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Association Between Food Outlet Density and Overweight/Obesity Among Adults in Delhi, India

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B.S.
Elon University
2014

Thesis Committee Chair: Dana Barr, PhD

An abstract of
A thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University
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Abstract

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Background/Objectives: The food environment has been implicated as an underlying contributor to the global obesity epidemic. However, few studies have evaluated the relationship between the food environment and overweight/obesity in low- and middle-income countries (LMICs). The aim of this study was to assess the association of food outlet density with overweight/obesity in Delhi, India.

Subjects/Methods: Data are from a cross-sectional, population-based study conducted in Delhi (2010-11). Participants were randomly sampled from 134 census enumeration blocks (CEBs) (n=5,364). GIS data were available for 131 CEBs (n=5,264). The number of food outlets (full service and fast food restaurants) within a 1-km buffer of CEBs was recorded by trained staff, and participants were assigned to tertiles of food outlet density based on their resident CEB. Height and weight were measured using standardized procedures and overweight/obesity was defined as a BMI ≥25 kg/m^2.

Results: The most common food outlets were Indian savory restaurants (57%), Indian sweet shops (25%), and pizza shops (7.7%). Only 5.0% of outlets were Western franchises (e.g., KFC, McDonald’s, and Subway). In unadjusted logistic regression models, participants in the highest versus lowest tertile of food outlet density were significantly more likely to be overweight/obese: OR (95% CI), 1.44 (1.24, 1.67). After adjustment for age, household income, and education, the effect was attenuated: 1.08 (0.92, 1.26). Results were consistent with further adjustment for tobacco and alcohol use, moderate physical activity, and owning a bicycle, motorized bike, or car.

Conclusions: Most food outlets were Indian, suggesting that the nutrition transition in this megacity may be better characterized by increases in unhealthy Indian food rather than Western food. Increased food outlet density in the residence area of adults in Delhi, India, is positively associated with overweight/obesity. This association was largely explained by socioeconomic status. Further research is needed that explores these associations in other LMICs.

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Introduction

Cardiovascular diseases (CVD) account for one-fourth of deaths in India [1] and CVD and diabetes are predicted to cost India $2.32 trillion USD from 2012-2030 [2]. Tobacco use, unhealthy diets, sedentary lifestyles, and overweight/obesity are among the leading risk factors for CVD worldwide and are becoming increasingly common in India [3]. Interventions and policies for prevention of these CVD risk factors are urgently needed.

One target for preventive efforts has been the food environment, defined as the physical presence of food and food stores that affects people's diet [4]. Previous studies have documented the nutrition transition in urban India, characterized by increased consumption of dairy products and decreased consumption of cereals and vegetables [5, 6]. However, no study has evaluated the impact of the food environment on dietary intake or overweight/obesity in urban India. Previous research has focused on self-reported fast food consumption among urban Indian school children and risk of overweight/obesity [7-9]. One cross-sectional study conducted in the relatively small northern Indian city of Aligarh found that children who consumed fast food ≥1 time/week were more likely to be overweight/obese [7]. In contrast, a cross-sectional study in the megacity of Delhi in northern India found that fast food consumption >3 times/week was negatively associated with body mass index (BMI) among adolescents [9]. Similarly, a cross-sectional study in the city of Chennai in southern India found that adolescents who consumed fast food 4-7 times/week were less likely to be overweight/obese compared to those who consumed fast food ≤3 times/week [8]. The authors hypothesized that the reason for these counterintuitive observations is reverse causality: overweight/obese adolescents are modifying their dietary behaviors in order to lose weight [8, 9].

Most of the research on food environment (in contrast to food consumption) and overweight/obesity has been conducted in the United States (U.S.) and other high-income countries. Two studies conducted in New York City categorized food outlets as body mass index BMI-healthy, BMI-intermediate, and BMI-unhealthy [10, 11]. One found a positive association between the proportion of BMI-unhealthy food outlets and BMI [10]. The other, which incorporated walkability into its categorization, found an inverse association between BMI-healthy food outlets and BMI and odds of obesity, but no association with BMI-unhealthy food outlets [11].

A study conducted in California observed a positive association between Retail Food Environment Index (RFEI)—the proportion of fast food restaurants and convenience stores in relation to grocery stores and produce vendors—and BMI [12]. Adults living in high RFEI (≥5.0) areas had a higher prevalence of obesity and diabetes compared to adults living in low RFEI (≤3.0) areas [12]. A study conducted in Canada found similar results: adults living in high RFEI (≥5.0) areas had greater odds of being obese compared to adults living in low RFEI (≤3.0) areas [13]. Two recent systematic reviews of studies of the food environment and obesity in the U.S. and Canada concluded that while some direct association may exist between fast food availability and obesity, results are largely inconsistent across studies and most studies are of poor quality [14, 15]. One of these reviews found that 42% of studies had at least one significant association, but 58% found none [15].

Results of studies evaluating the association between the food environment and overweight/obesity in LMICs have been mixed. In China, two cross-sectional studies reported a positive association between food retail environment (retail businesses including supermarkets) [16] and fast food [17] with BMI. Similarly, a prospective study in China found a positive association between changes in the number of Western fast food restaurants and waist-to-height ratio for men and women and waist-to-hip ratio for women in rural areas, but not with BMI in rural areas, and a negative association with BMI in urban women [18]. Two studies, one in Japan and the other in South Korea, reported a positive association between number of supermarkets and BMI and supermarket density and obesity, respectively [19, 20]. Another study on school children in Taiwan found fast food store density was associated with weight and BMI in boys, but not in girls and no association was found with waist circumference or triceps skinfold thickness in boys or girls [21]. Other studies among adolescents in Xi'an, China [22], Brazil [23]. Similarly, a study in Japan found no association between number of restaurants within a 0.5 mile radius of participants' residence and BMI [24].

The outcomes of these studies may not be directly applicable to urban India, especially those conducted in the U.S. and Canada, because of differences in climate, walkability, and access to food outlets and transportation. The aim of this study was to evaluate the relationship between food environment assessed using hand-held global positioning system (GPS) devices and (1) dietary intake and (2) overweight/obesity (BMI ≥ 25 kg/m^2) in a representative sample of Delhi, India.

Methods

Sample population

Data are from the Centre for Cardiometabolic Risk Reduction in South-Asia (CARRS) cross-sectional survey [25]. CARRS collected baseline data in 2010-2011 from three cities in South Asia: Delhi and Chennai in India, and Karachi in Pakistan. CARRS used a multistage probability sampling to select representative samples of the target populations. The response rate was 94.7% for questionnaire completion. This analysis included only participants from Delhi.

Delhi is the capital city of India and had a total population of 16.8 million in 2011, with a population density of 11,320 people per km^2. The city is divided into nine districts of varying sizes and population, and each district (except New Delhi) is divided into three subdivisions. Subdivisions are further divided into urban and rural areas, and urban areas are further divided into wards and wards into census enumeration blocks (CEBs). The areas covered in CARRS are under the purview of the Municipal Corporation of Delhi. Three districts (New Delhi, North, and South West districts) were excluded from CARRS. New Delhi and North Districts are primarily commercial areas and the South West district comprises defense personnel, marshy agricultural area, and expatriates who were likely to leave the country during the study period. CARRS did not include rural areas. A total of 134 randomly selected CEBs were sampled in CARRS.

Outcome assessment

Trained study staff used standardized procedures to measure weight and height. BMI was calculated as weight (kg) divided by height-squared (m^2). Obesity including overweight was defined as BMI ≥25 kg/m^2 [26]. The South Asian cut-point for overweight/obese of BMI ≥23 kg/m^2 was also evaluated [27]. Missing weight data (33.7%) were imputed using the multiple imputation chained equation approach (MICE) in Stata v12.0 (StataCorp LP, College Station, TX).

Food environment assessment

Food environment was defined as the number of food outlets, including fast food and full service restaurants, in a participant's residential neighborhood (e.g., CEB). Participant household locations were geocoded using hand-held GPS devices and validated by overlaying household addresses collected during the survey on satellite data using Google Earth. The outermost houses within a CEB were bound within a polygon. A 1-km buffer ring around the polygon was defined as the unit for analysis of all neighborhood environment characteristics [28]. The number of food outlets within a 1-km buffer of the CEB was recorded for each CEB by trained study staff. They recorded information about the facilities and captured GPS coordinates, such as household location, roads, open spaces, parks, health facilities, food outlets, transportation, alcohol outlets, water bodies, and schools/nurseries. To account for variation in CEB size (range of 3.2 to 4.2 km^2, mean ± SD of 3.5 ± 0.16), the number of food outlets in each CEB was divided by the size of the CEB in km-squared, thus the exposure variable included in the models was food outlet density (number of food outlets per km^2). Food outlet density was specified as tertiles in the models to account for the non-normal distribution. In order to visualize the association between food outlets and BMI, we overlaid a heat map of BMI levels with the GPS coordinates of the food outlets using ArcGIS (Environmental Systems Research Institute, Redlands, CA).

Covariate assessment

Socio-demographic information was collected by trained interviewers using surveys, and included age, sex, marital status (unmarried or married), educational status (up to primary school; high school up to secondary school; or graduate level or higher), employment status (not working, which includes students, housewives, retired; unskilled/semi-skilled; trained/skilled; white collar), and household income (<10,000 INR; 10,001-20,000 INR; or >20,000 INR). Additional socio-demographic and lifestyle behavior variables included car ownership (yes or no), motorized bike ownership (yes or no), bicycle ownership (yes or no), vegetarian diet (yes or no), and level of moderate physical activity (none; <150 minutes/week; or ≥150 minutes/week). Dietary intake was evaluated using a 26-item food propensity questionnaire [29] and frequency of consumption of food groups was categorized as never or <1 time/month, ≥1 time/month but <1 time/week, ≥1 time/week but <1 time/day, and ≥1 time/day.

Statistical analysis

All analyses were conducted in SAS version 9.4 (SAS Institute Inc., Cary, NC). SAS PROC MIANALYZE was used to calculate the average of the 10 complete-data estimates from the multiple imputations. The association between food outlet density and overweight/obesity was estimated using logistic regression. Linear regression was used to estimate the association between food outlet density and BMI. Covariates that were significantly associated with food outlet density and also risk factors for overweight/obesity were included in adjusted models. Four models were estimated: model 1 was unadjusted; model 2 was adjusted for age, household income, and education; model 3 was adjusted for the variables in model 2 plus tobacco and alcohol use; and model 4 was adjusted for the variables in model 3 plus level of moderate physical activity and ownership of a bicycle, car, or motorized bike.

Results

A total of n=5,364 adults in 134 CEBs participated in CARRS at the Delhi site. Three CEBs did not have GIS data, and therefore participants from those CEBs (n=100) were not included in this analysis. The final sample size was n=5,264. The number of food outlets in the CEBs ranged from 1 to 46, mean ± SD of 11 ± 10 food outlets. **Figure 1** provides the distribution of BMI and food outlets in urban Delhi. The most common food outlets were Indian sweet shops (e.g., Aggarwal and Bikaner Sweets) and savory shops (e.g., Apni Rasoi restaurant and Moti Mahal restaurant): 25% Indian sweet shops, 57% Indian savory food, 1.6% Western coffee shops, 7.7% pizza places, 5% other Western fast food outlets (such as KFC, McDonald's, and Subway), and 2.5% Chinese/Eastern food outlets. The mean ± SD (range) food outlet density for tertile 1 was 0.97 ± 0.53 (0.28 to 1.69) food outlets per km^2; for tertile 2 was 2.24 ± 0.38 (1.69 to 3.13) food outlets per km^2; and for tertile 3 was 6.18 ± 2.78 (3.17 to 13.43) food outlets per km^2.

All socio-demographic characteristics, except for sex, were significantly associated with food outlet density (**Table 1**). Participants in the highest versus lowest tertile of food outlet density were older and more likely to have a household income >20,000 INR, a white collar employment, graduate level or higher education, never used tobacco, and own a motorized bike or car.

All dietary intake variables, except fried foods, were significantly associated with food outlet density (**Table 2**). Participants in the highest versus lowest tertile of food outlet density were more likely to report consuming milk and milk products, nuts, legumes, fruit, vegetables, whole grains, desserts, and fruit juice at least once per day, and fish and shellfish never or less than once a month. Participants in the second tertile of food outlet density were least likely to report consuming refined cereals and fruit juice at least once per day. Participants in the second tertiles of food outlet density were most likely to report consuming meat and eggs at least once per day.

In the unadjusted logistic regression model, participants in the second and third tertiles of food outlet density had significantly higher odds of overweight/obesity compared to participants in the first tertile for both BMI cut-points ($\geq$25 kg/m^2 and $\geq$23 kg/m^2): OR (95% CI), 1.44 (1.24, 1.67) and 1.58 (1.35, 1.84), respectively (**Table 3**). After adjustment for age, household income, and education, the results were attenuated: OR (95% CI), 1.05 (0.90, 1.22) and 1.11 (0.95, 1.30), for BMI cut-points of ($\geq$25 kg/m^2 and $\geq$23 kg/m^2), respectively. Further adjustment for tobacco and alcohol use, owning a bicycle, car, or motorized bike, and moderate physical activity did not substantially impact effect estimates. When the outcome of BMI was modeled continuously, being in the highest versus lowest tertile of food outlet density was associated with a 1.1 kg/m^2 increase in BMI ($p<0.0001$). However, consistent with the models in which BMI was modeled as a binary outcome, further adjustment for age, household income, and education attenuated the effect: beta (SE), 0.2 (0.18), $p=0.18$.

Discussion

The results from this study demonstrate the relationship between food outlet density and overweight/obesity in Delhi, India. After adjustment for age and socio-economic factors, no significant association was observed between food outlet density and overweight/obesity or BMI. Participants living in areas with the highest food outlet density had higher household incomes and education, were more likely to have white collar employment, and more likely to own a car or motorized bike. These data therefore support that more affluent neighborhoods in urban megacities in developing countries are more likely to be undergoing the nutrition transition. More research is needed to improve our understanding of the food environment in urban areas of rapidly developing economies such as India.

As food outlet density increased, the consumption of milk and milk products and vegetables increased. This is in contrast to what would have been expected based on what has been observed in previous research on the nutrition transition in India [5, 6]. It was expected that areas with higher full-service and fast food restaurant densities, potential markers of the nutrition transition, would have the greatest consumption of milk and milk products and lowest consumption of vegetables. Consumption of desserts at least once a day also increased with increasing food outlet density. The data showed a large proportion of sweet and savory shops were Indian. A study conducted in three different cities across India suggested that participants preferred Indian sweets over Western sweets [30].

Many of the food outlets included in this dataset were Indian fast food, with few Western fast food outlets. A study done in north India asked participants about their perceptions of fast food [31]. Chain restaurants were more likely to be considered fast food outlets by those from high-income neighborhoods [31]. Participants from low-income neighborhoods considered street vendors as fast food outlets [31]. 35% of individuals from high-income and 50% of individuals from low-income neighborhoods reported not eating at Western-style fast food restaurants [31]. Furthermore, the majority of individuals from both high- and low-income neighborhoods reported they prefer and consider home cooked food to be healthier [31]. It seems that both Indian and Western food outlets are contributing towards the nutrition transition from home-cooked meals to meals consumed away-from-home in India.

A key finding of this study was the attenuation of the positive association between food outlet density and overweight/obesity after adjustment for socio-economic factors such as household income and education. Several studies assessing food environment and BMI in LMICs also demonstrated no significant association after adjustment for socio-economic status [20, 21, 23, 24]. A study in Mexico observed that food access was not as important as the large number of unhealthy food options and high price of foods [32]. Longitudinal studies in larger, representative cohorts are needed to further disentangle the effects of the food environment on weight status.

Past research has shown that varying nutrition and socioeconomic status across states in India have differing implications for disease risk [30, 33]. A previous study on dietary patterns in Delhi, Mumbai, and Trivandrum found differences in the types of cereals and protein consumed by participants in north and south regions [30]. Delhi participants' dietary patterns indicated a wider variety of foods available to, compared to Mumbai and Trivandrum [30]. The three-city study found fruit and dairy consumption was associated with abdominal adiposity and hypertension in Delhi, while fruit pattern was inversely associated with hypertension in Mumbai [30]. The results from this study showed that fruit and dairy intake was highest in the third food outlet density tertile compared to the first tertile. Several of the foods that were reported to be consumed at least once a day were highest in the third tertile, and the never or less than once a month were lowest in the third tertile. This supports findings from the three-city study regarding the wider variety of foods available in Delhi. The higher fruit and dairy intake in the third food outlet density tertile may indicate a greater access or availability of these products due to the food environment in these areas.

There were several limitations of this study. Street food is a very common food outlet for people in urban India [34, 35], but no data on these facilities were collected in CARRS due to an inability to efficiently record the number of street food vendors that exist in an area since this varies day-to-day. Several of the other studies done in other LMIC's have mentioned the need for data on street foods to appropriately capture how food environment relates to overweight/obesity because otherwise the food outlets captured are mainly capturing the relationship for high-income areas [21, 23]. Furthermore, information on grocery stores and markets was not collected, which could have served as a useful comparison in the evaluation of food environment and overweight/obesity. This study may not be representative of other regions in India due to varying dietary patterns, built environment, and access to various foods across the region. Finally, we did not have information on fast food consumption or frequency of eating meals away from home. This information would provide further insight on the influence of food environment on diet [18]. In Brazil, frequency of purchasing fruits and vegetables, means of transportation to obtain groceries, and perception of local food environment were identified as significantly associated with acquisition of minimally and ultra-processed food products [36]. These are important factors that may also play a role in the relationship between food outlet density and overweight/obesity in Delhi and valuable aspects to consider in future research.

Most food outlets were Indian, suggesting that the nutrition transition in this megacity may be better characterized by increases in unhealthy Indian food rather than Western food. Increased food outlet density in the residence area of adults in Delhi, India, is positively associated with overweight/obesity. This association was largely explained by socioeconomic status. Further research is needed that explores these associations in other LMICs and across different regions across India to capture urban and rural food environments and BMI to observe how they differ. Evaluating and identifying the diverse food outlets and stores could also help gain a better sense of how food environment affects BMI.

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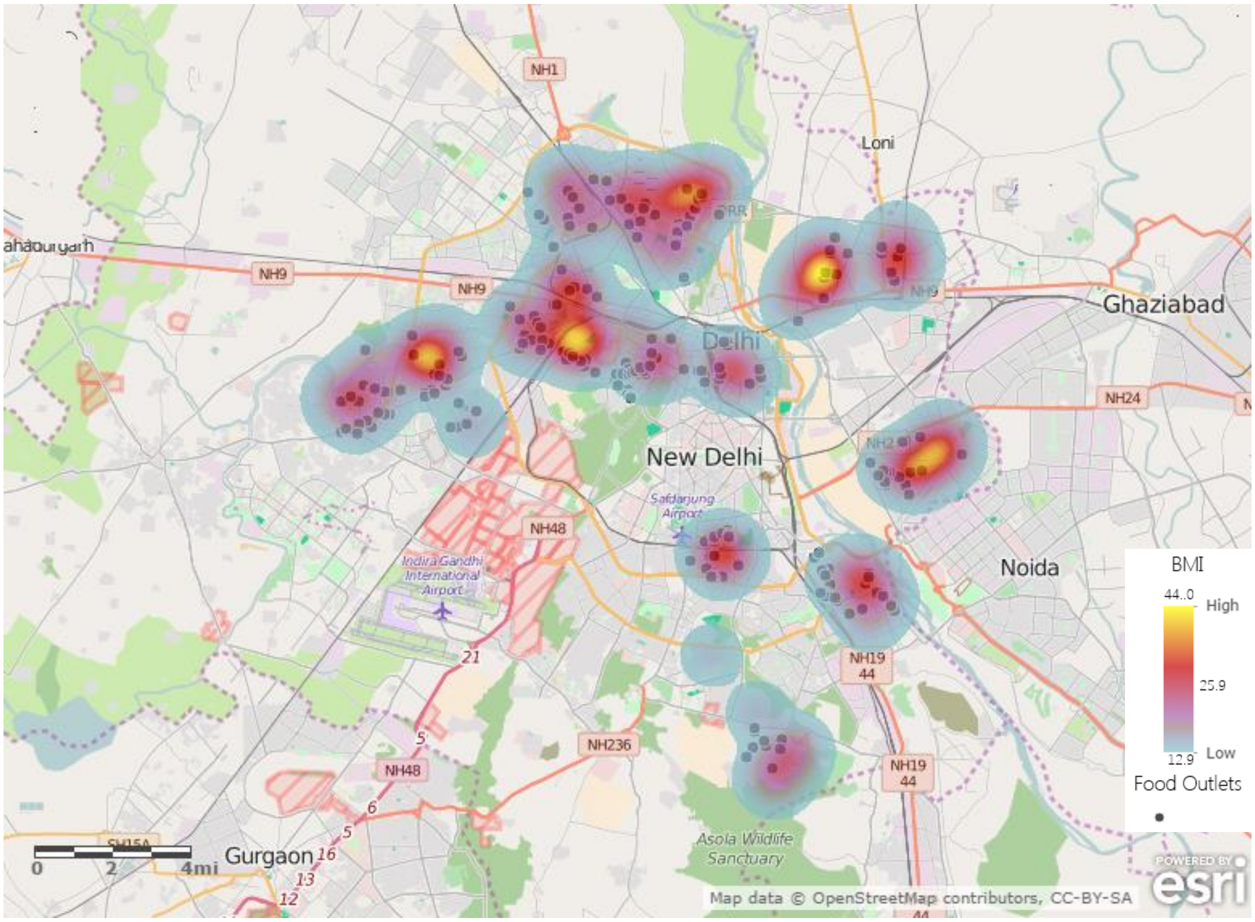

Figure 1. Distribution of body mass index (BMI) and food outlets in Delhi, India.

Table 1. Socio-demographic characteristics of participants according to food outlet density (n=5264).

	Food Outlet Density (tertiles)			
	1 (n=1737)	2 (n=1782)	3 (n=1745)	P-value[1]
Age (years)	43.7 (12.8)	44.1 (13.7)	45.6 (13.8)	<0.0001
Sex				0.97
Male	50.0 (869)	50.2 (894)	49.7 (868)	
Female	50.0 (868)	49.8 (888)	50.3 (877)	
Marital Status				0.009
Unmarried	10.1 (175)	10.4 (186)	13.1 (228)	
Married	89.9 (1562)	89.6 (1596)	86.9 (1517)	
Household Income				<0.0001
<10,000	57.3 (989)	56.9 (1008)	32.7 (566)	
10,001-20,000	20.5 (354)	20.4 (362)	26.5 (459)	
>20,000	22.1 (382)	22.7 (402)	40.8 (706)	
Employment Status				<0.0001
Not working	51.2 (889)	52.1 (928)	50.8 (887)	
Unskilled/semi-skilled	19.0 (330)	20.6 (367)	14.7 (257)	
Skilled/trained	24.8 (430)	24.2 (432)	25.6 (447)	
White collar	5.1 (88)	3.1 (55)	8.8 (154)	
Education				<0.0001
Up to Primary School	24.5 (425)	25.9 (461)	13.7 (239)	
High School up to Secondary School	53.3 (926)	54.0 (962)	53.1 (926)	
Graduate Level or Higher	22.2 (386)	20.2 (359)	33.2 (580)	
Tobacco use				0.0003
Never used	71.9 (1249)	73.5 (1310)	77.6 (1354)	
Used in past (but not currently)	1.8 (32)	2.2 (39)	2.5 (43)	
Currently using	26.3 (456)	24.3 (433)	19.9 (348)	

Table 1
Continued.

	Food Outlet Density (tertiles)			
	1 (n=1737)	2 (n=1782)	3 (n=1745)	P-value[1]
Alcohol use				0.0006
Never used	82.7 (1437)	85.1 (1517)	79.5 (1388)	
Used in past or currently use occasionally	12.8 (222)	11.3 (201)	15.0 (261)	
Currently using	4.5. (78)	3.6 (64)	5.5 (96)	
Motorized Bike				<0.0001
Yes	46.0 (799)	46.2 (822)	58.9 (1027)	
No	54.0 (937)	53.9 (959)	41.2 (718)	
Car				<0.0001
Yes	24.4 (423)	20.7 (368)	43.8 (765)	
No	75.6 (1313)	79.3 (1413)	56.2 (980)	
Bicycle				0.0006
Yes	30.2 (524)	24.5 (437)	26.3 (458)	
No	69.8 (1212)	75.5 (1344)	73.8 (1287)	
Vegetarian				<0.0001
Yes	54.5 (947)	57.7 (1029)	48.4 (845)	
No	45.5 (790)	42.3 (753)	51.6 (900)	
Moderate Physical Activity				0.006
None	55.3 (959)	59.9 (1065)	59.4 (1034)	
<150 minutes	22.7 (393)	18.0 (320)	19.1 (332)	
≥150 minutes	22.1 (383)	22.2 (394)	21.5 (375)	

Values are percent (n) or mean (SD).
[1]P-value from chi-square test.

Table 2. Dietary intake of participants according to food outlet density (n=5264).

	Food Outlet Density (tertiles)			
	1 (n=1737)	2 (n=1782)	3 (n=1745)	P-value[1]
Meat				<0.0001
Never or <1/mo	54.6 (948)	50.8 (906)	61.2 (1068)	
≥1/mo but <1/wk	19.0 (330)	20.9 (373)	20.1 (350)	
≥1/wk but <1/dy	25.3 (439)	26.6 (474)	18.1 (315)	
≥1/dy	1.2 (20)	1.6 (29)	0.7 (12)	
Poultry				<0.0001
Never or <1/mo	48.3 (839)	45.6 (813)	53.6 (936)	
≥1/mo but <1/wk	23.0 (399)	26.0 (463)	21.6 (377)	
≥1/wk but <1/dy	28.4 (493)	27.6 (491)	24.0 (418)	
≥1/dy	0.4 (6)	0.8 (15)	0.8 (14)	
Fish & shellfish				<0.0001
Never or <1/mo	69.2 (1202)	70.0 (1248)	77.3 (1348)	
≥1/mo but <1/wk	19.7 (342)	18.6 (331)	14.8 (258)	
≥1/wk but <1/dy	10.7 (186)	10.6 (189)	7.5 (130)	
≥1/dy	0.4 (7)	0.8 (14)	0.5 (9)	
Eggs				0.004
Never or <1/mo	44.7 (777)	42.5 (757)	48.5 (846)	
≥1/mo but <1/wk	15.4 (268)	17.5 (311)	15.8 (846)	
≥1/wk but <1/dy	34.5 (599)	34.3 (612)	31.9 (557)	
≥1/dy	5.4 (93)	5.7 (102)	3.8 (66)	
Milk & milk products				<0.0001
Never or <1/mo	30.8 (534)	30.6 (546)	23.2 (404)	
≥1/mo but <1/wk	9.2 (160)	8.6 (153)	8.2 (143)	
≥1/wk but <1/dy	22.4 (389)	21.6 (385)	23.7 (413)	
≥1/dy	37.7 (654)	39.2 (698)	45.0 (785)	
Nuts				<0.0001
Never or <1/mo	57.5 (998)	57.0 (1016)	50.5 (882)	
≥1/mo but <1/wk	17.9 (311)	18.7 (334)	18.2 (318)	
≥1/wk but <1/dy	17.4 (303)	16.6 (296)	20.5 (358)	
≥1/dy	7.2 (125)	7.6 (136)	10.7 (187)	
Legumes				<0.0001
Never or <1/mo	2.5 (44)	3.3 (58)	2.8 (49)	
≥1/mo but <1/wk	2.8 (49)	3.5 (62)	3.8 (66)	
≥1/wk but <1/dy	52.1 (905)	53.5 (953)	42.4 (739)	
≥1/dy	42.5 (739)	39.8 (709)	51.1 (891)	
Fruit				<0.0001
Never or <1/mo	8.0 (139)	8.4 (149)	7.1 (123)	
≥1/mo but <1/wk	12.6 (219)	15.7 (280)	9.2 (161)	
≥1/wk but <1/dy	58.0 (219)	54.9 (979)	49.2 (858)	
≥1/dy	21.4 (371)	21.0 (374)	34.6 (603)	

Table 2
Continued.

	Food Outlet Density (tertiles)			
	1 (n=1737)	2 (n=1782)	3 (n=1745)	P-value[1]
Vegetables				<0.0001
Never or <1/mo	0.5 (8)	0.2 (4)	0.6 (9)	
≥1/mo but <1/wk	0.4 (7)	0.6 (10)	0.2 (4)	
≥1/wk but <1/dy	26.9 (7)	25.1 (448)	19.7 (343)	
≥1/dy	72.3 (1255)	74.1 (1320)	79.6 (1389)	
Whole grains				0.05
Never or <1/mo	12.4 (216)	13.7 (244)	12.0 (209)	
≥1/mo but <1/wk	11.7 (204)	11.5 (204)	11.0 (191)	
≥1/wk but <1/dy	19.5 (338)	17.3 (309)	15.9 (278)	
≥1/dy	56.4 (979)	57.5 (1025)	61.2 (1067)	
Refined cereals				<0.0001
Never or <1/mo	9.3 (161)	6.9 (122)	6.9 (121)	
≥1/mo but <1/wk	9.4 (164)	8.1 (144)	5.4 (95)	
≥1/wk but <1/dy	44.8 (778)	50.6 (901)	48.1 (840)	
≥1/dy	36.5 (634)	34.5 (615)	39.5 (689)	
Desserts				<0.0001
Never or <1/mo	11.8 (205)	9.9 (177)	10.1 (177)	
≥1/mo but <1/wk	22.9 (397)	21.8 (388)	18.2 (318)	
≥1/wk but <1/dy	52.6 (913)	53.3 (949)	51.8 (903)	
≥1/dy	12.8 (222)	15.0 (268)	19.9 (347)	
Fried foods				0.39
Never or <1/mo	23.9 (415)	24.6 (438)	24.3 (424)	
≥1/mo but <1/wk	28.9 (502)	31.4 (559)	32.0 (559)	
≥1/wk but <1/dy	41.4 (719)	38.8 (691)	38.2 (666)	
≥1/dy	5.8 (101)	5.3 (94)	5.5 (96)	
Fruit juice				<0.0001
Never or <1/mo	49.7 (863)	54.4 (970)	45.6 (795)	
≥1/mo but <1/wk	19.2 (334)	18.6 (332)	19.5 (341)	
≥1/wk but <1/dy	23.6 (409)	19.8 (352)	24.7 (431)	
≥1/dy	7.5 (131)	7.2 (128)	10.2 (178)	
Cold beverages				<0.0001
Never or <1/mo	32.7 (568)	40.2 (717)	31.6 (569)	
≥1/mo but <1/wk	18.2 (316)	18.7 (333)	18.5 (323)	
≥1/wk but <1/dy	45.0 (782)	36.2 (645)	43.2 (754)	
≥1/dy	4.1 (71)	4.9 (87)	5.7 (99)	

Values are percent (n).
[1]P-value from chi-square test.

Table 3. Estimated association between food outlet density (number of outlets per km^2) and overweight/obesity among adults living in Delhi, India (n=5264).

	Food Outlet Tertile		
	1 (n=1737)	2 (n=1782)	3 (n=1745)
Overweight/obesity (BMI ≥25 kg/m^2)			
Model 1: Unadjusted	1.00 (Referent)	1.03 (0.90, 1.20)	1.44 (1.24, 1.67)
Model 2: Adjusted for age, household income, and education	1.00 (Referent)	1.05 (0.90, 1.22)	1.08 (0.92, 1.26)
Model 3: Model 2 + tobacco and alcohol use	1.00 (Referent)	1.03 (0.88, 1.20)	1.09 (0.93, 1.27)
Model 4: Model 3 + moderate physical activity and owning a bicycle, car, or motorized bike	1.00 (Referent)	1.05 (0.90, 1.23)	1.07 (0.91, 1.25)
Overweight/obesity (BMI ≥23 kg/m^2)			
Model 1: Unadjusted	1.00 (Referent)	1.09 (0.94, 1.27)	1.58 (1.35, 1.84)
Model 2: Adjusted for age, household income, and education	1.00 (Referent)	1.11 (0.95, 1.30)	1.18 (1.00, 1.39)
Model 3: Model 2 + tobacco and alcohol use	1.00 (Referent)	1.09 (0.93, 1.28)	1.18 (1.00, 1.40)
Model 4: Model 3 + moderate physical activity and owning a bicycle, car, or motorized bike	1.00 (Referent)	1.11 (0.95, 1.31)	1.16 (0.98, 1.38)

Values are odds ratios (95% confidence intervals) from logistic regression.