Area-Based Variations in Obesity Are More than a Function of the Food and Physical Activity Environment

Area-based Variations in Obesity

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ABSTRACT *This study examines the area-based variations in obesity from a community-based epidemiologic survey of Boston, MA, USA, using a geographic information system and multilevel modeling techniques. A combination of quantitative and qualitative methods was used to assess whether a function of the food and the physical activity (PA) environment can explain the body weight of residents. First, a series of multilevel analyses was conducted after accounting for the well-established individual determinants and capturing a wide range of environmental attributes to represent a more realistic portrayal of urban typology. Second, the results of multilevel analysis were framed into the theoretical model of area-based variations in obesity to qualitatively summarize the association of contextual factors with the body weight of residents. Based on the overall correlation, the area-based variations defined by a function of the food and PA environment seem to be insufficient in explaining the body weight of residents. By testing the cross-level interactions of gender and race/ethnicity with contextual factors, the results suggest that the concept of area-based variations in obesity will have to consider how residents behave differently within a given environment. More research is needed to better understand the contextual determinants of obesity so as to put forth population-wide interventions.*

KEYWORDS *Body mass index (BMI), Food environment, Obesity, Physical activity (PA) Environment, Multilevel analysis, Neighborhood characteristics*

INTRODUCTION

The obesity epidemic in the USA has been well-documented in recent reviews.^{1–3} In the USA, substantial disparities in the prevalence of obesity occur by gender, age, race/ethnicity, socioeconomic status (SES), and geographic location.^{1–6} Although “who you are” explains a lot of geographical variation in health outcomes, there is also the effect of “where you are.” For this reason, a “place” remains an important factor in addressing health outcomes. The built environment has been found to

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associate with the prevalence of obesity.^{7,8} Among the contextual factors of obesity, much of the attention has been paid to the food environment and the physical activity (PA) environment.

In principle, the food environment and the PA environment are the two main contextual determinants that directly contribute to people's energy intake and energy expenditure, respectively. Food choices and subsequent diet-related weight gain are associated with the food environment.⁹ The presence of supermarkets and convenience stores in residential neighborhoods has been found to associate with the prevalence of lower and higher rates of obesity, respectively.¹⁰ Grocery stores located at longer distances from the residential neighborhoods have been linked to an increase in the body weight of residents.¹¹ Residents who live in predominantly black neighborhoods tend to have higher exposure to fast-food restaurants, which have been found to increase the risk of obesity.¹²

On the energy expenditure side of the equation, the levels of PA and subsequent activity-related weight loss is associated with the PA environment.¹³ The important attributes of the urban environment are accessibility, opportunity, and aesthetics,¹⁴ but the mere existence of sidewalks, front porches, or small set-back distances are insufficient to encourage more walking.¹⁵ The social environment is also a contributing factor because fear of violent crimes and concern about neighborhood safety have been found to pose a barrier to exercising outdoors.¹⁶ In short, the level of PA is associated with both the social and physical characteristics of the urban environment.¹⁷

Previous studies have established a theoretical model of the food and PA environment as it relates to area-based variations in obesity. The risk of obesity is considered as a function of the food and PA environment.¹⁸ By definition, residents living in an obesogenic environment have a relatively high risk of obesity due to abundant sources of unhealthy foods and limited access to PA-related features. The obesogenic environment is linked to higher energy intake and lower energy expenditure, which leads to energy imbalance (weight gain). On the other hand, residents living in a leptogenic environment can maintain a relatively low risk of obesity because they have easier access to healthy foods and PA-related features. The leptogenic environment is linked to lower energy intake and higher energy expenditure, which leads to energy balance. In the conceptual framework of area-based variations in obesity, the leptogenic environment is the inverse of the obesogenic environment.

In addition to the food and PA environment, other attributes of the urban environment (such as density, diversity, and design) have been found to associate with the body weight of residents.^{9,10,19–22} These imply that various factors together with the food and PA environment interrelate, influence each other, and/or jointly shape the body weight of residents. In other words, the contextual determinants of obesity involve collective aspects of the urban environment. To date, previous studies have examined the food and PA environment separately, but no study has examined a combination of contextual factors together. Therefore, it is unclear whether the theoretical model of area-based variations in obesity can still be explained by a function of the food and PA environment.

In order to fill the gap, this study uses a combination of quantitative and qualitative methods to examine the area-based variations in obesity. With the use of a community-based epidemiologic survey of Boston, MA, USA, geographic information system (GIS) technology, and multilevel modeling technique, the study examined in detail the microlevel of individuals and the macrolevel of contexts simultaneously. The study also examined the disparities inherent in obesity, which has become a major public health concern in the USA.^{1–5} The results of multilevel

analysis were then framed into the theoretical model of area-based variations in obesity to assess whether a function of the food or the PA environment can explain the body weight of residents. By qualitatively summarizing the results of multilevel analysis, this study presents a different approach to understand the relationship between obesity and the urban environment.

METHODS

Individual-Level Variables

The Boston Area Community Health (BACH) survey was conducted using a two-stage stratified cluster design between 2002 and 2005 to recruit approximately equal numbers of Boston residents aged 30–79 years by gender and race/ethnicity (male and female; white, black, and Hispanic). The BACH participants were recruited across the city of Boston (Figure 1) from racially/ethnically diverse communities (Figure 2). Details of the BACH survey design and methodology have been previously published.²³

Interviewer-measured weight and height are generally more reliable than self-reported weight and height.²⁴ Therefore, based on a reliable measurement, body mass index (BMI) was calculated by the standard equation of weight (kilograms) divided by the square root of height (square meters). A total of 5,485 records of a continuous BMI were used as a dependent variable in the subsequent multilevel analysis.

Sociodemographics were self-reported in the BACH survey questionnaire. These include age (30–79 years), gender (male or female), race/ethnicity (white, black, or Hispanic), level of education (<12, 12, 13–15, or ≥16 years), household income (low, <\$30,000; middle, \$30,000–69,999; or high, ≥\$70,000), and presence of dependent(s) (yes or no).

Contextual-Level Variables

The administrative unit at the level of US census tract was used to denote the neighborhood environment. Demographic, environmental, social, and physical

FIGURE 1. Descriptive map of the study area. **a** Major roads in Boston, MA, USA and **b** location of BACH participants.

FIGURE 2. Demographic characteristics of Boston. **a** Population density (per square kilometer), **b** percent of white population, **c** percent of black population, and **d** percent of Hispanic population.

characteristics of each census tract were determined from four major sources: (1) US Census Summary File 3 (SF-3; <http://www.census.gov/>), (2) InfoUSA (InfoGroup Inc., Omaha, NE, USA), (3) Massachusetts Geographic Information System (MassGIS; <http://www.mass.gov/mgis/>), and (4) Global Land Cover Facility (GLCF; <http://glcf.umiacs.umd.edu/index.shtml>).

From the US Census 2000 SF-3, data in the following categories were extracted: demographic characteristics (total population of white, black, and Hispanic residents); mode of transportation to work (private vehicle, public transportation, bicycle, and walk); socioeconomic status (number of people who were employed, below poverty status, and had less than high school degree); median household income; and the median year structure built.

Based on the InfoUSA 2000 database, the standard industrial classification (SIC) code was used to extract six category of businesses likely to contribute to the area-based variations in obesity: food markets (SIC: 541101), convenience stores (SIC: 541103), grocers (SIC: 541105), restaurants (SIC: 581208), pizza stores (SIC: 581222), and gyms (SIC: 799101). These were geo-coded in ArcGIS Version 9.2 (Environmental System Research Institute Inc., Redlands, CA, USA) based on the

local street address. The success match rate was about 85 %. Google Earth was used to supplement the coordinates of addresses that failed to match in the geo-coding process. Approximately 3 % unmatched data were omitted from this study.

Via Web access to MassGIS, GIS data were downloaded to depict the physical environment: transportation systems (bus stops, commuter rail stations, highway exists, and subway stations); green spaces and urban amenities with public access (area of conservational and recreational spaces, conservational spaces, historical or cultural spaces, and recreational spaces); area of prime forest; impervious surfaces; and type of zoning (commercial, conservational, industrial, residential, and others). Efforts were made to be consistent in representing the neighborhood environment between the years 2002 and 2005, in which the BACH survey was conducted.

The vegetation cover for the summer (between July 28 and August 12) of 2005 was determined by satellite imagery provided via the GLCF. A raster resolution of 250×250 m was accompanied by the normalized difference vegetation index (NDVI, 0–250). Although NDVI does not indicate the actual canopy cover, a raw value was used to reflect the amount of vegetation present in a given area.

These variables were normalized to be consistent across census tracts of varying size in representing the density (per square kilometer), the mean, or the percentage using ArcGIS and/or MS Access (Microsoft Corp., Redmond, WA, USA). Since median household income (US dollars) and median year structure built (year) were both an aggregate, their ordinal values were simply used.

Principal Component Analysis

A principal component analysis (PCA) with an orthogonal varimax rotation was performed on a correlation matrix of the contextual-level variables. This procedure was used to explore their dimensionality and to achieve variable reduction by finding a small number of linear combinations of variables that capture most of the data variability. The results of this analysis are based on the eigenvalue decomposition, which returns rotated factor loadings and component scores. By specifying the five best components, the PCA was carried out using the principal function in R.²⁵ A set of five linear combinations of PCA factors was used as neighborhood-level variables in the subsequent analyses.

Area-Based Variations in Obesity

The risk of obesity cannot be determined by the food environment or the PA environment alone but by the interaction between the two.¹⁸ As shown in Figure 3, the risk of obesity is expected to show a gradient from the obesogenic food and PA environment (low–low quadrant) to the leptogenic food and PA environment (high–high quadrant).

To show how different urban typologies fit into this framework, the set of five linear combinations of neighborhood-level variables derived from the PCA were manually framed into the theoretical model of the area-based variations in obesity (Figure 3a). In this diagram, the placement of neighborhood-level variables was interpreted post hoc according to their positive and negative factor loadings in PCA. For instance, positive factor loadings of food sources (convenience stores, food markets, grocers, pizza stores, and restaurants) in PCA are regarded as a low-leptogenic food environment. Neighborhood-level variables with positive and negative factor loadings of food sources were plotted as low and high on the food environment axis, respectively. In a similar fashion, positive factor loadings of PA-related features (conservational spaces, historical and cultural spaces, recreational

FIGURE 3. Area-based variations in obesity as a function of the food and PA environment. **a** The neighborhood-level variables in relation to the characteristics of food and PA environment (after PCA) and **b** the association of neighborhood-level variables with changes in BMI (after controlling for individual- and neighborhood-level variables in the multilevel analysis). The unit of food and PA environment axes correspond to factor loadings in PCA (ranges from -1 to $+1$). The placement of neighborhood-level variables was interpreted post hoc according to their positive and negative factor loadings in PCA. Low-low and high-high quadrant represents a low- and high-leptogenic environment, respectively. Arrows denote the direction of coefficients that were statistically significant in the multilevel analysis. BMI body mass index; 1 wealthy white neighborhoods with vegetation; 2 high-density and high-accessibility neighborhoods; 3 low-density neighborhoods with amenities; 4 low-accessibility Hispanic neighborhoods; and 5 residential black neighborhoods with vegetation.

spaces, prime forests, etc.) in PCA are regarded as a high-leptogenic PA environment. Neighborhood-level variables with positive and negative factor loadings of PA-related features were plotted as high and low on the PA environment axis, respectively.

Multilevel Analysis

A multilevel (or hierarchical) analysis provides a means to combine traditionally distinct individual and ecological models, and also overcomes the limitations inherent in focusing only on one level. It is conceptualized as a two-stage regression: (1) the individual variation within each neighborhood is explained by an individual-level analysis, and (2) the variation across neighborhoods in the neighborhood-specific regression coefficient is explained by a neighborhood-level analysis. The basic concept behind each level of analysis is similar to that of the ordinary least squares. This two-stage regression examines how individual- and neighborhood-level variables may jointly shape the body weight of residents. Details of the statistical model used in this study are published elsewhere.^{26,27}

To decompose the variance of the dependent variable across levels of analysis, the intraclass correlation coefficient (ICC) for outcomes is calculated from the null (baseline) model, also referred to as an unconditional random effect model. For linear models, the estimation of the ICC is based on a model that contains only a continuous dependent variable, a fixed intercept term at the individual level, and a random intercept term at the neighborhood level. The ICC indicates the fraction of variance in an outcome that lies between neighborhoods and is estimated by $\tau_{00}/(\tau_{00} + \sigma^2)$

where τ_{00} =the variances of the neighborhood-level intercept and σ^2 =the variances of the individual-level intercept. Note that the estimation of ICC is not straightforward in linear models with random slopes or in nonlinear cases.

In this study, both the individual- and neighborhood-level variables were modeled as the fixed effects. The intercept at the neighborhood level was modeled as the random effects in all cases, and the slope at the neighborhood level was also modeled as the random effects once cross-level interactions were introduced to the analysis. A series of multilevel analyses was conducted using the linear mixed effect model, lme function, in R.²⁸

Reference Height

Based on the National Health and Nutrition Examination Survey 2001–2002, 2003–2004, and 2005–2006 (<http://www.cdc.gov/nchs/nhanes.htm>), the national average height of both gender and all race/ethnic groups over the age of 30 was 1.67 m, and 1.76 m among white males. Therefore, these were used as the reference heights to interpret the weights (kilograms) from the varying BMI in the analyses.

RESULTS

Among the 5,485 BACH participants, the mean BMI was 29.9 (Table 1); 41.3 % of them were determined to be obese ($\text{BMI} \geq 30$). The BACH participants represent a wide range of Boston residents across diverse communities (Figures 1 and 2). Table 2 shows the neighborhood-level variables derived from the PCA on a correlation matrix of the contextual-level variables. These five factors accounted for approximately 60 % of the shared variance in the contextual-level variables and were used as neighborhood-level variables to represent a more realistic portrayal of urban typology.

The first PCA factor captures the “wealthy white neighborhoods with vegetation.” This factor is characterized by positive loadings on the white population (percent), private vehicle used for commuting to work (percent), employed (percent), median household income (US dollars), prime forests (percent), and mean vegetation cover (NDVI). It is associated with negative loadings on the black population (percent), Hispanic population (percent), poverty (percent), no high school degree (percent), median year structure built (year), bus stop (per square kilometer), and impervious surfaces (percent).

The second PCA factor captures the “high-density and high-accessibility neighborhoods.” This factor is characterized by positive loadings on population (per square kilometer), bicycle used for commuting to work (percent), walked to work (percent), subway stations (per square kilometer), convenience stores (per square kilometer), food markets (per square kilometer), grocers (per square kilometer), pizza stores (per square kilometer), and restaurants (per square kilometer). It is associated with negative loadings on the black population (percent), private vehicle used for commuting to work (percent), mean vegetation cover (NDVI), and industrial zoning (percent).

The third PCA factor captures the “low-density neighborhoods with amenities.” This factor is characterized by positive loadings on median year structure built (year), conservational zoning (percent), historical or cultural spaces (percent), recreational spaces (percent), prime forests (percent), and other zoning (percent). It is associated with negative loadings on population (per square kilometer), bus stops (per square kilometer), impervious surfaces (percent), and residential zoning (percent).

TABLE 1 Description of a study sample

		Percent	Mean (range)	Number of observation
Outcome				
BMI			29.9 (11.6–67.4)	5,485
Individual-level variables				
Gender	Male	41.9		2,296
	Female	58.1		3,189
Age (years)			49.8 (30–79)	5,485
Race/ethnicity	White	33.8		1,852
	Black	32.1		1,763
	Hispanic	34.1		1,870
Level of education (years)	<12	28.2		1,548
	12	24.5		1,345
	13–15	19.8		1,086
	≥16	27.2		1,490
	N/A	0.3		16
Household income ^a	Low	56.1		3,077
	Middle	24.2		1,328
	High	13.6		748
	N/A	6.1		332
Presence of dependents	No	37.7		2,069
	Yes	62.0		3,400
	N/A	0.3		16

BMI body mass index (kg/m²), N/A not available

^aLow income refers to <\$30,000 per year, middle income refers to \$30,000–69,999 per year, and high income refers to ≥\$70,000 per year

The fourth PCA factor captures the “low-accessibility Hispanic neighborhoods.” This factor is characterized by positive loadings on the Hispanic population (percent) and residential zoning (percent). It is associated with negative loadings on walked to work (percent), commuter rail stations (per square kilometer), highway exists (per square kilometer), convenience stores (per square kilometer), pizza stores (per square kilometer), restaurants (per square kilometer), gyms (per square kilometer), impervious surfaces (percent), commercial zoning (percent), and other zoning (percent).

The fifth PCA factor captures the “residential black neighborhoods with vegetation.” This factor is characterized by positive loadings on the black population (percent), prime forests (percent), conservational spaces (percent), mean vegetation cover (NDVI), and residential zoning (percent). It is associated with negative loadings on the white population (percent), the Hispanic population (percent), public transportation used for commuting to work (percent), no high school degree (percent), employed (percent), impervious surfaces (percent), and industrial zoning (percent).

Figure 3a shows how these neighborhood-level variables align with the theoretical model of the area-based variations in obesity. The five neighborhood-level variables derived from the PCA were interpreted post hoc according to their positive and negative factor loadings. For example, neighborhood-level variables with positive factor loadings of food sources (convenience stores, food markets, etc.) in PCA were plotted as low on vertical axis (low-leptogenic food environment), whereas positive factor loadings of PA-related features (gyms, recreational spaces, etc.) in PCA were plotted as high on horizontal axis (high-leptogenic PA environment).

TABLE 2 Principal component analysis of contextual-level variables

Contextual-level variables	Units	Rotated factor loadings				
		Wealthy white neighborhoods with vegetation	High-density and high-accessibility neighborhoods	Low-density neighborhoods with amenities	Low-accessibility Hispanic neighborhoods	Residential black neighborhoods with vegetation
Population	/km ²	−0.278	0.615	−0.520	0.094	−0.219
White population	%	0.761	0.125	0.145	−0.183	−0.352
Black population	%	−0.441	−0.208	−0.184	0.024	0.612
Hispanic population	%	−0.577	0.049	0.061	0.375	−0.352
Private vehicle ^a	%	0.864	−0.226	−0.114	0.167	0.128
Public transportation ^a	%	0.173	0.305	−0.024	0.059	−0.641
Bicycle ^a	%	0.195	0.602	0.094	0.129	−0.196
Walk ^a	%	0.047	0.661	0.040	−0.494	−0.182
Employed	%	0.810	0.342	−0.073	−0.089	−0.327
Poverty	%	−0.858	0.037	0.086	0.001	0.043
No high school degree	%	−0.656	−0.124	−0.035	0.184	−0.335
Median household income	US \$	0.899	0.060	−0.084	−0.023	−0.052
Median year structure built	Year	−0.344	−0.079	0.415	−0.236	0.231
Bus stops	/km ²	−0.341	0.238	−0.271	0.162	−0.201
Commuter rail stations	/km ²	−0.020	0.029	0.024	−0.456	−0.008
Highway exists	/km ²	0.042	−0.038	0.115	−0.594	−0.195
Train stations	/km ²	0.007	0.537	0.156	−0.171	−0.252
Convenience stores	/km ²	0.044	0.578	−0.014	−0.558	0.119
Food markets	/km ²	−0.011	0.680	0.022	−0.002	0.007
Grocers	/km ²	−0.041	0.733	−0.099	0.110	−0.127
Pizza stores	/km ²	−0.010	0.765	−0.013	−0.323	0.094
Restaurants	/km ²	0.047	0.686	−0.002	−0.602	0.089
Gyms	/km ²	0.020	0.310	0.031	−0.754	0.027
Conservational and recreational spaces ^b	%	0.249	−0.012	0.136	0.093	0.054
Conservational spaces ^b	%	0.193	−0.107	0.224	0.047	0.397

TABLE 2 (Continued)

Contextual-level variables	Units	Rotated factor loadings				
		Wealthy white neighborhoods with vegetation	High-density and high-accessibility neighborhoods	Low-density neighborhoods with amenities	Low-accessibility Hispanic neighborhoods	Residential black neighborhoods with vegetation
Historical or cultural spaces ^b	%	0.227	-0.051	0.420	0.105	0.223
Recreational spaces ^b	%	-0.162	0.125	0.752	0.045	0.040
Prime forests	%	0.405	-0.069	0.446	0.194	0.336
Impervious surfaces	%	-0.387	0.304	-0.379	-0.310	-0.620
Mean vegetation cover	NDVI	0.470	-0.187	0.196	0.322	0.636
Commercial zoning	%	0.057	-0.042	-0.197	-0.494	-0.166
Conservational zoning	%	0.109	0.121	0.811	0.204	0.063
Industrial zoning	%	0.039	-0.295	0.048	-0.157	-0.484
Other zoning	%	-0.199	0.033	0.564	-0.332	-0.200
Residential zoning	%	0.047	0.078	-0.755	0.374	0.406
Eigenvalue		5.645	4.633	3.448	3.371	3.222
Proportional variance		0.161	0.132	0.099	0.096	0.092
Cumulative variance		0.161	0.294	0.392	0.488	0.581

NDVI normalized difference vegetation index (0–250).

^aMode of transportation to work.

^bWith public access.

Table 3 summarizes a series of linear multilevel analyses. In these models, 5,485 individuals were nested within 147 (out of 155) census tracts. Note that the BACH survey did not sample residents from all census tracts. Model 1 is a null model that includes only a continuous BMI, a fixed intercept term at the individual level, and the random intercept at the neighborhood level. The ICC is estimated as $0.03402 = [1.657 / (1.657 + 47.046)]$. This translates to about 3.4 % of the total variance in BMI was due to neighborhood variability. However, most of the variance was due to individual variability (96.6 %).

Individual-level variables were added to the model to determine how sociodemographics are associated with changes in BMI (Table 3; model 2). Except for the presence of dependent(s), five other individual-level variables were statistically significant. In brief, those who were female, older, and black indicated a higher BMI than their counterparts who were male, younger, and white, respectively. Conversely, those who had ≥ 16 years of education and had $\geq \$70,000$ of household income indicated a lower BMI than their counterparts who had < 12 years of education and had $< \$30,000$ of household income, respectively.

After including the individual-level variables, neighborhood-level variables were added to examine the association of neighborhood characteristics with changes in BMI (Table 3; model 3). Relative to model 2, household income showed a change in its level of statistical significance where the p value dropped from 0.0165 to 0.0853. Otherwise, the changes in other individual-level variables were negligible. From this two-level analysis, three neighborhood characteristics indicated statistical significances, which were all inversely associated with changes in BMI. People living in “wealthy white neighborhoods with vegetation” (factor 1), “low-density neighborhoods with amenities” (factor 3), and “low-accessibility Hispanic neighborhoods” (factor 4) had 0.609, 0.209, and 0.280 lower BMI, respectively. Using the white male whose height is 1.76 m as a reference, these changes in BMI correspond to weighing on average 1.89, 0.65, and 0.87 kg less than residents living in other types of neighborhood, respectively.

Figure 3b summarizes the type of contextual factors that are associated with changes in BMI and how the overall correlation of contextual factors aligns with the theoretical model of area-based variations in obesity. Both the “wealthy white neighborhoods with vegetation” (factor 1) and the “low-density neighborhoods with amenities” (factor 3) located away from downtown Boston (Figure 4b, d) aligned well with the theoretical model of areas-based variations in obesity. However, other three neighborhood characteristics did not.

To examine the presence of gender disparities within the neighborhood, a two-way cross-level interaction was added to the analysis (Table 3; model 4). Among the five neighborhood-level variables, only the “wealthy white neighborhoods with vegetation” had a statistically significant interaction with gender ($p < 0.0001$). Between genders, women on average had 0.502 higher BMI than the men. Using the height of 1.67 m as a reference, this gender difference translates to an average weight of 1.55 kg.

To examine the presence of racial/ethnic disparities within the neighborhood, a two-way cross-level interaction was included to the analysis (Table 3; model 5). Among the five neighborhood-level variables, only the “high-density and high-accessibility neighborhoods” had a statistically significant interaction with race/ethnicity ($p < 0.001$). Relative to white men, Hispanic men living in such neighborhoods were found to have 0.187 lower BMI. Using the white male whose height is 1.76 m as a reference, this difference translates to an average weight of 0.58 kg.

TABLE 3 Results of a two-level linear analysis

	Estimates (standard error)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed effects					
Intercept	29.648 (0.155)***	27.665 (0.587)***	27.804 (0.587)***	27.752 (0.586) ***	27.997 (0.601)***
Individual-level variables					
Gender					
Female		1.509 (0.194)***	1.495 (0.194)***	1.521 (0.199)***	1.509 (0.194)***
Age (years)		0.033 (0.008)***	0.035 (0.008)***	0.035 (0.008)***	0.033 (0.008)***
Race/ethnicity (ref=white)					
Black		1.383 (0.259)***	0.761 (0.283)**	0.733 (0.282)**	0.614 (0.337)
Hispanic		-0.079 (0.280)	-0.532 (0.289)	-0.533 (0.288)	-0.603 (0.320)
Level of education (year) (ref=<12)					
12		-0.033 (0.277)	0.013 (0.276)	0.013 (0.275)	0.004 (0.276)
13-15		-0.587 (0.301)	-0.503 (0.301)	-0.462 (0.301)	-0.507 (0.301)
≥ 16		-2.072 (0.318)***	-1.866 (0.321)***	-1.860 (0.320)***	-1.762 (0.322)***
Household income (ref=low)					
Middle		-0.286 (0.249)	-0.168 (0.250)	-0.126 (0.249)	-0.129 (0.250)
High		-0.826 (0.344)*	-0.597 (0.347)	-0.594 (0.346)	-0.510 (0.348)
Presence of dependents					
Yes		0.270 (0.212)	0.301 (0.212)	0.260 (0.211)	0.319 (0.212)
Neighborhood-level variables					
Wealthy white neighborhoods with vegetation			-0.609 (0.118)***	-0.029 (0.160)	-0.858 (0.191)***
High-density and high-accessibility neighborhoods			0.047 (0.100)	-0.024 (0.139)	-0.286 (0.170)
Low-density neighborhoods with amenities			-0.209 (0.099)*	-0.277 (0.150)	-0.299 (0.207)
Low-accessibility Hispanic neighborhoods			-0.280 (0.099)**	-0.180 (0.134)	-0.357 (0.139)*
Residential black neighborhoods with vegetation			-0.193 (0.105)	-0.056 (0.149)	-0.364 (0.177)*
Cross-level interaction on gender (ref= male×NLV)					
Female×wealthy white neighborhoods with vegetation				-0.990 (0.197)***	

Female × high-density and high-accessibility neighborhoods	0.108 (0.195)				0.263 (0.303)
Female × low-density neighborhoods with amenities	0.107 (0.199)				0.397 (0.275)
Female × low-accessibility Hispanic neighborhoods	−0.206 (0.193)				0.545 (0.300)
Female × residential black neighborhoods with vegetation	−0.237 (0.197)				0.702 (0.246)**
Cross-level interaction on race/ethnicity (ref = white × NLV)					
Black × wealthy white neighborhoods with vegetation					0.085 (0.292)
Hispanic × wealthy white neighborhoods with vegetation					0.143 (0.255)
Black × high-density and high-accessibility neighborhoods					0.498 (0.279)
Hispanic × high-density and high-accessibility neighborhoods					0.480 (0.298)
Black × low-density neighborhoods with amenities					0.092 (0.316)
Hispanic × low-density neighborhoods with amenities					0.249 (0.247)
Black × low-accessibility hispanic neighborhoods					
Hispanic × low-accessibility Hispanic neighborhoods					
Black × residential black neighborhoods with vegetation					
Hispanic × residential black neighborhoods with vegetation					
Random effects					
Neighborhood-level variance	1.657	0.283	0.071		
Male variance				0.000	
Female variance				0.200	
White variance					0.445

TABLE 3 (Continued)

	Estimates (standard error)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Black variance					0.640
Hispanic variance					0.000
Individual-level variance	47.046	45.824	45.712	45.400	45.400
Model fit statistics					
Akaike's information criterion	36,803.85	34,288.17	34,274.99	34,265.27	34,292.99
Bayesian information criterion	36,823.67	34,373.22	34,392.73	34,428.77	34,508.78
logLink	-18,398.92	-17,131.09	-17,119.50	-17,107.63	-17,113.49

Ref reference category, NLV neighborhood-level variables
*** $p<0.0001$; ** $p<0.001$; and * $p<0.05$

FIGURE 4. Relationship between the area-based variations in BMI and the neighborhood-level variables. **a** Mean BMI. **b** Wealthy white neighborhoods with vegetation. **c** High-density and high-accessibility neighborhoods. **d** Low-density neighborhoods with amenities. **e** Low-accessibility Hispanic neighborhoods. **f** Residential black neighborhoods with vegetation.

DISCUSSION

In a world of increasing obesity, a more comprehensive understanding of the mechanism that operates both at the individual and contextual levels is needed to combat obesity. Since human behaviors are influenced by where they live, a long-term solution should focus on making changes in the environment^{29,30} and targeting a certain subpopulation.³¹ In order to implement such efforts, assuring whether the theoretical model of area-based variations in obesity, defined as a function of the food and PA environment, can be used to explain the body weight of residents becomes crucial. To address such concern, a combination of quantitative and qualitative methods was used in this study.

A series of multilevel analysis first showed that overall variation in the BMI was due to individual-level variations and partially due to neighborhood-level variations (Table 3; model 1). After controlling for the individual-level variables (Table 3; model 2), the associations of sociodemographics with changes in BMI were consistent with the previous findings, except for the presence of dependent(s).¹⁻⁵ However, after adding the neighborhood-level variables in the model, household income became statistically insignificant (Table 3; model 3). This suggests that the place where people live is more strongly associated with changes in BMI than with their household income.

The result indicating the importance of contextual factors in explaining the body weight of residents, and thus, the prevalence of obesity is in good agreement with the previous findings.^{7,19,21,22} However, unlike previous studies, this study used PCA to comprehensively represent the neighborhood characteristics that are a more realistic portrayal of urban typology. After accounting for a wide range of environmental attributes, a two-level multilevel analysis was able to capture the neighborhood variability in BMI after adjusting for the individual-level variability (Table 3; model 3). This is a different approach than using factor analysis to form indices in examining how various contextual factors are associated with changes in BMI.

The inverse association of “wealthy white neighborhoods with vegetation” with changes in BMI (Table 3; model 3) is not straightforward but comprehensible. For instance, since driving to work and the presence of vegetation are two antagonizing factors of obesity, people may have compensated for the decrease in energy expenditure from driving to work by adding more PA using nearby prime forests and/or vegetated areas. Alternatively, it is probable that wealthy white residents have other means to increase their daily PA. The options include, but are not limited to, owning a private gym and/or cardio exercise equipment (treadmills or stationary bikes) and utilizing gym facilities that are not within their neighborhoods but accessible by car. Moreover, as these neighborhoods have less access to unhealthy foods (from convenience stores, food markets, grocers, pizza stores, and restaurants), they might have adopted healthy eating habits by consuming more homemade meals.

Although the direct benefits of urban vegetation remain to be elucidated, the presence of such greenery seems to have benefited the residents in the “wealthy white neighborhoods with vegetation.” Since the role of arboriculture encompasses a wide range of factors that contribute to human and community well-being,^{32,33} the inverse association of this neighborhood characteristic with changes in BMI might be capturing some of those associated benefits. In addition, selective migration might have also contributed this phenomenon. An increased probability of upward migration for both women and highly educated individuals was apparent in a

Dutch study.³⁴ Therefore, it is possible that healthy and physically active people who have developed a lifestyle to maintain their body weight choose to live in this type of neighborhood. The neighborhoods with high scores in this dimension are located in the southwestern part of Boston (Figure 4b) and have the lowest prevalence of obesity in the city (Figure 4a).

The inverse association of “low-density neighborhoods with amenities” with changes in BMI (Table 3; Model 3) is in good agreement with the previous findings. This type of neighborhood is interpreted as a place with easier access to historical or cultural spaces, recreational spaces, and prime forests (Table 2). Because urban vegetation provides a sense of safety and aesthetic quality to neighborhoods,^{32,33} the assumption follows that more PA results from such positive attributes in a neighborhood environment.^{14,35} In addition, this correlation may suggest that residents make use of the PA-related features and open spaces located near their home³⁶ and thus have lower stress and less likelihood of obesity.³⁷

Unlike the above two neighborhood characteristics, the inverse association of “low-accessibility Hispanic neighborhoods” with changes in BMI (Table 3; model 3) is difficult to comprehend. For instance, this type of neighborhood is interpreted as a place where residents have difficulty walking to work, have limited or no access to public transportation systems, and lack access to food sources (Table 2). Due to neighborhood disadvantages and deprivations, the predominantly Hispanic neighborhoods have been found to associate with increased body weight of residents.³⁸ Therefore, these “low-accessibility Hispanic neighborhoods” would be expected to associate with an increase in BMI, not with a decrease in BMI. Although a mere residential racial/ethnic composition cannot be translated as a residential segregation, it is possible that neighborhood disadvantages and deprivations influence Hispanics and their health outcomes differently than what has been known for black residents in the USA.^{20,22} More research is needed to better understand how Hispanics interact with their residential environment in the USA.

Although there are many uncertainties underlying these associations of neighborhood characteristics with changes in BMI, the implications can be better understood by framing them in the theoretical model of area-based variations in obesity (Figure 3b). Based on the qualitative assessment, except for the “wealthy white neighborhoods with vegetation” (factor 1) and the “low-density neighborhoods with amenities” (factor 3), the associations of other three neighborhood characteristics with changes in BMI did not align well with the theoretical model of area-based variations in obesity. In theory, both the “high-density and high-accessibility neighborhoods” (factor 2) and the “low-accessibility Hispanic neighborhoods” (factor 4) located in and around downtown Boston (Figure 4c and e, respectively) would be expected to associate with an increase in BMI due to a relatively obesogenic food and PA environment, respectively. On the other hand, the “residential black neighborhoods with vegetation” (factor 5) located on the outskirts of Boston (Figure 4f) would be expected to inversely associate with changes in BMI due to a relatively leptogenic food and PA environment. Taken together, the overall association of contextual factors with changes in BMI does not seem to align well with the theoretical model of area-based variations in obesity. In other words, it is likely that a mere function of the food and PA environment is insufficient to explain the body weight of residents.

One of the key components neglected in the concept of area-based variations in obesity is the consideration of differences among the subpopulation; how different groups of residents interact with their neighborhood environment. The gender and

racial/ethnic differences need to be properly addressed in the USA.^{1–5} In an effort to examine this concern, cross-level interactions were able to detect the presence of such differences in a couple of neighborhoods. First, the association of “wealthy white neighborhoods with vegetation” with changes in BMI varied by gender (Table 3; model 4). These neighborhoods are considered as high-lepogenic food and PA environments (Figure 3; factor 1); they are located in the southwestern part of Boston (Figure 4b) and have the least prevalence of obesity in the city (Figure 4a). In addition, the association of “high-density and high-accessibility neighborhoods” with changes in BMI varied by race/ethnicity, between whites and Hispanics (Table 3; Model 5). These neighborhoods are characterized as a combination of low-lepogenic food environment and high-lepogenic PA environment (Figure 3; factor 2) and are located near downtown Boston (Figure 4c).

Since the multilevel analysis does not have built-in assumptions about heterogeneity in neighborhoods, the result of gender and racial/ethnic differences reflects the complexity of environmental and health inequality,³⁹ which should be further examined in the future. Since the geography of health inequalities is drawn by the structuring of society and space,⁴⁰ it is possible that gender and racial/ethnic differences are the result of personal preference, social norm, selective placement, entrapment, and/or displacement. However, this finding does not directly imply that there is an elevated risk of obesity related to residential racial/ethnic composition.²² Particularly for the racial/ethnic difference, the role of psychosocial stress⁴¹ on the body weight of residents may have impacted the subpopulation differently. This was not examined in this study and has not been examined elsewhere.

Further prospective cohort and/or experimental studies are needed to better understand the mechanism of neighborhood variability and associated gender and race/ethnic differences. Based on a combination of quantitative and qualitative analysis, the result of this study suggests that a mere function of the food and PA environment seems to be insufficient in explaining the body weight of residents. This highlights the need for future efforts in the Boston area to be tailored at least by gender and race/ethnicity and specific to the neighborhood characteristics in which they live in. Strategies should be developed on the basis of multifactorial efforts that manage diet, PA, and behavioral changes through altering various contextual settings.^{29,31} Community-based strategies are recommended to promote good nutrition and PA by the US Centers for Disease Control and Prevention.⁴²

More Americans than ever before are engaging in sedentary behavior due to a combination of changes in the urban environment and the standard of living.⁴³ Although increasing the level of PA cannot completely dispel the comorbidities of obesity, it can significantly reduce body weight and improve health risks.⁴⁴ In particular, a physically active lifestyle is proven to play a vital role in both the management and prevention of diabetes.⁴⁵ Therefore, future efforts should include considering how to add approximately 20–30 min of walking to a resident’s lifestyle.^{46,47} A primary focus should be to incorporate design elements that promote accessibility, opportunity, and aesthetics in the urban environment.¹⁴ Further emphasis should not be placed solely on the creation of open spaces, recreational facilities, and walking trails; an equal amount of attention should be placed on addressing the disparities in access to healthy foods in the USA.⁴⁸ The availability and affordability of healthy foods are more likely to be offered by supermarkets than grocery stores.⁴⁹ However, accessibility to such supermarkets is limited in minority neighborhoods.⁵⁰

Taken together, obesity prevention and/or intervention programs need to alter the physical, sociocultural, institutional, organization, political, and economical environments to improve both the levels of nutrition and PA, and reduce the local barriers that exist in the minority neighborhoods.^{51,52} Obviously, there is no “one-size-fits-all” solution to this problem, and thus, it will require collaborative work among various professions. In particular, this calls for public health and urban planning professionals and/or researchers to work together to combat the rising obesity epidemic.⁵³ Unfortunately, there is not yet a bridge to connect these fields and professionals.

There are some limitations that need to be considered. First, this is a cross-sectional study that can only describe, summarize, and qualify patterns that are present in the BACH data. Therefore, the result of this study cannot infer causality. Second, as mentioned above, obesity is related to numerous factors that operate at different contextual levels. Thus, a crude measurement of neighborhood using an administrative unit defined by the US Census Bureau may have undermined the true associations. Third, in a similar context, a two-level (individual and neighborhood) analysis may have ignored other relationships that vary systematically by family, social network, workplace, and other levels of social and/or physical bounds. In both cases, defining the appropriate boundaries of residential environments and identifying the specific features of contextual factors that are most important for health remain a major challenge.²⁶ Fourth, this study overlooked the factors contributing to neighborhood safety that may have affected daily PA, which in turn affects the body weight of residents.¹⁶ However, the association of neighborhood safety with the body weight of residents has been rather mixed.^{7,54} Finally, this study focused on the city of Boston during the years between 2002 and 2005. Consequently, the results may be unique and not generalizable to other cities.

Since the BACH survey is longitudinal,²³ a follow-up survey is currently underway. Therefore, future studies will compensate for some of the limitations listed above. Although it may not be possible to address all shortcomings of this present study, future efforts will offer a more comprehensive understanding of the complex relationship between obesity and the urban environment in Boston.

CONCLUSION

With the use of a community-based epidemiologic survey of Boston, MA, USA, GIS technology, and multilevel modeling techniques, this study examined whether the theoretical model of area-based variations in obesity can be used to explain changes in BMI. A combination of quantitative and qualitative assessment suggests that a mere function of the food and PA environment seems to be insufficient to explain the body weight of residents. The cross-level interactions showed that people behave differently within a given neighborhood environment. In particular, the gender and racial/ethnic differences were evident in certain neighborhoods. These findings highlight the needs for future prevention and/or intervention programs in the Boston area to be tailored at least by gender and race/ethnicity and to be specific to the neighborhood characteristics in which they live in. Further prospective cohort and/or experimental studies are needed to better understand the mechanism behind these neighborhood variabilities and associated gender and race/ethnic differences. More research is needed to understand how the individual and contextual factors interrelate, influence each other, and/or jointly shape the body weight of residents.

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