracies that emerged while merging the participant data and significant attrition as a result of the COVID-19 pandemic.

The third chapter utilized the latest data from the Kenya Demographic and Health Survey (KDHS), a nationally representative survey carried out by the KNBS and the Ministry of Health (MoH) from February 17 to July 31, 2022. This survey contained 42,022 households with information on health, nutrition, and sociodemographic factors. We used the individual record (IR) file's dataset for women, with 32,156 women between the ages of 15 and 49. This dataset offers data on participant height and weight, maternal and child health, health expenditures, women's dietary diversity, and sociodemographic variables.

Chapter 2: Role of food choice motives in the socio-economic disparities in diet diversity and obesity outcomes in Kenya[1]

2.1 Introduction

The rise in the prevalence of overweight and obesity in Sub-Saharan Africa is a significant concern because it is associated with an increased risk of NCDs, such as type 2 diabetes, cardiovascular disease, and cancers. The trend in Kenya is like that of other countries in the region, with a steady increase in overweight and obesity prevalence in recent years (Abarca-Gómez et al., 2017; Oluyombo et al., 2022). According to the KDHS, the levels of overweight and obesity among women of childbearing age increased from 33% to 45% between 2014 and 2022 (Kenya National Bureau of Statistics, 2014; Kenya National Bureau of Statistics et al., 2022). Concurrently, there was an increase from 24% to 31% in the total disability-adjusted life years (DALYs) due to NCDs (Murray et al., 2020). Because many countries in SSA have weak healthcare systems, a disproportionate number of deaths have resulted from poor NCD diagnosis, treatment, and control.

The increase in overweight and obesity rates in SSA can be attributed to the adoption of unhealthy diets from globalized food systems; these diets have caused a shift towards highly processed foods that are high in calories, saturated fats, and sugars (Costa-Font & Mas, 2016; Qaim, 2017; Drewnowski & Popkin, 1997; Fox et al., 2019; Popkin, 2001). The rise in social, cultural, and economic interconnectedness has led to the expansion of transnational food companies that promote and distribute these highly processed foods, which are appealing due to their taste, flavor, and texture (Binks, 2016; World Benchmarking Alliance, 2018). This dietary shift has also been driven by several demand-side factors, such as income growth and increased urbanization. As countries experience higher incomes and increased urbanization, there is a corresponding rise in demand for processed and unhealthy foods (Drewnowski & Popkin, 1997). For instance, imports of snack foods in Kenya from the global market grew by 20.7% over five years, from 2016 to 2020 (USDA, 2022). Consequently, this dietary transition—coupled with reduced physical activity—has led to a rise in overweight and obesity rates (Drewnowski & Popkin, 1997). Socio-economic position factors such as income and education create variations in dietary behaviors and weight outcomes among different socioeconomic groups (Frazão, 1999). The 2022 country-wide KDHS data shows minimum

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dietary diversity among women (consumed at least 5 of 10 food groups) aged 20-49 rises with wealth index and education levels. In the lowest wealth quintile, only 22.4% achieve minimum dietary diversity, compared to 65.3% in the highest quintile (Kenya National Bureau of Statistics et al., 2022). Similarly, 19.8% of women with no education achieve minimum dietary diversity, while 65.2% of those with more than a secondary education do. Overweight and obesity levels also increase with wealth and education levels. Among women with no education, 26% are overweight or obese, contrasting with 50% of those with more than a secondary education (Kenya National Bureau of Statistics et al., 2022). In the lowest wealth quintile, approximately one in five women aged 20–49 are overweight or obese, compared to 60% in the highest wealth quintile.

This trend can be attributed to multiple factors within the food system, such as food affordability and accessibility (Fanzo et al., 2017). Individuals with lower incomes tend to spend a larger proportion of their budget on food, which may lead them to purchase cheaper foods that are less diverse and nutritious than those consumed by people with higher incomes (Clements & Si, 2018). In developed countries, affordable food options often contain high levels of calories, added sugars, and fats, while nutrient-rich foods, such as fresh fruits and vegetables, tend to be more costly (Drewnowski & Darmon, 2005). Therefore, individuals of lower socio-economic status consume these readily available foods, resulting in a higher prevalence of overweight and obesity. Developing countries exhibit a reverse pattern, where households with high incomes and education tend to have higher rates of overweight and obesity (Agyemang et al., 2014; Templin et al., 2019; Ziraba et al., 2009). As both national and personal incomes rise in developing countries, people start having greater access to diverse food choices and the resources to procure them. Consequently, traditional carbohydrate and fiber-rich diets are replaced with new foods that are often higher in fats and sugars and require less time to prepare (Drewnowski & Popkin, 1997).

Consumer behavior also plays a key role in the variations seen in food consumption patterns and weight outcomes among different socio-economic groups. Consumer behavior within the food system encompasses the choices and decisions regarding what food to acquire, store, prepare, cook, and eat (Fanzo et al., 2017). Food choice motives are defined as the reasons and motivations influencing consumers in selecting their food (Onwezen et al., 2019). The food choice process involves decisions that maximize the consumer’s utility. The consumer’s utility function contains a deterministic component related to product attributes and a stochastic component that includes differences in personal preferences that have been shown to differ by socioeconomic position (Gorton & Barjolle, 2014). The literature highlights several factors influencing food choices at the individual level. Among these factors, sensory needs play a significant role, encompassing taste, smell, flavor, texture, and overall palatability of food. These sensory aspects have a direct impact on the consumption of certain components like saturated fats, salt, and sugar. These types of food play a crucial role in enhancing the sensory attributes of a diet, making it more flavorful, diverse, and rich (Drewnowski, 1989b, 1992; Shepherd, 1988). Health concerns in food selection refer to the concerns related to disease prevention and overall appearance, which influence the intake of foods perceived to provide these benefits (Kristal et al., 1990; Steptoe & Wardle, 1999). Negative emotions and overall mood have been demonstrated to influence food choice, particularly when food serves as a coping mechanism (Gardner et al., 2014; Leigh Gibson, 2006; Oliver et al., 2000). Time constraints also play a significant role in food selection decisions, affecting convenience factors such as the time spent on purchasing, preparing, and cooking food (Drewnowski & Monsivais, 2020). Additionally, familiarity is a key determinant in food selection, it refers to the importance that an individual attaches to eating food they are accustomed to, as opposed to being adventurous and trying new foods (Steptoe et al., 1995). There are differences in the ranking of food choice motives by country. In Europe, price was the most important factor in five countries: Spain, Greece, Ireland, Portugal, and the Netherlands. Sensory appeal ranked first in three countries: Norway, Germany, and the UK. Natural content was the top factor in Poland. Familiarity and ethical concern were consistently ranked as the least important factors across all countries (Markovina et al., 2015). In six Balkan countries, sensory appeal, convenience, health, and natural content were ranked the highest while Pacific Islanders prioritized price, health, and sensory appeal (Buksh, 2024; Milošević et al., 2012). In Persian and Kuala Lumpur populations, sensory appeal and health are crucial (Asraf Mohd-Any et al., 2014; Jalali-Farahani & Amiri, 2023). In Cape Verde health and mood emerged as important (Cabral et al., 2017). In Malawi, the sensory appeal of food was not the dominant factor in food choices; other factors, such as mood, health, price, and convenience, played a key role (Gama et al., 2018b). Additionally, studies in developed countries have shown that individuals in higher SEPs prioritize health motives when choosing food, while lower SEP groups are more concerned with price, familiarity, and time costs (Aggarwal et al., 2011; Cabral et al., 2017; Hoenink et al., 2020; Konttinen et al., 2013; Pechey & Monsivais, 2016; Robinson et al., 2022). Steptoe et al. (1995) using a sample of 358 adults in the UK, found that lower-income groups prioritize price and the familiarity of foods (Steptoe et al., 1995). Robinson et al. (2022) utilizing a larger sample of 4,130 adults in the UK and 1,898 adults in the US, found evidence suggesting that individuals from lower socioeconomic backgrounds are less motivated by health when making food choices (Robinson et al., 2022). This can be attributed to the fact that as income or wages increase, the cost of poor health also rises since being sick means losing time and income (Grossman, 1972). Additionally, individuals with higher SEPs tend to be more knowledgeable about the benefits of healthy diets and have the resources to purchase a balanced diet (Konttinen et al., 2013).

The significance of consumer behavior is often under-researched in developing countries. Despite available research in developed countries, there is still a gap in understanding how food choice motives operate in the context of SSA. Therefore, the paper aims to understand the role of food choice motives in explaining the differences in diet diversity and weight outcomes among different socio-economic groups in Kenya. Studies in SSA have focused on the relationship between SEP and weight outcomes without disentangling the role that psychological factors play. To our knowledge, this is the first study to explore the underlying behavioral pathways through which socio-economic status influences diet diversity and weight outcomes within the SSA context, where incomes are rising and obesity is increasingly prevalent among higher socio-economic groups. This analysis will provide valuable insights into the motivations behind individuals in higher SEPs utilizing their increasing incomes to adopt a wider variety of foods, including those that may contribute to higher weight outcomes. Furthermore, it will offer guidance for developing public health interventions that effectively address the escalating prevalence of overweight and obesity in the context of economic growth and evolving dietary behaviors.

This study addresses four research questions: 1) Are there differences in food choice motives by household income and education level? 2) Which food choice motives are associated with diet diversity and weight outcomes? 3) To what extent do food choice motives mediate the relationship between SEP and weight outcomes? 4) To what extent do food choice motives mediate the relationship between SEP and diet diversity? We hypothesize that food choice motives differ by income and education level and significantly contribute to explaining the observed differences in weight outcomes and diet diversity among socio-economic groups. The study successfully achieved its overall aim of understanding the mediating role of food choice motives.

2.2 Materials and methods

Ethics statement

The study received ethical approval from the University of Bonn and a research license from the Kenya National Commission on Science, Technology, and Innovation (NACOSTI). Additionally, we obtained verbal permission to conduct interviews from the local authorities, and written informed consent was obtained from all the participants.

2.2.1 Study design

This study uses cross-sectional data collected between 11th May and 18th June 2022 from individuals in four counties in Kenya: Kiambu, Murang'a, Uasin Gishu, and Nakuru counties. These counties were selected based on their varying levels of overweight and obesity rates. According to the 2015 WHO STEPS survey, Murang'a, Kiambu, and Nakuru had the highest rates of overweight and obesity among Kenyan counties, with percentages of 46.5%, 44.6%, and 43.88%, respectively (R. Mkuu et al., 2021a). In comparison, the rate of overweight and obesity in Uasin Gishu County was 24.02%. The high rates of overweight and obesity in the three counties are likely driven by high incomes and urbanization, which may lead to greater consumption of unhealthy foods. For example, Nakuru and Kiambu rank among the top five contributors to the country's economy due to their significant economic activities (Kenya National Bureau of Statistics, 2021).

The sampling strategy employed in this study builds on a prior household survey that was conducted countrywide in 2015 (Kenya National Bureau of Statistics, 2015). The sampling frame for the survey was derived from the fifth National Sample Surveys and Evaluation Program (NASSEP V) master sample frame, created by the Kenya National Bureau of Statistics (KNBS), to ensure representation by gender and residence, including both urban and rural areas (Kenya National Bureau of Statistics, 2015). The survey used a three-stage cluster sample design, where 200 clusters were selected from one sub-sample of the NASSEP V frame using an equal probability selection method, 30 households were chosen from each cluster using a systematic sampling method with a random start, and one adult individual was randomly selected from all eligible listed household members using a programmed sampling method (Kenya National Bureau of Statistics, 2015).

The final sample comprised 381 adults aged 18 and above, with 196 women and 185 men. Among these, 279 were from rural areas, and 102 were from urban areas. This data is representative of the four counties where the data was collected. Interviews were conducted in the local language to ensure completeness, using structured questionnaires to gather self-reported information on various variables, including demographics (age, gender, household size), diet diversity, food choice motives, and health habits (smoking and alcohol consumption). Additionally, trained enumerators measured weight, height, waist circumference, and hip circumference.

Pregnant women were excluded from analysis involving body mass index (BMI) because physiological changes during pregnancy can affect the results. As a result, 12 participants were removed, reducing the sample size for the BMI analysis to 369. Power calculations have shown that with a population size of 381 observations and the observed effect sizes from the regressions, using a significance criterion of 95%, the statistical power ranges between 0.85 and 0.98.

2.2.2 Data

Food choice motives

The food choice questionnaire (FCQ) was employed to assess the influences of food selection at the individual level. The original FCQ, developed by Steptoe, Pollard, and Wardle (1995), contained 36 items distributed among nine factors (Steptoe et al., 1995). Table 2.1 shows the FCQ structure used in this study, which contained 33 items grouped into eight factors (health, mood, convenience, sensory appeal, natural content, price, weight control, and familiarity). Respondents were asked to rank the importance of each of the motives in their food selection on a typical day ("It is important to me that the food I eat on a typical day…") using a 7-point Likert scale that ranged from 1 – Strongly disagree, 2 – Disagree, 3 – Somewhat disagree, 4 – Neither agree nor disagree, 5 – Somewhat agree, 6 – Agree, 7 – Strongly agree (Cabral et al., 2017).

A confirmatory factor analysis was performed to test the hypothesized structures underlying these variables and to establish whether the data fits the original factor structure of the FCQ developed by Steptoe, Pollard, and Wardle (1995) (Steptoe et al., 1995). Several goodness of fit indices indicated acceptability, with the standardized root mean square residual (RMSR) at 0.081, a Tucker–Lewis index (TLI) of 0.781, and a comparative fit index (CFI) of 0.806, suggesting an acceptable fit (Pituch & Stevens, 2015). Therefore, we proceeded with the analysis using the eight factors. Factor scores were obtained by summing up the item ratings and then obtaining the average.

Table 2.1. Food choice questionnaire structure

It is important to me that the food I eat on a typical day … **1 – Strongly disagree, 2 – Disagree, 3 – Somewhat disagree, 4 – Neither agree nor disagree, 5 – Somewhat agree, 6 – Agree, 7 – Strongly agree**
Factor 1—Health
Contains a lot of vitamins and minerals
Keeps me healthy
Is nutritious
Is high in protein
Is good for my skin/teeth/hair/nails etc
Is high in fiber and roughage
Factor 2—Mood
Helps me cope with stress
Helps me to cope with life
Helps me relax
Keeps me awake/alert
Cheers me up
Makes me feel good
Factor 3—Convenience
Is easy to prepare
Can be cooked very simply
Takes very little time to prepare
Can be bought in shops close to where I live or work
Is easily available in shops and supermarkets
Factor 4—Sensory Appeal
Smells nice
Looks nice
Has a pleasant texture
Tastes good
Factor 5—Natural Content
Contains no additives
Contains natural ingredients
Contains no artificial ingredients
Factor 6—Price
Is not expensive
Is cheap
Is good value for money
Factor 7—Weight Control
Is low in calories
Helps me control my weight
Is low in fat
Factor 8—Familiarity
Is what I usually eat
Is familiar
Is like the food I ate when I was a child

Diet diversity score

This study used the household dietary diversity score to measure diet quality. It is defined as the number of food groups consumed within the past seven days. Developed by the Food and Nutrition Technical Assistance III Project for food security, this indicator is highly correlated with better micronutrient adequacy and diversity in the consumption of micro- and macro-nutrients (Swindale & Bilinksy, 2006). Twelve food groups were used to calculate this score. These food groups include cereals, roots and tubers, vegetables, fruits, meat/poultry, eggs, fish and seafood, pulses/legumes/nuts, milk and milk products, oil/fats, sugar/honey, and miscellaneous items. The score is calculated by assigning a value of 1 if a particular food group was consumed or 0 if it was not. We then sum up the total number of food groups consumed. The score ranges from 0-12, with a higher score indicating high diet diversity.

Weight outcomes

The weight outcomes indicator used in this study is the BMI, widely used to define overweight and obesity. It is obtained by dividing weight by height squared (kg/m^2). The value was calculated from anthropometric measurements of weight and height collected during the survey from non-pregnant individuals. The BMI scores were grouped into three categories: underweight (<18.5 kg/m^2), normal (18.5-24.9 kg/m^2), and overweight and obese (≥25 kg/m^2) (World Health Organization, 1995). BMI was categorized to better understand the food choice motives associated with overweight and obese individuals.

Socio-economic measures and covariates

The primary measures of socio-economic position used in this study were the household wealth and the education level of the respondents. Household wealth was assessed using principal component analysis (PCA), which involved creating an asset score based on questions about household asset ownership. This score was determined by considering household ownership of items such as radios, televisions, cars, the type of dwelling, and ownership of agricultural land and livestock. A value of 1 was assigned to indicate household possession of an item, while 0 was assigned if the household did not possess the item. Principal component analysis was then conducted, and the first factor produced was used as the asset score. The asset score was also used to generate the asset index quintiles, with 1 representing very poor, 2 representing poor, 3 representing average, 4 representing rich, and 5 representing richest. Education, measured in years of schooling, was standardized for easier interpretation of the mediation results.

Covariates used in this analysis were age, gender, household size, marital status, alcohol consumption, smoking status, employment type, and physical activity levels (time spent sitting daily and a binary variable "walk or cycle for more than 10 minutes every day"). These controls were added to account for their potential influence on BMI and diet diversity.

2.2.3 Statistical methods

All statistical analyses were performed using Stata version 17.0. Collinearity diagnostic tests, including Variance Inflation Factors (VIFs), revealed no evidence of significant collinearity among the food choice variables and other control variables used in the study. Analysis for the first objective used ordinary least squares (OLS) regression models to assess whether socio-economic measures were associated with food choice motives. We considered each food choice motive as a dependent variable, with education and asset score serving as independent variables[2]. In addition, age, gender, alcohol consumption, and smoking status were included as covariates to account for their potential influence on food choice motives.

For the second objective analysis, we used OLS regressions to investigate whether food choice motives, treated as independent variables, were associated with diet diversity. The diet diversity score is a count variable. Therefore, Poisson regression was additionally conducted for sensitivity analysis, which supported our OLS results in terms of the significance of the variables. Ultimately, OLS regression was used in the main analysis and the mediation analysis since the Karlson-Holm-Breen (KHB) outcomes that entail mediation estimation through Poisson regression models are considered experimental (Kohler et al., 2011). Furthermore, we employed ordered logistic regressions to assess whether food choice motives were linked to BMI categories while controlling for socio-economic variables. The proportional odds assumption was tested using a likelihood ratio test. A non-significant result suggests that there is no significant difference in the coefficients between the models being compared. This implies that the proportional odds assumption holds, meaning that the odds of an outcome remain constant across different outcome levels. Lastly, we conducted mediation analyses for the third and fourth objectives using only the food choice motives that displayed significant associations with both socio-economic variables and either BMI or diet diversity as mediators.

[2] For robustness checks for the 8 OLS regressions with the 8 food choice motives as dependent variables, we used the Box–Cox power transformation to ensure normal distribution of residuals, as confirmed by non-significant Shapiro–Wilk test results. The OLS regressions with the box-cox power transformed variables yielded results consistent with our non-transformed OLS estimates in terms of significance and direction of association. Please see Tables A2.1 - A2.8 in the appendix for details. We included the OLS regressions with non-transformed variables in the main analysis for ease of interpretation. Additionally, this analysis served to identify which food choice motives are significantly associated with SEP factors for mediation analysis, rather than determining effect magnitude and making inferences from it.

In this study, the KHB method was used to conduct the mediation analysis, which examines whether the effect of a predictor variable *X* on the outcome variable *Y* is partially explained by a third mediator variable *Z* (Kohler et al., 2011). When there is no mediator, the effect of the independent variable X on the dependent variable Y is called the total effect. The total effect can be broken down into two parts: one part that is mediated by *Z*, called the indirect effect, and another part that is unmediated by Z, called the direct effect. In this study, there are two main outcome variables: diet diversity, which is treated as a continuous variable, and BMI with three ordered categories. Therefore, both linear and non-linear probability models were used. The total effect is obtained from the reduced model shown in Equation 2.1 below. This model only contains the predictor variable with no mediator.

$$Y_i = \alpha_0 + \alpha_1 X_{1i} + \alpha_2 X_{2i} + \epsilon_i \qquad (2.1)$$

In this equation, Y_i is the outcome variable for the individual *i*, α_0 is the constant term, X_{1i} is the predictor variable whose effect is to be decomposed and α_1 is the total effect. X_{2i} is a vector of variables that are determinants of *X*, *Z*, and *Y* and confound the direct and indirect effects. In this analysis, we control for the confounding influence of age, gender, household size, marital status, physical activity, smoking status, alcohol consumption, and employment type. The full model is shown in equation 2.2 below.

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 Z_i + \mu_i \qquad (2.2)$$

Here, Z_i is included as the variable that is hypothesized to mediate the *X*-*Y* relationship. β_1 is the direct effect of *X* on *Y*, given *Z*, β_3 is the partial effect of *Z* on *Y*, given *X*, and μ_i is the error term. In linear regression models where Y is continuous, the difference in the coefficients for X_{1i} in the two equations would be the indirect effect ($\alpha_1 - \beta_1$), which is the magnitude to which the *X*-*Y* relationship is explained or mediated by *Z*.

In non-linear probability models (NLPM), where *Y* is ordered, the coefficients are scaled relative to the residual standard deviation of the underlying linear model (Kohler et al., 2011). Adding a mediator variable in the full model, which is correlated with the outcome, results in a decrease in the residual standard deviation. Therefore, when comparing coefficients across models, it is difficult to distinguish whether coefficient differences are due to mediation or the rescaling of coefficients across models. The KHB method resolves this by regressing the mediator variable, *Z*, on the variable, *X*, and using the residual *R* in the reduced regression model as shown in equation 2.3 below so that the residual standard deviation is the same in the reduced model as in the full model.

$$Y_i = \tilde{\alpha}_0 + \tilde{\alpha}_1 X_{1i} + \tilde{\beta} R + \tilde{\alpha}_2 X_{2i} + \varepsilon_i \tag{2.3}$$

In NLPM, we use eq (2.3) as the reduced model to obtain the indirect effect. The full model in equation 2.2 offers no greater predictiveness than the reduced model equation 2.3 since *R* and *Z* differ only in the component in *Z* that is correlated with *X* therefore, the residuals have the same standard deviation $\sigma'_R = \sigma_F$ (Kohler et al., 2011). With σ'_R being the standard deviation of the residuals in equation 2.3 and σ_F the standard deviation of the residuals in equation 2.2. Additionally, $\tilde{\alpha}_1 = \alpha_1$, therefore, the indirect effect is obtained as the difference between the total effect and the direct effect which is divided by a common scale as shown in equation 2.4 below:

$$\frac{\tilde{\alpha}_1}{\sigma'_R} - \frac{\beta_1}{\sigma_F} = \frac{\alpha_1 - \beta_1}{\sigma_F} \tag{2.4}$$

This mediation analysis does not have a causal interpretation because it does not satisfy the two sequential ignorability assumptions (SIA) (Imai, Keele, & Tingley, 2010; Imai, Keele, & Yamamoto, 2010). The first assumption is that the predictor variables in this analysis (asset score and education) are independent of unobservables, given the covariates; this assumption can be satisfied with a randomized experiment that was not conducted in this study. The second assumption is that the mediator variables (the food choice factors) are independent of unobserved characteristics (such as cultural influences and genetic predispositions), given the covariates and the predictor variable; this condition was also not satisfied in this setting, and it is therefore impossible to rule out self-selection bias. As much as we try to control for some confounders in this analysis, we cannot rule out the possibility of other unobserved confounders that may affect the predictor, mediator, and outcome relationships. Therefore, the analysis does not claim causal effects.

The food choice motives used in this mediation analysis were those significantly associated with both the socio-economic variables and the outcome variables—either BMI or diet diversity based on objectives 1 and 2, similar to the analytical approach by Robinson et al. (2022) (Robinson et al., 2022). We conducted the mediation analysis, including multiple mediators whenever possible, to assess the contribution of each mediator. Average partial effects (APE) were reported for the ordered logit model for ease of interpretation on the probability scale. The APE is not constant across ordered outcomes; therefore, this paper shows the decomposition using the average partial effect on the probability of an overweight and obese outcome. For the APE results, the confounding ratios and percentages are the same as those of the regression coefficients. The standard errors of difference are not known for the APE method. Therefore, we rely on the ordered logit coefficients to establish the significance of the differences. The alpha level that defines statistical significance was 0.10.

2.3 Results

2.3.1 Sample characteristics and food choice motives

The prevalence rates of overweight and obesity are as follows: Nakuru at 55.8%, Kiambu at 46.7%, Murang'a at 45.6%, and Eldoret at 40.7%. Descriptive statistics of the sample are presented in Table 2.2. The average BMI for the sample was 25.1 kg/m^2, which falls in the overweight category. The top food choice motives for the sample population were price, convenience, and health motives, while familiarity and weight concerns were ranked the lowest.

Table 2.2. Characteristics of the study participants

	Mean	SD	IQR
Age (years)	52.40	15.11	23.00
Education (years)	8.70	4.46	5.00
Married (Yes=1)	0.69	0.46	1.00
Asset score	0.00	0.10	1.90
Household size	2.83	1.49	1.00
BMI (kg/m^2)	25.07	5.63	7.87
Walk or Cycle more than 10mins daily (=1 if yes)	0.73	0.45	1.00
Time sitting daily (Minutes)	192.46	135.96	120.00
Person prepares food employed (=1 if yes)	0.34	0.48	1.00
Diet diversity score	8.48	1.34	1.00
Smoke (=1 if yes)	1.37	0.69	0.00
Drink alcohol (=1 if yes)	1.49	0.74	1.00
Food choice motives			
Health	5.57	1.49	1.00
Mood	5.24	1.45	1.50
Sensory	5.31	1.34	2.00
Weight	5.06	1.67	2.00
Convenience	5.70	1.22	1.00
Price	5.84	1.18	1.00
Familiarity	5.01	1.61	1.67
Natural	5.47	1.58	1.667

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

2.3.2 Association between socioeconomic variables and food choice motives

Regression results, with food choice motives as the dependent variables, showed a significant association between measures of SEP and food choice motives. For details, see Tables 2.3 and 2.4 and the complete tables with additional socioeconomic regressors (Tables A2.9–A2.16) in the appendix. An increase of one standard deviation in the asset score was linked to higher ratings for health, mood, sensory, and weight concerns and lower ratings for price concerns.

Convenience, familiarity, and natural motives were not significantly associated with the asset score. Higher education was associated with being less motivated by familiarity concerns and being more motivated by health and sensory motives when selecting food. Mood, weight, convenience, price, and natural motives were not significantly associated with education levels. Fig 2.1 shows the relationship between education level and food choice motives.

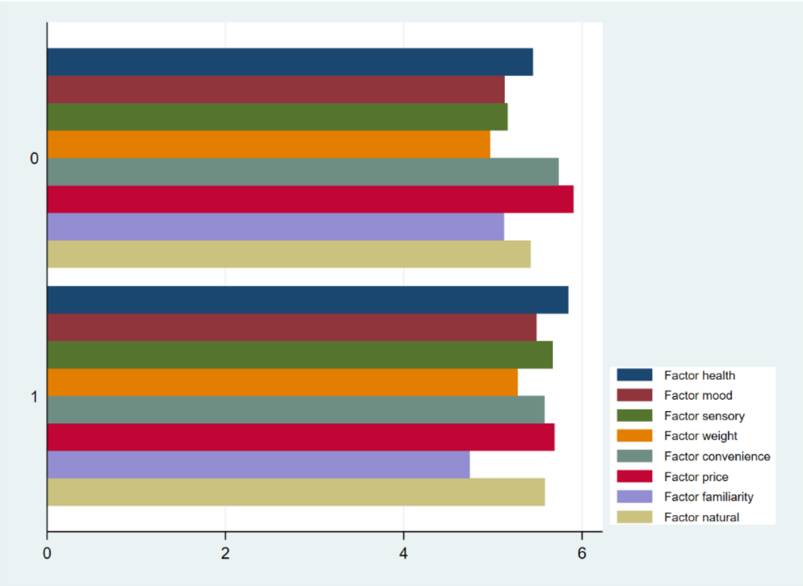

Figure 2.1. Food choice motives by education levels.
Education levels are represented numerically: '1' denotes completion of secondary school and beyond, while '0' signifies education levels up to incomplete secondary school.

Table 2.3. Food choice motives by income group

	Poorest		Second		Middle		Fourth		Richest	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Health	5.18***	1.32	5.52	1.21	5.73	0.94	5.54	1.19	5.87	0.94
Mood	4.70***	1.72	5.21	1.32	5.51	1.15	5.13	1.46	5.64	1.41
Sensory	4.07***	1.32	4.74	1.20	5.86	0.89	5.83	1.06	6.20	0.86
Weight	4.51**	1.83	5.07	1.63	5.25	1.42	5.10	1.69	5.37	1.64
Convenience	5.61**	1.37	6.06	0.83	5.69	1.01	5.66	1.28	5.46	1.45
Price	5.94***	1.21	6.01	1.00	6.19	0.71	5.55	1.36	5.50	1.36
Familiarity	5.26	1.35	5.09	1.46	5.25	1.44	4.82	1.67	4.75	2.03
Natural	5.06*	1.87	5.40	1.45	5.71	1.40	5.61	1.54	5.57	1.55

Mean values were significantly different among income groups (ANOVA). Standard deviation reported in parentheses: *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

2.3.3 Association between food choice motives, diet diversity, and BMI

Various food choice motives were associated with diet diversity, as shown in Table 2.5 and the full table with additional socioeconomic regressors (Table A2.17) in the appendix. Higher concerns for health and sensory aspects were associated with an increase in diet diversity by 0.23 and 0.10, respectively, while higher convenience concerns were associated with a decrease in diet diversity by 0.12. Diet diversity was not significantly associated with other food choice motives. However, mood, weight, price, and natural concerns exhibited a negative relationship, while familiarity displayed a positive association—although these associations were not statistically significant. These results were robust to variations in the model specification, results of the Poisson regression are presented in Table 2.6. The sign and significance levels of the coefficients are similar to the OLS results.

Table 2.4. Linear regression examining the SEP predictors of food choice motives

	Health	Mood	Sensory	Weight	Convenience	Price	Familiarity	Natural
Years schooling	0.21* (0.12)	0.16 (0.17)	0.09** (0.04)	0.02 (0.20)	-0.09 (0.15)	-0.14 (0.14)	-0.09*** (0.02)	0.09 (0.18)
Asset score	0.05* (0.02)	0.09** (0.04)	0.18*** (0.04)	0.15** (0.07)	-0.07 (0.05)	-0.10** (0.05)	-0.06 (0.05)	0.05 (0.04)
Gender (Male=1)	-0.06 (0.12)	-0.17 (0.18)	-0.11 (0.16)	0.03 (0.21)	-0.10 (0.16)	0.18 (0.15)	-0.02 (0.21)	-0.16 (0.20)
Age	-0.02*** (0.00)	-0.01* (0.00)	-0.00 (0.00)	-0.01** (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.02*** (0.01)	0.00 (0.01)
Constant	6.73*** (0.23)	5.90*** (0.34)	5.06*** (0.33)	5.50*** (0.42)	6.18*** (0.29)	6.17*** (0.25)	6.94*** (0.44)	5.70*** (0.34)
R-squared	0.13	0.05	0.12	0.05	0.01	0.03	0.09	0.02

Coefficient estimates are shown with robust standard errors (adjusted for heteroscedasticity) in parentheses. *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

Table 2.5. Regression results for the estimation of food choice motives associated with diet diversity and BMI

	Diet Diversity		BMI	
	OLS		Ordered logit	
	Coef.	St. Err.	Coef.	St. Err.
Health	0.23**	0.09	-0.07	0.15
Mood	-0.04	0.07	-0.16	0.12
Sensory	0.10*	0.06	0.58***	0.12
Weight	-0.03	0.05	0.19**	0.09
Convenience	-0.12**	0.06	-0.23**	0.12
Price	0.03	0.07	0.05	0.12
Familiarity	0.07	0.05	0.20**	0.09
Natural	-0.05	0.06	-0.23*	0.12
Constant	6.43***	0.72		
R-squared	0.21			
chi-square			156.13***	
Number of observations	381		369	

Coefficient estimates are shown with robust standard errors. *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

Results indicated that a unit increase in sensory, weight, and familiarity motives would lead to a 0.58, 0.19, and 0.20 increase in the log odds of being in a higher BMI category, respectively.

A unit increase in convenience and natural motives would lead to a decrease in the log odds of being in a higher BMI category (results presented in Table 2.5, full table with additional socioeconomic regressors (Table A2.18) in the appendix. The likelihood ratio tests performed to test the proportional odds assumption had a non-significant result, which indicated that the relationship between groups was the same. The coefficients for health, mood, and price concerns were not statistically significant, although health and mood exhibited a negative relationship with BMI.

Table 2.6. Poisson regression results for the estimation of food choice motives associated with diet diversity

	Coef.	St. Err.
Health	0.027**	0.011
Mood	-0.005	0.008
Sensory	0.012*	0.006
Weight	-0.003	0.006
Convenience	-0.015**	0.007
Price	0.003	0.008
Familiarity	0.009	0.006
Natural	-0.006	0.007
Constant	1.901***	0.079
Pseudo R-squared	0.011	
Number of observations	381	

Coefficient estimates are shown with robust standard errors. *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

2.3.4 Mediation analyses

The food choice motives used as mediators in the mediation analysis between SEP and BMI were sensory, weight, and familiarity concerns because they were significantly associated with both SEP variables and BMI. Health and sensory motives were used as mediators in the SEP and diet diversity mediation analysis. Other food choice motives that did not exhibit significant associations with either the outcome variables or SEP variables were not used in the mediation analysis.

The KHB estimates of the total, direct, and indirect effects of the socio-economic key variables through food choice motives on BMI and diet diversity are presented in Tables 2.7 and 2.8. Table 2.7 displays the estimated total, direct, and indirect effects of the asset score and years of schooling on BMI. The ordered logit models reveal a positive association between household income and education with BMI, holding other covariates constant. The total effect of the asset score on BMI shows that a one standard deviation increase in the asset score results in a 1.04 increase in the log odds of being in a higher BMI category. The average partial effects indicate that, on average, the probability of an overweight and obese BMI outcome increases by 19 percentage points for a one standard deviation change in the asset score. The relationship between household income and BMI is significantly mediated by sensory and weight concerns. An increase in the asset score leads to higher sensory and weight concerns, resulting in a six-percentage point increase in the probability of being overweight and obese. Sensory concerns account for 28.97% of the household income-BMI association (total effect contribution), while weight concerns explain 3.01% of the household income-BMI association.

The mediation models investigating the relationship between years of schooling and BMI revealed a positive and significant association, indicating that education is also linked to overweight and obesity. The average partial effects show an 8% increase in the probability of being overweight and obese for a one standard deviation increase in the years of schooling. Sensory and familiarity concerns significantly explained this relationship.

Table 2.7. KHB decomposition results of the direct, indirect, and total effects on outcome BMI

Socio-economic variable	Mediators		Ordered logit		Average Partial Effects for outcome overweight and obese			
			Coef.	Std. Err	Coef.	Std. Err	Indirect effect contribution	Total effect contribution
Asset score	Sensory Weight	Reduced model (total effect)	1.04***	0.18	0.19***	0.03		
		Full model (direct effect)	0.71***	0.20	0.13***	0.04		
		Difference (indirect effect)	0.33***	0.09	0. 06			
		Confounding ratio	1.47					
		Confounding percentage	31.98					
	Contribution	Sensory	0.30	0.09	0.06	0.01	90.58	28.97
		Weight	0.03	0.04	0.01	0.01	9.42	3.01
Education	Sensory Familiarity	Reduced model	0.44**	0.14	0.08**	0.03		
		Full model	0.32**	0.15	0.06**	0.03		
		Difference	0.11**	0.05	0.02			
		Confounding ratio	1.34					
		Confounding percentage	25.91					
	Contribution	Sensory	0.13	0.04	0.02	0.01	113.85	29.50
		Familiarity	-0.02	0.02	-0.00	0.00	-13.85	-3.59

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

Higher levels of education are associated with increased sensory concerns and decreased familiarity concerns, resulting in an overall 2% higher likelihood of being overweight and obese. Sensory concerns account for 29.50% of the education-BMI relationship. In contrast, familiarity concerns have a negative indirect effect, explaining -3.59% of the education-BMI relationship.

The results of the mediation analysis for the diet diversity score revealed that higher education was positively associated with increased diet diversity while controlling for other relevant factors, as presented in Table 2.8. The coefficient representing the total effect was statistically significant ($\beta = 0.36$, $P < 0.001$) for the education-diet diversity score relationship. This relationship was found to be positively mediated by health and sensory concerns, with confounding percentages of 10.84% and 3.98%, respectively. However, health and sensory motives did not significantly mediate the relationship between the asset score and diet diversity, as none of the coefficients in this mediation analysis reached statistical significance. Fig 2.2 summarizes the mediation results with the coefficient estimates from the linear and ordered logit regressions.

Table 2.8. KHB decomposition results of the direct, indirect, and total effects on outcome Diet Diversity Score

Socio-economic variable	Mediators		OLS			
			Coef.	Std. Err	Indirect effect contribution	Total effect contribution
Asset score	Health Sensory	Reduced model (total effect)	0.09	0.07		
		Full model (direct effect)	0.06	0.07		
		Difference (indirect effect)	0.03	0.02		
		Confounding ratio	1.46			
		Confounding percentage	31.78			
	Contribution	Health	0.02	0.01	60.85	19.34
		Sensory	0.01	0.01	39.15	12.44
Education	Health Sensory	Reduced model	0.36***	0.08		
		Full model	0.31***	0.08		
		Difference	0.05**	0.02		
		Confounding ratio	1.17			
		Confounding percentage	14.81			
	Contribution	Health	0.04	0.02	73.15	10.84
		Sensory	0.01	0.01	26.85	3.98

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

2.4 Discussion

The counties included in the study exhibited high rates of overweight and obesity among the sampled participants, surpassing 40%. This high prevalence is of concern for public health, as overweight and obesity serve as risk factors for various NCDs. The study also found significant differences among socio-economic groups regarding their food consumption motives, dietary behaviors, and weight outcomes. The primary objective was to investigate whether the variations in the importance attributed to food choice motives partly account for the relationship between socio-economic factors and outcomes, such as BMI and diet diversity.

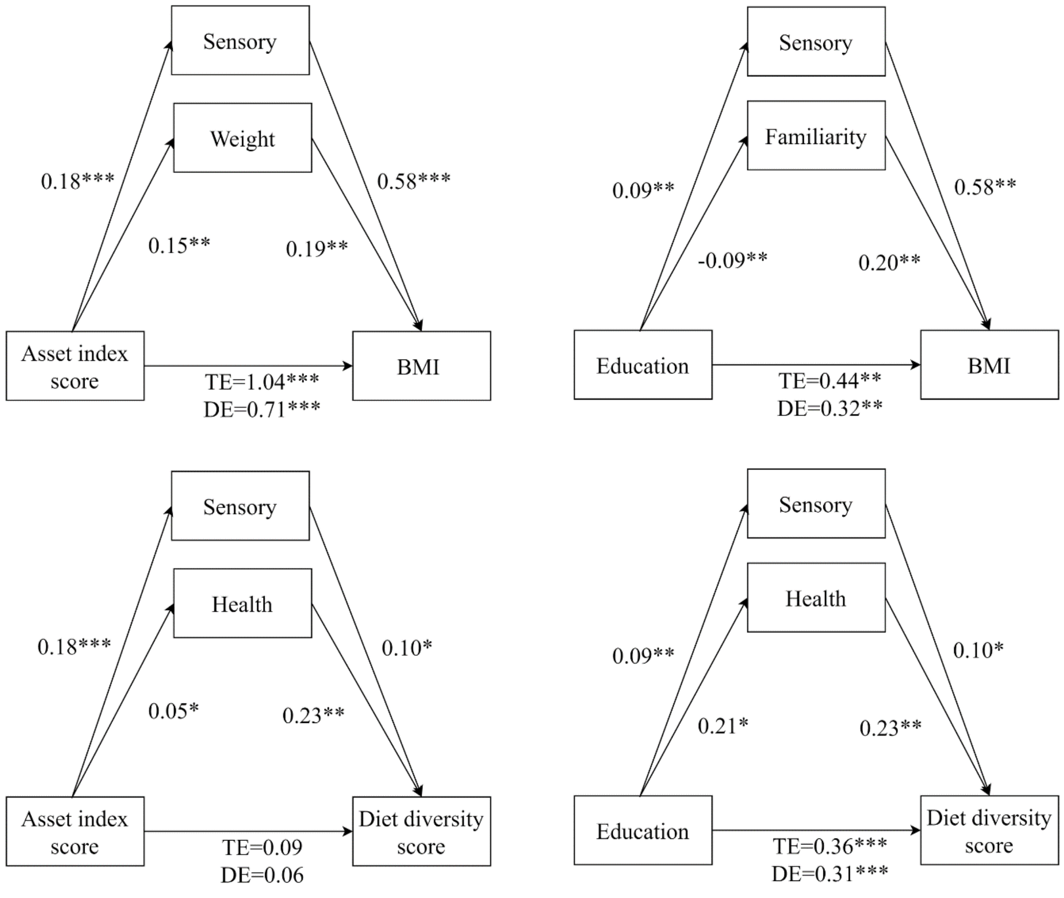

Figure 2.2. Direct and indirect effect regression coefficients.
Mediation models between measures of SEP and diet diversity, BMI. Values represent the individual regression coefficients, TE is the total effect, and DE is the direct effect. *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

Results from objective 1 revealed differences in the importance placed on food choice motives by socio-economic status. Individuals with higher asset scores rated health, mood, sensory, and weight concerns higher while rating price concerns lower. These findings suggest that individuals with more resources can consider various food choice concerns without being constrained by price. Additionally, more years of schooling was correlated with increased concerns placed on health and sensory motives when making food choices and less concern with familiarity. This indicates that higher education may result in a greater focus on the healthiness of food and a reduced food neophobia (Helland et al., 2023). Furthermore, higher health and sensory motives predicted greater diet diversity, whereas an emphasis on convenience concerns was linked to lower dietary diversity. A stronger emphasis on sensory, weight, and familiarity motives was associated with a higher likelihood of belonging to a higher BMI category. In contrast, an increased focus on convenience and natural motives was associated with a reduced likelihood of being in a high BMI category.

Empirical results from the mediation analysis support previous findings in developing countries, indicating that higher socio-economic status is associated with a greater likelihood of being overweight and obese (Dinsa et al., 2012). The findings reveal that a one-standard-deviation increase in the asset score increases the likelihood of overweight and obesity by 19 percentage points, while a one-standard-deviation increase in years of schooling raises the likelihood by 8 percentage points. Sensory concerns positively and significantly mediated these relationships. Individuals with higher socio-economic status rate sensory concerns highly, which, in turn, is associated with a higher probability of overweight and obesity outcomes. These findings suggest that as household income and education levels increase, households can afford to incorporate a wider variety of foods into their diets while considering sensory preferences. As socio-economic status improves, individuals diversify their diets, embracing a variety of foods that cater to their sensory needs that were previously inaccessible due to lower incomes. These food choices, in turn, elevate their risk of overweight and obesity.

These findings also support greater diet diversity among individuals with high socio-economic status. One standard deviation increase in education is linked to a 0.36 increase in the diet diversity score. This relationship is also significantly mediated by higher sensory concerns. Elevated sensory concerns imply that individuals seek a wider range of foods in their diet, encompassing various sensory properties like textures, flavours, odours, and colours. However, this inclination may put them at risk of increased consumption of unhealthy foods (Helland et al., 2023).

Another food choice motive that positively mediated the relationship between household income and BMI was the weight motive, which is consistent with findings in the literature. Robinson et al. (2022) found that higher weight control motives were associated with higher BMI, possibly reflecting that individuals who are already overweight tend to be more concerned about their weight when making food choices (Robinson et al., 2022). A greater desire to lose weight is also counterintuitively associated with weight gain, possibly due to poor weight loss measures (Jacquet et al., 2020).

Furthermore, health concerns also mediated the relationship between education and diet diversity. High health concerns led to greater diet diversity, as improved education enhances knowledge about the significance of nutrition and health. A diverse diet is recommended as one aspect of improving health outcomes.

Study limitations

The first limitation of this study is the use of cross-sectional data; therefore, we cannot establish causality or rule out reverse causality in our analysis. The study can only show the potential mediating effects of food choice factors, which provides valuable insights into the effects of psychological factors on consumption and weight outcomes. The second limitation is the use of BMI, which simply measures weight for height without differentiating fat from lean mass, which might misclassify a significant percentage of people as obese. The percentage of fat and health risk varies by age, gender, and race and cannot be accurately captured by this measure (Burkhauser & Cawley, 2008). Alternative measures of adiposity include waist circumference (measures subcutaneous and visceral adipose tissues), adiposity phenotyping, waist-to-hip circumference ratio, waist-to-height ratio, and a body roundness index. Because these measures eventually tend to be highly correlated with BMI in assessing health outcomes, obesity guidelines recommend the continued use of BMI and other measures of adiposity. The third limitation is the single measure of diet diversity. Future studies should include other measures of diet quality, such as the diet quality index and caloric intake, to provide more insights into the influence of food choice motives. While diverse diets are associated with micronutrient adequacy, it does not measure other aspects of a diet, such as adequacy, moderation, and balance, that are linked to the development of obesity and non-communicable diseases (Swindale & Bilinksy, 2006). Despite this, the use of the diet diversity score can provide initial insights into the mediating role of food choice motives on diet quality. Additionally, the sampling design was created to ensure representation by gender and residence only. Future studies should base the design on different socio-economic backgrounds for a more comprehensive analysis of the impact of socio-economic disparities on overweight and obesity.

2.5 Conclusions

The findings in this paper indicate that the increasing prevalence of overweight and obesity among high socio-economic groups can be partially explained by the importance that they place on food choice motives, which are correlated with the household's socio-economic status. It is important to understand food choice motives, diet diversity, and nutritional outcomes among different population groups to implement relevant policies aimed at improving dietary behaviors.

The study results reveal that adverse weight outcomes among individuals in high socio-economic positions can be partially attributed to sensory food choice motives. Highly palatable foods rich in fats, salt, and sugar are associated with increased energy intake. Findings also reveal that diet quality is not a mere consequence of socio-economic variables but that food choice motives explain diet diversity patterns. Health concerns are significantly associated with high diet diversity (Yeomans, 1998). Policy implications may include the following: Educational campaigns must create awareness and focus on providing information on the dire health consequences of food choices based on sensory impulses. The infiltration of multinational companies that seek to exploit individuals' predisposition for sensory stimulation for profit can be combated through restricted marketing of energy-dense foods. Investments should be made in developing low-calorie taste compounds in food that sustain the sensory component but have low calories. Public health messages should emphasize increased diet diversity and caution on macronutrient moderation so that individuals are aware of daily recommendations on fat, cholesterol, sugar, and salt intake and take measures to stay within the recommended cut-off points.

Chapter 3: The impact of physical activity on obesity and NCD outcomes: insights from Kenyan panel data[3]

3.1 Introduction

The increasing prevalence of overweight and obesity in developing countries warrants concern due to its significant role as a primary risk factor for NCDs and the resulting financial burden it places on the healthcare system. In Kenya, it is estimated that if the rise in overweight and obesity is halted by 2025, more than 7.4 million new cases of NCDs will be prevented by 2044 (Wanjau et al., 2022). Additionally, the projected direct and indirect economic costs of overweight and obesity are expected to increase by 12 to 25 times in low- and middle-income nations by the year 2060 (Okunogbe et al., 2022). This will impact public healthcare expenditures and lead to constraints on public spending.

Obesity and NCDs are multifaceted; they result from the interaction of biological and genetic factors, as well as extrinsic contributors such as social, environmental, and behavioral factors (Dhurandhar, 2022; A. Lee et al., 2000). Physical activity (PA) is a health-related behavior that is considered a modifiable risk factor for overweight, obesity, and NCDs (Blair et al., 1996; Brown et al., 2007; Prentice & Jebb, 2004). The WHO recommends that adults engage in at least 150 minutes of moderate PA or 75 minutes of intense PA per week for substantial health benefits (World Health Organization, 2020). Failure to do so would result in being classified as physically inactive and result in poor health outcomes such as hypertension, cardiovascular diseases, various cancers, and type-2 diabetes (Homer et al., 2019). Physical inactivity is linked to over 3.2 million deaths each year, with 2.6 million of these deaths occurring in LMICs (K. Boakye et al., 2023). Sedentary behavior is an additional modifiable risk factor that includes any waking activity involving sitting or reclining that is characterized by an energy expenditure of less than 1.5 metabolic equivalents (METs) (Tremblay et al., 2017). It has been identified as a risk factor for all-cause mortality, obesity, and NCDs independent of the level of PA (Patel et al., 2010; Rezende et al., 2016; Thivel et al., 2018).

The main domains of PA include occupational, leisure, transport, and household activities (DiPietro et al., 2020). The PA distribution varies widely by region; in SSA, occupational, transport, and household activities account for the majority of PA, whereas in high-income countries, leisure-related PA constitutes a larger proportion of total PA (Hallal et al., 2003;

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Macniven et al., 2012; Trinh et al., 2008). The high levels of work-related PA are due to the dominance of labor-intensive industries and a large informal sector that results in physically demanding jobs in agriculture, construction, and artisanal work (Atkinson et al., 2015). Transport-related PA accounts for a substantial portion of total PA in SSA due to underdeveloped or unreliable transportation infrastructure. As a result, many individuals rely on walking, cycling, or other active forms of transportation to meet their mobility needs (Sietchiping et al., 2012). This is compounded by limited access to leisure sports facilities, which are often scarce or expensive. There have been few empirical studies conducted on the relationship between PA and sedentary behaviors with weight, as well as the probability of an NCD outcome, especially in SSA (F. K. Assah et al., 2011; Iyer et al., 2021; I.-M. Lee et al., 2012; Sobngwi et al., 2002). Muti et al. (2023) investigated the link between self-reported PA in various domains (work, leisure, and transport) and BMI. This study analyzed cross-sectional data from 9,388 adult participants in four SSA countries and revealed that meeting PA guidelines of at least 150 minutes per week was associated with a BMI reduction of 0.82 kg/m² for men and 0.68 kg/m² for women (Muti et al., 2023). In other cross-sectional studies within SSA, physical inactivity was also found to be among the predictors of overweight and obesity (F. Assah et al., 2015; Mbochi et al., 2012; R. Mkuu et al., 2021a; R. S. Mkuu et al., 2018; Muthuri et al., 2015; Pengpid & Peltzer, 2020), while sedentary time and low levels of PA were identified as risk factors for NCDs (H. Boakye et al., 2023; Gerber et al., 2022; M. E. Hendriks et al., 2012; Iyer et al., 2021; Micklesfield et al., 2017; Twinamasiko et al., 2018).

However, these studies are not sufficiently grounded in economic theory, and using cross-sectional data fails to account for biases related to unobserved differences among individuals. This study aims to first analyze the trends in various types of PA over the years utilizing a unique sub-sample panel survey conducted in four counties in Kenya in 2015 and 2022. Subsequently, it will fill the gap in the literature by distinguishing and determining the effects of work, leisure, and transport-related PA, together with sedentary time, on weight and NCD outcomes, taking into account the intensity, frequency, and duration of physical activities. We further differentiate between vigorous and moderate work-related PA to investigate how varying levels of energy expenditure demands in the workplace over time impact health outcomes. The use of panel data will help control for unobserved heterogeneity biases, such as preferences, motivation, and the opportunity cost of time, which may affect both PA and health outcomes. We further provide robustness against observable heterogeneity by utilizing entropy balancing to establish whether participation in PA leads to health improvements.

This paper addresses four research questions: 1) What is the impact of work, leisure, and transport-related physical activities on BMI? 2) To what extent does an increase in sedentary time contribute to a higher BMI? 3) What is the impact of work, leisure, and transport-related physical activities on NCD outcomes? Finally, 4) To what extent does increased sedentary time contribute to a higher probability of an NCD outcome? Consistent with the literature, we hypothesize a negative relationship between physical activity, BMI, and NCD outcomes and a positive association between sedentary time, BMI, and NCD outcomes.

3.2 Methods

3.2.1 Study population

The dataset used in this study is from two waves of surveys conducted in 2015 and 2022, comprising adults aged 18 years and above. The first wave was obtained from the 2015 WHO STEPS survey, which was a nationally representative survey conducted in 2015 to collect information on the determinants and risk factors for NCDs, injuries, and oral health (Ministry of Health, 2015). This survey used a three-stage cluster sampling method. Initially, 200 clusters were selected through an equal probability selection method from the fifth National Sample Surveys and Evaluation Program master sample frame created by the Kenya National Bureau of Statistics. Within each cluster, 30 households were chosen to participate in the survey through a systematic sampling method with a random start. Finally, one adult was randomly selected from each of these selected households to participate in the survey. Each county had 23 clusters, each comprising 30 individuals.

The follow-up study was conducted from May to June 2022 in 4 counties that were chosen based on their overweight and obesity rates in 2015. The results of the 2015 survey showed that Murang'a, Kiambu, and Nakuru had the highest rates of overweight and obesity (46.5%, 44.6%, and 43.9% respectively) among Kenyan counties (R. Mkuu et al., 2021a). In comparison, the rate of overweight and obesity in Uasin Gishu County was 24.02%. The same individuals who had participated in the baseline study conducted in 2015 in the four selected counties were chosen for follow-up interviews.

The final sample consisted of 166 respondents, including 101 women and 65 men, with 142 individuals residing in rural settings and 60 in urban areas. The final analysis included 332 person-year observations. There were significant attrition rates in urban areas due to the economic impacts of the COVID-19 pandemic. These effects caused individuals who faced job losses in urban regions to return to their rural homes, posing challenges in tracking their phone numbers and whereabouts. In contrast to rural settings, where extended families commonly reside in the same locale for multiple generations, urban households experience more frequent relocations.

Both surveys used structured questionnaires to collect detailed self-reported information from participants regarding their socio-demographics, the intensity, frequency, and duration of transport, work, and leisure-related physical activities, daily sedentary time, health conditions, and dietary behaviors. Additionally, survey enumerators took physical measurements of participants' height and weight for BMI calculations.

3.2.2 Study variables

Outcome variables

The first outcome variable used in the study was BMI, which was obtained by dividing weight by height squared (kg/m^2). BMI values were transformed to the natural logarithm scale to reduce non-linearity. Additionally, BMI scores were categorized into three groups: underweight (<18.5 kg/m^2), normal (18.5-24.9 kg/m^2), and overweight and obese (≥ 25 kg/m^2) for additional model specifications (World Health Organization, 1995).

The second outcome variable is a binary NCD outcome variable. It takes the value 1 if the respondent has been diagnosed with either high blood pressure or diabetes or has experienced a heart attack or stroke at any point. If none of these conditions apply, it takes the value 0.

Physical activity variables

The main explanatory variables in this study were self-reported measures of PA. Respondents were asked to report whether they engaged in vigorous work-related PA (requiring significant physical exertion causing large increases in breathing or heart rate), moderate work-related PA (requiring moderate physical effort and resulting in minor increases in breathing or heart rate), leisure activities such as sports, fitness, and recreational activities and transport-related PA such as walking or cycling. The work-related PA in this study encompassed unpaid household chores, harvesting crops, and fishing or hunting for food. Subsequently, respondents were asked to report their participation (yes/no), frequency (number of days per week), and duration (number of hours per day) in these activities, specifically focusing on activities lasting a minimum of 10 minutes.

Based on this information, we computed a MET-hours score by taking into account the energy requirements of each activity, measured in metabolic equivalents (METs). The MET is a ratio that compares the metabolic rate of an activity to the resting metabolic rate while quietly sitting, set at 1.0 kg^{-1} h^{-1} (Ainsworth et al., 2000). To calculate MET-hours, we multiplied the MET score of an activity by the number of hours and the number of days in a week spent doing that activity. This accounts for both the intensity of the activity and the time spent engaging in it (IPAQ Research Committee, 2005).

The MET values for each activity used in this study were based on the International Physical Activity Questionnaire (IPAQ) scoring protocol (IPAQ Research Committee, 2005). This protocol contains the average METs for vigorous work (8 METs) and moderate work (4 METs), cycling (6 METs), walking (3.3 METs), and vigorous and moderate leisure activities (8 and 4 METs). We ultimately obtained values for vigorous work, moderate work, total transport, and total leisure PA, measured in MET-hours per week. These values represent the energy expenditure from various types of physical activities over a week.

The participants also provided information about their sedentary behavior. This data included the total amount of time spent in a sedentary position, such as sitting or reclining, during various activities such as work, home life, commuting, or socializing with friends. However, it does not include the time spent sleeping. This variable was then converted to daily sedentary time in minutes.

Other variables

We included several explanatory variables in our analysis. One of these variables was the "dietary healthy behaviors index," to account for the potential influence of dietary habits on BMI. To construct this index, we conducted a principal component analysis (PCA) using standardized data on dietary behaviors, including the frequency of fruit and vegetable consumption, sugar and salt intake, use of spices, meals eaten outside the home, and consumption of carbonated drinks. The first factor produced was used as the healthy behaviors score. Subsequently, the score was divided into quintiles to establish a categorical dietary healthy behaviors index, with 1 representing poor dietary behaviors and 5 indicating excellent dietary behaviors.

Other explanatory variables in the analysis were age and age squared as continuous variables to account for the fact that metabolism changes with age (Henry, 2005). We categorized age into the following age groups: 18-29, 30-44, 45-59, 60-69, and over 70 years. The asset index, an important determinant of PA, was used to measure income in this study (Cerin & Leslie, 2008; Humphreys & Ruseski, 2011). The index was created based on the yes/no responses on the ownership of household items such as radios, televisions, cars, type of dwelling, and ownership of agricultural land and livestock. These responses were coded as 1=yes and 0=no. PCA was then conducted, and the first factor produced was used to generate quintiles with 1=poor to 5=richest. Other explanatory variables were marital status (0=no/divorced/ widowed and 1=married), employment status (0=no, 1=employed), and household size.

3.2.3 Economic framework

The economic model proposed to understand time allocation and the decision to participate in physical activities integrates Becker's model of labor and leisure with Grossman's model of health demand (Becker, 1965; Grossman, 1972). Individuals weigh the utility benefits of their behavior against potential future welfare losses due to poor health outcomes (Cawley, 2004; Grossman, 1972). Economic factors influence this decision, as leisure and transport-related physical activities compete with time that could otherwise be spent working (Humphreys & Ruseski, 2011). Despite limitations in applying this model to African contexts due to informal economies, poor infrastructure, and human capital constraints, it offers valuable insights into the decision to participate in PA.

Cawley (2004) then introduces the SLOTH model of time allocation, which maximizes utility based on a set number of hours in a day based on the following utility function:

$$\max U(S, L, O, T, H, C, W(S, L, O, T, H, C), H.(S, L, O, T, H, C, W), Y) \qquad (3.1)$$

Daily time is allocated among sleeping (S), leisure (L) (includes physically active and sedentary leisure activities), paid work (O), time spent in different forms of transportation (T), and home production that involves unpaid work (H). These activities impact utility indirectly by affecting weight (W) and health (H.) (Cawley, 2004). Argument C represents caloric or food intake, and Y represents all other goods. Choosing to engage in PA might momentarily reduce immediate utility due to costs and time constraints, but it can enhance discounted lifetime utility by fostering future healthy days. Therefore, factors such as enjoyment, motivation, time preference, home commitments, and labor market position can significantly influence how time is allocated to active leisure, sedentary time, and transport-related physical activities (Sarma et al., 2014).

The rise in overweight and obesity and poor health outcomes can be attributed to economic transformations that have led to changes in the marginal utility obtained from the activities within the SLOTH framework. For instance, the increase in the number of sedentary activities and the marginal utility obtained from them leads to a reallocation of time toward these sedentary activities, resulting in a rise in overweight, obesity, and NCDs.

3.2.4 Empirical modeling

The study's main objective was to distinguish and analyze the effects of work PA, leisure PA, transport PA, and sedentary time on the health outcomes of BMI and NCDs. We first estimate the following panel data regression model for the relationship between PA and BMI:

$$H_{it} = \beta_0 + \beta_1(VWPA)_{it} + \beta_2(MWPA)_{it} + \beta_3(LPA)_{it} + \beta_4(TPA)_{it} + \beta_5(ST)_{it} + \delta X_{it} + \omega\tau + \mu_i + \varepsilon_{it} \quad (3.2)$$

In equation 3.2, H_{it} is the health outcome for individual i at time t, in this case, it is the log of BMI. The main explanatory variables are; $VWPA_{it}$ is the vigorous work-related PA, $MWPA_{it}$ is the moderate work-related PA, LPA_{it} is the leisure-related PA, TPA_{it} is the transport-related PA, and ST_{it} is the sedentary time. X_{it} is the vector of observable regressors that includes age, age squared, wealth status, household size, marital status, employment status, and the dietary healthy behaviors index. τ represents the time trend, μ_i represents the individual-specific effects, and ε_{it} is the idiosyncratic error term. We hypothesize negative and significant coefficient estimates for β_1, β_2, β_3, and β_4 to indicate that PA has a negative influence on BMI. We also expect a positive and statistically significant coefficient for β_5, demonstrating that increased sedentary time is associated with a higher BMI.

In the analysis, the models were estimated with fixed effects (FE) estimators. The FE model allows for the main PA regressors to be endogenous and correlated with the time-invariant component of the error μ_i, while remaining uncorrelated with the time-varying idiosyncratic error term ε_{it}. To accurately estimate the coefficients, we need to control for μ_i through differencing techniques; therefore, we cannot estimate the coefficients of time-invariant variables. The random effects (RE) model assumes that the regressors are exogenous and uncorrelated with μ_i. We theorize that PA is not exogenous and can be influenced by unobserved factors such as time preference, motivation, and genetics. These potential influences could lead to biased estimates in the RE model. We expect the FE model to provide consistent estimates. We conducted the Hausman test to determine the presence of unobserved heterogeneity. We found a significant test statistic, suggesting that the FE specification is more appropriate. Additionally, we clustered the standard errors at the individual level.

We also estimated heterogeneous fixed-effects models that included interaction terms to capture how the relationship between BMI and total PA varies across gender, age groups, BMI categories, and health status (whether or not the individual has ever been diagnosed with an NCD). To prevent collinearity, we ran separate models for each interaction term.

In the second part of the analysis, we estimated the following probit model of an NCD outcome:

$$H_i^* = \gamma_0 + \gamma_1(VWPA)_i + \gamma_2(MWPA)_i + \gamma_3(LPA)_i + \gamma_4(TPA)_i + \gamma_5(ST)_i + \rho X_i + \varepsilon_i \qquad (3.3)$$

We utilized the latest cross-sectional data from 2022 to assess the influence of PA on an NCD outcome, excluding individuals who reported being diagnosed with an NCD in 2015. In equation 3.3, H_i^* is the unobservable latent health stock for individual i. Instead, we observe $H_i = 1$ if $H_i^* \geq 1$ or otherwise $H_i = 0$. H_i represents whether individual i has ever been diagnosed with either high blood pressure, or diabetes, or has had a heart attack or stroke, taking the value of one or zero otherwise. The main explanatory variables are similar to eq. 3.2: vigorous work-related PA ($VWPA$), moderate work-related PA ($MWPA$), leisure-related PA (LPA), transport PA (TPA), and sedentary time (ST). X_i represents a vector of individual or household characteristics and ε_{it} is the error term. We clustered the standard errors at the individual level.

3.2.5 Robustness checks

To further establish whether PA leads to improved BMI status and a lower probability of an NCD outcome, we employ entropy balancing as proposed by Hainmueller (2012). This method uses a matching technique based on entropy balancing to provide robustness against observable heterogeneity by ensuring that the covariate distributions in the treatment and control groups are comparable. The technique preprocesses data with binary treatments by adjusting the covariate distribution of the control group to resemble that of the treatment group through reweighting, ensuring specified balancing requirements (e.g., means, variances, and skewness) are met (Hainmueller, 2012). This reweighting minimizes the entropy distance metric to achieve maximum balance between the groups.

We created binary treatment variables to indicate participation in different types of physical activities, including vigorous work, moderate work, leisure, and transport-related PA. Using a maximum entropy reweighting scheme, we matched the treated and untreated groups based on a set of key covariates—age, wealth status, household size, marital status, employment status, and dietary habits. These covariates were selected based on their theoretical relevance to PA and health outcomes, ensuring that the resulting estimates account for potential confounders. We set balance constraints to match the means, variances, and skewness of the covariates between the treatment and control groups, ensuring that the distribution of characteristics in the reweighted control group is similar to that of the treatment group (Hainmueller & Xu, 2013). Once the entropy balancing weights were obtained, we performed regression analysis to estimate the treatment effects of PA on BMI and NCD probability. This was done by regressing BMI and the probability of an NCD outcome on the treatment indicator, incorporating the entropy weights while controlling for the covariates used in the matching process. By employing entropy balancing, we aim to derive robust, unbiased estimates of the causal effect of different types of physical activity on health outcomes, accounting for the intensity, frequency, and duration of activities

3.3 Results

3.3.1 Descriptive results

The summary statistics for the key variables are shown in Table 3.1. The average BMI for the sample increased from 24.6 kg/m^2 in 2015 to 25.7 kg/m^2 in 2022. Both men and women experienced significant increases in the rates of overweight and obesity. Among women, the rate increased from 56.1% to 63.2%, while among men, it increased from 23.4% to 35.1%. Figure 3.1 illustrates the trend in BMI category changes among respondents over the years. The incidence of NCDs also increased during this period. Among the respondents in the sample, reported diagnoses of high blood pressure increased from 21% to 23%, high blood sugar from 3% to 6%, and reports of a heart attack or stroke rose from 5% to 9%.

In 2022, the main contributors to PA in the sample were work-related PA, with 97.6 MET-hours per week, transport-related PA at 27.6 MET-hours per week, and leisure-related PA at 2.9 MET-hours per week. The total level of PA declined in the sample, as shown in Figure 3.2. The percentage of individuals who reported engaging in work PA decreased over the years. Work-related PA decreased by 39.2 MET-hours per week from 2015 to 2022. Vigorous work-related PA declined notably more than moderate work PA, dropping by 32.9 MET-hours per week (4.10 hours) versus 6.4 MET-hours per week (1.59 hours). There was also a decline in leisure-related PA within the sample population. The proportion of individuals reporting participation in leisure-related PA dropped from 63% to 31%, while the total number of MET-hours per week decreased from 4.5 to 2.9 (0.30 hours). Fewer individuals (78%) reported walking or cycling for more than 10 minutes in 2022 compared to 86% in 2015. Despite this decline, transport-related MET-hours per week increased by 2.6 MET-hours per week (0.56 hours). Sedentary time increased from an average of 154.9 minutes per day to 176.1 minutes, suggesting that people were spending more time in sedentary activities, which may have contributed to the decline in PA levels.

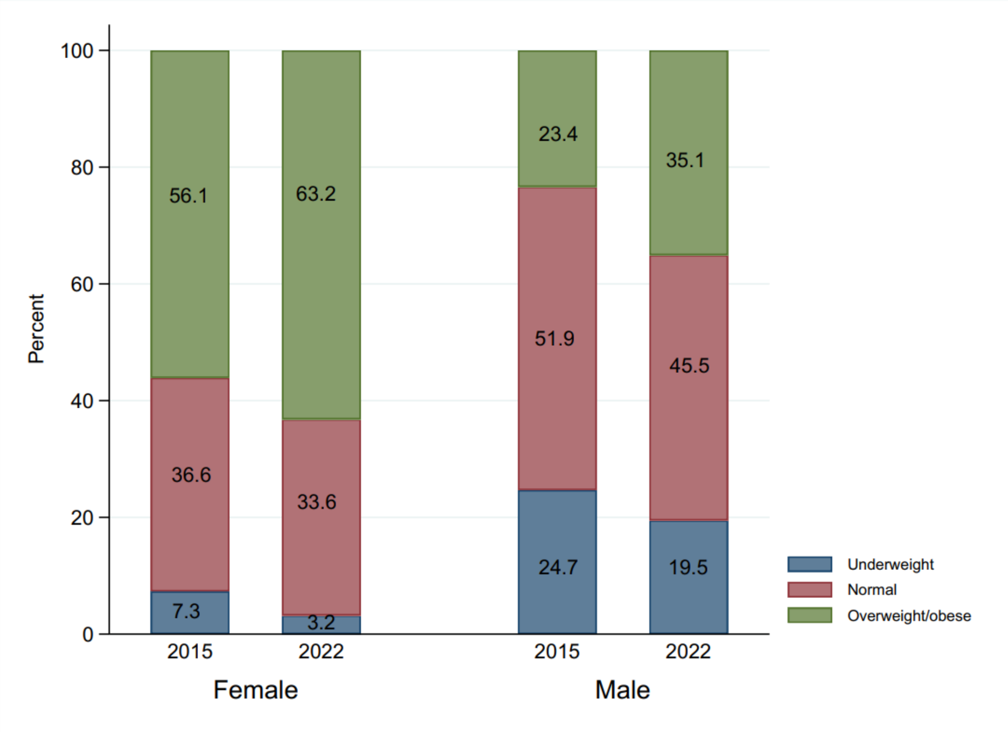

Figure 3.1. Change in BMI of respondents (2015-2022)

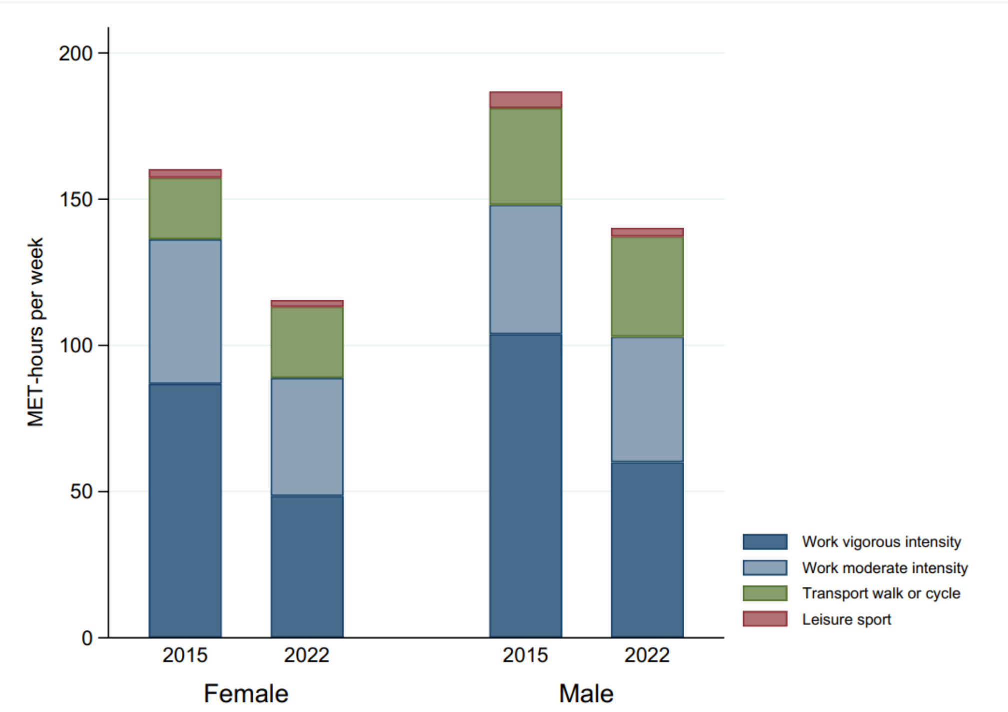

Figure 3.2. Physical activity levels in MET-hours per week

Table 3.1. Descriptive statistics for adults

	2015	2022	Change (2015-2022)
BMI (Kg/m^2)	24.56 (5.69)	25.73 (5.66)	1.17**
Age (years)	42.58 (12.48)	50.05 (12.48)	7.46***
Asset index (5=Richest)	3.04 (1.13)	2.97 (1.43)	-0.07
Years schooling	8.71 (4.01)	8.88 (4.02)	0.18
Employed (1=Yes)	0.70 (0.46)	0.81 (0.40)	0.11**
Household size	1.83 (0.91)	2.80 (1.53)	0.97***
Healthy behaviors index (5=excellent)	3.03 (1.46)	2.93 (1.36)	-0.10
Physical activity			
Transportation walk or cycle (1=Yes)	0.86 (0.35)	0.78 (0.42)	-0.08**
Transportation Hrs/week	5.39 (8.03)	5.94 (8.31)	0.56
Transportation (MET-hrs/week)	25.04 (37.31)	27.63 (38.63)	2.58
Vigorous work (1=Yes)	0.53 (0.50)	0.45 (0.50)	-0.08
Vigorous work Hrs/week	11.16 (15.18)	7.05 (11.77)	-4.10***
Vigorous work (MET-hrs/week)	89.25 (121.40)	56.40 (94.14)	-32.85***
Moderate work (1=Yes)	0.72 (0.45)	0.68 (0.47)	-0.04
Moderate work Hrs/week	11.89 (15.64)	10.30 (15.30)	-1.59
Moderate work (MET-hrs/week)	47.56 (62.56)	41.21 (61.21)	-6.35
Total work (MET-hrs/week)	136.81 (129.61)	97.61 (96.30	-39.20***
Leisure PA (1=Yes)	0.63 (1.68)	0.31 (1.16)	-0.32**
Leisure PA Hrs/week	0.71 (2.08)	0.41 (1.71)	-0.30
Leisure PA (MET-hrs/week)	4.46 (14.56)	2.89 (13.10)	-1.56
Sedentary time (Minutes)	154.94 (104.20)	176.08 (112.77)	21.14*
Has an NCD	0.25 (0.43)	0.33 (0.47)	0.08*
High blood pressure (1=Yes)	0.21 (0.41)	0.23 (0.42)	0.02
High blood sugar (1=Yes)	0.03 (0.17)	0.06 (0.24)	0.03
Had a heart attack or stroke (1=Yes)	0.05 (0.23)	0.09 (0.29)	0.04

Standard deviations in parentheses. ***Difference between 2015 and 2022 is significant at 1% level; **Difference between 2015 and 2022 is significant at 5% level; *Difference between 2015 and 2022 is significant at 10% level.

3.3.2 Regression results

Effect of physical activity on BMI

Table 3.2 displays the results of the panel fixed-effects regression models with the log of BMI as the dependent variable. The second column displays the results of BMI regressed against total PA. In column 4, we disentangle PA domains and incorporate additional covariates to control for their confounding effects.

The results presented in the second column indicate that total PA is negatively and significantly related to the BMI of adults in Kenya with a coefficient of -0.0029. With the addition of the covariates, an increase of one MET-hour per week of vigorous work, transport, and leisure-related PA was associated with a 0.025%, 0.052%, and a 0.160% decrease in BMI, respectively. Moderate work-related PA and sedentary time did not exert significant effects on BMI. An additional estimation with the dependent variable BMI in 3 categories of underweight, normal, and overweight/obese is reported in Table A3.1 in the appendix. The results indicate statistically significant negative coefficients for vigorous work, active transport methods, and leisure-related PA. These results indicate that these physical activities reduce the odds of being in a higher BMI category.

Table 3.3 displays the outcomes with interaction terms. The first model examines age groups and total PA, showing that increased PA is linked to reduced BMI across younger age categories 18-29, 30-44, and 45-59 (0.052%, 0.024%, and 0.029%, respectively). The second model explored gender and total PA and revealed negative associations between PA and BMI for both men and women (0.041% and 0.016%, respectively). In the third model, the interaction between PA and the healthy and NCD groups revealed negative effects on BMI in both groups. The fourth model evaluates the influence of PA on BMI across different BMI categories, showing decreases in BMI for underweight and normal-weight individuals, while the effects for overweight and obese individuals were insignificant.

Results of the robustness checks

We initially pre-processed the data using entropy balancing to investigate the link between PA and BMI to derive the treatment effect based on observable factors. We estimated four separate models, each focusing on a specific type of PA. In each model, individuals engaging in a particular PA were classified as the treatment group, while those not participating in that type of PA served as the control group. Covariate distributions in the control group were adjusted using entropy weights to match those of the treatment group, ensuring balance across the key variables.

Table 3.2. Effect of physical activity on body mass index

	(1)		(2)	
BMI (log)	Coef.	SE	Coef.	SE
Total PA	-0.00289*	0.00157		
Vigorous work (MET-hrs/week)			-0.00025***	0.00009
Moderate work (MET-hrs/week)			-0.00002	0.00014
Transportation (MET-hrs/week)			-0.00052**	0.00025
Leisure sport (MET-hrs/week)			-0.00161**	0.00080
Sedentary time			-0.00008	0.00010
Age (years)			0.01319**	0.00648
Age^2			-0.00020***	0.00006
Asset index				
Second			0.00250	0.03132
Middle			0.02068	0.03296
Fourth			0.00447	0.04256
Richest			0.04845	0.04259
Household size			0.01627**	0.00677
τ (time trend)			0.06067**	0.02882
Marital status				
Married			0.10847**	0.05448
Employment status				
Employed			0.02758	0.02777
Healthy behaviors index				
Fair			-0.00531	0.03279
Good			-0.07063**	0.03439
Very good			-0.04846	0.03450
Excellent			-0.07575**	0.03347
F-value			7.28000***	
Number of observations			324	

*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level

Following this, we conducted fixed effects panel regressions to estimate the treatment effects. The results are presented in Table 3.4. Participation in vigorous work, moderate work, and leisure-related PA was associated with an average decrease in BMI of 3.5%, 3.3%, and 10.4%, respectively. While the effect of transport-related PA was negative, it was not statistically significant.

Table 3.3. Interactive effects of PA and age, gender, health, and BMI categories on BMI

	(1)	(2)	(3)	(4)
Total PA x Age group				
18-29	-0.00052*** (0.00019)			
30-44	-0.00024*** (0.00009)			
45-59	-0.00029** (0.00013)			
60-69	0.00002 (0.00018)			
>70	0.00065 (0.00061)			
Total PA x Gender				
Female		-0.00016* (0.00009)		
Male		-0.00041*** (0.00010)		
Total PA x NCD outcome				
Never been diagnosed			-0.00021*** (0.00008)	
Diagnosed			-0.00022** (0.00019)	
Total PA x BMI category				
Underweight				-0.00077*** (0.00012)
Normal				-0.00047*** (0.00008)
Overweight/obese				0.00014 (0.00011)

Robust standard errors are in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level

Table 3.4. Effect of participation in PA on BMI after entropy balancing

	(1)	(2)	(3)	(4)
Vigorous work (MET-hrs/week)	-0.0357** (0.0175)			
Moderate work (MET-hrs/week)		-0.0329* (0.0185)		
Transportation (MET-hrs/week)			-0.0146 (0.0262)	
Leisure sport treatment				-0.1040** (0.0420)

Robust standard errors are in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level

Effect of physical activity on NCD outcomes

In this section, we report the results of a probit regression on the effect of PA on the probability of an NCD outcome (diabetes, high blood pressure, and heart attack or stroke). The columns in Table 3.5 represent the estimated average partial effects of the PA variables. Column 2 shows that total PA negatively influences the probability of having an NCD. A unit increase in MET-hours per week of physical activity decreases the probability of having an NCD by 0.09%. Column 3 represents the coefficients of the PA variables controlling for other covariates. An increase of one unit in the MET-hours per week for vigorous work, moderate work, and leisure-related PA is associated with a 0.15%, 0.11%, and 0.53% decrease in the probability of developing an NCD. Conversely, sedentary time is associated with a 0.18% increase in the probability of developing an NCD.

Table 3.5. Probit estimates of the effect of physical activity on NCD outcomes – Average partial effects

	(1)	(2)
Total PA	-0.0009**	
	(0.0003)	
Vigorous work (MET-hrs/week)		-0.0015***
		(0.0004)
Moderate work (MET-hrs/week)		-0.0011*
		(0.0006)
Leisure sport (MET-hrs/week)		-0.0053***
		(0.0019)
Transportation (MET-hrs/week)		0.0002
		(0.0007)
Sedentary time		0.0018***
		(0.0003)
Age (years)		0.0366*
		(0.0195)
Asset index		
Second		-0.0412
		(0.0624)
Middle		0.1593**
		(0.0666)
Fourth		0.2706***
		(0.0833)
Richest		0.1135
		(0.0754)
Household size		0.0986***
		(0.0216)
Marital status		
Married		0.2471***
		(0.0378)
Employment status		
Employed		0.1670***
		(0.0554)
Healthy behaviors index		
Fair		-0.0020
		(0.0724)
Good		-0.0688
		(0.0853)
Very good		-0.0246
		(0.0859)
Excellent		0.4724
		(0.0756)
Number of obs		146

Robust standard errors in parentheses.*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level

Robustness Check Results

The results of the probit models after entropy balancing (Table 3.6) support previous estimates of the negative influence of participation in PA on the probability of developing an NCD. We found significant negative treatment effects of all forms of physical activity—vigorous work, moderate work, transport, and leisure-related PA—on chronic diseases. Participation in these activities was associated with a 16.4%, 20.1%, 20.8%, and 24.9% reduction in the probability of having an NCD.

Table 3.6. Probit estimates of the effect of PA on NCD outcomes – Average partial effects after entropy balancing

	(1)	(2)	(3)	(4)
Vigorous work (MET-hrs/week)	-0.164** (0.070)			
Moderate work (MET-hrs/week)		-0.201*** (0.069)		
Transportation (MET-hrs/week)			-0.208** (0.087)	
Leisure sport				-0.249*** (0.081)

*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level

3.4 Discussion

Physical activity is one of the modifiable risk factors that can be addressed to mitigate the increasing prevalence of overweight, obesity, and NCDs. This study builds upon previous research by using panel data that accounts for unobserved heterogeneity and entropy balancing to adjust for differences in observed covariates between the treatment and control groups to establish the empirical association between various forms of PA, weight status, and NCD outcomes in Kenya.

Physical activity was mainly conducted through work and transport-related activities. Between 2015 and 2022, there was a significant decline in overall PA levels. Leisure sports PA levels also declined and did not compensate for work- or transport-related PA reductions, indicating that decreases in these areas were not offset by increased recreational physical activity. During this study period, there was an increase of 21.2 minutes per day in sedentary time and a rise in the average BMI of 1.2 kg/m². There was also an increase in the prevalence of high blood pressure, high blood sugar, and self-reported incidents of heart attacks or strokes. This trend aligns with previous research indicating an increased prevalence of physical inactivity globally, with high-income countries recording higher rates than low-income countries (Guthold et al., 2018; Ng & Popkin, 2012).

Advancements in labor-saving technologies have contributed to the decline in PA levels. Occupations are now more sedentary, transportation more motorized, and less energy is expended at work or home (Lakdawalla et al., 2005; Ng & Popkin, 2012). Overall, work-related

PA has experienced a significant decline, driven by reductions in vigorous work. The adoption of labor-saving technologies might have resulted in this decline. Based on the work categories in our dataset, we observed a decline in vigorous work MET-hours per week and an increase in moderate work PA among government employees, indicating a shift toward lower PA levels in the workplace. For the self-employed and homemakers, total work MET-hours per week decreased from 164.3 to 105.8 and 133.2 to 82.6, respectively, as detailed in Tables A3.2–A3.4 in the appendix. Self-employment in this study includes occupations such as farming and retail businesses. In Kenya, the shift toward agricultural mechanization has significantly reduced labor demands, particularly for plowing and weeding (Diiro et al., 2021). The decline in energy expenditure among homemakers may be attributed to technologies that simplify household chores or a decrease in the number of individuals identifying as homemakers. Transportation has also become more motorized in Kenya; between 2014 and 2022, ownership of motorcycles increased from 7% to 13%, while bicycle ownership decreased from 21% to 16.3% (Kenya National Bureau of Statistics, 2014; Kenya National Bureau of Statistics et al., 2022). Motorcycles are increasingly preferred due to their affordability, fuel efficiency, and suitability for areas with poor road networks. Additionally, leisure-time activities have shifted towards more passive pursuits like watching television and internet use, as indicated by the increase in household television ownership, which has risen from 35% in 2014 to 50.1% in 2022 (Kenya National Bureau of Statistics, 2014; Kenya National Bureau of Statistics et al., 2022).

The results indicated negative associations between total PA, vigorous work, transport, and leisure-related PA with BMI. This is consistent with previous research. Ng et al. (2012) applied dynamic panel estimation techniques on a longitudinal sample from China from 1991 – 1996 and found that an increase of 10 MET-hours per week of work and home PA was associated with a weight loss of 0.029kg (Ng et al., 2012). Similarly, using panel data, Sarma et al. (2014) reported that engaging in leisure-time PA, such as 30 minutes of walking, was linked to a reduction in BMI by 0.14 points in males and 0.20 points in females. Additionally, participation in work-related PA was associated with a BMI decrease ranging from 0.19 points in males to 0.28 points in females (Sarma et al., 2014). In terms of transport-related PA, Martin et al. (2015) demonstrated that switching from private motor transport to active travel was linked to a reduction of 0.32 kg/m^2 in BMI (Martin et al., 2015).

Multiple robustness checks, including an ordered logit model with BMI categories, support the findings. After employing entropy balancing, it was revealed that participants who engaged in vigorous work, moderate work, and leisure-related PA exhibited, on average, lower BMIs than non-participants. Participating in transport-related PA did not significantly affect BMI in this model.

Interaction terms revealed varying relationships between PA and BMI across different groups. Negative effects of PA on BMI were significant for younger age groups, both genders (with a stronger effect in men), different health statuses, and the underweight/normal weight categories. This may be because older individuals, particularly those over 60, tend to engage in less work-related PA, likely due to increased injury risk and retirement. The absence of significant negative effects among the overweight and obese groups could be attributed to physiological differences (Jacquet et al., 2020). Gender differences in PA effects may be explained by men's higher muscle mass and lower body fat percentage, which contribute to greater weight loss (Christensen et al., 2018).

This paper also revealed that PA leads to a reduction in the probability of an NCD outcome such as high blood pressure, diabetes, heart attack, or stroke. A unit increase in MET-hours per week in vigorous work, moderate work, and leisure-related PA is associated with a decreased probability of having an NCD. Conversely, sedentary time is associated with increased risk of developing an NCD. Following entropy balancing, the results indicated significant negative effects for all types of PA, correlating with a reduction in the likelihood of developing an NCD. Previous evidence on the effects of PA on NCD outcomes is mixed; Sarma et al. (2015) found that active leisure PA reduced obesity risk by 5% in Canada, with no significant effects on diabetes, high blood pressure, or heart disease (Sarma et al., 2015). In contrast, Humphreys et al. (2011) reported a 2.4% decrease in diabetes risk and a 3.8% decrease in HBP risk with daily leisure PA (Humphreys & Ruseski, 2011).

Sedentary time is significantly linked to a higher NCD risk, with each extra minute of sitting increasing the risk by 0.18%. Numerous studies have demonstrated the adverse effects of prolonged sedentary time on chronic diseases, including cardiovascular disease and diabetes (Diaz et al., 2017; Guo et al., 2020; Homer et al., 2019; Huang et al., 2019; Matthews et al., 2012; Yerramalla et al., 2022). In a study on British participants, Yerramalla et al. (2022) found a 20% higher risk of cardiovascular disease with a one-hundred-minute increase in sedentary time (Yerramalla et al., 2022). Huang et al. (2019), using the 1970 British birth cohort, found that prolonged sedentary time was adversely associated with diabetes biomarkers (Huang et al., 2019). In the United States, sedentary behaviors, like excessive television viewing, were associated with increased mortality risk, including cardiovascular and cancer mortality (Matthews et al., 2012).

Study limitations

Limitations in this study include using self-reported PA questionnaires to measure the duration and intensity of physical activities, which can be biased and less accurate than using devices such as accelerometers and pedometers. Electronic devices are usually more accurate but more expensive to implement. The study was also limited in sample size, which might impact the generalizability of the data. The results might indicate a causal relationship between PA and health outcomes, but this is not conclusive since leisure-related PA is optional and, therefore, considered endogenous. Further instrumentation may be necessary for this variable to mitigate potential feedback effects. Nonetheless, we employed entropy balancing using observed covariates to establish a causal relationship, as this method effectively addresses confounding and selection bias by reweighting the sample to create a balanced comparison group, thereby providing a robust alternative to traditional instrumentation approaches. The study did not also account for the influence of retirement on PA, which might affect factors such as the opportunity cost of time. Despite these limitations, the study provides a first insight into the empirical association between PA and health outcomes in the SSA context.

3.5 Conclusions

The findings in this paper show that participation in PA is declining over time while the daily sedentary time is increasing. Without intervention, this trend is set to continue with technological innovations reducing the amount of physical activity required. This paper aimed to establish the empirical relationship between work PA, leisure PA, transport PA, and sedentary time with health outcomes such as overweight, obesity, and NCDs. Findings indicate that PA has a significant effect on health outcomes. Transport-related PA is linked to lower BMI outcomes. Vigorous work and leisure-related PA are linked to a reduction in both weight and the probability of an NCD outcome. Moderate work-related PA is associated with a lower probability of developing an NCD. Sedentary behavior was also significantly linked to the probability of having an NCD. In addition, the large coefficient for leisure-related PA in all the models is an indication that leisure activity significantly reduces BMI and the likelihood of developing an NCD.

This study has shown that promoting PA can help reduce poor health outcomes by lowering BMI and decreasing the risk of NCDs. With evidence of a rising trend in physical inactivity and sedentary behavior, it has become even more crucial to advocate for increased PA. In order to encourage individuals to engage in leisure recreational activities, we need investments in the provision of public sports facilities and safe open spaces, such as parks. Policies need to be implemented to promote non-motorized means of transportation by ensuring safe cycling and walking infrastructure. Work-related physical activities need to be promoted through the provision of gyms, promoting the use of stairs, and encouraging breaks to prevent prolonged sedentary times at work. Community engagement and public awareness also needs to be created to inform people about the health benefits of physical activities and engage them in community sports events.

Chapter 4: Private and social costs of obesity among women in Kenya

4.1 Introduction

The current food system imposes significant health costs because it incentivizes producing, promoting, and consuming unhealthy foods. This has been attributed to the fact that market prices fail to account for the costs associated with harmful foods or the benefits provided by healthy foods (von Braun & Hendriks, 2023). As a result, unhealthy food has become cheaper and more accessible than healthier options. Furthermore, economic growth in developing countries has increased the supply and demand for foods high in salt, fats, and sugar, contributing to dietary shifts toward high-calorie foods. This trend has led to a rise in overweight and obesity rates, which is further exacerbated by technological changes that promote more sedentary lifestyles (Popkin, 2001). According to the latest KDHS, 45% of women and 19% of men between the ages of 20 and 49 years are overweight or obese in Kenya (Kenya National Bureau of Statistics et al., 2022). This high prevalence, particularly among women, raises significant concerns. Overnutrition has been shown to have a causal association with over 27 NCDs, including 18 cancers, six types of cardiovascular conditions, type 2 diabetes, and chronic kidney diseases (Murray et al., 2020; Wanjau et al., 2022). In 2019, obesity accounted for 6.2% of all deaths and ranked 7th among the top 10 risk factors contributing to total Disability-Adjusted Life Years (DALYs) across all age groups in Kenya (Murray et al., 2020). In addition to its contribution to the disease burden, overweight and obesity imposes psychosocial consequences such as depression, stress, and anxiety (Hecker et al., 2022).

The health externalities of the current food system—driven by unhealthy diets that increase the risk of overweight, obesity, and NCDs—have a significant economic impact. By calculating the direct and indirect costs, we can estimate the extensive impact of overnutrition on society. Direct medical costs quantify healthcare goods and services utilized due to diseases attributed to overweight and obesity (Okunogbe et al., 2022). Individuals with obesity are more likely to experience higher rates of inpatient admissions and outpatient visits, require more medications, incur long-term care costs, and need additional home health care services. Costs, such as informal caregiver costs and transportation, are quantified as direct non-medical costs. Indirect costs include lost wages and decreased productivity due to death or illness, which can lead to absenteeism, reduced work hours, or diminished performance while at work (presenteeism) (Goettler et al., 2017). Various cost-of-illness techniques have been used to assess the cost of obesity. Lord (2023) estimated the hidden costs of agrifood systems, revealing that in 2020, the largest hidden costs stemmed from health costs due to unhealthy diets. Global productivity losses from obesity and related NCDs were estimated at US$8 to US$10 trillion of the total US$13 trillion, exceeding the environmental and social costs associated with the food system. Other studies approximate that direct and indirect costs of overweight and obesity accounted for about 2.2% of global GDP in 2019. This estimate is projected to rise to 3.3% by 2060 (Okunogbe et al., 2022). These costs vary significantly by region, with estimates ranging from US$20 per capita in Africa to US$872 per capita in the Americas. In LMICs, they are projected to rise substantially, with increases expected to be 12 to 25 times higher (Okunogbe et al., 2022). Regional estimates show that, on average, Organization for Economic Cooperation and Development (OECD) countries allocate US$209 per capita annually to treat high body mass index (BMI) ($\geq$25 kg/m^2) and its associated conditions, which represent 8.4% of the health budgets (Vuik et al., 2019). This spending is primarily driven by treatment costs for diabetes, cardiovascular diseases, and cancers (Vuik et al., 2019). In South Africa, the total economic burden of overweight and obesity in 2020 was estimated to reach 15.4% of government health expenditure and 0.7% of GDP (Boachie et al., 2022).

At the individual level, COI studies employing econometric methods consistently demonstrate that individuals with obesity generally incur higher medical care costs (Biener et al., 2020; Bozzi & Nicholas, 2021; Cawley et al., 2021; Cawley & Meyerhoefer, 2012; Meyer, 2016; Qin & Pan, 2016; Ward et al., 2021). In the US, a correlation study by Finkelstein (2009) demonstrated that obese individuals incurred per capita medical expenses that were $1,429 higher than those of normal-weight individuals, representing a 42% increase (Finkelstein et al., 2009). Cawley and Meyerhoefer (2012), utilizing the US Medical Expenditure Panel Survey (MEPS) for 2000–2005, addressed endogeneity issues using an instrumental variable (IV) approach, utilizing the BMI of the respondent's first biological child as an IV for parental weight. Their findings suggest that the impact of obesity on medical costs is significantly greater than previously estimated in non-IV analyses. While traditional estimates indicated a $656 increase in annual medical care costs, IV results showed a $2,741 rise. Cawley (2021) further updated these findings by analyzing the MEPs data from 2001 to 2016, revealing that adults with obesity incurred significantly higher annual medical care costs, amounting to $2,505, which is a 100% increase compared to those with normal weight (Cawley et al., 2021). The costs associated with obesity also increased with the severity of obesity, ranging from a 68.4% rise for class 1 obesity to a 233.6% increase for class 3 obesity, affecting all categories of care (Cawley et al., 2021). In Spain, causal estimates showed that severe obesity leads to an average increase of €160 per patient per year in direct medical costs, which represents a 26% increase compared to normal-weight individuals. Moderate obesity leads to a more modest cost increase of €97 or 16%, while being overweight raises costs by €51 or 8.5% (Mora et al., 2015).

In Kenya, the national total cost of obesity in 2019 was estimated at $742.6 million, based on regional averages (Okunogbe et al., 2022). This includes $131.2 million for direct medical expenses, $5.7 million for direct non-medical expenses, $65.7 million for absenteeism, $146.6 million for presenteeism, and $393.4 million for premature mortality. The per capita cost of obesity was $14.1, representing 0.7% of the GDP. Kenya ranked 8th among African countries in terms of total costs, and with the rising prevalence of obesity, projections indicate that costs could rise to $106.8 per capita by 2060 (Okunogbe et al., 2022). It is crucial to understand the economic impact of overweight and obesity in Kenya to help policymakers and stakeholders comprehend the magnitude of the challenge, thereby facilitating the prioritization of policies, interventions, and resource allocation efforts. Wanjau et al. (2022) present a compelling investment case for prioritizing the prevention of overweight and obesity in Kenya. Based on the 2019 population, their findings indicate that eliminating high BMI could save approximately 83.5 million health-adjusted life years (HALYs) over a lifetime, prevent over 7.4 million new cases of BMI-related diseases within 25 years, postpone half a million BMI-related deaths, and avert 867,664 prevalent cases of musculoskeletal disease by 2044 (Wanjau et al., 2022).

This paper aims to provide evidence on the impact of overnutrition in Kenya by employing an econometric approach to estimate the costs attributed to overweight and obesity among women aged 15-49, utilizing nationally representative data from the 2022 KDHS. To our knowledge, this represents one of the initial efforts in the region to derive such estimates using nationally representative data and internationally comparable methodologies. First, we estimate the difference in medical costs among categories of normal weight and overweight/obese women using a two-part model (2PM) that accounts for the nature of the medical expenditure data. To further support the findings, we obtain causal estimates by employing an instrumental variable to address the endogeneity of weight using a novel two-stage residual inclusion (2SRI) model, which offers less biased estimates than a two-stage least squares (2SLS) model. We instrument the woman's BMI using the percentage of the overweight/obese population within the respondent's wealth quintile in their residential community. We also include the estimates of direct non-medical costs and the social costs of overweight and obesity, which include travel costs, caregiver time costs, and indirect costs (absenteeism and presenteeism). Understanding the impact of overweight and obesity on health expenditures, particularly among women, is crucial, as women have a higher prevalence of overweight and obesity than men. This disparity can increase women's health expenditures, further exacerbating their already challenging economic conditions. Women have a lower employment rate (60.3%) compared to men (70.4%) and face an unadjusted gender pay gap of 31.3% at the monthly level in Kenya; therefore, increased health costs can significantly impact women financially, potentially worsening their economic disadvantage (World Bank, 2024).

This paper addresses the following research questions: 1) What is the impact of BMI on outpatient and inpatient medical expenditures among adult women in Kenya? 2) What social costs are associated with overweight and obesity in Kenya?

4.2 Materials and methods

4.2.1 Data

This study used data from the 2022 KDHS, a nationally representative survey conducted by the Kenya National Bureau of Statistics (KNBS) and the Ministry of Health (MoH) between February 17 and July 31, 2022, to collect data on sociodemographic, nutrition, and health indicators. The survey employed a two-stage stratified sampling design. In the first stage, 1,692 clusters were selected using the equal probability selection method from the Kenya Household Master Sample Frame. All households within the chosen clusters were listed, and then 25 households were selected from each cluster to participate, resulting in a total of 42,022 households sampled. We used the dataset from the individual record (IR) file, which includes all women (32,156) aged 15–49 who were regular members of the selected households or had stayed in the households the night before the survey. This dataset included information on sociodemographic characteristics, women's dietary diversity, and maternal and child health. Additionally, survey enumerators measured the height and weight of participants to obtain the BMI.

In this study, the outcome variable was the self-reported outpatient and inpatient medical expenditures. For the inpatient costs, respondents were asked to report the average annual expenditure for household members who stayed overnight in a health facility in the 12 months before the survey. This encompasses all costs, including charges paid in cash, by insurance, or in kind for laboratory tests, drugs, and other items. The breakdown includes how much of the total was covered by cash, national health insurance fund (NHIF), private insurance, in-kind contributions, and other means (Kenya National Bureau of Statistics et al., 2022). Outpatient costs refer to the average monthly expenditure for household members who received care from a healthcare provider, pharmacy, or traditional healer without staying overnight at a health facility in the month before the survey. This includes all costs for the visit, including any charges paid in cash, by insurance, or in kind for laboratory tests, drugs, and other items. During the analysis, we ensured that we matched the line number of the person incurring the costs with the corresponding line number in the women's data to confirm that the same individual bore the medical expenses.

The explanatory variable of interest was the BMI, obtained by dividing weight by height squared (kg/m²). We used BMI as a continuous variable to assess how incremental changes in BMI affect healthcare spending across the full BMI distribution. The BMI scores were further grouped into normal weight (18.5-24.9 kg/m²) and overweight and obese (≥25 kg/m²) (World Health Organization, 1995). Additionally, we decomposed BMI into six categories: underweight (<18.5 kg/m²), normal (18.5-24.9 kg/m²), overweight (25-29.9 kg/m²), obesity class I (30-34.9 kg/m²), obesity class II (35-39.9 kg/m²), and obesity class III (≥40 kg/m²) for the summary statistics in the appendix (Purnell, 2000). We analyzed only a subset of the population, women with height and weight information. Pregnant women and women with children under 2 months old were excluded due to the physiological changes during pregnancy, resulting in a final sample size of 15,377.

Control variables used in the analyses include age, number of household members, years of education, marital status, occupation, religion, ethnicity, and type of residence (rural or urban).

4.2.2 Empirical model

Two-part model of medical expenditures

To estimate the impact of BMI on medical spending, we employ a two-part model (2PM) to account for the medical expenditures data distribution shape. This approach is necessary due to the large number of respondents with zero medical expenditures and the highly positively skewed nature of medical spending (Belotti et al., 2015). The first part of the 2PM is a binary choice model that estimates the probability of observing positive medical expenditures versus zero expenditures. This is represented in Equation 4.1, which captures the systematic difference between medical users and non-users. In the second part (Equation 4.2), conditional on a positive outcome, we estimate the amount of medical expenditures by fitting a regression model for the positive outcomes. Therefore, we estimate the following 2PM for an individual’s medical expenditure:

$$\Pr(y_i > 0 | \, Oab_i, X_i) = G(\alpha . Oab_i + \beta X_i + u_i) \quad (4.1)$$

$$y_i = \exp(\delta . Oab_i + \theta X_i) + e_i, \text{for } y_i > 0 \quad (4.2)$$

In this case, y is the medical expenditure incurred by the individual *i*. *Oab* indicates whether the person is overweight or obese; the coefficients α and δ signify the impacts of overweight and obesity on both the likelihood of medical usage and the conditional medical expenditure. In both parts of the model, X_i are vectors of the control variables. The first part is estimated using either a probit or logit model. For the second part, there are two options: (1) Ordinary Least Squares (OLS) applied to the logarithm of the dependent variable; and (2) The Generalized Linear Model (GLM) estimator. A notable limitation of the log OLS method is the necessity of understanding the degree and form of heteroscedasticity for accurate re-transformation of estimates to the original scale (Cawley & Meyerhoefer, 2012). In our context, diagnosing and addressing heteroscedasticity accurately would be challenging. Therefore, the GLM approach is more appealing by comparison and is widely used in this type of studies (Cawley & Meyerhoefer, 2012). In this analysis, the first part is estimated as a logit model, where *G* represents the cumulative distribution function of the logistic distribution. In the second part, we use a GLM with a Gamma variance structure specified for e_i and a log link function.

Instrumental variable approach

To estimate the causal effect, we further employ an instrumental variable approach due to endogeneity issues. Instruments must be strongly correlated with the individual's BMI and valid, meaning the instrument should not be correlated with unobserved factors that might affect the respondent's medical expenditure. Findings suggest that non-instrumented models tend to underestimate the medical costs associated with obesity (Biener et al., 2014; Cawley et al., 2021; Cawley & Meyerhoefer, 2012; Mora et al., 2015). We employ an alternative IV, which is the percentage of the overweight/obese population within the respondent’s wealth quintile in their community of residence. We adopt this IV because of strong evidence in the literature of the peer effects that result in the clustering of body weight among people within a group or community. This is because individuals within a group share the same food environment and access to the same resources (recreational parks, sports facilities) or share the same social norms that might influence their perceptions regarding body weight (Qin & Pan, 2016). We confirmed that our instrument is strongly correlated with the individual level overweight and obesity level, with F statistics of 10.6 and 22.1 in the first stage of the instrumental variables models for outpatient and inpatient medical expenditures, respectively. These values exceed the F > 10 standard for a powerful instrument (Stock & Yogo, 2002). This instrument is also valid, meaning that the income group-based share of overweight/obesity within a community should not be directly correlated with individual health expenditures unless it's through the individual BMI. By focusing on the wealth quintile within a residential community, the IV accounts for socio-economic factors (e.g., access to health services, education level) that may affect community BMI and individual health expenditures, helping to isolate the specific effect of BMI.

We employ the 2SRI model to estimate the causal relationship between BMI and health expenditures among women in the KDHS data. We choose 2SRI because it provides an unbiased estimate compared to the 2SLS approach when the outcome is a nonlinear function of covariates and unobservables, particularly when the endogenous treatment is continuous. The 2SRI method involves a two-stage approach to estimate the local average treatment effect. In the first stage, we employ an OLS specification to obtain a consistent estimate of a woman i's BMI, denoted as W_i, based on the income-group overweight and obesity prevalence, denoted as Z_i, while controlling for covariates denoted as X_i. Equation 4.3 illustrates the relationship below:

$$W_i = \pi\left(\varphi Z_j + \rho_j X_{ij}\right) + \varepsilon_i \tag{4.3}$$

In the second stage of 2SRI, the outcome is predicted using the participant's BMI, covariates, and residuals from the first stage, denoted as $\hat{R}_i$. When the included residuals are significant, it indicates that endogeneity was indeed present and effectively controlled for in the model, as was the case in our regressions. In this equation 4.4, μ represents the outcome's functional form, and ϵ denotes the error term.

$$Y_i = \mu\left(\sigma W_i + \beta_j X_{ij} + \vartheta \hat{R}_i\right) + \epsilon_i \tag{4.4}$$

Similar to the 2PM model, we selected the GLM with a Gamma variance structure and a log link function. Since we generated the residuals from the first step, bootstrapping is recommended to obtain the correct standard errors (Terza, 2017). We employ bootstrapping with up to 500 replications for the 2SRI estimated models. We ran all models, including the DHS sample weights.

4.3 Results

4.3.1 Descriptive statistics

Table 4.1 lists the descriptive statistics for the primary variables used in the analysis. The sample had 15,377 adult women respondents with a mean BMI of 29.7 kg/m² in the overweight and obese group, and 21.7 kg/m² in the normal weight group. The average age of the sample was 29 years, women in the overweight and obese group were slightly older (33.6 years) than those of normal weight (27.4 years), indicating that BMI increases with age. Compared to normal-weight women, the overweight and obese group had more years of education (9.5 vs. 8.6), a higher employment rate (73% vs. 54%), a higher marriage rate (67% vs. 47%), more children (2.5 vs. 1.9), and belonged to a higher wealth index (3.8 vs. 3.0). The overweight and obese group reported poorer self-rated health status compared to the normal weight group and also had a higher percentage of insurance coverage. Additionally, overweight and obese women had more inpatient admissions (10% compared to 8% for the normal weight group) and reported receiving more outpatient medical care (25% compared to 20% for the normal weight group) further descriptives by BMI class are provided in Table A4.1 in the appendix.

Figures 4.1 and 4.2 illustrate the relationship between BMI and annual inpatient and outpatient medical expenditures. The average annual inpatient medical expenditure for overweight and obese women was 38,178.0 Kenyan shillings (KES) or $309.45 (US dollars, using current exchange rates), which was higher than the KES 22,088.3 ($179.04) for normal-weight women; however, this difference was not statistically significant. In contrast, outpatient costs showed a significant difference, with overweight and obese women incurring KES 1,728.5 ($14.01) per month compared to KES 1,277.8 ($10.36) for normal-weight women. Only 28% of women are covered by some form of health insurance. The most common form of health insurance is the NHIF, which covers over 90% of the respondents with insurance, followed by private insurance at 15%. A larger portion of inpatient and outpatient costs is paid out-of-pocket, while the smaller remaining share is covered by the NHIF and/or private insurance.

Women in the overweight and obese group also exhibit higher mean diet diversity scores and unhealthy food consumption scores compared to those in the normal weight group. Additionally, they report higher incidences of high blood pressure, diabetes, depression, and arthritis—all conditions linked to excess weight. Children of overweight and obese women generally have higher BMIs, while children of normal-weight women tend to have lower BMIs compared to the overall average for children in the sample, indicating a correlation between parental and child weight.

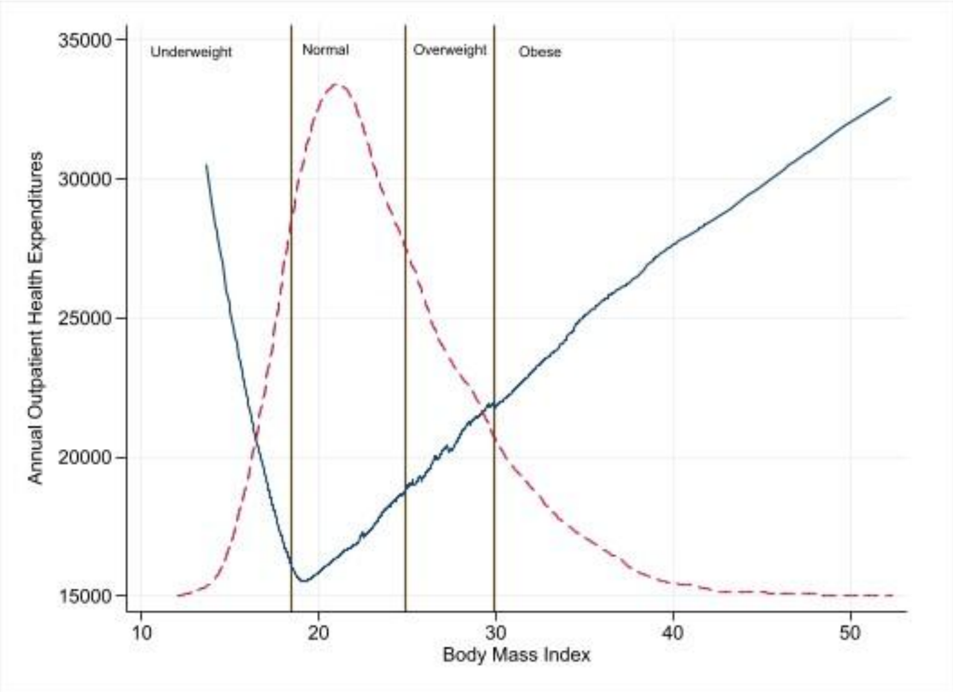

Figure 4.1. Relationship between BMI and outpatient health expenditures
The solid line denotes medical expenditures, while the dotted line indicates the distribution of individuals in the population.

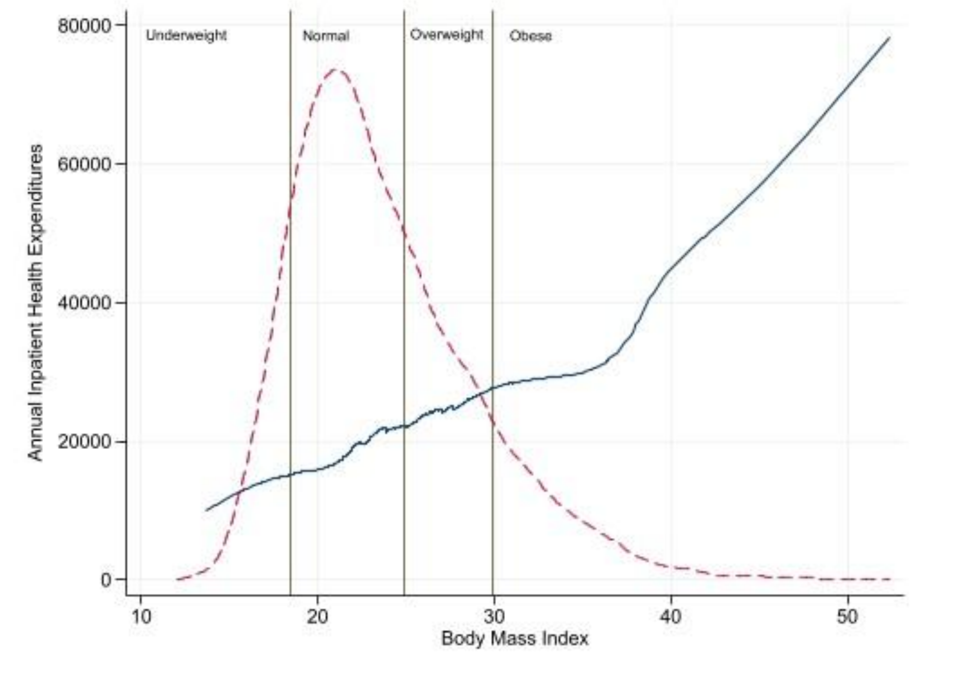

Figure 4.2. Relationship between BMI and inpatient health expenditures
The solid line denotes medical expenditures, while the dotted line indicates the distribution of individuals in the population.

Table 4.1. Summary statistics of the sample

	Full sample	Normal weight	Overweight/obese
BMI	24.34 (5.27)	21.69*** (1.81)	29.71 (3.92)
Age	29.31 (9.51)	27.37*** (9.53)	33.57 (8.23)
Years education	9.59 (0.06)	9.45***(0.07)	10.23 (0.08)
Employed (1=yes)	0.60 (0.49)	0.54*** (0.51)	0.73 (0.43)
Married (1=yes)	0.55 (0.50)	0.47***(0.51)	0.67 (0.45)
Household members	5.08 (2.50)	5.24***(2.59)	4.78 (2.19)
Number of children	2.10 (2.05)	1.88*** (2.15)	2.54 (1.78)
Wealth index (5=wealthiest)	3.24 (1.42)	3.03*** (1.43)	3.76 (1.19)
Self-reported health status (5=very bad)	2.01 (0.73)	1.99**(0.74)	2.03 (0.71)
Covered by health insurance (1=yes)	0.28 (0.45)	0.23*** (0.43)	0.40 (0.47)
Insurance type: NHIF (1=yes)	0.90 (0.28)	0.90 (0.29)	0.91 (0.27)
Insurance type: Private/Commercial (1=yes)	0.15 (0.35)	0.14 (0.34)	0.17 (0.35)
Insurance type: community-based (1=yes)	0.02 (0.13)	0.02 (0.12)	0.01 (0.10)
Annual total medical expenditures	22,291.14 (65,816.75)	18,983.61** (64,090.40)	28,630.41 (73,297.02)
Hospitalized overnight in the past 12 months (1=yes)	0.09 (0.29)	0.08*** (0.27)	0.10 (0.29)
Annual total inpatient costs overnight stay	26,048.05 (83,120.53)	22,088.28 (75,245.01)	38,177.97 (100,501.90)
Amount paid overnight by cash	13,383.99 (34,774.67)	13,790.78 (36,184.12)	14,786.18 (37,066.20)
Amount paid overnight by NHIF	9,018.89 (36,917.06)	6,516.73** (32,755.42)	14,291.87 (44,255.05)
Amount paid overnight by private insurance	7,110.22 (57,979.78)	2,936.24 (19,522.86)	14,197.16 (82,974.24)
Amount paid overnight in-kind	563.83 (10,729.38)	136.06 (2,422.75)	1,223.26 (15,623.47)
Received outpatient medical care in the last 4 weeks (1=yes)	0.22 (0.42)	0.20*** (0.41)	0.25 (0.42)
Total outpatient costs (monthly)	1,468.41 (3,845.16)	1,277.84** (4,000.84)	1,728.50 (3,846.37)
Amount paid outpatient by cash	1,211.94 (2,740.29)	1,016.71** (2,433.11)	1,438.77 (3,009.74)
Amount paid outpatient by NHIF	185.43 (2,187.35)	229.91 (3,196.73)	160.27 (1,002.36)
Amount paid outpatient by private insurance	70.23 (1,184.97)	38.20* (437.21)	109.62 (1,647.45)
Amount paid outpatient in-kind	15.86 (209.53)	11.97 (197.91)	23.49 (238.52)
Diet diversity score	4.50 (1.73)	4.38*** (1.69)	4.81 (1.70)
Unhealthy foods score (2=unhealthy)	0.33 (0.47)	0.34 (0.48)	0.35 (0.46)
Oldest child BMI (Standard deviation)	-0.07 (1.15)	-0.13*** (1.11)	0.13 (1.07)
Has high blood pressure (1=yes)	0.09 (0.28)	0.05*** (0.23)	0.14 (0.34)
Has high blood sugar or diabetes (1=yes)	0.01 (0.09)	0.00*** (0.06)	0.02 (0.12)
Has depression (1=yes)	0.03 (0.17)	0.03** (0.16)	0.03 (0.17)
Has arthritis (1=yes)	0.03 (0.17)	0.02*** (0.14)	0.04 (0.20)
N (unweighted)	15,377	8,145	5,287

Statistics reported are the sample mean with the standard deviations in parentheses. All monetary values are expressed in 2022 Kenyan shilling (KES). ***Difference between normal weight and overweight/obese groups is significant at 1% level; **Difference between normal weight and overweight/obese groups is significant at 5% level; *Difference between normal weight and overweight/obese groups is significant at 10% level.

Women in the oldest age group (40–49) had the highest total medical expenditures, including the highest inpatient costs, as detailed in Table A4.2 in the appendix. Insurance coverage was also high among older age groups, with 36% and 37% of women aged 30–39 and 40–49, respectively, having coverage. In contrast, total outpatient expenditures were higher for women in the 20–29 age group. Overall, medical expenditures were significantly higher for those with insurance, averaging KES 21,766.5 ($176.43) compared to KES 3,930.6 ($31.86) (Table A4.3 in the appendix). Inpatient costs for insured individuals averaged KES 56,330.2 ($456.58) compared to KES 9,047.5 ($73.33) for the uninsured.

4.3.2 Obesity and medical expenditures estimates

The probability of spending and the amount of spending, conditional on any spending, increases with the BMI category, as shown in Table 4.2. Individuals in the overweight and obese category have 3.3 times higher log odds of incurring outpatient health expenditures compared to those in the normal weight category, holding other variables constant. Among those with any outpatient spending, expenditures for the overweight and obese group are 31% higher than for the normal weight group.

Being overweight or obese significantly increases the likelihood of incurring inpatient health expenditures compared to normal-weight individuals. Specifically, the log odds of inpatient expenditure were 1.4 times higher for overweight or obese individuals. Conditional on any spending, those in the high BMI group had inpatient health expenditures that were 46% higher than normal-weight individuals. On average, obesity raised monthly outpatient medical expenditures by KES 445.0 ($3.61) and annual inpatient medical spending by KES 16,942.8 ($137.33) among Kenyan women.

The model estimates that normal-weight individuals would incur monthly outpatient medical expenditures of KES 720.3 ($5.80), compared to KES 1,251.6 ($10.14) for overweight and obese individuals (Table 4.3). For inpatient care, normal-weight individuals are expected to spend KES 14,778.1 ($119.78) annually, while overweight and obese individuals would spend KES 50,273.6 ($407.49).

Table 4.2. Average marginal effect of obesity on outpatient and inpatient medical expenditures

	Outpatient health expenditures			Inpatient health expenditures		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	logit	glm	Avg marginal effect	logit	glm	Avg marginal effect
Overweight/obese	3.34**	0.31***	445.01***	1.44***	0.46**	16,942.79**
	(1.45)	(0.06)	(95.58)	(0.55)	(0.21)	(8,090.06)
Age	-0.12	0.00	6.86	2.10	0.68	38,838.28
	(0.14)	(0.01)	(7.69)	(2.48)	(0.60)	(32,740.51)
Years education	0.31	0.02**	34.66***	-2.63	0.86	8,123.78
	(0.21)	(0.01)	(12.87)	(2.23)	(0.77)	(11,072.03)
Married	1.03	-0.67***	-498.10***	-0.80	-0.53	-20,853.90
	(1.75)	(0.10)	(106.78)	(1.19)	(0.44)	(21,942.29)
Household members	0.41	0.05***	62.64***	0.32**	-0.00	-1,326.34
	(0.31)	(0.02)	(19.66)	(0.15)	(0.05)	(1,812.22)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 4.3. Predicted mean expenditures

VARIABLES	Predicted mean outpatient health expenditure	Predicted mean inpatient health expenditure
Normal weight	720.28	14,778.06
	(617.38, 823.18)	(10,837.59, 18,718.54)
Overweight/obese	1,251.62	50,273.61
	(1,067.04, 1,436.20)	(24,953.08, 75,594.14)
No health insurance	864.76	8,579.49
	(747.82, 981.71)	(6,763.31, 10,395.67)
Covered by health insurance	1,359.02	57,543.40
	(1,082.55, 1,635.50)	(30,527.95, 84,558.86)
Residence urban	1,468.79	45,697.23
	(1,178.44, 1,759.16)	(19,988.36, 71,406.09)
Residence rural	789.45	17,896.14
	(704.63, 874.28)	(10,402.02, 25,390.26)

Confidence intervals in parentheses. *** p<0.01, ** p<0.05, * p<0.10

4.3.3 Obesity and medical expenditures estimate: IV estimates

In this section, we assessed the causal effects of BMI on healthcare spending. Table 4.4 reports the average marginal effects of BMI on outpatient and inpatient medical expenditures, showing the change in healthcare spending for each unit increase in BMI. The 2SRI results indicate that an additional unit of BMI raises monthly outpatient medical expenditures by KES 277.9 ($2.25) and annual inpatient medical expenditures by KES 5,119.0 ($41.49). These 2SRI estimates are significantly higher than the non-IV GLM estimates, which show that an additional unit of BMI increases outpatient medical expenditures by KES 44.0 ($0.36) and inpatient costs by KES

1,165.5 ($9.45). Results of the 2SLS model also show that there is a positive and significant association between BMI and healthcare expenditures as shown in Table A4.4 in the Appendix. We find the coefficient of an additional unit of BMI on outpatient health expenditures to be 0.17 while that of inpatient health expenditures to 0.25.

These findings suggest that, after accounting for the endogeneity of weight, an increase in BMI leads to higher medical expenditures. This relationship can be interpreted as causal since the IV model mitigates the endogeneity bias caused by factors such as omitted variables, reverse causality or measurement errors.

Table 4.4. Regressions of health care spending on measures of BMI

	Outpatient		Inpatient	
	GLM	2SRI	GLM	2SRI
BMI	43.98**	277.87***	1,165.54*	5,118.96*
	(17.70)	(87.43)	(698.01)	(3,039.70)
Age	763.37	400.48	1,551.45***	793.70
	(856.41)	(878.91)	(589.32)	(631.99)
Years education	65.58**	29.28	18,010.36***	15,107.63**
	(30.44)	(34.54)	(5,855.17)	(6,020.94)
Married/living with partner	110.92	-734.61**	-68,256.18	-67,652.12*
	(183.78)	(359.18)	(39,417.22)	(36,843.29)
Household members	85.41*	50.99	2,561.07	2,821.86
	(47.25)	(47.74)	(2,057.76)	(1,921.42)

Standard errors in parentheses. 2SRI standard errors are bootstrapped 500 times. *** p<0.01, ** p<0.05, * p<0.10

4.3.4 Social costs estimation

In this section, we estimated the societal impact of overweight and obesity by calculating the direct and indirect costs and summing them up to get the total economic cost for adult women in Kenya (full estimation tables are available in Appendix Tables A4.5–A4.16). Direct costs include medical expenses from treating related conditions as well as non-medical costs such as transportation to and from healthcare facilities and informal caregiver (ICG) costs. To estimate the direct medical cost of overweight and obesity among women of reproductive age (15-49) in Kenya, we used the 2022 KDHS data to determine the excess annual costs (for inpatient and outpatient medical expenses) per BMI group as shown below (applying survey weights in all the estimations derived from the KDHS):

$$\text{Excess cost (overweight/obese)} = \text{Average expenditure (overweight/obese)} - \text{Average expenditure (normal weight)} \quad (4.5)$$

After determining the excess cost, we obtained the prevalence of overweight and obesity among adult women from the survey population, which was 24% and 14%, respectively. This was then multiplied by the national population of adult women (age 15-49 years) in 2022, that was estimated to be 12.9 Million women (proportion of adult women × Kenya's female population) to obtain the number of overweight and obese women (World Bank, 2024). We then calculated the direct medical costs of overweight/obese adult women in 2022 as follows:

Total direct cost (overweight/obese)=Excess cost (overweight/obese)×population with overweight/obesity (4.6)

We derived the inpatient and outpatient travel costs (direct non-medical costs) by multiplying the average transport cost (ATC) per trip by the number of women who are overweight and obese and then by the average number of inpatient and outpatient consultations between the population with overweight/obesity compared with the normal weight population represented as N_i and N_o respectively as shown in equation 4.7 and 4.8 (Okunogbe et al., 2022). We obtained an estimate of the ATC from the 2018 Kenya Household and Health Expenditure survey, which contains information on transport costs for both inpatient and outpatient visits (Kenya National Bureau of Statistics, 2018).

$$\text{Inpatient Travel Costs} = \text{ATC} \times N_i \times \text{Population with Overweight/obese} \tag{4.7}$$

$$\text{Outpatient Travel Costs} = \text{ATC} \times N_o \times \text{Population with Overweight/obese} \tag{4.8}$$

Informal caregiver time costs for inpatient care were determined by estimating the wage lost during the time spent in the hospital giving care to a person with an overweight/obesity-related condition (Okunogbe et al., 2022). This was calculated by multiplying the average daily wage for both men and women (ADW) (obtained from the 2022 KDHS survey) by the average number of hospitalisation days by the population with overweight/obesity compared with the normal weight Population (N_d) (estimates from Australia) and the proportion of employed ICGs among the population with overweight/obesity given by equation 4.10. The proportion of employed ICGs among the population with overweight/obesity is derived from the employment rate, the total working-age population, and the obesity prevalence shown in equation 4.9 (Kenya National Bureau of Statistics et al., 2022; Korda et al., 2015; Okunogbe et al., 2022). The travel cost for ICGs was computed in the same way as that for inpatient travel costs.

Employed ICGs for Pop. with Obesity=employment rate × working age population× obesity prevalence (4.9)

ICG Time Costs = ADW × N_d × Employed ICGs for Pop. with Obesity (4.10)

Indirect costs represent the costs of overweight and obesity on labor market outcomes. It includes missed days of work (absenteeism), reduced productivity while at work (presenteeism) and also premature death[4]. Productivity losses from absenteeism arise when employees are absent from work due to illness or health issues associated with overweight/obesity. To calculate the cost of lost productivity due to excess absenteeism among the working population with obesity, we use the formula below (Okunogbe et al., 2022):

Absenteeism Cost = Employed Population with Obesity × Excess Days Absent × ADW (4.11)

For the excess days absent, we used the estimate of a longitudinal study of an Australian population (Keramat et al., 2020b). Here, the employed population with obesity is obtained as shown in equation 4.12 (Okunogbe et al., 2022). The employment rate differs by BMI status, as obtained from the KDHS survey. In Kenya, the working-age population consists of all women between 15 and 49.

Employed Population with Obesity = Employment rate × Working Age Population × Obesity Prevalence (4.12)

Presenteeism is defined as being at work despite ill health, such as an obesity-related impairment leading to decreased productivity while at work (Aronsson & Gustafsson, 2005; Brunner et al., 2019; Cartwright & Cooper, 2009; Hemp, 2004; Karanika-Murray & Cooper, 2018; VingÅrd et al., 2004). We estimated presenteeism by multiplying the employed women population with obesity by the excess presenteeism rate, which is the rate of reduced productivity among employees with obesity (also obtained from an Australian longitudinal study) and the average annual wages (from the 2022 KDHS) represented as follows (Keramat et al., 2020a; Okunogbe et al., 2022):

Presenteeism Cost = Employed Population with Obesity × Excess Presenteeism Rate × Average Annual Wages (4.13)

Results

[4] It is acknowledged that indirect costs of overweight and obesity may include burden of human suffering. This aspect is not quantified in the estimations.

Table 4.5 presents the estimated social costs of overweight and obesity among adult women aged 15-49 in Kenya, expressed in US dollars ($) using current exchange rates (see Table A4.17 for estimates in Kenyan shillings (KES) in the appendix). In 2022, the total social cost for both conditions amounted to $1.11 billion, representing 0.98% of the country's GDP. The average cost per adult woman for overweight and obesity was KES 10,557.2 ($85.57), which constitutes 5% of their average annual income (KES 120,687.8[5] obtained from the KDHS survey). The cost per woman for overweight was KES 6,147.5 ($49.83), while for obesity, it was KES 4,245.9 ($34.42). However, the average cost per obese individual is higher than that for overweight individuals (KES 242 vs KES 207). Direct medical costs accounted for the largest share of expenses, making up 35% of the total costs, followed by productivity losses due to presenteeism, representing 30%. Outpatient travel costs were also significant, comprising 18% of the total. In contrast, absenteeism contributed the least to overall costs, accounting for only 2%. In the obese category, the largest contribution to total costs came from presenteeism, accounting for 46% of the overall expenses, followed by medical costs at 20%. Among the overweight group, direct medical costs represented the largest share at 47%, with presenteeism and outpatient travel costs each contributing 18%.

Table 4.5. Total costs of overweight and obesity in the sample in USD (current exchange rates)

	Overweight	Obese (≥ 30 kg/m²)	Overweight & Obese	% of Total costs[2]
Direct medical costs	305,253,290.60	88,244,315.64	388,756,545.56	35%
Inpatient travel costs	34,641,491.52	20,127,683.15	59,021,327.03	5%
Outpatient travel costs	116,188,602.06	75,363,181.23	199,915,564.22	18%
Informal caregiver time costs	24,162,528.59	21,055,285.27	50,592,690.76	5%
Informal caregiver travel costs	34,641,491.52	20,127,683.15	59,021,327.03	5%
Absenteeism	15,243,735.86	17,315,464.10	18,694,277.22	2%
Presenteeism	117,548,526.54	205,103,304.98	336,266,670.33	30%
Total indirect costs	132,792,262.40	222,418,769.08	354,960,947.55	32%
Total costs	647,679,666.69	447,336,917.52	1,112,268,402.14	
Costs per overweight or obese individual	207.36	242.02	223.71	
Total costs per capita[1]	49.83	34.42	85.57	
% Annual income	0.03	0.02	0.05	

[1]denominator is the total number of women aged 15-49 in Kenya. [2]this is % of total costs for the overweight & obese category

[5] This was defined as the average monthly earnings in the last one month before the survey for all employed women and men who were paid in cash or kind for their work.

4.4 Discussion

The prevalence of overweight and obesity is increasing in Kenya, especially among women. This raises significant concerns since overweight and obesity increase the risk of diseases such as hypertension, type 2 diabetes, coronary heart disease, congestive heart failure, stroke, gallstones, cancer (endometrial, breast, prostate, and colon), and osteoarthritis. Consequently, individuals with obesity are much more likely to experience increased inpatient admissions, outpatient visits, and a higher use of medications. These costs will place a significant financial burden on both the healthcare system and individuals. Given the low insurance uptake in the population, most expenses are covered out-of-pocket, which may lead to financial hardship. Therefore, it is crucial to determine the impact of rising BMI on health expenditures, especially among women, to support policies aimed at curbing its increase.

This study aimed to estimate the effect of BMI on healthcare expenditures and determine the social costs of overweight and obesity among Kenyan women aged 15-49, using the latest KDHS data. Women in the overweight and obese group were generally older, had more years of education, higher employment and marriage rates, more children, and belonged to a higher wealth index compared to those in the normal-weight group. This is consistent with obesity literature in SSA, which indicates that overweight and obesity is associated with higher age, wealth, education, and parity (R. Mkuu et al., 2021b; Yeshaw et al., 2020). Overweight and obese women in the sample reported more inpatient admissions (10% vs 8%) and sought outpatient care more frequently than those in the normal-weight category (25% vs 20%). Consequently, the overweight and obese group incurred higher inpatient and outpatient medical expenditures compared to the normal-weight group. This further supports the evidence that increased weight is associated with poorer health outcomes, leading to more frequent hospital visits and higher medical expenditures. Consistent with a study from Ghana that sampled adults over 50, overweight and obesity were linked to 75% and 159% more inpatient admissions, respectively. Obesity was also associated with 53% more outpatient visits compared to individuals of normal weight. The study further revealed that direct costs for the overweight and obese group were significantly higher, at US$121 million, compared to US$64 million for the normal-weight group (Lartey et al., 2020). We also found fewer than 30% of the women had health insurance since most medical costs were paid out-of-pocket. This low insurance uptake has been attributed to issues of affordability and lack of awareness despite the low monthly premiums for the NHIF (KES 500 or $4.05) for informal sector workers (Mugo, 2023).

This study found that the likelihood of incurring healthcare expenses and the amount spent, conditional on any spending, increase with higher BMI categories. These findings are consistent with evidence from studies conducted in other countries (Buchmueller & Johar, 2015; Shi et al., 2017). Individuals in the overweight and obese category have higher log odds of incurring outpatient and inpatient health expenditures compared to those in the normal weight category. The predicted monthly outpatient medical expenditure for normal-weight individuals was KES 720.2 ($5.80), compared to KES 1,251.6 ($10.14) for those who are overweight or obese. It was also estimated that the effects of obesity increased outpatient medical expenditures by KES 445 ($3.61). Normal-weight individuals spend KES 14,778.1 ($119.78) on inpatient medical expenses annually, compared to KES 50,273.6 ($407.49) for those who are overweight or obese. Being overweight or obese is estimated to increase inpatient medical spending by about KES 16,942.8 ($137.33).

We extend our analysis to get the causal estimates of healthcare spending attributable to BMI. Our analysis shows that increasing BMI by one kg/m^2 raises marginal outpatient healthcare monthly spending by KES 277.9 ($2.25) and marginal annual inpatient healthcare spending by KES 5,119.0 ($41.49). The non-IV GLM estimates show lower values, with KES 44.0 ($0.36) for outpatient health care costs and KES 1,165.5 ($9.45) for inpatient health care costs. These results suggest that non-IV models underestimate the impact of high BMI on health expenditures, indicating that endogeneity biases the estimation downwards. Our results are similar to other studies where they have found the non-IV estimates to be much lower than the IV estimates (Biener et al., 2020; Bozzi & Nicholas, 2021; Cawley & Meyerhoefer, 2012; Dixon et al., 2020). Cawley and Meyerhoefer (2012) determined that obesity correlates with a $656 increase in yearly medical care expenses. However, the IV analysis showed that obesity increases annual medical costs by $2,741. Meyer (2016) found that after factoring in individual traits, health status, and regional variations, the control function model forecasts that a one-point rise in BMI elevates healthcare expenditures by CHF253. Conversely, the non-IV regression indicated a CHF34 increase.

Overall, our study finds that weight raises costs in the two categories of health expenditures. Being that a large share of medical care costs are covered through out-of-pocket payments, this can result in catastrophic health expenditures (Chuma & Maina, 2012; Salari et al., 2019). The second source of funding for medical costs is the NHIF, which is primarily funded through mandatory contributions from those in the formal sector (Mbau et al., 2020). This suggests that obesity incurs significant adverse externalities, providing an economic rationale for government intervention to prevent and mitigate obesity.

We also show that being overweight and obese imposes social costs. We estimated the direct and indirect costs and found that the total social cost amounted to $1.11 billion, representing 0.98% of the country's GDP, and per adult woman cost of KES 10,557.2 ($85.57). The average cost per obese woman ($242) was higher than the average cost per overweight woman ($207), indicating higher healthcare needs among obese women. The largest portion of costs was direct medical expenses at $388.8 million, followed by productivity costs at $336.2 million. The total cost of obesity alone is $447.3 million, with $205.1 million attributed to presenteeism and $88.2 million for direct medical expenses. A previous estimate that used regional estimates for both men and women in Kenya in 2019 indicated that obesity-related costs totaled $742.6 million. The largest portion, $393.4 million, was attributed to premature mortality, followed by $146.6 million for presenteeism and $131.2 million for direct medical expenses (Okunogbe et al., 2022).

These costs are set to increase if the country does not significantly increase its investment in the treatment and prevention of overweight and obesity. In resource-constrained countries like Kenya, these policies must also be evaluated for cost-effectiveness. The WHO's proposed 'best buy' interventions suggest affordable, cost-effective strategies to reduce unhealthy diets and physical inactivity. Some of these interventions, which cost less than $100 per DALY averted in LMICs, include front-of-pack nutrition labelling, revision of food and beverage policies to eliminate trans fats and reduce saturated fats, establishing public food procurement and service policies to promote healthy food consumption, mass media and communication campaigns for healthier diets, implementing policies to restrict harmful food marketing to children, promoting breastfeeding practices, and community-wide public education campaigns on physical activity (World Health Organization, 2024c). Interventions that may cost more than $100 per DALY averted include taxing sugar-sweetened beverages (SSBs) and integrating physical activity counselling and referrals into routine primary health care services (World Health Organization, 2024c). In Kenya, a modelling study assessed the impact of four interventions to control overweight and obesity (Wanjau et al., 2021). The results showed that over the lifetime of the 2019 population, a 20% SSB tax would cost $9.9 million to implement but could reduce healthcare costs by around $140 million and lead to productivity gains of $1.8 billion, with a cost-effectiveness of $49 per healthy life year (HALY) gained. Mandatory kilojoule menu labelling would cost $12.0 million and could result in healthcare savings of $83 million, productivity gains of $1.2 billion, and cost-effectiveness of $92 per HALY gained. A shift in consumption patterns linked to supermarket food purchases could yield over $1.9 billion in healthcare cost savings and productivity gains of $27 billion. Furthermore, a return to the 1975 average national energy intake levels could result in healthcare savings of $6.2 billion and productivity gains of $92 billion (Wanjau et al., 2021). Other studies conducted in high-income countries have shown that implementing school-based interventions to increase physical activity would cost $10 million, offsetting over $641 million in healthcare costs, while restricting television advertising would cost $6 million and offset $784 million in costs (Ananthapavan et al., 2020). Kenya has yet to implement WHO-recommended policies to address unhealthy diets and physical inactivity, such as salt and sodium reduction, regulation of fatty acids and trans fats, restrictions on marketing unhealthy foods to children, restrictions on breast milk substitute marketing, front-of-pack nutrition labeling, or public campaigns to encourage physical activity (Asiki et al., 2020).

As new anti-obesity medications become more widely available and reasonably priced, new options for treating overweight and obesity in developing nations emerge. In industrialized nations, especially the US, drugs like Ozempic, Wegovy, Mounjaro, and Zepbound have become increasingly popular. Some of these medications were first developed to treat other conditions like diabetes but have also been demonstrated to help treat obesity, reduce the risk of heart attacks and strokes, and lessen chronic kidney disease (Drucker, 2024; Myerson & Paparodis, 2024). These medications act on various organs and also suppress cravings, and reduce feelings of reward from food (Gudzune & Kushner, 2024). As incomes rise in developing countries, so does the preference for unhealthy savory foods, which contributes to increasing obesity rates (Maina et al., 2024). Consequently, pharmaceutical companies are exploring ways to expand distribution to these countries by developing more cost-effective formulations and minimizing side effects. However, a population-wide approach to the primary prevention of obesity and its associated diseases is likely to be more effective than focusing solely on individual treatments like bariatric surgery and pharmaceutical drugs. The downside of these pharmaceutical drugs is that they still require more research to understand their mechanisms fully, they lack long-term evidence of health benefits, and may necessitate lifelong use, which could become costly over time (Lawlor & Chaturvedi, 2006). These medications may eventually introduce a moral hazard, where people might adopt unhealthy eating habits, relying on medication as a cure.

There are several limitations to this study. Health expenditure estimates were based on self-reports; therefore, they might be inaccurate as it may be difficult to recall medical expenditures precisely, both for the main respondent and for other household members. Due to a lack of data availability, we could not estimate the cost of premature mortality in the sample or the burden of suffering due to obesity. Therefore, our estimations of the social costs of overweight and obesity do not capture the full extent of these costs. Due to limitations in data availability, we adopted absenteeism and presenteeism rates from high-income countries. These values may not accurately reflect the Kenyan context, as labor market conditions differ significantly. The use of BMI to define overweight and obesity has been criticized because it does not capture the distribution of fat in the body or differentiate between muscle and fat (Nuttall, 2015). However, this measure is still used within obesity literature to define overweight and obesity. In this case, the KDHS did not have other more acceptable measures, such as the hip-to-waist ratio or percent body fat.

4.5 Conclusions

The aim of this paper was to investigate the impact of overweight and obesity on medical expenditures and estimate the social costs among women in Kenya of reproductive age. The results provide evidence that overweight and obesity significantly impact the probability and the conditional amount of health expenditure in Kenya, which results in a substantial financial burden for households and the national health insurance scheme. Causal estimates showed that for inpatient and outpatient services, a higher BMI or an additional unit of BMI increases medical care costs. Furthermore, overnutrition contributes to significant social costs.

The prevalence of overweight and obesity in Kenya is expected to continue rising, resulting in a corresponding increase in healthcare costs. Therefore, policymakers are obliged to address this trend. There are a set of suggestions of cost-effective interventions from previous studies that the country can implement, which can substantially reduce future healthcare costs, such as a 20% SSB tax, mandatory kilojoule menu labelling, and mass media campaigns to promote physical activity and healthy diets (Biesma & Hanson, 2023; Wanjau et al., 2021)Such policies can control the growing prevalence of obesity and result in significant savings in households and national healthcare expenditures.

Chapter 5: General conclusion and policy implications

This dissertation aimed to establish the drivers and implications of the rising prevalence of overweight, obesity and associated NCDs in Kenya. Using a combination of both primary and secondary datasets, we provide evidence that differences in food choice motives across socio-economic groups, along with low physical activity levels, are associated with higher weight outcomes. Low physical activity levels are also linked to a greater probability of NCDs. Significant private and social costs also result from overweight and obesity among women of reproductive age in Kenya.

5.1 Summary of key findings

Overweight, obesity, and related NCDs have increased as a result of dietary changes and increased physical inactivity brought on by economic and societal changes. These trends have resulted in substantial private and social costs for the population. In the second chapter of this study, we studied consumer behavior in Kenya across different socio-economic groups, focusing on how they select food, the factors they prioritize, and how these factors influence dietary diversity and weight outcomes. Food choice behavior in this context differs significantly from that of developed countries and is not adequately understood or documented. The social patterning of diet is evident in the health outcomes, with a higher incidence of overweight and obesity among upper social classes. We used cross-sectional data collected from adults in four counties in Kenya in 2022 to examine whether significant differences in food choice motives exist across socio-economic groups and whether these differences mediate the disparities in diet diversity, as well as overweight and obesity outcomes. Our study employed the Food Choice Motives Questionnaire developed by Steptoe et al. (1995), which was validated for this population. The findings reveal evidence of differences in food choice motives by socio-economic groups. A higher asset score is associated with greater concern for health, mood, sensory, and weight factors and with lower concern for price when selecting food. Similarly, higher education levels are linked to being less motivated by familiarity and more driven by health and sensory considerations. Food choice motives also influence diet diversity and overweight/obesity outcomes. Greater concerns for health and sensory aspects are associated with increased diet diversity, while higher concerns for convenience are linked to decreased diet diversity. Moreover, sensory, weight, and familiarity motives increase the odds of being in a higher BMI category, whereas convenience and natural motives decrease these odds. The relationship between income and BMI was significantly mediated by sensory and weight concerns, with sensory concerns accounting for 29% of the association and weight concerns for 3%. The relationship between education and BMI was significantly mediated by sensory and familiarity concerns, with sensory concerns explaining 30% of the relationship, and familiarity concerns negatively impacted this relationship by -4%. Higher education was associated with increased diet diversity that was positively mediated by health and sensory concerns, contributing 11% and 4%, respectively. These findings differed from those of developed countries, where health greatly mediated the relationship between socio-economic position and weight outcomes, negatively accounting for -18 to -28% of the association between lower SEP and higher BMI in the US and the UK. Among the Finnish population, price, familiarity, and ethicality mediated the effects of income and education on the intake of vegetables, fruits, and energy-dense foods (Konttinen et al., 2013; Robinson et al., 2022). Some of our findings align with observations in other emerging economies. In Brazil, hedonistic food choice motives, which refers to pleasure-related factors, were ranked highest among the high socioeconomic status group. In contrast, the low socioeconomic status group in Brazil had most of its food choice predictors linked to social context aspects, including traditional eating, social norms, social image, and price (Moraes et al., 2020). Similarly, family wealth was negatively linked to the health, convenience, and price subscale in Indonesia (Maulida et al., 2016). No mediation analysis has been conducted in the emerging economies so far.

Chapter 3 examines the relationship between different types of physical activities (work, leisure, and transport) and sedentary time on BMI and NCD outcomes. Using panel data from 2015 and 2022, we computed the MET-hours score for each physical activity variable. This score is calculated by multiplying the weekly hours spent on an activity by its MET value. We applied fixed effects panel regression to account for unobserved heterogeneity and probit models. We further used entropy balancing, as proposed by Hainmueller (2012), which provides robustness against observable heterogeneity to further examine whether physical activity improves BMI and reduces the probability of NCD outcomes. Our findings indicate that during the study period, overall physical activity levels declined, while sedentary time, BMI, and incidences of NCDs increased. Work-related PA was the main contributor to total PA, with an average of 97.6 MET-hours per week, transport-related PA at 27.6 MET-hours per week, and leisure-related PA at 2.9 MET-hours per week. We found that vigorous work, active transport methods, and leisure-related PA were negatively related to BMI.

An increase of one MET-hour per week of vigorous work, leisure, and transport PA was associated with a 0.025%, 0.16%, and 0.052% decrease in BMI, respectively. Entropy balancing results showed an average BMI decrease of 3.5%, 3.3%, and 10.4% from engaging in vigorous work, moderate work, and leisure-related PA, respectively. An increase of one unit in MET-hours per week for vigorous work, moderate work, and leisure-related PA was associated with a 0.15%, 0.11%, and 0.53% decrease in the probability of developing an NCD, respectively. Sedentary time was associated with a 0.18% increase in the probability of developing an NCD. Entropy balancing results showed significant negative treatment effects of vigorous work, moderate work, transport, and leisure-related PA on chronic diseases, with participation in these activities reducing the probability of having an NCD by 16.4%, 20.1%, 20.8%, and 24.9%, respectively. Leisure PA showed a larger negative impact on weight and the probability of NCD outcomes compared to other PA activities.

The last chapter investigates the implications of overweight and obesity on the Kenyan society, focusing on the private and social costs associated with these conditions among women of reproductive age. We find that overweight and obesity is associated with a 3.3 and 1.4 times higher likelihood of outpatient and inpatient medical expenditures. For any given expenditure, the amount spent increases with the BMI category; women who are overweight and obese incur higher monthly outpatient and yearly inpatient costs of KES 445.0 ($3.61) and KES 16,942.8 ($137.33), respectively. IV estimation results indicate that a one-unit increase in BMI raises marginal outpatient healthcare spending by KES 277.8 ($2.25) and marginal inpatient healthcare spending by KES 5,119.0 ($41.49). We also find that there are substantial social costs associated with overweight and obesity among adult women in Kenya that amounted to $1.11 billion in 2022, which translated to per adult woman cost of KES 10,557.2 ($85.57). The average cost per obese woman ($242) exceeded that of per overweight woman ($207), reflecting higher healthcare needs among obese women. Direct medical expenses accounted for the largest share of costs at $388.8 million, followed by productivity costs at $336.2 million.

5.2 Policy implications

The findings from the three chapters have important policy implications for countries in SSA experiencing an increase in overweight and obesity and the associated prevalence of NCDs. In Chapter 2, we gained insights into consumer behavior and its impact on dietary practices and weight outcomes. We found that socioeconomic status influences food choice motives, which affects diet diversity and also the frequency of overweight and obesity in different groups.

Understanding the social patterning of diet and obesity is crucial for drafting effective policies to improve dietary behaviors in Kenya. In order to create and maintain demand for healthy, sustainable diets, it is essential to understand the motives behind food choices. This knowledge will inform the design of targeted interventions that influence personal food choices and ultimately shape consumer demand for healthier diets. Shifting consumer preferences will also incentivize the production of healthier foods and improve the food environment. Sensory motives have emerged as a significant factor in the relationship between high socio-economic status, increased diet diversity, and overweight and obesity outcomes. These motives are challenging to alter due to their inherent appeal and strong marketing. This problem can be successfully addressed by several demand-side structural measures. For example, taxes can limit the consumption of highly processed foods that are heavy in fat, sugar, and salt—known for their sensory appeal. Implementing policies to limit unhealthy contents, such as trans fats and saturated fats in foods, will encourage the reformulation of products to minimize harmful ingredients. Important tactics also include stringent marketing regulations that restrict the advertising of foods high in energy. Governments should also address the aggressive expansion of multinational companies into LMICs, which often prioritize sensory stimulation for profit, by limiting their food product portfolio to only healthy options. Structural interventions include subsidizing the agricultural production of fruits and vegetables and also the promotion of indigenous foods that have high nutritional value; this should be done particularly targeting high socioeconomic groups. Governments could also implement agentic interventions that will empower consumers to make better-informed choices. These interventions include nutrition education programs aimed at high-income groups to raise awareness about the dangers of unhealthy foods and the benefits of healthy diets, developing contextually relevant food-based dietary guidelines, conducting mass media campaigns to promote the benefits of healthy eating, and implementing front-of-pack nutrition labeling. These interventions must also consider economic trade-offs and the complex decisions consumers make regarding income, time, and other factors. For instance, healthy foods that require extensive preparation may not be widely adopted if perceived as time-consuming.

The findings from the second chapter reveal a concerning trend: people in the studied population are becoming less physically active over time while spending more time being sedentary. At the same time, rates of overweight, obesity, and NCDs are on the rise. To address this, it is essential to recognize the critical long-term role physical activity plays in maintaining health and preventing NCDs. Promoting the benefits of staying active and highlighting the risks of a sedentary lifestyle through educational programs and mass media campaigns can help raise awareness. Creating an environment that supports physical activity is key to fostering healthier habits. This means making affordable gyms and sports facilities widely available, designing parks, and establishing dedicated spaces for leisure activities—all of which have been shown to greatly benefit health. Such measures can help replace the decline in physical activity at work with more leisure-based options. Local area planning can put a focus on developing safe spaces for active forms of transportation, such as walking and cycling. The decrease in work-related PA emphasizes the importance of workplace programs designed to increase PA, like providing gyms, promoting stair use, and encouraging activity breaks to prevent prolonged sitting periods. Schools also play a key role in building lifelong healthy habits by setting children on a path to staying active as adults. Physical activity should be included in curriculums with proper spaces for recreation. Similarly, urban living spaces should be planned with health in mind. For example, apartment buildings can be more conducive to daily activity by including gyms and common areas for exercise and sports.

The third chapter highlights the importance of implementing the policies outlined in the first two chapters to tackle overweight and obesity. The findings reveal that these issues come with substantial personal and societal costs, especially for women of reproductive age. Women who are overweight and obese have higher log odds of incurring inpatient and outpatient expenditures compared to those of normal weight, and they experience higher costs overall. These substantial expenses can lead to catastrophic health expenditures due to limited insurance coverage and higher out-of-pocket costs. Obesity rates have decreased or stabilized in certain countries due to effective prevention interventions. Japan, for instance, has the lowest obesity rate in the Western world at 4.5% because of its regulations governing school nutrition programs and its unparalleled universal screening and lifestyle intervention for abdominal obesity (Nakao et al., 2018). The Netherlands has also maintained a relatively low and stable obesity rate through active physical activity promotion. Kenya must therefore gather learnings from other countries and implement cost-effective preventative measures. Some of the suggested cost effective measures in literature include taxes on sugar-sweetened beverages (SSBs), mandatory kilojoule menu labeling, front-of-pack nutrition labeling, developing laws governing the procurement of public foods and the removal of unhealthy ingredients, mass media, and communication campaigns advocating for healthier diets, limiting the marketing of harmful foods to children, breastfeeding promotion, and community-wide public education campaigns on physical activity. This can be supplemented with affordable healthcare screenings, counseling, and support for weight management. Universal healthcare programs introduced in SSA countries should include affordable packages for preventive care and treatment interventions for obesity-related conditions.

5.3 Limitations and suggestions for future research

There are several limitations to this research. First, we used BMI to define overweight and obesity, which has been criticized because the cut-off values for BMI do not apply across different populations, and it also does not capture fat distribution or differentiate between muscle and fat mass. Consequently, relying solely on BMI, which measures weight relative to height without distinguishing between fat and lean mass, may result in a significant misclassification of individuals as obese. The percentage of body fat and associated health risks vary by age, gender, and race and cannot be fully captured by this measure alone. Alternative measures of adiposity, such as waist circumference (which measures subcutaneous and visceral adipose tissue), adiposity phenotyping, waist-to-hip ratio, waist-to-height ratio, and body roundness index, offer more detailed assessments. Ultimately, these measures are highly correlated with BMI in assessing health outcomes; obesity guidelines recommend using BMI alongside other adiposity measures. The second limitation is the reliance on self-report measures for data collection for all three chapters, which may introduce bias and reduce accuracy. Due to recollection issues, self-reported data may suffer from overestimation or underestimation, resulting in reporting errors and inaccuracies even though we made efforts to address any mismeasurement issues during data cleaning. The third limitation relates to proving causation. We only demonstrated the mediating impacts of food choice motives in the first chapter due to using cross-sectional data, which restricts our capacity to establish causal linkages. We need further instrumentation in the second chapter since leisure PA is considered endogenous. While we employed entropy balancing with observed covariates to approach causality, better instruments are needed. The fourth limitation is the restricted sample size in the first and second chapters, with data collected from only four counties. This limitation means that the findings may not represent the entire country, impacting external validity. The final limitation is using presenteeism and absenteeism rates from high-income countries to calculate social costs within the Kenyan context. Currently, there are no studies in Sub-Saharan Africa to establish such rates. We used rates obtained from extensive panel data analysis from Australia to estimate these costs. Despite these limitations, the study provides valuable initial insights into the drivers and implications of overweight and obesity in Kenya. Future studies need to conduct more extensive, nationally representative surveys on food choice motives and physical activity to enhance the external validity of the estimates. Studies can use accelerometers and pedometers to assess physical activity levels more accurately and lower the possibility of over- or under-estimation that comes with memory techniques. Payment data from hospitals could also help capture health expenditure information more accurately. Most current research use single measures of diet diversity, which does not capture many aspects of a diet. In order to provide more insights into the composition of diets and their impact on health outcomes, additional measures of diet quality, such as the Diet Quality Index and caloric intake, need to be incorporated into future investigations. To support policymaking, economic, and policy evaluations of various intervention strategies aimed at preventing obesity in the Kenyan context need to be done. There is also a need to design and assess the effectiveness of physical activity programs targeting older adults and women, who typically engage in less work-related physical activity, as well as programs to incorporate physical activity among informal sector workers. Finally, as the social costs of obesity continue to rise in countries like Kenya, it is crucial to explore the opportunities of new pharmaceutical treatment options. As this research will ultimately reduce the social costs associated with obesity by promoting longer, healthier, and more productive lives.

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Appendices

1. Supplementary tables

Appendix to Chapter 2

Table A2.1 Box-cox power transformed dependent variable health

bchealth	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Gender							
Male	-18.682	16.468	-1.130	0.257	-51.064	13.701	
Age years	-1.549	0.476	-3.250	0.001	-2.486	-0.612	***
Education							
Post secondary	30.418	15.713	1.940	0.054	-0.478	61.315	*
Asset score	7.365	3.688	2.000	0.047	0.114	14.617	**
Drinks alcohol	0.587	11.112	0.050	0.958	-21.263	22.437	
Smokes cigarettes	-37.695	12.485	-3.020	0.003	-62.244	-13.146	***
Constant	401.481	28.389	14.14	0	345.657	457.304	***
R-squared		0.128	Number of obs			380	

*** *p<.01,* ** *p<.05,* * *p<.1*

Table A2.2 Box-cox power transformed dependent variable sensory

bcsensory	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Gender	0	.	.	.	.	.	
Male	-1.706	3.333	-0.510	0.609	-8.260	4.847	
Age years	0.067	0.093	0.730	0.468	-0.115	0.250	
Education	1.681	0.956	1.760	0.079	-0.198	3.560	*
Asset score	3.879	0.874	4.440	0	2.159	5.598	***
Drinks alcohol	3.167	2.480	1.280	0.202	-1.709	8.044	
Smokes cigarettes	-5.508	2.388	-2.310	0.022	-10.204	-0.812	**
Constant	43.956	7.220	6.090	0	29.759	58.152	***
R-squared		0.122	Number of obs			380	

*** *p<.01,* ** *p<.05,* * *p<.1*

Table A2.3 Box-cox power transformed dependent variable weight

bcweight	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Gender	0.000	.	.	.	.	.	
Male	0.802	5.778	0.140	0.890	-10.559	12.164	
Age years	-0.241	0.166	-1.450	0.148	-0.567	0.086	
Education	0.000	.	.	.	.	.	
Post secondary	1.944	5.594	0.350	0.728	-9.056	12.944	
Asset score	4.241	1.739	2.440	0.015	0.821	7.662	**
Drinks alcohol	1.302	3.934	0.330	0.741	-6.434	9.038	
Smokes cigarettes	-6.629	3.983	-1.660	0.097	-14.461	1.204	*
Constant	73.080	10.919	6.690	0	51.609	94.551	***
R-squared		0.043	Number of obs			380	

*** *p<.01,* ** *p<.05,* * *p<.1*

Table A2.4 Box-cox power transformed dependent variable familiarity

bcfam	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Gender	0.000	.	.	.	.	.	
Male	1.864	3.857	0.480	0.629	-5.720	9.447	
Age years	-0.279	0.108	-2.580	0.010	-0.491	-0.066	**
Education	-1.460	0.411	-3.550	0.000	-2.267	-0.652	***
Asset score	-0.372	0.784	-0.470	0.635	-1.915	1.170	
Drinks alcohol	4.968	2.583	1.920	0.055	-0.112	10.047	*
Smokes cigarettes	-10.340	2.447	-4.230	0.000	-15.152	-5.528	***
Constant	80.764	8.167	9.890	0.000	64.705	96.822	***
R-squared		0.081	Number of obs			380	

*** *p<.01,* ** *p<.05,* * *p<.1*

Table A2.5 Box-cox power transformed dependent variable convenience

bcconv	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Gender	0.000	.	.	.	.	.	
Male	-36.128	41.237	-0.880	0.382	-117.214	44.958	
Age years	-1.215	1.118	-1.090	0.278	-3.413	0.983	
Education	0.000	.	.	.	.	.	
Post secondary	4.508	40.087	0.110	0.911	-74.317	83.332	
Asset score	-17.375	12.149	-1.430	0.154	-41.264	6.514	
Drinks alcohol	21.489	29.966	0.720	0.474	-37.436	80.413	
Smokes cigarettes	-24.167	30.214	-0.800	0.424	-83.578	35.245	
Constant	691.524	75.175	9.200	0.000	543.704	839.345	***
R-squared		0.015	Number of obs			380	

*** *p<.01,* ** *p<.05,* * *p<.1*

Table A2.6 Box-cox power transformed dependent variable price

bcprice	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Gender	0.000	.	.	.	.	.	
Male	112.542	76.440	1.470	0.142	-37.766	262.850	
Age years	-0.631	2.057	-0.310	0.759	-4.675	3.414	
Education	0.000	.	.	.	.	.	
Post secondary	-88.115	69.421	-1.270	0.205	-224.620	48.391	
Asset score	-34.661	20.780	-1.670	0.096	-75.521	6.199	*
Drinks alcohol	-16.673	50.825	-0.330	0.743	-116.613	83.266	
Smokes cigarettes	-104.874	48.648	-2.160	0.032	-200.533	-9.215	**
Constant	1162.829	123.369	9.430	0.000	920.244	1405.414	***
R-squared		0.035	Number of obs			380	

*** *p<.01,* ** *p<.05,* * *p<.1*

Table A2.7 Box-cox power transformed dependent variable natural

bcnat	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Gender	0.000	.	.	.	.	.	
Male	-9.919	24.971	-0.400	0.691	-59.022	39.183	
Age years	0.573	0.707	0.810	0.418	-0.817	1.963	
Education	0.000	.	.	.	.	.	
Post secondary	6.165	23.894	0.260	0.797	-40.818	53.148	
Asset score	8.441	5.102	1.650	0.099	-1.592	18.473	
Drinks alcohol	-5.840	17.992	-0.320	0.746	-41.218	29.537	
Smokes cigarettes	-15.996	18.913	-0.850	0.398	-53.186	21.194	
Constant	312.554	43.462	7.190	0.000	227.092	398.016	***

R-squared	0.015	Number of obs	380

*** *p<.01,* ** *p<.05,* * *p<.1*

Table A2.8 Box-cox power transformed dependent variable mood

bcmood	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Gender	0.000	.	.	.	.	.	
Male	-5.722	7.029	-0.810	0.416	-19.543	8.098	
Age years	-0.392	0.199	-1.970	0.050	-0.783	0.000	**
Education	0.000	.	.	.	.	.	
Post secondary	4.793	7.152	0.670	0.503	-9.270	18.856	
Asset score	4.650	1.661	2.800	0.005	1.384	7.916	***
Drinks alcohol	1.975	4.983	0.400	0.692	-7.825	11.774	
Smokes cigarettes	-8.109	5.289	-1.530	0.126	-18.509	2.291	
Constant	125.215	12.791	9.790	0.000	100.065	150.366	***
R-squared	0.065		Number of obs			380	

*** *p<.01,* ** *p<.05,* * *p<.1*

Table A2.9 SEP predictors of food choice motive health

Factor Health	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Gender	0.000	.	.	.	.	.	
Male	-0.062	0.123	-0.510	0.612	-0.303	0.179	
Age years	-0.015	0.004	-3.660	0.000	-0.023	-0.007	***
Education	0.000	.	.	.	.	.	
Post secondary	0.205	0.118	1.740	0.082	-0.026	0.437	*
Asset score	0.046	0.024	1.890	0.059	-0.002	0.093	*
Drinks alcohol	0.063	0.102	0.620	0.538	-0.138	0.264	
Smokes cigarettes	-0.365	0.125	-2.910	0.004	-0.612	-0.119	***
Constant	6.731	0.228	29.57	0	6.283	7.178	***
R-squared	0.128						
Number of obs	380						

*** *p<.01,* ** *p<.05,* * *p<.1*

Table A2.10 SEP predictors of food choice motive sensory

Factor Sensory	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Gender							
Male	-0.109	0.156	-0.700	0.482	-0.416	0.197	
Age years	0.001	0.004	0.330	0.742	-0.007	0.010	
Education	0.092	0.044	2.100	0.037	0.006	0.178	**
Asset score	0.178	0.041	4.380	0	0.098	0.258	***
Drinks alcohol	0.128	0.117	1.090	0.275	-0.102	0.359	
Smokes cigarettes	-0.203	0.121	-1.680	0.093	-0.440	0.034	*
Constant	5.060	0.329	15.380	0	4.412	5.707	***
R-squared	0.119						
Number of obs	380						

*** *p<.01,* ** *p<.05,* * *p<.1*

Table A2.11 SEP predictors of food choice motive mood

Factor Mood	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Education							
Post secondary	0.165	0.175	0.940	0.346	-0.178	0.508	
Asset score	0.088	0.039	2.280	0.023	0.012	0.164	**
Gender							
Male	-0.180	0.182	-0.990	0.325	-0.538	0.179	
Age years	-0.009	0.005	-1.680	0.093	-0.020	0.002	*
Drinks alcohol	0.127	0.130	0.980	0.329	-0.129	0.383	
Smokes cigarettes	-0.251	0.143	-1.760	0.080	-0.531	0.030	*
Constant	5.903	0.342	17.250	0	5.230	6.576	***
R-squared	0.055						
Number of obs	380						

*** *p<.01, ** p<.05, * p<.1*

Table A2.12 SEP predictors of food choice motive weight

Factor weight	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Educatio							
Post secondary	0.018	0.205	0.090	0.930	-0.385	0.421	
Asset score	0.148	0.067	2.210	0.028	0.016	0.280	**
Gender							
Male	0.034	0.208	0.160	0.872	-0.375	0.442	
Age years	-0.014	0.006	-2.210	0.028	-0.026	-0.002	**
Drinks alcohol	0.099	0.150	0.660	0.510	-0.195	0.393	
Smokes cigarettes	-0.244	0.161	-1.510	0.131	-0.561	0.073	
Constant	5.500	0.418	13.160	0	4.678	6.322	***
R-squared	0.046						

*** *p<.01, ** p<.05, * p<.1*

Table A2.13 SEP predictors of food choice motive convenience

Factor convenience	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Education							
Post secondary	-0.090	0.153	-0.590	0.555	-0.392	0.211	
Asset score	-0.067	0.050	-1.330	0.185	-0.166	0.032	
Gender							
Male	-0.105	0.163	-0.640	0.523	-0.426	0.217	
Age years	-0.004	0.004	-0.960	0.337	-0.013	0.004	
Drinks alcohol	0.074	0.100	0.750	0.455	-0.121	0.270	
Smokes cigarettes	-0.071	0.105	-0.680	0.498	-0.278	0.135	
Constant	6.180	0.294	20.990	0	5.601	6.759	***
R-squared	0.014						

*** *p<.01, ** p<.05, * p<.1*

Table A2.14 SEP predictors of food choice motive price

Factor Price	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Education							
Post secondary	-0.141	0.144	-0.980	0.325	-0.424	0.141	
Asset score	-0.096	0.045	-2.130	0.034	-0.185	-0.007	**
Gender							
Male	0.179	0.152	1.180	0.239	-0.119	0.478	
Age years	-0.003	0.004	-0.740	0.458	-0.012	0.005	
Drinks alcohol	0.005	0.093	0.050	0.959	-0.178	0.188	
Smokes cigarettes	-0.155	0.095	-1.620	0.106	-0.342	0.033	
Constant	6.175	0.247	25.020	0	5.689	6.660	***
R-squared	0.037						

*** *p<.01, ** p<.05, * p<.1*

Table A2.15 SEP predictors of food choice motive familiarity

Factor familiarity	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Education	-0.090	0.024	-3.780	0.000	-0.136	-0.043	***
Asset score	-0.062	0.047	-1.320	0.187	-0.154	0.030	
Gender	0.000	.	.	.	.	.	
Male	-0.019	0.208	-0.090	0.929	-0.428	0.391	
Age years	-0.018	0.006	-3.140	0.002	-0.029	-0.007	***
Drinks alcohol	0.270	0.135	2.000	0.047	0.004	0.536	**
Smokes cigarettes	-0.417	0.140	-2.970	0.003	-0.693	-0.141	***
Constant	6.944	0.441	15.740	0.000	6.077	7.812	***
R-squared		0.093	Number of obs			380	

*** *p<.01, ** p<.05, * p<.1*

Table A2.16 SEP predictors of food choice motive natural

Factor Natural	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Education							
Post secondary	0.086	0.181	0.480	0.634	-0.269	0.441	
Asset score	0.055	0.041	1.330	0.183	-0.026	0.136	
Gender							
Male	-0.161	0.204	-0.790	0.430	-0.562	0.240	
Age years	0.000	0.006	0.040	0.969	-0.011	0.011	
Drinks alcohol	0.019	0.152	0.130	0.899	-0.280	0.319	
Smokes cigarettes	-0.157	0.168	-0.940	0.350	-0.486	0.172	
Constant	5.697	0.348	16.39	0	5.013	6.381	***
R-squared		0.016	Number of obs			380	

*** *p<.01, ** p<.05, * p<.1*

Table A2.17 Full OLS results food choice motives associated with diet diversity score

	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Health	0.227	0.091	2.500	0.013	0.048	0.406	**
Mood	-0.041	0.069	-0.600	0.551	-0.177	0.095	
Sensory	0.097	0.057	1.710	0.089	-0.015	0.209	*
Weight	-0.028	0.051	-0.540	0.588	-0.129	0.073	
Convenience	-0.123	0.058	-2.130	0.034	-0.237	-0.009	**
Price	0.030	0.072	0.410	0.679	-0.112	0.171	
Familiarity	0.070	0.049	1.440	0.152	-0.026	0.165	
Natural	-0.051	0.058	-0.880	0.379	-0.165	0.063	
Male	0.038	0.194	0.200	0.843	-0.343	0.420	
Age years	0.002	0.006	0.380	0.703	-0.010	0.015	
Education	0.000	.	.	.	.	.	
Beyond secondary school	0.490	0.155	3.170	0.002	0.186	0.795	***
Asset score	0.082	0.050	1.640	0.102	-0.016	0.180	
Smoking status	0.000	.	.	.	.	.	
Currently smoke	-0.147	0.231	-0.640	0.525	-0.600	0.307	
Used to smoke	0.112	0.237	0.470	0.635	-0.353	0.578	
Household size	-0.018	0.046	-0.380	0.701	-0.107	0.072	
HH head Female	0.282	0.250	1.130	0.259	-0.209	0.774	
Currently married	0.431	0.333	1.290	0.197	-0.225	1.086	
Separated	0.581	0.365	1.590	0.113	-0.137	1.298	
Divorced	0.345	0.534	0.650	0.519	-0.706	1.396	
Widowed	0.358	0.356	1.010	0.315	-0.341	1.058	
Non-government employee	-0.195	0.345	-0.570	0.572	-0.873	0.483	
Self-employed	-0.181	0.298	-0.610	0.545	-0.767	0.406	
Student	0.923	0.663	1.390	0.165	-0.382	2.228	
Homemaker	0.004	0.370	0.010	0.992	-0.724	0.731	
Retired	0.084	0.419	0.200	0.841	-0.740	0.908	
Unemployed (able to work)	0.020	0.367	0.060	0.956	-0.702	0.743	
Unemployed (unable to work)	-0.619	0.413	-1.500	0.134	-1.431	0.192	
Who mainly prepare meals	0.000	.	.	.	.	.	
House help	-0.614	0.414	-1.480	0.139	-1.428	0.200	
Other female	-0.290	0.228	-1.270	0.204	-0.738	0.158	
Father	-0.267	0.310	-0.860	0.389	-0.877	0.343	
Other male in the	0.090	0.637	0.140	0.888	-1.164	1.343	
Person making food employed	0.000	.	.	.	.	.	
yes	0.647	0.163	3.970	0.000	0.326	0.967	***
Drinks alcohol	0.097	0.117	0.830	0.409	-0.133	0.326	
Constant	6.427	0.723	8.890	0.000	5.005	7.850	***

*** p<.01, ** p<.05, *p<.1

Table A2.18 Full ordered logit results food choice motives associated with BMI

	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Health	-0.066	0.153	-0.430	0.668	-0.366	0.235	
Mood	-0.162	0.124	-1.300	0.192	-0.406	0.081	
Sensory	0.579	0.123	4.720	0.000	0.339	0.820	***
Weight	0.192	0.091	2.110	0.034	0.014	0.371	**
Convenience	-0.225	0.115	-1.970	0.049	-0.450	-0.001	**
Price	0.054	0.119	0.460	0.648	-0.178	0.287	
Familiarity	0.195	0.091	2.150	0.032	0.017	0.373	**
Natural	-0.229	0.115	-1.990	0.046	-0.454	-0.004	**
Male	-1.029	0.342	-3.010	0.003	-1.699	-0.360	***
Age years	0.131	0.054	2.410	0.016	0.024	0.237	**
Years schooling	0.079	0.037	2.120	0.034	0.006	0.152	**
Asset score	0.242	0.110	2.210	0.027	0.027	0.457	**
wealth2	-0.016	0.022	-0.740	0.459	-0.058	0.026	
Currently smoke	0.392	0.404	0.970	0.332	-0.400	1.184	
Used to smoke	-1.716	0.428	-4.010	0.000	-2.555	-0.877	***
Household size	-0.041	0.080	-0.520	0.605	-0.198	0.115	
Female	0.098	0.516	0.190	0.850	-0.914	1.109	
Currently married	-0.052	0.630	-0.080	0.934	-1.287	1.182	
Separated	0.459	0.777	0.590	0.555	-1.064	1.982	
Divorced	-0.265	1.024	-0.260	0.796	-2.272	1.743	
Widowed	-0.244	0.563	-0.430	0.664	-1.348	0.859	
Non-government employee	0.685	0.687	1.000	0.318	-0.661	2.032	
Self-employed	0.474	0.601	0.790	0.430	-0.703	1.651	
Student	-1.867	1.486	-1.260	0.209	-4.780	1.046	
Homemaker	0.957	0.767	1.250	0.212	-0.546	2.461	
Retired	0.291	0.845	0.340	0.731	-1.366	1.948	
Unemployed (able to work)	0.583	0.772	0.760	0.450	-0.930	2.096	

Unemployed (unable to work)	0.578	0.815	0.710	0.478	-1.020	2.176	
House help	0.506	0.932	0.540	0.587	-1.321	2.333	
Other female	-0.105	0.414	-0.250	0.800	-0.918	0.707	
Father	-0.463	0.587	-0.790	0.431	-1.614	0.688	
Other male in the	0.108	1.089	0.100	0.921	-2.026	2.242	
yes	0.748	0.284	2.640	0.008	0.192	1.304	***
Age squared	-0.001	0.000	-2.120	0.034	-0.002	0.000	**
Yes	-0.238	0.285	-0.840	0.402	-0.796	0.319	
Drinks alcohol	-0.218	0.199	-1.090	0.275	-0.608	0.173	

*** p<.01, ** p<.05, * p<.1

Appendix to Chapter 3

Table A3.1 Effect of physical activity on BMI categories

	(1)		(2)	
BMI (categories)	Coef.	St.Err.	Coef.	St.Err.
Total physical activity	-0.0025**	0.0007		
Vigorous work (MET-hrs/week)			-0.0106**	0.0047
Moderate work (MET-hrs/week)			-0.0049	0.0053
Leisure sport (MET-hrs/week)			-0.0598**	0.0284
Transportation (MET-hrs/week)			-0.0473**	0.0224
Sedentary time			-0.0046	0.0046
Healthy behaviors index				
Fair			0.4037	1.1389
Good			0.2272	1.2669
Very good			-1.8190	1.3221
Excellent			-0.9513	1.3559
Wald			43.93***	
Number of observations			178	

*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level

Table A3.2 Changes in vigorous work related PA across occupational categories

	2015		2022	
	MET-hours/week	N	MET-hours/week	N
Government employee	36.8	10	23.6	9
Non-government employee	35.4	19	70.0	20
Self-employed	114.9	85	64.8	105
Student	192.0	2	0	0
Homemaker(housewife. Househusband)	80.5	26	56.3	14
Retired	24.0	2	32.0	2
Unemployed (able to work)	73.3	19	10.7	9
Unemployed (unable to work)	32.0	3	0	7
Total	89.3	166	56.4	166

Table A3.3 Changes in moderate work related PA across occupational categories

	2015		2022	
	MET-hours/week	N	MET-hours/week	N
Government employee	50.8	10	96.3	9
Non-government employee	51.5	19	31.2	20
Self-employed	49.5	85	40.9	105
Student	12.0	2	0	2
Homemaker(housewife. Househusband)	52.7	26	26.3	14
Retired	0	2	0	2
Unemployed (able to work)	41.2	19	60.0	9
Unemployed (unable to work)	9.3	3	19.8	7
Total	47.6	166	41.3	166

Table A3.4 Changes in total work related PA across occupational categories

	2015		2022	
	MET-hours/week	N	MET-hours/week	N
Government employee	87.6	10	119.9	9
Non-government employee	86.8	19	101.2	20
Self-employed	164.3	85	105.8	105
Student	204	2	0	2
Homemaker(housewife. Househusband)	133.2	26	82.6	14
Retired	24.0	2	32.0	2
Unemployed (able to work)	114.4	19	70.7	9
Unemployed (unable to work)	41.3	3	19.8	7
Total work	136.8	166	97.6	166

Appendix to Chapter 4

Table A4.1 Descriptives by BMI level women ages 15-49

	Underweight (<18.5)	Normal (18.5–24.9)	Overweight (25.0–29.9)	Obesity class I (30.0–34.9)	Obesity class II (35.0–39.9)	Obesity class III (> 40)
Age	25.05*** (11.09)	27.36 (9.44)	32.37 (8.43)	35.37 (7.31)	36.21 (7.43)	36.09 (6.78)
Years education	7.37*** (4.48)	8.62 (3.54)	9.45 (3.48)	9.63 (3.41)	9.50 (3.67)	9.63 (3.09)
Self-reported health status (5=very bad)	2.01** (0.87)	1.99 (0.74)	2.00 (0.69)	2.11 (0.71)	2.01 (0.71)	2.03 (0.73)
Employed (1=yes)	0.42*** (0.57)	0.54 (0.50)	0.70 (0.44)	0.78 (0.39)	0.79 (0.39)	0.70 (0.43)
Wealth index	2.50*** (1.60)	3.03 (1.42)	3.63 (1.22)	3.94 (1.08)	4.00 (1.08)	4.37 (0.88)
Covered by health insurance						
No	0.85 (0.42)	0.77 (0.43)	0.62 (0.46)	0.55 (0.47)	0.52 (0.48)	0.52 (0.47)
Yes	0.15 (0.41)	0.23 (0.42)	0.37 (0.46)	0.45 (0.47)	0.48 (0.48)	0.47 (0.46)
Don’t know	0.00 (0.08)	0.01 (0.09)	0.01 (0.08)	0.00 (0.06)	0.00 (0.03)	0.00 (0.04)
Insurance type: NHIF (1=yes)	0.87*** (0.38)	0.90 (0.29)	0.90 (0.28)	0.90 (0.28)	0.94 (0.24)	0.99 (0.10)
Insurance type: Private/commercial	0.07*** (0.29)	0.14 (0.34)	0.16 (0.35)	0.19 (0.37)	0.18 (0.38)	0.08 (0.25)
Insurance type: community based	0.08*** (0.31)	0.02 (0.12)	0.01 (0.11)	0.01 (0.10)	0	0.03 (0.16)
Insurance type: Other	0	0.00 (0.05)	0.00 (0.04)	0.00 (0.04)	0	0
Visited health facility in the last 12 months	0.44*** (0.57)	0.51 (0.50)	0.57 (0.47)	0.61 (0.45)	0.56 (0.48)	0.53 (0.47)
Total medical expenditures	3,647.72*** (11,966.24)	8,318.10 (45,106.66)	17,195.13 (74,862.37)	8,132.09 (22,863.06)	7,734.38 (15,312.98)	10,308.80 (34,154.99)
Admitted to an overnight stay in a medical facility in the last 12 months	0.07*** (0.37)	0.09 (0.42)	0.12 (0.44)	0.10 (0.33)	0.12 (0.40)	0.05 (0.21)
Total inpatient costs overnight stay	9,263.47*** (18,634.93)	22,088.28 (75,191.64)	46,327.96 (121,990.60)	22,671.07 (35,607.41)	20,812.86 (22,359.28)	43,825.93 (83,514.69)
Amount paid overnight cash	9,779.48 (20,151.73)	13,790.78 (36,157.72)	15,430.90 (42,256.82)	13,479.88 (24,438.84)	11,250.71 (10,901.10)	28,090.28 (69,068.02)
Amount paid overnight NHIF	1,802.70*** (5,803.27)	6,516.73 (32,731.54)	1,6032.65 (51,451.18)	11,686.57 (24,183.30)	8,453.29 (20,983.97)	15,735.64 (61,645.83)
Amount paid overnight private insurance	290.89** (6,704.30)	2,936.24 (19,508.62)	20,911.63 (101,425.80)	1,976.22 (13,857.04)	1,406.67 (9,872.85)	0
Amount paid overnight in-kind	25.31 (253.45)	136.06 (2,420.98)	1,882.35 (19,250.16)	0	0	0

Amount paid overnight other	63.65 (927.04)	9.88 (195.62)	0	469.55 (6,043.18)	0	0
Received outpatient medical care in the last 4 weeks	0.20*** (0.63)	0.22 (0.54)	0.25 (0.48)	0.28 (0.52)	0.27 (0.49)	0.30 (0.43)
Total outpatient costs	852.31*** (2,869.27)	1,277.84 (3,994.47)	1,623.21 (3,518.36)	1,811.47 (3,914.63)	1,714.61 (1,908.74)	3,041.16 (8,899.92)
Amount paid outpatient cash	848.81* (2,831.71)	1,016.71 (2,429.62)	1,355.16 (2,502.61)	1,413.86 (2,833.63)	1,547.19 (1,731.11)	2,948.60 (8,905.75)
Amount paid outpatient NHIF	34.98 (701.46)	229.91 (3,192.14)	126.77 (903.93)	238.70 (1219.98)	172.79 (978.01)	69.96 (596.04)
Amount paid outpatient private insurance		38.20*** (436.60)	127.05 (2,059.68)	111.07 (711.01)	23.12 (271.84)	
Amount paid outpatient in-kind	3.74 * (57.60)	11.97 (197.63)	36.53 (305.14)	5.37 (35.32)	0	0
Wages last month	5,122.21*** (9,227.08)	9,780.69 (30,075.54)	18,199.58 (56,876.35)	17,124.68 (37,590.65)	13,893.05 (25,462.80)	12,739.07 (21,304.47)
High blood pressure or hypertension	0.03*** (0.20)	0.05 (0.23)	0.11 (0.30)	0.17 (0.36)	0.24 (0.41)	0.29 (0.43)
High blood sugar or diabetes	0.00*** (0.07)	0.00 (0.06)	0.01 (0.10)	0.03 (0.15)	0.02 (0.14)	0.04 (0.19)
Heart disease	0.01*** (0.11)	0.01 (0.10)	0.01 (0.08)	0.00 (0.06)	0.00 (0.04)	0.00 (0.04)
Depression	0.03 (0.18)	0.03 (0.16)	0.03 (0.17)	0.04 (0.18)	0.03 (0.17)	0.05 (0.20)
Arthritis	0.02*** (0.15)	0.02 (0.14)	0.03 (0.17)	0.06 (0.22)	0.05 (0.20)	0.17 (0.35)
Diet diversity score	4.02*** (1.93)	4.38 (1.67)	4.73 (1.63)	4.93 (1.78)	4.91 1.69	5.21 1.80
Unhealthy foods	0.30 0.53	0.34 0.48	0.34 0.45	0.36 0.45	0.34 0.46	0.34 0.45
Sweet beverages	0.70 0.53	0.69 0.47	0.70 0.44	0.70 0.43	0.74 0.42	0.70 0.43
Currently breastfeeding	0.20* 0.46	0.19 0.39	0.17 0.36	0.19 0.37	0.14 0.33	0.16 0.35
Number of children	1.67*** 2.55	1.88 2.13	2.40 1.83	2.77 1.61	2.79 1.73	2.95 1.49
Use tobacco	0.03*** 0.21	0.01 0.11	0.01 0.08	0.01 0.09	0.00 0.02	0.03 0.17
Drink alcohol	0.05* 0.24	0.05 0.21	0.07 0.24	0.07 0.24	0.08 0.26	0.07 0.24
Comm. Worker visited	0.07*** 0.30	0.05 0.23	0.05 0.21	0.04 0.18	0.05 0.21	0.05 0.21
Has bank account	0.14*** 0.40	0.22 0.42	0.39 0.46	0.46 0.47	0.51 0.48	0.45 0.47
Has a job but currently absent	0.03** 0.19	0.03 0.17	0.05 0.22	0.06 0.23	0.04 0.19	0.06 0.21
Reads newspaper at least once a week	0.07** 0.28	0.08 0.27	0.09 0.28	0.11 0.30	0.08 0.27	0.06 0.23
Listens radio at least once a week	0.52*** 0.58	0.60 0.50	0.65 0.45	0.69 0.44	0.67 0.46	0.71 0.43

Watches TV at least	0.34***	0.50	0.65	0.71	0.75	0.83
once a week	0.55	0.51	0.46	0.42	0.42	0.35
Web use	0.27***	0.39	0.52	0.60	0.63	0.64
	0.51	0.49	0.48	0.46	0.47	0.45
Oldest child bmi	-0.69***	-0.13	0.07	0.19	0.41	0.09
	1.37	1.09	1.05	1.07	1.10	0.99
N (unweighted)	1,945	8,145	3,346	1,378	437	126

Standard deviation in parentheses. Mean values were significantly different among BMI categories: *P < 0.10, **P < 0.05, ***P < 0.001

Table A4.2 Descriptives by age group

	15-19	20-29	30-39	40-49
Years education	7.86***	9.87	8.51	8.15
	(2.06)	(3.63)	(4.13)	(3.87)
Employed	0.18***	0.61	0.74	0.79
	(0.39)	(0.49)	(0.43)	(0.41)
Wealth index	2.89***	3.42	3.31	3.17
	(1.43)	(1.39)	(1.42)	(1.38)
Self-reported health	1.86***	1.94	2.07	2.25
status (5=very bad)	(0.70)	(0.68)	(0.76)	(0.78)
BMI	21.26***	23.61	26.09	26.25
	(3.45)	(4.58)	(5.57)	(5.64)
Covered by health insurance				
No	0.82	0.75	0.64	0.63
	(0.40)	(0.43)	(0.48)	(0.49)
Yes	0.17	0.24	0.36	0.37
	(0.39)	(0.42)	(0.48)	(0.48)
Don’t know	0.01	0.01	0.00	0.01
	(0.08)	(0.09)	(0.06)	(0.07)
Insurance type: NHIF	0.86**	0.90	0.93	0.90
(1=yes)	(0.35)	(0.29)	(0.25)	(0.29)
Insurance type:	0.15	0.14	0.14	0.18
Private/commercial	(0.36)	(0.33)	(0.33)	(0.37)
Insurance type:	0.02	0.01	0.02	0.02
community based	(0.13)	(0.10)	(0.14)	(0.14)
Insurance type: Other	0.01	0.00	0.00	0.00
	(0.07)	(0.03)	(0.04)	(0.03)
Visited health facility in	0.37***	0.61	0.58	0.53
the last 12 months	(0.49)	(0.49)	(0.50)	(0.50)
Total medical	7,844.57	9,477.17	8,786.51	13,632.69
expenditures	(66,034.31)	(48,028.29)	(33,780.11)	(64,109.71)
Admitted to an overnight	0.07***	0.13	0.10	0.08
stay in medical facility in	(0.44)	(0.43)	(0.38)	(0.38)
last 12 months				
Total inpatient costs	21,962.62*	20,020.56	24,655.81	52,766.37
overnight stay	(119,388.50)	(70,534.19)	(58,680.07)	(117,646.10)
Amount paid overnight	11,235.50	9,881.38	12,772.95	25,527.83
cash	(48,642.42)	(22,245.18)	(25,702.91)	(57,118.22)
Amount paid overnight	3,069.56*	6,254.38	12,009.30	14,934.31
NHIF	(16,171.47)	(25,554.03)	(40,728.83)	(56,358.91)

Amount paid overnight private insurance	1,911.17 (14,261.69)	9,610.60 (71,622.74)	2,833.27 (21,986.96)	11,385.75 (63,078.43)
Amount paid overnight in-kind	24.36 (219.75)	1.74 (76.56)	60.18 (545.95)	3,385.42 (25,356.88)
Amount paid overnight other		1.32 (69.25)	12.01 (219.82)	317.63 (4,904.90)
Received outpatient medical care in the last 4 weeks	0.16*** (0.43)	0.22 (0.53)	0.27 (0.49)	0.31 (0.64)
Total outpatient costs	1,116.17 (3,203.17)	1,552.47 (4,225.17)	1,499.17 (4,191.55)	1,478.77 (2,696.18)
Amount paid outpatient NHIF	170.24 (2,366.48)	245.54 (3,211.30)	124.27 (1,049.14)	192.49 (1,076.64)
Amount paid outpatient private insurance	19.64** (247.77)	62.33 (696.85)	78.91 (1,821.49)	95.44 (710.36)
Amount paid outpatient cash	952.82 (2,251.13)	1,221.36 (2,486.01)	1,309.03 (3,241.40)	1,187.42 (2,447.01)
Amount paid outpatient in-kind	15.41 (129.46)	23.99 (249.30)	1.86 (22.41)	24.51 (309.08)
Amount paid outpatient other				
High blood pressure or hypertension	0.02*** (0.13)	0.06 (0.24)	0.11 (0.31)	0.17 (0.38)
High blood sugar or diabetes	0.00*** (0.04)	0.00 (0.06)	0.01 (0.11)	0.02 (0.14)
Heart disease	0.01 (0.10)	0.01 (0.08)	0.01 (0.09)	0.01 (0.09)
Depression	0.01*** (0.12)	0.02 (0.15)	0.04 (0.19)	0.04 (0.21)
Arthritis	0.01*** (0.10)	0.01 (0.10)	0.03 (0.17)	0.08 (0.27)
Wages last month	3,126.36*** (4,771.16)	11,397.15 (36,470.38)	14,940.61 (45,317.53)	13,847.89 (36,688.48)
Diet diversity	4.41*** 1.66	4.57 1.70	4.46 1.77	4.52 1.78
Unhealthy	0.42*** 0.51	0.36 0.48	0.29 0.46	0.24 0.43
Sweet beverages	0.70*** 0.47	0.71 0.45	0.70 0.46	0.66 0.47
Work absent	0.01*** 0.10	0.06 0.23	0.06 0.26	0.06 0.25
Old child BMI	0.11*** 1.21	-0.05 1.12	-0.09 1.18	-0.30 1.17
Observations	3,297	5,820	4,623	2,933

Standard deviation in parentheses. Mean values were significantly different among age groups:*P < 0.10, **P < 0.05, ***P < 0.001

Table A4.3 Medical expenditures by insurance coverage

	No Insurance	Has insurance	Don't know
Total medical costs	3,930.61	21,766.48	1,025.14
	14,797.62	79,513.74	945.17
Total inpatient costs overnight stay	9,047.46	56,330.15	2,061.97
	(22,989.27)	125,054.20	466.24
Total outpatient costs	1,302.62	1,809.10	596.93
	3,357.07	4,550.15	733.49
Amount paid overnight cash	10,544.47	17,885.60	2,061.97
	24,786.07	44,173.57	466.48
Amount paid overnight NHIF	898.24	21,934.67	
	7,050.11	53,762.78	
Amount paid outpatient NHIF	21.84	518.27	
	758.86	3,462.50	
Amount paid outpatient private insurance	0	212.55	
		1,954.90	
Amount paid overnight private insurance	91.21	18,026.67	
	1,873.92	86,998.4	
Amount paid overnight in-kind	98.26	1,288.78	
	2,049.51	16,085.47	
Amount paid overnight other	13.39	120.02	
	303.02	3,118.13	
Amount paid outpatient cash	1,273.62	1,092.16	679.62
	3,155.90	1,775.00	752.96
Amount paid outpatient in-kind	14.51	18.75	
	186.06	244.64	
Visited health facility in the last 12 months	0.50	0.63	0.62
	0.51	0.46	0.46

Table A4.4 2SLS Regressions of Health Care Spending on Measures of BMI

	Outpatient	Inpatient
BMI	0.17**	0.25***
	(0.08)	(0.08)
Age	0.39	-0.04*
	(0.60)	(0.02)
Years education	0.04	0.17***
	(0.03)	(0.04)
Married/living with partner		-1.40***
		(0.51)
Covered by health insurance	-0.43*	0.65**
	(0.26)	(0.28)
Husband completed primary	-0.06	
	(0.53)	
R-squared	-0.10	0.27

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table A4.5 Direct medical costs estimation

Category	Normal weight	Overweight	Obese	Overweight and obese
Average total annual medical expenditure (KES)	18,983.61	31,040.73	24,873.73	28,630.41
Excess cost		12,057.12	5,890.12	9,646.80
Proportion of each category		0.24	0.14	0.38
Country population of women aged 15-49	12,998,250.00	12,998,250.00	12,998,250.00	12,998,250.00
Number of people in each category		3,123,479.48	1,848,351.15	4,971,830.63
Total direct cost for population		37,660,166,847.61	10,887,010,075.64	47,962,255,673.25

Table A4.6 Mean hospitalizations estimation

	mean hospitalizations	Nin	mean outpatient	Nout
Normal	0.08		0.20	
overweight	0.10	1.29	0.24	1.21
obese	0.10	1.27	0.27	1.32
Overweight & Obese	0.11	1.39	0.26	1.31

Table A4.7 Inpatient travel costs estimation

	ATC (KES)	Nin	Population with Obesity	Inpatient Travel Costs
Overweight	1,057	1.29	3,123,479.48	4,273,842,054.56
Obese	1,057	1.27	1,848,351.15	2,483,222,716.75
Overweight & Obese	1,057	1.39	4,971,830.63	7,281,667,690.40

Table A4.8 Outpatient travel costs estimation

	ATC	Nout	Population with Obesity	Monthly Outpatient travel cost	Annual outpatient travel
Overweight	316.66	1.21	3,123,479.48	1,194,549,541.34	14,334,594,496.09
Obese	316.66	1.32	1,848,351.15	774,818,286.67	9,297,819,440.04
Overweight & Obese	316.66	1.31	4,971,830.63	2,055,356,905.16	24,664,282,861.96

Table A4.9 Working age population in Kenya

Age dependency ratio. young (% of working-age population)	total population	working age population
64%	54,027,487.00	34,442,522.96

Table A4.10 Employed ICGs for Pop. with Obesity estimation

	employment rate	working age population	obesity prevalence	Employed ICGs for Pop. with Obesity
Overweight	0.60	34,442,522.96	0.24	4,949,149.73
Obese	0.60	34,442,522.96	0.14	2,928,710.33
Overweight & Obese	0.60	34,442,522.96	0.38	7,877,860.05

Table A4.11 ICGs time costs estimation

	Average Daily Wage	Nd	Employed ICGs for Pop. with Obesity	ICG Time Costs = Average Daily Wage × Nd × Employed ICGs for Pop. with Obesity
Overweight	512.70	1.17	4,949,149.73	2,981,015,720.82
Obese	512.70	1.73	2,928,710.33	2,597,664,237.75
Overweight & Obese	512.70	1.55	7,877,860.05	6,241,797,333.12

Table A4.12 ICGs inpatient travel costs estimation

	ATC	Nin	Population with Obesity	ICG Travel Costs
Overweight	1057	1.29	3,123,479.48	4,273,842,054.56
Obese	1057	1.27	1,848,351.15	2,483,222,716.75
Overweight & Obese	1057	1.39	4,971,830.63	7,281,667,690.40

Table A4.13 ICGs outpatient travel costs estimation

	ATC	Nout	Population with Obesity	Outpatient Travel Costs
Overweight	316.66	1.21	3,123,479.48	1,194,549,541.34
Obese	316.66	1.32	1,848,351.15	774,818,286.67
Overweight & Obese	316.66	1.31	4,971,830.63	2,055,356,905.16

Table A4.14 Employed Pop. with Obesity

	Employment rate	Working Age Pop country total	Obesity Prevalence	Employed Pop. with Obesity
Overweight	0.69	12,998,250.00	0.24	2,183,165.97
Obese	0.78	12,998,250.00	0.14	1,434,054.88
Overweight & Obese	0.70	12,998,250.00	0.38	3,473,333.30

Table A4.15 Absenteeism Costs

	Employed Pop. with Obesity	Excess Days Absent annual	Average Daily Wages	Productivity losses Absenteeism Cost = Employed Pop. with Obesity × Excess Days Absent × Average Daily Wages
Overweight	2,183,165.97	1.42	606.65	1,880,673,046.30
Obese	1,434,054.88	2.77	537.15	2,136,269,410.15
Overweight & Obese	3,473,333.30	1.22	545.40	2,306,378,410.66

Table A4.16 Presenteeism Costs

	Employed Pop. with Obesity	Excess Presenteeism Rate	Average Annual Wages	Presenteeism Cost = Employed Pop. with Obesity × Excess Presenteeism Rate × Average Annual Wages
overweight	2,183,165.97	0.03	221,427.25	14,502,373,138.72
Obese	1,434,054.88	0.09	196,058.76	25,304,312,596.40
Overweight&obese	3,473,333.30	0.06	199,071	41,486,396,052.04

Table A4.17 Total Costs in Kenya shillings

	Overweight	**Obese (≥ 30 kg/m²)**	**Overweight & Obese**
Direct medical costs	37,660,166,847.61	10,887,010,075.64	47,962,255,673.25
Inpatient travel costs	4,273,842,054.56	2,483,222,716.75	7,281,667,690.40
Outpatient travel costs	14,334,594,496.09	9,297,819,440.04	24,664,282,861.96
Informal caregiver time costs	2,981,015,720.82	2,597,664,237.75	6,241,797,333.12
Informal caregiver travel costs	4,273,842,054.56	2,483,222,716.75	7,281,667,690.40
Absenteeism	1,880,673,046.30	2,136,269,410.15	2,306,378,410.66
Presenteeism	14,502,373,138.72	25,304,312,596.40	41,486,396,052.04
Total indirect costs	16,383,046,185.02	27,440,582,006.55	43,792,774,462.70
Total costs	79,906,507,358.67	55,189,521,193.49	137,224,445,711.82
Total costs per capita	6,147.48	4,245.92	10,557.15
% annual income	0.03	0.02	0.05

2. Questionnaire

UNIVERSITÄT BONN

zef
Center for
Development Research
University of Bonn

Study title	KENYA DIETARY BEHAVIORS AND PHYSICAL ACTIVITY SURVEY 2022
Researcher	Cecilia Maina Junior Researcher, Center for Development Research at the University of Bonn

We're inviting you to participate in a research study. Participation is completely voluntary. If you agree to participate now, you can always change your mind later. There are no negative consequences, whatever you decide.

What is the purpose of this study?

The overall purpose of this field research will be to gain a better understanding on the drivers of obesity in Kenya. This study will aim to identify: dietary habits, physical activity levels and sedentary behaviors that are associated with a change in weight and the development of non-communicable diseases such as diabetes, high blood pressure, stroke and heart disease. The research will also seek to understand why people make the food choices that they do.

What will I do?

In order to accomplish the purpose of this study you will be asked a set of questions regarding your:

- Age, Education, Employment, Income
- Eating habits
- Reasons behind food choice
- Physical activity levels
- Health outcomes such as history of diabetes, high blood pressure, heart attack and stroke
- Childhood factors

For the second part of the survey will involve a data collector taking some simple measurements of your:

- Height
- Weight
- Waist and hip circumference

The interview will take approximately one hour. We do not know of any possible risks associated with this study.

Your rights

It is your right to:

• Decline to take part in the study;

• Withdraw your consent at any time;

• Decline to answer any question in the interview that you do not wish to answer.

Confidentiality

You will be asked to provide your name and contact information so that you can be contacted if there is any need to follow up with you after the survey is conducted. Your participation and data provided will be completely confidential. Your name will not be used in any report of the study.

Other Study Information

Possible benefits	• By measuring your weight and height we will be able to inform you if your weight falls in the at risk category • By understanding the overall dietary patterns and weight outcomes we can make recommendations for health policies that will benefit the Kenyan population as a whole.
Estimated number of participants	• 500 Households
Results	• The results of this survey will be used to help plan strategies in reducing the risk factors that contribute to NCDs in your community. The results will be published in research publications, media briefings, fact sheets, and reports and can be made available to you through the local researchers.
How data is kept secure?	• All identifying information is removed and replaced with a study ID. • We'll remove all identifiers • We'll store all electronic data on a password-protected, encrypted computer. • We'll store all paper data in a locked filing cabinet in a locked office. • We'll keep your identifying information separate from your research data, but we'll be able to link it to you by using a study ID. We will destroy this link after we finish collecting and analyzing the data.

Contact information:

For questions about the research, problems, or complaints	Cecilia Maina Center for Development Research University of Bonn	cecilia.cmaina@uni-bonn.de

Remember, your participation is completely voluntary, and you're free to withdraw from the study at any time. Do you have any questions about the study? Do you agree to participate?

Yes	
No	

If the answer is no please do not proceed with the interview

KENYA DIETARY BEHAVIORS AND PHYSICAL ACTIVITY SURVEY 2022

(Paper version, we used CSPro an online data collection tool to collect participant data)

1.Survey Information & Socio-demographics

Location and Date	**Response**
Cluster/Centre/Village ID (4 digits)	
Cluster/Centre/Village name (20 characters)	
County Name (20 digits)	
Location \Residence	Rural 1 Urban 2
Household number	
Interviewer	
Date of interview	dd mm year
Consent, Interview Language and Name Response Code	
Consent has been read and obtained	Yes 1 No 2 If NO, END
Interview Language	English 1 Kiswahili 2 Other 3
Time of interview	__: __ (24 hour clock) hrs mins
Family Surname	
First Name	
Contact phone number where possible (10 digits)	
Sex (Record Male / Female as observed)	Male 1 Female 2
What is your date of birth? Don't Know 77 77 7777	_____/______/________ dd mm year
How old are you?	Years └─┴─┘
In total, how many years have you spent at school and in full-time study (excluding pre-school)?	Years └─┴─┘

What is the highest level of education you have completed? [INSERT COUNTRY-SPECIFIC CATEGORIES]	No formal schooling 1 primary school incomplete 2 Primary school completed 3 Secondary school incomplete 4 Secondary school completed 5 A-level completed 6 College/University completed 7 Post graduate degree 8 Refused 88
What is your marital status?	Never married 1 Currently married 2 Separated 3 Divorced 4 Widowed 5 Cohabitating 6 Refused 88
Which of the following best describes your main work status over the past 12 months?	Government employee 1 Non-government employee 2 Self-employed 3 Non-paid/volunteer 4 Student 5 Homemaker (housewife/house husband) 6 Retired 7 Unemployed (able to work) 8 Unemployed (unable to work) 9 Refused 88
How many people older than 18 years, including yourself, live in your household?	Number of people └─┴─┘
Who is the head of the household	Male Female Other
How much money do you earn per month?	Less than KES 20,000 KES 20,000 – 50,000

	KES 50,000 – 100,000 Above 100,000 Not willing to share
What type of fuel does your household mainly use for cooking?	Electricity 01 Liquefied Petroleum Gas (LPG) 02 Natural gas 03 Biogas 04 Kerosene 05 Coal / Lignite 06 Charcoal 07 Wood 08 Straw/shrubs/grass 09 Animal dung 10 Agricultural crop residue 11 Other (specify) 96 No food cooked in the household 97
Does this household or any member of their household own any of the following items?	Electricity 1 =Yes, 2=No Internet connection 1 =Yes, 2=No Radio 1 =Yes, 2=No Television 1 =Yes, 2=No Mobile Telephone 1 =Yes, 2=No Is the mobile a smartphone 1 =Yes, 2=No Non-Mobile Telephone 1 =Yes, 2=No Refrigerator 1 =Yes, 2=No Freezer (attached to a refrigerator or stand-alone) 1 =Yes, 2=No Microwave 1 =Yes, 2=No Stove 1 =Yes, 2=No Oven 1 =Yes, 2=No Electrical grill Washing machine 1 =Yes, 2=No Computer 1 =Yes, 2=No

	Watch 1 =Yes, 2=No Bicycle 1 =Yes, 2=No Motorcycle/scooter 1 =Yes, 2=No Animal Drawn Cart 1 =Yes, 2=No Car\Truck 1 =Yes, 2=No Boat with motor 1 =Yes, 2=No
If you have electricity, how many times in the past 7 days have you experienced power outages /black outs?	Number ____
Do you or someone living in this household own this dwelling or do you rent this dwelling?	Own 1 Rent 2 Rent free/squatter/other 3
Does your household employ any help (such as house help, shamba man etc)?	Yes 1 No 2
Does any member of this household own any agricultural land?	Yes 1 No 2
Does this household own any livestock, herds, other farm animals, or poultry?	Yes 1 No 2
Do you smoke cigarettes ?	1 Yes, I currently smoke 2 No, but I used to smoke and quit 3 No, I have never smoked
Do you drink alcohol	Yes, I currently drink alcohol No, but I used to drink alcohol and quit No, I have never used alcohol

2.Fruits and vegetable intake		
The next questions ask about the fruits and vegetables that you usually eat. One serving of fruit is usually one fruit. As you answer these questions please think of a typical week in the last year. Vegetables include: Dark-Green Vegetables (Sukuma wiki, spinach), Red and Orange Vegetables (carrots, pumpkin, red and orange bell peppers, red chilli peppers, sweet potato, tomatoes, butternut) Beans, peas and lentils, other vegetables (cassava, corn, plantains, white potatoes, avocado, bean sprouts, cabbage, cucumbers, mushrooms, onions)		
Question	Response	Code

In a typical week, on how many days do you eat fruit?	Number of days ___ Don't Know 77 If Zero days, go to section 3 (on Dietary salt intake)	
How many servings of fruit do you eat on one of those days?	Number of servings ____ Don't Know 77	
In a typical week, on how many days do you eat vegetables?	Number of days ____ Don't Know 77 If Zero days, go to section 3 (on Dietary salt intake)	
How many servings of vegetables do you eat on one of those days? (1 cup of cooked vegetables or 2 cups raw)	Number of servings ____ Don’t know 77	

3.Dietary salt

With the next questions, we would like to learn more about salt in your diet. Dietary salt includes ordinary table salt, unrefined salt such as sea salt, iodized salt, salty stock cubes and powders, and salty sauces such as soya sauce or fish sauce. The following questions are on adding salt to the food right before you eat it, on how food is prepared in your home, on eating processed foods that are high in salt such as packaged salty snacks e.g crisps, and questions on controlling your salt intake. Please answer the questions even if you consider yourself to eat a diet low in salt.

Question	Response	Code
How often do you add salt or a salty sauce such as soya sauce to your food right before you eat it or as you are eating it?	Always (every meal) 1 Often (most meals) 2 Sometimes (every week) 3 Rarely (not every week) 4 Never 5 Don't know 77	
How often is salt, salty seasoning or a salty sauce put in the food when cooking or preparing foods in your household?	Always (every meal) 1 Often (most meals) 2 Sometimes (every week) 3 Rarely (not every week) 4 Never 5 Don't know 77	
How often do you eat processed food high in salt? By processed food high in salt, I mean foods that have been altered from their natural state, such as njugu karanga, packaged salty snacks, canned salty food including pickles and preserves, salty food prepared at a fast food restaurant, cheese, bacon and processed meat	Always (every meal) 1 Often (most meals) 2 Sometimes (every week) 3 Rarely (not every week) 4	

	Never 5 Don't know 77	
How much salt or salty sauce do you think you consume?	Far too much 1 Too much 2 Just the right amount 3 Too little 4 Far too little 5 Don't know 77	
How important to you is lowering the salt in your diet?	Very important 1 Somewhat important 2 Not at all important 3 Don't know 77	
Do you think that too much salt or salty sauce in your diet could cause a health problem?	Yes 1 No 2 Don't know 77	
The following diseases or health problems are related to high sodium or salt intake	Deficit Vitamin D: Agree=1, Disagree=2, Not sure =3 Underweight Agree=1, Disagree=2, Not sure =3 Heat disease Agree=1, Disagree=2, Not sure =3	
Do you do any of the following on a regular basis to control your salt intake? (RECORD FOR EACH)		
Limit consumption of processed foods	Yes 1 No 2 Don't know 77	
Buy low salt/sodium alternatives	Yes 1 No 2 Not applicable 3	
Use spices other than salt when cooking	Yes 1 No 2 Not applicable 3	

Avoid eating foods prepared outside of a home	Yes 1 No 2 Not applicable 3	
Do other things specifically to control your salt intake	Yes 1 No 2 Not applicable 3 Other (specify)	
4.Meals not prepared at home		
The next questions ask about the oil or fat that is most often used for meal preparation in your household, and about meals that you eat outside a home.		
What type of oil or fat is most often used for meal preparation in your household? (SELECT ONLY ONE)	Vegetable oil (liquid) 1 Vegetable fat (solid) 2 Lard or suet 3 Butter or ghee 4 Margarine 5 Palm Oil 6 Coconut Oil 7 Other 8 None in particular 9 None used 10 Don't know 77 Other |__|__|__|__|__|__|__|	
On average, how many meals per week do you eat that were not prepared at a home? By meal, I mean breakfast, lunch and dinner.	Number _____ Don't know 77 I do not eat meals prepared outside of the home (Skip to section 5)	
About how long would it take to get from your home to the place where you buy prepared meals most often, if you walked there?	10 minutes or less 11 to 20 minutes 21 to 30 minutes More than 30 minutes I do not eat out of home prepared meals	
Please mark whether you agree or disagree with the following statements about the restaurant or food vendor where you go most often:		

	1 Strongly disagree	2 somewhat disagree	3 Neither agree nor disagree	4 Somewhat agree	5 Strongly agree
There are many healthy menu options at the restaurant					
It is hard to find a healthy option when eating out at the restaurant					
It is easy to find healthy fruit and vegetable choices at the restaurant.					
It is important to me to be able to make a healthy food choice when eating out.					
The restaurant provides nutrition information (such as calorie content) on a menu board or on the menu					
Signs and displays encourage overeating or choosing unhealthy foods from the menu					
The menu or menu board highlights and promotes the healthy options at the restaurant					
It costs more to buy the healthy options					

I generally prefer ordering what is considered unhealthy options when eating outside of the home because I find it more tasty	Yes 1 No 2	

5.Dietary sugar intake

With the next questions, we would like to learn more about sugar in your diet. Dietary sugar includes ordinary sugar, refined sugar such as candy, chocolate, fizzy drinks. The following questions are on adding sugar to beverages right before you drink them, on how sweet beverages foods are prepared in your home, on eating processed foods that are high in sugar such as packaged snacks and questions on controlling your sugar intake. Please answer the questions even if you consider yourself to eat a diet low in sugar.		
Question	Response	Code
How often do you add sugar to your beverages right before you drink them or as you are drinking them?	Always (every drink) 1 Often (every day but not every drink) 2 Sometimes (every week) 3 Rarely (not every week) 4 Never 5 Don't know 77	
In a typical week on how many days do you take soda (carbonated drinks) like fanta, coca cola,7-up, Afya, Softa, Vimto, or other sugary drinks?	Number of days ___ Don't Know 77	
How may 300ml bottles do you take each time you drink soda on one of those days?	Number of servings ___ Don't Know 77	
How often do you eat processed food high in sugar? By processed food high in sugar, I mean biscuits, wafers, cakes, candy, sweets and chocolate and alike?	Always (every meal) 1 Often (every day) 2 Sometimes (every week) 3 Rarely 4 Never 5 Don't know 77	
How much sugar do you think you consume?	Far too much 1 Too much 2 Just the right amount 3 Too little 4 Far too little 5 Don't know 77	
How important to you is lowering the sugar in your diet?	Very important 1 Somewhat important 2 Not at all important 3 Don't know 77	

Do you think that too much sugar in your diet could cause a health problem?	Yes 1 No 2 Don't know 77	
Do you do any of the following on a regular basis to control your sugar intake? (RECORD FOR EACH)		
Minimize the amount of sugar used in beverages	Yes 1 No 2	
Limit consumption of soda and sugary drinks	Yes 1 No 2	
Limit consumption of processed foods	Yes 1 No 2	
Use of natural/unrefined alternatives	Yes 1 No 2	
Do other things specifically to control your sugar intake	Yes 1 No 2	
Other (please specify)	______________	

6.Household food consumption		
Now, I would like to talk to you about the food consumed in your household during the past 7 days. How many days during the past 7 days, did members of your household consume the following food items, prepared or eaten at home?		
CODES FOR SOURCE OF FOOD 21 = OWN PRODUCTION (CROPS, ANIMAL) 24 = PURCHASED 27 = GIFT FROM FAMILY, FRIENDS 22 = FISHING, HUNTING, GATHERING 25 = BEGGED 28 = FOOD AID FROM CIVIL SOCIETY, NGO, GOVERNMENT 23 = LOANED, BORROWED 26 = EXCHANGED FOR LABOR 96 = OTHER		
Question	Response	Code
Cereals and grains such as rice, pasta, bread, sorghum, millet, or maize?	Did you consume this in the previous 24 hrs Yes 1 No 2 Number of days eaten in the past 7 days └─┴─┘ **If** One or more	

	What was the main source (refer to code) └──┴──┘	
Roots and tubers such as potato, yam, cassava, normal sweet potatoes, taro, cooking banana/plantain or other tubers?	Did you consume this in the previous 24 hrs Yes 1 No 2 Number of days eaten in the past 7 days └──┴──┘ **If** One or more What was the main source (refer to code) └──┴──┘	
Pulses/nuts such as beans, cowpeas, peanuts, lentils, soy, pigeon peas, or other nuts?	Did you consume this in the previous 24 hrs Yes 1 No 2 Number of days eaten in the past 7 days └──┴──┘ **If** One or more What was the main source (refer to code) └──┴──┘	
Orange vegetables such as carrots, red peppers, pumpkin, orange sweet potato?	Did you consume this in the previous 24 hrs Yes 1 No 2	

	Number of days eaten in the past 7 days └──┴──┘ **If** One or more What was the main source (refer to code) └──┴──┘	
Green leafy vegetables such as sukumu wiki, spinach, broccoli, amaranth, cassava leaves, or other dark green leaves?	Did you consume this in the previous 24 hrs Yes 1 No 2 Number of days eaten in the past 7 days └──┴──┘ **If** One or more What was the main source (refer to code) └──┴──┘	
Other vegetables such as onion, tomatoes, cucumber, radishes, green beans, peas, lettuce?	Did you consume this in the previous 24hrs Yes 1 No 2 Number of days eaten in the past 7 days └──┴──┘ **If** One or more What was the main source (refer to code) └──┴──┘	

Orange fruits such as mango, paw paw, tree tomato?	Did you consume this in the previous 24hrs Yes 1 No 2 Number of days eaten in the past 7 days |__|__| **If** One or more What was the main source (refer to code) |__|__|	
Other fruits such as banana, apple, lemon?	Did you consume this in the previous 24hrs Yes 1 No 2 Number of days eaten in the past 7 days |__|__| **If** One or more What was the main source (refer to code) |__|__|	
Meat such as goat, beef, chicken, pork? (meat in large quantities and not as a condiment)	Did you consume this in the previous 24 hrs Yes 1 No 2 Number of days eaten in the past 7 days |__|__| **If** One or more	

	What was the main source (refer to code) └─┴─┘	
Liver, kidney, heart, or other organ meats?	Did you consume this in the previous 24 hrs Yes 1 No 2 Number of days eaten in the past 7 days └─┴─┘ **If** One or more What was the main source (refer to code) └─┴─┘	
Fish or shellfish such as dried fish, canned tuna, or other seafood? (seafood in large quantities and not as a condiment)	Did you consume this in the previous 24 hrs Yes 1 No 2 Number of days eaten in the past 7 days └─┴─┘ **If** One or more What was the main source (refer to code) └─┴─┘	
Eggs	Did you consume this in the previous 24 hrs Yes 1 No 2	

	Number of days eaten in the past 7 days └──┴──┘ **If** One or more What was the main source (refer to code) └──┴──┘	
Milk and other dairy products such as yogurt or cheese	Did you consume this in the previous 24 hrs Yes 1 No 2 Number of days eaten in the past 7 days └──┴──┘ **If** One or more What was the main source (refer to code) └──┴──┘	
Oil, fat, and butter?	Did you consume this in the previous 24 hrs Yes 1 No 2 Number of days eaten in the past 7 days └──┴──┘ **If** One or more What was the main source (refer to code) └──┴──┘	

Sugar or sweet things such as honey, jam, cakes, candy, biscuits, pastries, sugary drinks	Did you consume this in the previous 24 hrs Yes 1 No 2 Number of days eaten in the past 7 days └──┴──┘ **If** One or more What was the main source (refer to code) └──┴──┘	
Condiments and spices such as tea, coffee, cocoa, salt, garlic, spices, yeast, baking powder, tomato sauce, meat or fish in very small quantities as condiments	Did you consume this in the previous 24 hrs Yes 1 No 2 Number of days eaten in the past 7 days └──┴──┘ **If** One or more What was the main source (refer to code) └──┴──┘	

7.Food Choice Questionnaire		
In this section we would like to understand which factors influence your food choice. It measures the reported importance given to nine factors underlying food choice.		
It is important to me that the food I eat on a typical day …	Loading	Code
Factor 1—Health		

Contains a lot of vitamins and minerals	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Keeps me healthy	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Is nutritious	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Is high in protein	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Is good for my skin/teeth/hair/nails etc	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree	

	5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Is high in fibre and roughage	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Factor 2—Mood		
Helps me cope with stress	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Helps me to cope with life	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Helps me relax	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree	

	7 – Strongly agree	
Keeps me awake/alert	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Cheers me up	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Makes me feel good	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Factor 3—Convenience		
Is easy to prepare	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Can be cooked very simply	1 – Strongly disagree 2 – Disagree	

	3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Takes no time to prepare	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Can be bought in shops close to where I live or work	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Is easily available in shops and supermarkets	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Factor 4—Sensory Appeal		
Smells nice	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree	

	6 – Agree 7 – Strongly agree	
Looks nice	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Has a pleasant texture	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Tastes good	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Factor 5—Natural Content		
Contains no additives	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Contains natural ingredients	1 – Strongly disagree	

	2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Contains no artificial ingredients	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Factor 6—Price		
Is not expensive	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Is cheap	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Is good value for money	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree	

	5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Factor 7—Weight Control		
Is low in calories	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Helps me control my weight	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Is low in fat	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Factor 8—Familiarity		
Is what I usually eat	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree	

	7 – Strongly agree	
Is familiar	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	
Is like the food I ate when I was a child	1 – Strongly disagree 2 – Disagree 3 – Somewhat disagree 4 – Neither agree or disagree 5 – Somewhat agree 6 – Agree 7 – Strongly agree	

8.Physical Activity		
Next I am going to ask you about the time you spend doing different types of physical activity in a typical week. Please answer these questions even if you do not consider yourself to be a physically active person. Think first about the time you spend doing work. Think of work as the things that you have to do such as paid or unpaid work, study/training, household chores, harvesting food/crops, fishing or hunting for food, seeking employment. [Insert other examples if needed]. In answering the following questions 'vigorous-intensity activities' are activities that require hard physical effort and cause large increases in breathing or heart rate, 'moderate-intensity activities' are activities that require moderate physical effort and cause small increases in breathing or heart rate.		
Question	Response Code	Question
Does your work involve vigorous-intensity activity that causes large increases in breathing or heart rate like carrying or lifting heavy loads, digging or construction work for at least 10 minutes continuously?	Yes 1 No 2	
In a typical week, on how many days do you do vigorous-intensity activities as part of your work?	Number of days └─┘	
How much time do you spend doing vigorous intensity activities at work on a typical day?	Hours : minutes └─┴─┘ : └─┴─┘ hrs mins	

Does your work involve moderate-intensity activity, that causes small increases in breathing or heart rate such as brisk walking or carrying light loads for at least 10 minutes continuously?	Yes 1 No 2	
In a typical week, on how many days do you do moderate-intensity activities as part of your work?	Number of days └─┘	
How much time do you spend doing moderate intensity activities at work on a typical day?	Hours : minutes └─┴─┘ : └─┴─┘ hrs mins	

9.Travel to and from places, recreational activities		
Question	Response	Code
The next questions exclude the physical activities at work that you have already mentioned. Now I would like to ask you about the usual way you travel to and from places. For example to work, for shopping, to market, to place of worship.		
Do you walk or use a bicycle (pedal cycle) for at least 10 minutes continuously to get to and from places?	Yes 1 No 2	
In a typical week, on how many days do you walk or bicycle for at least 10 minutes continuously to get to and from places?	Number of days └─┘	
How much time do you spend walking or bicycling for travel on a typical day?	Hours : minutes └─┴─┘ : └─┴─┘ hrs mins	
Do you do any vigorous-intensity sports, fitness or recreational (leisure) activities that cause large increases in breathing or heart rate like running or playing football for at least 10 minutes continuously?	Yes 1 No 2	
In a typical week, on how many days do you do vigorous-intensity sports, fitness or recreational (leisure) activities?	Number of days └─┘	
How much time do you spend doing vigorous intensity sports, fitness or recreational activities on a typical day?	Hours : minutes └─┴─┘ : └─┴─┘ hrs mins	
Do you do any moderate-intensity sports, fitness or recreational (leisure) activities that cause a small increase in breathing or heart rate such as brisk walking, cycling, swimming, volleyball for at least 10 minutes continuously?	Yes 1 No 2	

In a typical week, on how many days do you do moderate-intensity sports, fitness or recreational (leisure) activities?	Number of days └─┘	
How much time do you spend doing moderate intensity sports, fitness or recreational (leisure) activities on a typical day?	Hours : minutes └─┴─┘ : └─┴─┘ hrs mins	

10.Sedentary behavior		
The following question is about sitting or reclining at work, at home, getting to and from places, or with friends including time spent sitting at a desk, sitting with friends, traveling in car, bus, train, reading, playing cards or watching television, but do not include time spent sleeping.		
How much time do you usually spend sitting or reclining on a typical day?	Hours : minutes └─┴─┘ : └─┴─┘ hrs mins	
Do you read a newspaper or magazine/book at least once a week, less than once a week or not at all?	Daily 1 At least once a week 2 Once a month 3 Not at all 4	
How many hours do you spend reading in one day?	Number of hours └─┘	
Do you listen to the radio at least once a week, less than once a week or not at all?	Almost every day 1 At least once a week 2 Once a month 3 Not at all 4	
How many hours in a day do you spend listening to the radio	Number of hours └─┘	

Do you watch television at least once a week, less than once a week or not at all?	Almost every day 1 At least once a week 2 Once a month 3 Not at all 4	
How many hours do you spend watching tv in a day	Number of hours ⎿⏌	
If you watch tv on a weekly basis, how many hours do you spend watching tv in a week?	Number of hours ⎿⏌	
Do you usually eat a snack while watching television?	Yes 1 No 2	
Have you ever used the internet from any location on any device?	Yes 1 No 2	
In the last 12 months, have you used the internet? From which location and from which device?	Yes 1 No 2	
During the last one month, how often did you use the internet, almost every day, at least once a week, once a month, not at all	Almost every day 1 At least once a week 2 Once a month 3 Not at all 4	
How many hours in a day do you spend using the internet in a day?	Number of hours ⎿⏌	
Usual internet activity	Emails 1 Online games 2 Facebook 3 Youtube 4 Twitter 5 Online shopping 6 News 7 Other 8	

Have you ever purchased a food item or beverage that you saw in a commercial/advertisement for the first time and wanted to try it?	Yes 1 No 2 Not sure 3	
How would you categorize this purchased product	1 healthy 2 non-healthy 3 not sure	
Why did you want to purchase or try out this food item or beverage?	1. Nutrition claim benefits advertised 2. Price 3. Sale (discount advertised) 4. Brand representation (nice packaging, had a catchy tag line or jingle) 5. lifestyle represented/ social status representation 5. Other	
How often do you see advertisements for food related items or beverages from media sources such as radios/tvs/ internet/ newspapers/ billboards in a day	1 Very Frequently 2 Frequently 3 Occasionally 4 Rarely 5 Very Rarely 6 Never	
Do you think advertisements are a useful source of information for foods and drinks	1 yes 2 No 3 Not sure	
Do food advertisements have an influence on what you eat and drink?	1 yes 2 No 3 Not sure	

11.History of raised blood pressure		
Question	Response	Code

Have you ever had your blood pressure measured by a doctor or other health worker?	Yes 1 No 2	
Have you ever been told by a doctor or other health worker that you have raised blood pressure or hypertension?	Yes 1 No 2	
Have you been told the above in the past 12 months?	Yes 1 No 2	
In the past two weeks, have you taken any drugs (medication) for raised blood pressure prescribed by a doctor or other health worker?	Yes 1 No 2	
Have you ever seen a traditional healer for raised blood pressure or hypertension?	Yes 1 No 2	
Are you currently taking any herbal or traditional remedy for your raised blood pressure?	Yes 1 No 2	

12.History of diabetes		
Have you ever had your blood sugar measured by a doctor or other health worker?	Yes 1 No 2	
Have you ever been told by a doctor or other health worker that you have raised blood sugar or diabetes?	Yes 1 No 2	
Have you been told in the above past 12 months?	Yes 1 No 2	
In the past two weeks, have you taken any drugs (medication) for diabetes prescribed by a doctor or other health worker?	Yes 1 No 2	
Are you currently taking insulin for diabetes prescribed by a doctor or other health worker?	Yes 1 No 2	
Have you ever seen a traditional healer for diabetes or raised blood sugar?	Yes 1 No 2	
Are you currently taking any herbal or traditional remedy for your diabetes?	Yes 1 No 2	

13.History of Cardiovascular Diseases		
Have you ever had a heart attack or chest pain from heart disease (angina) or a stroke (cerebrovascular accident or incident)?	Yes 1 No 2	

Are you currently taking aspirin regularly to prevent or treat heart disease?	Yes 1 No 2 Don't know 3	
Are you currently taking statins (Lovastatin/Simvastatin/Atorvastatin or any other statin) regularly to prevent or treat heart disease?	Yes 1 No 2 Don't know 3	

14.Lifestyle Advice		
During the past three years, has a doctor or other health worker advised you to do any of the following? (RECORD FOR EACH)		
Quit using tobacco or don't start using it Reduce the use of alcohol/ don't start it	Yes 1 No 2 Yes 1 No 2	
Reduce salt in your diet	Yes 1 No 2	
Reduce use of refined sugar in your diet	Yes 1 No 2	
Eat at least five servings of fruit and/or vegetables each day	Yes 1 No 2	
Reduce fat in your diet	Yes 1 No 2	
Start or do more physical activity	Yes 1 No 2	

Maintain a healthy body weight or lose weight	Yes 1 No 2	
Did not see a physician within the last 3 years	Yes 1 No 2	
Where is your primary source of health care?	Self-medication 1 Herbal/alternative therapy 2 Dispensaries 3 Community Health Worker 4 Health centre 5 Sub county/district hospitals 6 County referral hospital (provincial) 7 National referral 8	

	Private clinic 9 Private hospital 10 OTC/pharmacy 11	

15.Body measurements		
For women: Are you pregnant?	Yes 1 If Yes, Do not take any measurements and proceed to the next section 16 No 2	
Device IDs for height and weight	Height └─┴─┘ Weight └─┴─┘	
Height	in Centimetres (cm) └─┴─┴─┘ . └─┘	
Weight If too large for scale 666.6	in Kilograms (kg) └─┴─┴─┘ . └─┘	
Waist circumference	in Centimetres (cm) └─┴─┴─┘ . └─┘	
Hip Circumference	in Centimetres (cm) └─┴─┴─┘ . └─┘	

16.Food Environment
Please indicate your perceptions of the availability of foods in your neighborhood. Please answer these questions thinking about the food stores in the neighborhood near where you live. Think of your neighborhood as the area within about a 20-minute walk or 10 -15 minute drive from your home.

It is easy to buy fresh fruits and vegetables in my neighborhood.	1 Strongly disagree 2 Somewhat disagree 3 Neither agree nor disagree 4 Somewhat agree 5 Strongly agree	
The fresh produce in my neighborhood is of high quality	1 Strongly disagree 2 Somewhat disagree 3 Neither agree nor disagree 4 Somewhat agree 5 Strongly agree	
There is a large selection of fresh fruits and vegetables in my neighborhood	1 Strongly disagree 2 Somewhat disagree 3 Neither agree nor disagree 4 Somewhat agree 5 Strongly agree	
There is a large selection of low-fat products available in my neighborhood.	1 Strongly disagree 2 Somewhat disagree 3 Neither agree nor disagree 4 Somewhat agree 5 Strongly agree	
How often do you usually shop for food?	1 More than once a week 2 Once a week 3 Once every 1-2 weeks 4 Once a month 5 Other (please specify):	
Is there one particular shop/supermarket/stall (or other) or more than one shop where you do most of your food shopping	1 One shop 2 Two shops 3 More than two shops	
What type of store is the store where you buy most of your food? (Choose the best answer)	1 supermarket 2 Open or wet markets (public/traditional market)	

<table>
<tr><td></td><td>3 Small stands (kibandas)
4 Independent family-run stores (dukas/kiosks)
5 other</td><td></td></tr>
<tr><td>Thinking about the store where you buy most of your food, how do you usually travel to this store? (check all that apply)</td><td>1 Walk
2 Bicycle
3 Bus or other public transportation
4 Drive your own car
5 Get a ride
6 Other (please specify):</td><td></td></tr>
<tr><td>About how long would it take to get from your home to the store where you buy most of your food, if you walked there</td><td>1 10 minutes or less
2 11 to 20 minutes
3 21 to 30 minutes
4 More than 30 minutes</td><td></td></tr>
<tr><td>How important are each of the following factors in your decision to shop at the store where you buy most of your food

Near your home
Near or on the way to other places where you spend time
Selection of foods
Quality of foods
Prices of foods
Access to public transport</td><td><table><tr><td>1 Not at all impor tant</td><td>2 A little impor tant</td><td>3 Some what impor tant</td><td>4 Very impor tant</td></tr><tr><td></td><td></td><td></td><td></td></tr><tr><td></td><td></td><td></td><td></td></tr><tr><td></td><td></td><td></td><td></td></tr><tr><td></td><td></td><td></td><td></td></tr><tr><td></td><td></td><td></td><td></td></tr><tr><td></td><td></td><td></td><td></td></tr><tr><td></td><td></td><td></td><td></td></tr></table></td><td></td></tr>
<tr><td>At the store where you buy most of your food, how hard or easy is it to get each of these types of foods?</td><td></td><td></td></tr>
<tr><td colspan="2"><table><tr><td></td><td>1 Very easy</td><td>2 Somewha t easy</td><td>3 Somewha t hard</td><td>4 Very hard</td></tr><tr><td>1. Fresh fruits and vegetables</td><td></td><td></td><td></td><td></td></tr><tr><td>2.Canned or frozen fruits and vegetables</td><td></td><td></td><td></td><td></td></tr><tr><td>3.Lean meats</td><td></td><td></td><td></td><td></td></tr><tr><td>4.Candy and snack chips</td><td></td><td></td><td></td><td></td></tr><tr><td>5.Low fat products</td><td></td><td></td><td></td><td></td></tr></table></td><td></td></tr>
</table>

	6.Regular soda or other sugary drinks						

At the store where you buy most of your food, how would you rate the price of fresh fruits and vegetables?	Very inexpensive Not expensive Somewhat expensive Very expensive	
Where do you usually purchase fruits and vegetables? Please select all that apply	1 supermarket 2 Open or wet markets (public/traditional market) 3 Small stands (kibandas) 4 Independent family-run stores (dukas/kiosks) 5 other 6 I don't buy fresh fruit and vegetables	
Please mark whether you agree or disagree with the following statements for the store where you buy most of your food and your shopping habits at that store. Questions about unhealthy foods mean those foods often considered to be high in sugar, salt, fat and calories, such as candy, chips, regular soda, sugary cereals, bakery desserts, and so on		
I notice signs that encourage me to purchase healthy foods.	1 Strongly disagree 2 Somewhat disagree 3 Neither agree nor disagree 4 Somewhat agree 5 Strongly agree	
I often buy food items that are located near the cash register	1 Strongly disagree 2 Somewhat disagree 3 Neither agree nor disagree 4 Somewhat agree 5 Strongly agree	
The unhealthy foods are usually located near the end of the aisles	1 Strongly disagree 2 Somewhat disagree 3 Neither agree nor disagree 4 Somewhat agree 5 Strongly agree	

I often buy items that are eye-level on the shelves	1 Strongly disagree 2 Somewhat disagree 3 Neither agree nor disagree 4 Somewhat agree 5 Strongly agree	
There are a lot of signs and displays encouraging me to buy unhealthy foods.	1 Strongly disagree 2 Somewhat disagree 3 Neither agree nor disagree 4 Somewhat agree 5 Strongly agree	
I see nutrition labels or nutrition information for most packaged foods at the store.	1 Strongly disagree 2 Somewhat disagree 3 Neither agree nor disagree 4 Somewhat agree 5 Strongly agree	
The foods near the cash register are mostly unhealthy choices.	1 Strongly disagree 2 Somewhat disagree 3 Neither agree nor disagree 4 Somewhat agree 5 Strongly agree	
17.Food consumer behaviour		
Who mainly prepares the meals in the home?	Mother House help Other female household mem Father Other male in the house	
Is the person who mainly prepares food employed?	Yes No	
How many hours on average do you spend preparing, cooking, and cleaning up from meals each time?	Less than 1 hour/day 1–2 hours/day More than 2 hours/day	

How often does your family eat evening meals together?	Never Occasionally Sometimes Usually or always	
How often does your family eat meals in front of the TV, with the TV turned on?	Never Occasionally Sometimes Usually or always	
Do you take a shopping list to the shop ?	Yes No	
I snack two to three times every day	Yes No	
I sometimes snack even when I am not hungry	Yes No	
I always eat breakfast	Yes No	
Have you ever tried to lose weight ? if yes how would you describe the results?	Yes No Lost all I wanted to lose and kept it off Lost part of the weight I wanted to lose and kept it off Lost weight, but gained some of it back Lost weight, but gained all of it back Didn't lose any weight Still on a diet now	
Do you have any relatives that have been diagnosed as overweight/obese ? if yes can you describe your relation	1. Yes 2. No 1. Father	

	2. Mother 3. Grandparents 4. Children 5. Extended family (Aunt/Uncle/Cousins) 6. Spouse 7. Other	
Did you experience any of the following in childhood and adolescence (defined as 0–18 years of age)	Severe undernutrition (wasting, stunting, underweight) Exposed to famine/ starvation marasmus or kwashiorkor Overweight/Obesity I don’t know	
Is your income significantly different from that of your parents	Yes No	
Which county and sub county did you reside as a child 0-12 years?		

18.Food Knowledge		
This section assesses you overall understanding of food and nutrition.		
Where do you get information about nutrition?	A. Radio B. Health personnel (doctor, clinical attendants, nurse) C. Fliers D. Television E. Social media F. Religious gathering G. Family members H. Schools I. Markets	
How many portions of fruit the “health experts” recommend consuming per day?	A. 0 B. 2 servings	

Choose only one of the options listed below. *One serving of fruit could be for example one apple or one orange*	C. 5 servings D. More than 5 E. Not sure	
How many portions of vegetables the "health experts" recommend consuming per day? Choose only one of the options listed below. (*One serving of vegetable could be for example 1/2 plate of tomatoes/ carrots exc...)*	A. 0 B. 2 servings C. 5 servings D. More than 5 E. Not sure	