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Food environments and obesity: A geospatial analysis of the South Asia Biobank, income and sex inequalities

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ABSTRACT

Introduction: In low-middle income countries (LMICs) the role of food environments on obesity has been understudied. We address this gap by 1) examining the effect of food environments on adults' body size (BMI, waist circumference) and obesity; 2) measuring the heterogeneity of such effects by income and sex.

Methods: This cross-sectional study analysed South Asia Biobank surveillance and environment mapping data for 12,167 adults collected between 2018 and 2020 from 33 surveillance sites in Bangladesh and Sri Lanka. Individual-level data (demographic, socio-economic, and health characteristics) were combined with exposure to healthy and unhealthy food environments measured with geolocations of food outlets (obtained through ground-truth surveys) within 300 m buffer zones around participants' homes. Multivariate regression models were used to assess association of exposure to healthy and unhealthy food environments on waist circumference, BMI, and probability of obesity for the total sample and stratified by sex and income.

Findings: The presence of a higher share of supermarkets in the neighbourhood was associated with a reduction in body size (BMI, $\beta = -3{\bullet}23$; $p < 0{\bullet}0001$, and waist circumference, $\beta = -5{\bullet}99$; $p = 0{\bullet}0212$) and obesity (Average Marginal Effect (AME): $-0{\bullet}18$; $p = 0{\bullet}0009$). High share of fast-food restaurants in the neighbourhood was not significantly associated with body size, but it significantly increased the probability of obesity measured by BMI (AME: $0{\bullet}09$; $p = 0{\bullet}0234$) and waist circumference (AME: $0{\bullet}21$; $p = 0{\bullet}0021$). These effects were stronger among females and low-income individuals.

Interpretation: The results suggest the availability of fast-food outlets influences obesity, especially among female and lower-income groups. The availability of supermarkets is associated with reduced body size and obesity, but their effects do not outweigh the role of fast-food outlets. Policies should target food environments to promote better diets and reduce obesity.

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1. Introduction

In 2020, the Lancet Diabetes Commission issued as a key recommendation for the prevention of non-communicable diseases (NCDs), the creation of a health-enabling environment that promotes healthy eating and physical activity to reduce the number of people with obesity and diabetes in the community (Chan et al., 2020). This recommendation underpins evidence of the role obesity and poor nutrition play in the increased global prevalence of NCDs, with findings from the Global Burden of Diseases Study showing that poor diet and high-body mass index (BMI) are among the top ten leading risk factors of death and disability among males and females globally in 2019 (Murray et al., 2020). Although historically obesity affected disproportionately more high-income countries, in recent years its prevalence and the associated disease burden has increased over-proportionally in low-middle income countries (LMICs), with the levels of obesity converging among country income groups (Popkin et al., 2020).

Although the aetiology of obesity is complex and multifactorial and highly determined by genetic factors (Lindgren et al., 2009), multiple studies show genetic variants that affect obesity do not explain obesity differences between ethnic groups (Scott et al., 2016). LMICs are experiencing rapid shifts in lifestyle and food environments driven by the rapid nutrition transition, globalisation, urbanisation, and economic development. These changes have been hypothesised to drive the obesity rates in most LMICs (Popkin et al., 2020).

In this work, we assessed the role food environment plays on adults' weight and obesity in two understudied LMICs, Bangladesh and Sri Lanka, where the rate of obesity has been growing unprecedently (8,4% average annual rate of increase in the South-East Asia region (Biswas et al., 2019), with 25.9% adults in 2018 in Bangladesh and 45.2% adult women in 2016 in Sri Lanka being overweight or obese (WOF, 2021).

Whilst there is a growing consensus that food environments may play a key role in determining body weight and obesity, evidence for LMICs is scant (Turner et al., 2020). Supermarket shopping has been found to correlate with adult obesity in Guatemala (Asfaw, 2008), Kenya (Demmler et al., 2017; Kimenju et al., 2015), and Zambia (Khonje et al., 2020) but not in Indonesia (Umberger et al., 2015). These studies relied on small sample sizes and examined the associations between monthly or yearly household food expenditures in supermarkets and obesity. The exposure to broader food environments was not assessed comprehensively in these studies. Only one study used Geographic Information System (GIS) to assess the associations of fast-food restaurant density with obesity among a sample of 5364 adults in India living in urban areas (Patel et al., 2017). It was found that a higher number of fast-food restaurants around participants' home addresses was significantly associated with an increased probability of being obese in comparison to participants living in a neighbourhood with less fast-food restaurants within one km. However, when controlling for socio economic status (SES) the association was attenuated. This study did not consider the density of other (especially, healthy) food outlets within individuals' homes, which might be equally affecting their weight status. Considering the limited and somewhat inconclusive evidence, the effect of the food environment in LMICs on adults' weight and obesity is still unclear. We build on this literature by examining the association between the availability of healthy and unhealthy food outlets around a resident's home address and the range of weight and obesity related outcomes, objectively measured through surveillance data- BMI, waist circumference and obesity. Our study proposes a novel approach of examining the effect of exposure to food environments on weight and obesity in LMICs, by merging geotagged environment data on all types of food outlets and surveillance data for 12,167 individuals in Bangladesh and Sri Lanka.

Notably, we assess the heterogeneity of these effects by sex and income. Evidence suggests that obesity is more prevalent among certain subpopulations (Swinburn et al., 2011). For example, in high income countries, obesity is greater among individuals of low SES, lower education, occupational status, and is similar among both sexes. In LMICs, obesity was found to be generally higher among wealthy groups and women which could be related to the fact that higher-income consumers often shop at conveniently located modern stores that offer a diverse range of food products, whereas low-income individuals may often need to travel long distances to shop at cheaper retail markets or street stalls (Seidler, 2001). However, recent evidence suggests that as the LMIC's gross domestic product (GDP) increases, the rates of obesity among low SES group increases with the shift of obesity occurring first in low SES women (Templin et al., 2019). With this shift in obesity prevalence among income groups documented in other LMICs, it is likely that food environments play a different role across the income and sex groups in Bangladesh and Sri Lanka. To our knowledge, no previous study has documented this heterogeneity in LMICs.

2. Methods

2.1. Study design and data

We created a unique dataset combining cross-sectional surveillance and environmental mapping data to examine the associations between the density of food outlets, body size and obesity outcomes. We used surveillance data from the South Asia Biobank (SAB) launched in 2018, a cross-sectional population-based study recruiting a representative sample of the adult population in Bangladesh, India, Pakistan, and Sri Lanka (Song et al., 2021). We focused on Bangladesh and Sri Lanka, as environmental mapping data from Pakistan and India were not available. The cohort was composed of 500–1000 adults in a surveillance site with a total of 33 surveillance sites selected based on national administrative data. One or more community clinics within each site were randomly selected and determined as the surveillance site. All eligible residents in a surveillance site were invited to participate. Eligibility criteria included being 18 years or above, having a south Asian ancestry, and being a permanent resident of the surveillance site (residence for 12 months or more and not planning to move out in the next 12 months). People with specific conditions such as pregnancy, or serious illness expected to reduce life expectancy to less than 12 months were excluded as individuals with such health conditions might lead to biased estimates not representative of general healthy population. For our analysis, we included 12,167 surveillance participants (8534 in Bangladesh, and 3633 in Sri Lanka). Even though, we used a subsample of the population described in Song et al. (2021), our sample does not differ statistically in the variables used when compared to the sample in Song et al. (2021). Data for participants included physical measurements (e.g. height, weight, waist circumference) as well as survey data on behavioural risk factors, personal and family medical history, medications, socioeconomic and demographic characteristics. The survey also collected the participants' geolocation indicating their place of residence.

The data were merged at the individual level, with food-environment data characterizing the availability of different categories of food outlets in the immediacy of a participant's home. In each SAB surveillance site, trained local researchers systematically walked all streets to collect geolocations and the type of each outlet supplying food using KoboToolBox (https://www.kobotoolbox.org) a common method in the literature (Duncan et al., 2014).

In the absence of food outlets classification for South Asia, food outlets were characterized in five groups based on the Food Environment Index (RFEI) and NAICS classifications, which describe food outlets in high income countries: 1) fast-food restaurants (where people can purchase sweetened beverages and ready-to-eat food that is highly processed and high in calories, and thus considered unhealthy), 2) supermarkets (self-service shop selling fresh fruit, vegetables, other healthy foods, household goods and therefore considered healthy), 3) corner stores (small shop selling foods and a limited range of household goods), 4) mobile carts (temporary structure that is readily moveable), 5) stationary carts (moveable structure but occupies a specific location) (Babey et al., 2008; NAICS). Since we did not observe what is sold in

Table 1
Descriptive Statistics of sample characteristics, food environment, BMI and obesity in Bangladesh and Sri Lanka.

VARIABLES	Mean % (SD) N = 12,167	Male (%) N = 4897	Female (%) N = 7256	Lower income (%) N = 6031	Higher income (%) N = 6048	Sri Lanka (%) N = 3633	Bangladesh (%) N = 8534
(A) General characteristics							
Sex	59•71 (49.05)	0	100	61•75	57•66	69•12	55•7
Female	59•71	–	–	61•75	57•66	69•12	55•7
Male	40•29	–	–	38•25	42•34	30•88	44•3
Age (years)	45•47 (14•42)	47•03	44•41	47•05	43•87	49•68	43•67
Marital Status (category)	87•01 (33•61)	90•06	84•99	86•69	88•61	81•15	89•51
Married	87•01	90•06	84•99	86•69	88•61	81•15	89•51
Unmarried	12•99	9•94	15•01	13•31	11•39	18•85	10•49
Religion (category)	32•17 (12•35)	33•87	31•03	32•68	31•67	15•01	39•38
Buddhist	21•53	16•27	25•06	19•43	23•63	72•80	0
Christian	3•05	2•16	3•65	2•70	3•39	10•30	0
Hindu	7•67	8•19	7•33	9•67	5•69	11•20	6•20
Muslim	67•60	73•28	63•78	68•00	67•20	5•37	93•73
Other Religion	0•15	0•10	0•18	0•20	0•10	0•34	0•07
School Years	9•54 (8•05)	9•52	9•57	9•51	9•58	8•48	9•99
Income (USD PPP)	700•73 (1860•13)	741•42	672•67	318•94	1081•44	901•23	616•51
Paid employment	43•94 (49•63)	85•56	15•81	41•62	46•25	40•69	45•30
Employed	43•94	85•56	15•81	41•62	46•25	40•69	45•30
Unemployed	56•06	14•44	84•19	58•38	53•75	59•31	54•70
Household Composition	3•09 (1•35)	3•17	3•04	2•81	3•37	3•21	3•04
Self-Assessed Health (Category)	24•26 (82•20)	24•84	23•86	23•78	24•73	26•86	23•16
Poor	14•59	11•89	16•41	17•01	12•17	7•22	17•68
Fair	34•19	34•55	33•93	33•33	35•05	30•34	35•81
Good	46•25	47•80	45•22	45•40	47•11	51•30	44•13
Very good	3•97	4•69	3•48	3•28	4•65	8•87	1•90
Excellent	1•00	1•07	0•96	0•98	1•03	2•27	0•47
PA Vigurous Activity (mins/w)	397•98 (1050•53)	753•19 (1440•63)	159•01 (554•54)	492•66 (1178•79)	309•35 (903•13)	126•63 (473•65)	513•49 (1197•21)
PA Moderate Activity (mins/w)	793•76 (1043•02)	580•30 (1037•80)	938•07 (1021•95)	855•411 (1093•19)	743•84 (990•75)	455•08 (576•60)	937•95 (1157•56)
PA Transport Week (mins/w)	152•26 (253•58)	217•49 (301•25)	108•23 (204•11)	163•37 (262•87)	143•39 (244•79)	128•11 (284•36)	162•54 (238•55)
(B) Healthcare Utilization							
Increase Fruit Veg	40•04 (49•00)	36•55 (48•16)	42•45 (49•43)	37•42 (48•40)	42•66 (49•46)	32•52 (46•85)	43•20 (49•54)
Received advice	40•04	36•55	42•45	37•42	42•66	32•52	43•20
Did not receive advice	59•96	63•45	57•55	62•58	57•34	67•48	56•80
Reduce Fat Content in Diet	30•86 (46•19)	28•18 (44•99)	32•69 (46•91)	27•89 (44•85)	33•81 (47•31)	36•69 (48•20)	28•40 (45•10)
Received advice	30•86	28•18	32•69	27•89	33•81	36•69	28•40
Did not receive advice	69•14	71•82	67•31	72•11	66•19	63•31	71•60
Increase Physical Activity	20•71 (40•53)	17•67 (38•14)	22•80 (41•95)	17•68 (38•15)	23•74 (42•55)	31•07 (46•28)	16•36 (37•00)
Received advice	20•71	17•67	22•80	17•68	23•74	31•07	16•36
Did not receive advice	79•29	82•33	77•20	82•32	76•26	68•93	83•64
Lose Weight	21•38 (41•00)	16•95 (37•52)	24•38 (42•94)	17•44 (37•95)	25•30 (43•48)	30•48 (46•04)	17•55 (38•04)
Received advice	21•38	16•95	24•38	17•44	25•30	30•48	17•55
Did not receive advice	78•62	83•05	75•62	82•56	74•70	69•52	82•45
Reduce Sugary Beverages	18•32 (38•69)	16•47 (37•10)	19•56 (39•67)	16•32 (36•95)	20•32 (40•24)	29•44 (45•59)	13•65 (34•33)
Received advice	18•32	16•47	19•56	83•68	20•32	29•44	13•65
Did not receive advice	81•68	83•53	80•44	16•32	79•68	70•56	86•35
(C) Food environment							
FFR Share	7•77 (9•74)	7•74	7•79	7•36	8•20	6•56	8•29
Corner Store Share	50•79 (33•20)	50•47	50•99	48•20	53•48	53•55	49•61
Stationary Cart Share	11•76 (18•39)	11•99	11•59	11•85	11•71	9•96	12•52
Mobile Cart Share	1•57 (5•16)	1•52	1•60	1•51	1•63	1•75	1•49
Supermarket Share	0•87 (3•37)	0•79	0•93	0•70	1•06	1•99	0•40
(D) Outcome variables							
BMI (kg/m^2)	23•81 (4•47)	22•73	24•54	23•05	24•54	25•34	23•16
Waist Circumference (cm)	81•66 (11•66)	81•58	81•71	79•74	83•55	85•25	80•14
Obese (BMI ≥30)	9•52 (29•35)	4•20	13•10	7•49	11•33	16•08	6•75
Obese (BMI ≥27.5)	20•21 (40•15)	11•87	25•86	15•98	24•25	30•63	15•82
Obese (WC ≥ 102 M, ≥8 F)	19•96 (39•97)	3•99	30•77	16•97	22•79	30•56	15•47
Obese (WC ≥ 90 M, ≥80 F)	43•06 (49•51)	24•17	55•87	37•39	48•64	59•10	36•26

Note: Results are presented in percentages (%).Mean (SD): mean and standard deviation of total sample (Sri Lanka and Bangladesh). Low income and high income were defined as below or above the median income in USD PPP per each country. PA Vigorous Activity refers to the minutes of vigorous physical activity per week at work, home, or recreational centres; PA Moderate Activity refers to minutes of moderate physical activity per week at work, home, or recreational centres. PA Transport Week refers to the minutes spent walking or bicycling as a mode of transportation per week. Health Utilization in panel (B) refers to going to the doctors and receiving an advice of to increase fruit and vegetables, or to the reduce fat content in their diet, or to increase the physical activity, or to lose weight, or to reduce the consumption of sugary beverages. Share of FFR (fast food restaurants), Corner Store, Stationary Cart, Mobile Cart, and Supermarket are defined as the number of each food outlet per total number of food outlets within 300 m of a resident's home address. BMI (Kg/m^2) and Waist Circumference (cm): values are presented as a continuous variables. Obese (BMI): categorical variable, with a BMI ≥30 (&≥27•5 for sensitivity analysis). Obese (WC): waist circumference, categorical variable, with a WC ≥ 102 (&≥90 for sensivity) for males (M) or WC ≥ 88 (&≥80 for sensitivity) for females (F).

each outlet, in commenting the results, we followed the literature in classifying supermarkets as healthy food outlets as they are more likely to sell healthy options and fast-food restaurants as unhealthy food outlets (Babey et al., 2008). Note that any outlet is likely to sell both healthy and unhealthy foods, the extent to which unhealthy food is available is likely to impact the effect size of interest. For stationary and mobile carts there is no consensus in the literature on their classification and therefore we remain agnostic on whether they are healthy or unhealthy.

2.2. Study variables

The four main outcome variables are BMI (kg/m2), waist circumference (cm), obesity defined using BMI, and waist circumference. BMI and waist circumference were derived from measurements of height, weight, and waist of study participants by trained SAB data collectors. Obesity using BMI was a binary variable using 30+ international cutoff, while obesity using waist circumference was a binary variable using 102+ for males and 88+ for females. For sensitivity analyses, we ran separate regressions using the suggested Asian cut-offs with BMI 27•5+ and waist circumference 90+ for males and 80+ for females (see Appendix 3) (Consultation, 2004).

There were two main independent variables: densities of supermarkets and fast-food restaurants defined as the share of each food outlet type relative to all food outlets within the 300 m buffer of the home address of each participant (using geolocation). Similar distance has been used in the literature and enables capturing more variation in terms of individual exposure to the food environments (Duncan et al., 2014). In addition to supermarkets and fast-food restaurants, we also built densities of other food outlet types such as stationary carts, mobile carts, and corner stores. Further details are in Appendix 1. Geospatial analyses were conducted in ArcMap 10.3.

2.3. Data analysis

From the original dataset several observations had missing values and were dropped from the regression analyses. See Appendix 1, for Consort diagram on sample selection process. For the outcome variables, we excluded 80 and 33 outliers, respectively for BMI and waist circumference (defined as values with 3SD larger or smaller than the mean) in order to exclude values that look implausible (e.g., BMI of 9). Our results remain robust to the inclusion of these outliers (available from authors). Therefore, the final regression sample includes n = 11,987 for the BMI outcome and n = 12,034 for waist circumference outcome.

We ran Ordinary Least Squares (OLS) regressions for BMI and waist circumference and logistic regressions for obesity using BMI and waist circumference, all with cluster robust standard errors.

In all regression analyses, we controlled for a broad range of characteristics that have been found in the literature to correlate with the outcome variables, including demographic characteristics (sex, age, country, marital status, religion), socio-economic status (paid employment, school years, income, household composition) (Dinsa et al., 2012), self-assessed-health, healthcare utilization (receiving doctor's advice to reduce the consumption of products high in fat, sugary beverages, or to increase daily intake of fruits and vegetables, or to lose weight, or do more physical activity) (Pool et al., 2014), and physical activity habits (weekly minutes of vigorous or moderate physical activity spent at work, home or recreational facilities, walking or cycling as a mode of transportation) (Janssen et al., 2004). Income is reported in USD dollars adjusted for purchasing power parity for comparability between the two countries and was deflated using 2018 prices. Evidence from LMICs indicates that fast food restaurants and supermarkets tend to selectively locate in higher income, urban, neighbourhoods (Hawkes, 2008; Seidler, 2001). Therefore, all regressions include site fixed effects to control for site specific time invariant confounders. The analyses were well powered as the minimum sample needed for a partial-correlation

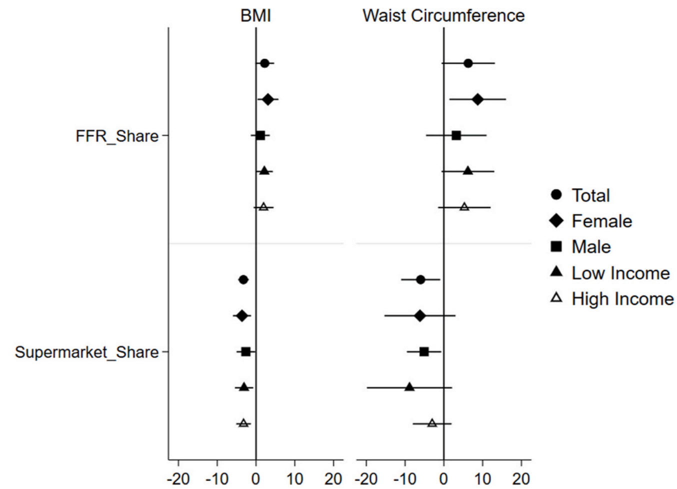

Fig. 1. Association between density of food outlets and BMI (left side) and waist circumference (right side). Note: Results represent OLS coefficients and 95% CI. For all regressions in Fig. 1 we controlled for: demographic characteristics (sex, age, country, marital status, religion), socio-economic status (paid employment, school years, income, household composition), health status measured (e.g. self-assessed health), healthcare utilization (e.g. whether participants received doctor's advice to either reduce fat or sugar beverages consumption, or to increase daily intake of FV, or to lose weight, or to do more physical activity), physical activity habits (e.g. minutes per week of vigorous or moderate physical activity spent at work, home or recreational facilities, walking or cycling as a mode of transportation), and for site specific time invariant characteristics. In the stratified regressions (by sex and income) we controlled for the same variables except for the one used to define the strata.

test in a multiple linear regression (with 40 control variables including individual characteristics and site fixed effects) between the share of fast-food restaurants and BMI (correlation of 0•0482, p-value<0•001) was about 300 (using the command-power pcorr).

We ran several models namely: for the total sample and stratified by sex, income, and by country (Appendix 2 for models' specifications). The low- and high-income strata were defined based on whether each individual had an income of above (henceforth high-income) or below (henceforth low-income) the median income in each country proxied by the median income of the sample in that country. In the stratified regressions we controlled for the same variables except for the variables used to define the strata. All regressions were conducted in STATA MP 16.

Role of the funding source

The funder had no role in study design, data collection, analysis, interpretation, or writing of the report.

3. Results

Table 1 shows the descriptive statistics on the sample characteristics. For the total sample 12,167 in Bangladesh and Sri Lanka, the mean age was 45•5 (14•42 SD) years, and the mean education level 9•5 (8•05 SD) school years, and median monthly income 489•30 USD (IQR: 326•20; 815•50). 60% of the sample (N = 7256) were females, 44% (49•63SD) in paid employment. For the primary outcomes, the mean BMI was 23•8 (4•47 SD) kg/m^2 and mean waist circumference was 81•7 (11•66 SD) cm. The proportions of obese were 9•52% (29•35% SD) and 19•96% (39•97% SD) using BMI (≥30 kg/m^2) and waist circumference, respectively. Obesity prevalence was higher among females and higher income participants. Regarding the food environment, the average share of fast-food restaurants within 300 m of a resident's home address was 8% (9•74% SD). Corner stores and supermarket shares were 51%

Table 2
Associations between food outlets density and BMI (panel A) and waist circumference (panel B).

VARIABLES	Total	Male	Female	Low income	High income	Sri Lanka	Bangladesh
(A) BMI							
Supermarket Share	−3•23** (−4•58, −1•88)	−2•60*(-5•00, −0•21)	−3•61**(-5•94, −1•28)	−3•09*(-5•45, −0•73)	−3•21**(-5•09, −1•32)	−3•59**(-5•16, −2•02)	−2•21 (-5•08, 0•67)
FFR Share	2•25 (-0•17, 4•67)	1•11 (-1•33, 3•55)	3•09*(0•39,5•80)	2•15 (-0•02, 4•33)	1•96 (-0•60, 4•51)	−0•28 (-2•66, 2•11)	2•74 (-0•48, 5•97)
Corner Store Share	0•24 (-0•41, 0•88)	0•34 (-0•33, 1•02)	0•14 (-0•53, 0•82)	0•41 (-0•30, 1•12)	−0•11 (-0•69, 0•48)	−0•24 (-0•68, 0•21)	0•31 (-0•50, 1•13)
Stationary Cart Share	−0•44 (-1•14, 0•27)	−0•85*(-1•67, −0•02)	−0•16 (-0•83, 0•52)	−0•33 (-1•14, 0•48)	−0•58 (-1•22, 0•06)	0•24 (-0•58, 1•06)	−0•46 (-1•07, 0•14)
Mobile Cart Share	1•67 (-0•46, 3•80)	0•64 (-1•42, 2•70)	2•51 (−1•11, 6•13)	2•78** (0•86, 4•70)	0•45 (−2•09, 3•00)	0•89 (-2•92, 4•70)	1•60 (-0•50, 3•69)
Observations	11,988	4843	7145	5987	6001	3517	8471
Controls	YES	YES	YES	YES	YES	YES	YES
Site FE	YES	YES	YES	YES	YES	YES	YES
(B) Waist Circumference							
Supermarket Share	−5•99* (−11•03, −0•95)	−5•11*(-9•54, −0•69)	−6•16 (−15•32, 3•00)	−8•86 (−19•84, 2•11)	−3•02 (−8•01, 1•97)	−5•70*(-10•14, −1•26)	−10•55**(-11•68, −9•43)
FFR Share	6•28 (-0•58, 13•14)	3•20 (−4•60, 11•00)	8•73* (1•43, 16•02)	6•19 (−0•61, 12•99)	5•29 (−1•47, 12•05)	0•23 (-4•88, 5•35)	7•31 (-1•62, 16•24)
Corner Store Share	0•40 (−1•75, 2•55)	0•48 (−1•98, 2•94)	0•34 (−1•70, 2•38)	0•70 (−1•49, 2•89)	−0•29 (−2•30, 1•73)	−1.11 (-2.25, 0•02)	0•66 (-2•18, 3•50)
Stationary Cart Share	−1•90* (−3•49, −0•30)	−3•28** (−5•08, −1•47)	−0•84 (−2•71, 1•02)	−1•79 (−3•64, 0•06)	−1•88* (−3•29, 0•48)	−0•73 (-4•00, -2•54)	−1•76*(-3•42, −0•09)
Mobile Cart Share	4•07 (−2•16, 10•29)	3•23 (−1•75, 8•22)	5•04 (−4•85, 14•92)	7•91* (1•64, 14•18)	0•08 (−5•66, 5•82)	−0•90 (-15•48, 13•67)	4•31 (-1•35, 9•98)
Observations	12,032	4847	7185	6014	6018	3543	8489
Controls	YES	YES	YES	YES	YES	YES	YES
Site FE	YES	YES	YES	YES	YES	YES	YES

Results represent OLS coefficients and 95% CI in brackets. **p < 0•01, *p < 0•05. Note: "Outlets Share" is defined as the number of each outlet out of the total number of outlets. For example, supermarket share is defined as the number of supermarkets within a 300 m buffer around a partcipant's home address out of all food outlets within a 300 m buffer. For all regressions in Table 2 controls included: demographic characteristics (gender, age, country, marital status, religion), socio-economic status (paid employment, school years, income, household composition), health status measured (e.g. self-assessed health), healthcare utilization (e.g. whether participants received doctor's advice to either reduce fat or sugar beverages consumption, or to increase daily intake of FV, or to lose weight, or to do more physical activity), and physical activity habits (e.g. minutes per week of vigorous or moderate physical activity spent at work, home or recreational facilities, walking or cycling as a mode of transportation). Site FE stands for Site Fixed Effects, where in all regressions we controlled for site specific time invariant characteristics. In the stratified regressions (by sex and income) we controlled for the same variables except for the one used to define the strata.

(33•20% SD) and 0•9% (3•37% SD), respectively. The share of fast-food restaurants was higher in Bangladesh, whilst the share of corner stores and supermarkets were higher in Sri Lanka. The share of supermarkets was zero in rural areas, indicating all supermarkets in our sample were in urban sites.

Fig. 1 shows the associations between fast-food restaurants and supermarkets densities and BMI (panel A) and waist circumference (panel B) (full set of results in Table 2). No statistically significant results were found for the share of corner stores, stationary and mobile carts (Table 2). A higher supermarket share was associated with a 3•23 BMI decrease (95% CI: −4•58, −1•88; p < 0•0001). Supermarket shares were associated with a higher BMI reduction in females (β = −3•61; 95% CI: −5•94, −1•28; p = 0•0035) than in males (β = −2•60; 95% CI: −5•00, −0•20; p = 0•0346). The association between supermarkets density on BMI benefits both low- and high-income groups with the effects being larger for high-income individuals (β = −3•21; 95% CI: −5•09, −1•32; p = 0•0015). The share of fast-food restaurants was not positively associated with BMI for the total sample. However, it was found to correlate with females BMI (β = 3•09; 95% CI:0•39, 5.8; p = 0•0265).

With regards to waist circumference, results follow similar patterns. The share of supermarkets was significantly associated with a six cm waist circumference reduction and therefore, lower central obesity risk for the total sample (β = −5•99; 95% CI: −11•03, −0•95; p = 0•0212). Similar findings were observed for the analyses stratified by country, though with larger effects observed in Bangladesh (Table 2). No statistically significant effects were observed for females, but the availability of supermarkets was associated with a decrease in BMI for males (β = −5•11; 95% CI: −9•54, −0•69; p = 0•0253). Similarly, to BMI, no effects were found between waist circumference and density of fast-food restaurants for the total sample, however, a positive association was found for females (β = 8•73; 95% CI:1•43, 16•02; p = 0•0205). No differences were found across income groups.

Fig. 2 shows the average marginal effects for the associations between fast-food restaurants and supermarket outlets density and obesity using BMI (panel A) and waist circumference (panel B) (full set of results for other types of food outlets in Table 3). Results showed that the share of supermarkets in the neighbourhood was inversely associated with the probability of obesity. A one percent increase in the share of supermarkets near an individual's home was associated with 18% decrease in the probability of obesity, using BMI (AME: −0•18; 95% CI: −0•29, −0•07; p = 0•0009). Similarly, a one percent increase in the share of supermarkets near an individual's home was associated with 12% decrease in the probability of obesity, using waist circumference (AME: −0•12; 95% CI: −0•21, −0•03; p = 0•0078). In terms of availability of fast-food restaurants, a one percent increase in the share of fast-food restaurants near a household was associated with nine percentage points increase in the likelihood of obesity, using BMI (AME: 0•09; 95% CI: 0•01, 0•18; p = 0•0234) and a 21% increase, using waist circumference (AME: 0•21; 95% CI: 0•08, 0•34; p = 0•0021).

The negative association between the density of supermarkets and the likelihood of obesity was only statistically significant for low-income populations using waist circumference (AME: −0•18; 95% CI: −0•34, −0•02; p = 0•0317) and for females using BMI (AME: −0•23; 95% CI: −0•43, −0•02; p = 0•0279).

The association between fast-food restaurants density and obesity was mainly among females and low-income participants when using both metrics, BMI (for females, AME: 0•15, 95% CI: 0•05, 0•25, p = 0•0047, and low-income, AME: 0•10; 95% CI: 0•05, 0•16; p = 0•0001) and waist circumference (for females, AME:0•34; 95% CI:0•15,0•53; p

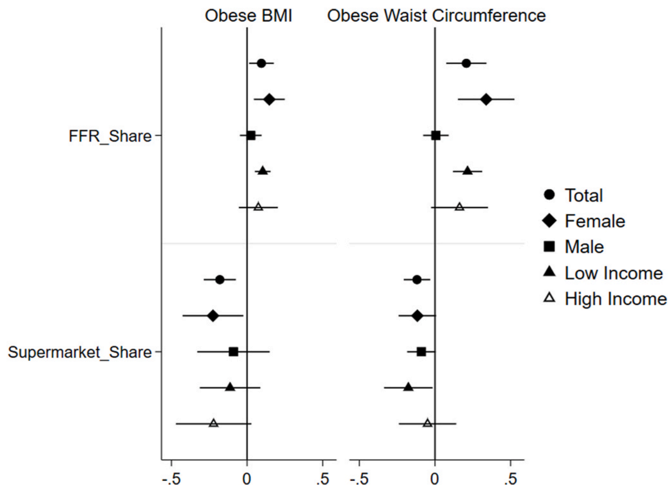

Fig. 2. Average marginal effects for the association between density of food outlets and obesity as measured by BMI (left side) and waist circumference (right side)

Note: Results represent average marginal effects and 95% CI from logistic regression. Obese BMI was determined as BMI≥30. Obese Waist Circumference was determined as waist circumference ≥102 cm for males, and ≥88 cm for female). For all regressions in Fig. 2 we controlled for: demographic characteristics (sex, age, country, marital status, religion), socio-economic status (paid employment, school years, income, household composition), health status measured (e.g. self-assessed health), healthcare utilization (e.g. whether participants received doctor's advice to either reduce fat or sugar beverages consumption, or to increase daily intake of FV, or to lose weight, or to do more physical activity), physical activity habits (e.g. minutes per week of vigorous or moderate physical activity spent at work, home or recreational facilities, walking or cycling as a mode of transportation), and for site specific time invariant characteristics. In the stratified regressions (by sex and income) we controlled for the same variables except for the one used to define the strata.

= 0•0004, and low-income, AME:0•22; 95% CI: 0•12,0•31; p < 0•0001). Results remain qualitatively similar when South Asian obesity thresholds were considered (full set of results in Appendix 3).

In all specifications we control for a range of confounders described in the Methods section and for site fixed effects.

4. Discussion

We measured the association between the availability of healthy and unhealthy food outlets on adults' body size and the probability of obesity, as well as the heterogeneity of such effects by sex and income in Bangladesh and Sri Lanka. We provide evidence from a unique dataset that merged individual-level surveillance data with individual exposure to healthy and unhealthy food environments.

We show that the food environment in Bangladesh and Sri Lanka is associated with body size and obesity. A higher availability of fast-food restaurants near the individual's home was associated with higher BMI, waist circumference, and significantly greater likelihood of obesity. In contrast, higher availability of supermarkets near an individual's home was significantly associated with decreased BMI, waist circumference, and the probability of obesity. Whilst these results are consistent with patterns observed in some of the previous literature in high-income countries (Cobb et al., 2015), they contrast with other findings reporting that supermarkets in Guatemala, Kenya, and Zambia increase BMI and the probability of obesity (Asfaw, 2008; Demmler et al., 2017; Khonje et al., 2020; Kimenju et al., 2015). This inconsistency could be due to differences in research design, with most examining the effect of buying in the nearest supermarket to home and not comprehensively measuring exposure to healthy and unhealthy food environments around an individual's home. Furthermore, most of the literature is from Kenya, Zambia, and Guatemala rather than South Asian countries, implying that existing evidence may not be generalizable to varied settings.

Although, the availability of fast-food restaurants and supermarkets within a 300 m buffer plays an important role in body size and obesity, our results suggest that these tend to mostly impact females and low-income individuals. While we show these groups also benefit from the availability of healthy foods in their food environments, the effect of the density of unhealthy foods in fast-food restaurants was higher in magnitude, implying that overall, food environments are associated with increased weight and obesity for these groups. These findings are consistent with previous literature showing obesity rates in Bangladesh and Sri Lanka to be substantially higher among females in comparison to males (Morita et al., 2006). Overweight and obesity among men and women varies greatly within and between countries, and globally, more women are obese than men. These sex inequalities are more salient among women in developing countries due to a myriad of sociocultural dynamics which exacerbate sex disparities in excess weight gain (Morita et al., 2006). For example, in some countries, cultural values favour larger body size among women or men as a sign of fertility, healthfulness, or prosperity. In addition, the biological factor of menopause affects fat distribution and may, therefore, convey a higher risk of obesity in women than men (Morita et al., 2006), an important consideration given that the average age of women in the sample is 44,5 years.

Further, previous literature indicates that in low-income countries, the affluent and educated groups were more vulnerable to obesity (Swinburn et al., 2011). Although in our sample the proportion of obesity was higher among those with high-income in comparison to low-income, we show the availability of fast-food restaurants was significantly associated with higher probability of obesity among low-income individuals and not with high-income individuals, even when controlling for education. This finding is consistent with evidence in high income countries showing that the availability of fast-food restaurants affects mainly females and low-income households (Atanasova et al., 2022). Further, this finding is consistent with trends observed in LMICs, where the prevalence of obesity shifts to low SES groups as the country's GDP increases, with this shift of obesity occurring first among women (Templin et al., 2019). This could be the case, especially in Bangladesh, which has experienced substantial economic growth and a reduction in poverty rates achieving LMIC status (from low-income status) in 2015 (World Bank, 2021). To our knowledge this is a novel finding since such shifting trends in obesity have not been observed before in either Sri Lanka or Bangladesh suggesting further research is needed to examine the socio-economic transitions and their effect on obesity in these countries.

5. Policy implications

Our findings have important policy implications. We show exposure to obesogenic food environments is detrimental to body size and obesity, important risk factors of type-2 diabetes mellitus and cardiovascular diseases, the two major public health concerns in the assessed countries (Ghaffar et al., 2004). To attain the WHO target to halt the rise in diabetes and obesity prevalence by 2025 in these countries, it is thus important to implement comprehensive policies targeting food environments with the potential of shaping individuals' nutrition (WHO, 2014). A recent study examining the implementation of international best practices targeting food environment to promote better nutrition, indicated that almost none of the recommended policies were implemented in Bangladesh and Sri Lanka (Pineda et al., 2022). For instance, food retail policies (e.g. zoning laws to encourage the availability of outlets selling fresh fruit and vegetables and to place limits on density or placement of outlets selling mainly unhealthy fast foods) for the regulation of obesogenic food environments have not been launched in these countries. Both countries implemented dietary guidelines and programmes focused on the provision of food to vulnerable populations to target the prevention of starvation and food insecurity rather than the

Table 3
Average Marginal Effects on the associations between food outlets density and obesity using BMI (panel A) and waist circumference (panel B).

VARIABLES	Total	Male	Female	Low income	High income	Sri Lanka	Bangladesh
(A) Obese BMI (BMI≥30 kg/m^2) Marginal Effects							
Supermarket Share	−0•18**(-0•29, −0•07)	−0•09 (−0•33, 0•15)	−0•23* (−0•43, −0•02)	−0•11 (−0•31, 0•09)	−0•22 (−0•47, 0•03)	−0•29**(-0•45, −0•14)	0•07 (-0•06, 0•19)
FFR Share	0•09* (0•01, 0•18)	0•02 (−0•05, 0•10)	0•15** (0•05, 0•25)	0•10** (0•05, 0•16)	0•07 (−0•05, 0•20)	−0•02 (−0•17, 0•12)	0.12**(0•05, 0•19)
Corner Store Share	−0•00 (−0•02, 0•02)	0•00 (−0•01, 0•02)	−0•00 (−0•03, 0•02)	0•01 (−0•02, 0•04)	−0•02 (−0•05, 0•02)	−0•02 (-0•05, 0•02)	−0•00 (-0•02, 0•02)
Stationary Cart Share	−0•03 (−0•05, 0•00)	−0•01 (−0•04, 0•02)	−0•03 (−0•08, 0•01)	0•02 (−0•02, 0•05)	−0•09** (−0•13, −0•04)	−0•06 (-0•16, 0•04)	−0•01 (-0•03, 0•01)
Mobile Cart Share	0•03 (−0•05, 0•11)	0•03 (−0•03, 0•09)	0•04 (−0•09, 0•17)	0•07 (−0•02, 0•15)	−0•00 (−0•12, 0•11)	0•16 (−0•08, 0•40)	−0•00 (-0•07, 0•06)
Observations	11,967	4670	7132	5976	5982	3496	8471
Controls	YES	YES	YES	YES	YES	YES	YES
Site FE	YES	YES	YES	YES	YES	YES	YES
(B) Obese WC (WC ≥ 102 cm in men, ≥88 cm in females) Marginal Effects							
Supermarket Share	−0•12** (−0•21, −0•03)	−0•09 (−0•18, 0•00)	−0•12 (−0•24, 0•01)	−0•18* (−0•34, −0•02)	−0•05 (−0•24, 0•14)	−0•13 (-0•28, 0•03)	−0•14**(-0•18, −0•10)
FFR Share	0•21** (0•08, 0•34)	0•01 (−0•08, 0•09)	0•34** (0•15, 0•53)	0•22** (0•12, 0•31)	0•16 (−0•03, 0•35)	0•09 (-0•16, 0•33)	0•22**(0•08, 0•36)
Corner Store Share	−0•01 (−0•04, 0•03)	−0•01 (−0•03, 0•01)	−0•01 (−0•06, 0•04)	0•01 (-0•03, 0•05)	−0•04 (−0•08, 0•01)	−0•03 (-0•07, 0•01)	−0•01 (-0•05, 0•03)
Stationary Cart Share	−0•04 (−0•09, 0•01)	−0•03 (−0•06, 0•00)	−0•05 (−0•12, 0•02)	−0•01 (−0•07, 0•05)	−0•07** (−0•11, −0•03)	−0•04 (-0•17, 0•09)	−0•03 (-0•08, 0•01)
Mobile Cart Share	0•11 (−0•02, 0•23)	0•06 (−0•01, 0•13)	0•14 (−0•05, 0•32)	0•21** (0•11, 0•32)	−0•03 (−0•26, 0•20)	0•26 (-0•19 - 0•71)	0•06 (-0•06, 0•17)
Observations	12,032	4620	7185	6014	6008	3543	8489
Controls	YES	YES	YES	YES	YES	YES	YES
Site FE	YES	YES	YES	YES	YES	YES	YES

Results represent average marginal effects. 95% CI in brackets. **p < 0•01, *p < 0•05. "Outlets Share" is defined as the number of each outlet out of the total number of outlets. For example, supermarket share is defined as the number of supermarkets within a 300 m buffer around a partcipant's home address out of all food outlets within a 300 m buffer. For all regressions in Table 3 controls included: demographic characteristics (gender, age, country, marital status, religion), socio-economic status (paid employment, school years, income, household composition), health status measured (e.g. self-assessed health), healthcare utilization (e.g. whether participants received doctor's advice to either reduce fat or sugar beverages consumption, or to increase daily intake of FV, or to lose weight, or to do more physical activity), and physical activity habits (e.g. minutes per week of vigorous or moderate physical activity spent at work, home or recreational facilities, walking or cycling as a mode of transportation). Site FE stands for Site Fixed Effects, where in all regressions we controlled for site specific time invariant characteristics. In the stratified regressions (by sex and income) we controlled for the same variables except for the one used to define the strata.

prevention of obesity and the creation of healthy food environments (Pineda et al., 2022). Notably, our results suggest that the heterogeneity of effects depends on the element of the environment as well as individual characteristics. These findings are aligned with previous evidence indicating that, while food environments may influence diets and obesity, one size fits-all built environment interventions have not led to improved health outcomes (Atanasova et al., 2022; Freedman et al., 2021). Future research ought to determine which specific elements of the food environment could lead to improved outcomes in this geographical region and population.

Furthermore, our results indicate that income plays a role on the association between the food environment and obesity. This implies the importance of upstream approaches that target socio economic inequalities in preventing obesity. For example, low-income populations may have reduced economic power to acquire healthy foods and poorer nutritional literacy leading to poorer diets regardless of what is on offer in the environment (Farrell et al., 2018). They may also have reduced access to healthy food offerings due to mobility or time constraints. Therefore, in addition to the availability of food outlets that facilitate unhealthy food choices, relative prices and the absence of fiscal policies and regulations on accessibility to healthy food outlets and healthy foods may influence more disproportionately those in lower-income groups. As such upstream policies guided by a 'health in all policies' approach that explicitly target the key social, economic, and structural determinants of health and behaviours is essential to prevent obesity (Swinburn et al., 2013). Examples of key complementary policies include subsidies for healthy foods, improving nutritional literacy, regulation of advertising of unhealthy food, better urban planning and subsidized transport that facilitate access to healthy foods and encourage physical activity (Swinburn et al., 2013). Therefore, our findings highlight the need for further developing and implementing policies targeting food environments in these countries.

6. Limitations

Our study has several limitations. First, we captured only part of the environment with the 300 m buffer. Even though this is commonly used in the literature to examine built environment and health behavior/outcomes, the approach implies that we may imperfectly capture exposure to obesogenic food environments (Duncan et al., 2014). Second, we measured food environments using residency geolocation, however participants may consume their meals far from home. Third, data on individual shopping and consumption patterns were not available, which could be important to further identify the heterogeneity of the observed effects. Fourth, we categorized the extent to which food environments are healthy and unhealthy based on the international classification in the absence of a classification for South Asian countries. Since we did not observe food sold in these food outlets and lacked consumption data, the magnitude of the effects may reflect the mix of healthy and unhealthy foods available in these outlets in particular supermarkets. The findings confirm that, for the assessed countries, fast food restaurants and supermarkets can be classified as, respectively, unhealthy and healthy as in high income countries (Babey et al., 2008). While for the remainder of the outlets, namely stationary and mobile carts, and corner stores we cannot conclude based on our results whether they are healthy or unhealthy.

Although BMI has been used as a proxy for obesity for many years, evidence in South Asian populations suggests that BMI is an imperfect predictor of cardiovascular diseases and total mortality (Gajalakshmi et al., 2018), and that waist circumference has been found to be a better proxy of obesity (WHO, 2008). Therefore, we used waist circumference for sensitivity analyses and our results remain qualitatively the same.

In addition, our findings and their policy implications are not generalizable to pregnant women or populations that suffer from serious illness. Another potential limitation of this study is the absence of genetic data which could have been a potential confounder in our statistical models. Considering that obesity results from a complex interaction between genetic susceptibility and exposure to an environment that encourages energy-dense food overconsumption, inclusion of genetic data could provide clearer evidence for the development of policies and regulations of the wider food environment which may offset obesity risk both for individuals at high genetic susceptibility to obesity and for those living in deprivation (Jackson et al., 2020).

Lastly, while our analyses unpack important associations between food environments and obesity, the cross-sectional nature of our data prevented us from inferring causal associations between the environment, BMI, and waist circumference. Individuals with higher BMIs may select (or be forced to select) into neighbourhoods with unhealthy food access. Thus, there could be unobserved factors associated with both the individual area of residence and the location of food outlets that may confound our estimates (Handy et al., 2006).

Despite these caveats, our study provides novel evidence on the association between food environment and obesity as well as its unequal effect by sex and income.

Declaration of interests

No competing interest to declare.

Ethics approval

The South Asia Biobank is conducted in accordance with the recommendations for physicians involved in research on human subjects, adopted by the 18th World Medical Assembly, Helsinki, 1964, and later revisions. Research approval was obtained from the Imperial College London Research Ethics Committee (reference: 18IC4698) and local institutional review boards in each of the participating countries.

Contributions

MM, FS, GF, AK conceptualized the research question and analyses. JCC, PK, MKM, SJ, RMA, KIK conceived the SAB study and data collection. AK, DK, MM conceptualized the environmental mapping and AK coordinated the data collection. BK, VR, DJ, SI, LDS, MMH, AAMH, MH, PA, DK, EP collected and cleaned the data. PA, DK, EP, MM conducted data analyses. PA, DK, EP, MM drafted and JCC, FS, GF provided inputs to the manuscript. All authors approved the final version of the manuscript.

Data sharing

The surveillance and the environmental data are available to all researchers upon request. Requests to the surveillance data should be made via email to the study Steering Committee (john.chambers@imperial.ac.uk) and for the environmental data to the corresponding author (m.miraldo@imperial.ac.uk).

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2022.101055.

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