International Journal of Obesity (2014) 38, 912–918

www.nature.com/ijo

PEDIATRIC ORIGINAL ARTICLE

A multi-level analysis showing associations between school neighborhood and child body mass index

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OBJECTIVE: The objective of this study is to examine associations between aspects of the environment in school neighborhoods and childhood body mass index percentile (BMIp).

METHODS: Trained medical students visited 46 elementary schools in the Kansas City metropolitan area to conduct medical screenings that included the height and weight measurements of 12 118 boys and girls 4–12 years of age in the academic year 2008–2009. For the same time period, aspects of the built environment in a 2-mile radius around each school was obtained from the Walkscore database. Other environmental characteristics (for example, population change) of these areas were also obtained from various sources. Hierarchical linear modeling was used to estimate the associations between neighborhood- and individual-level factors and BMIp.

RESULTS: Population size along with the number of fast-food restaurants and grocery stores were positively associated with BMIp, whereas population change along with the number of parks and fitness centers were inversely associated with BMIp.

CONCLUSIONS: After considering individual-level factors and the random effects of schools, environmental elements of school neighborhoods predict childhood BMIp. This study offers evidence of the health influence of school neighborhoods in a way that can inform neighborhood redevelopment efforts.

International Journal of Obesity (2014) **38,** 912–918; doi:10.1038/ijo.2014.64

Keywords: BMI; children; school neighborhood; obesogenic neighborhoods

INTRODUCTION

Childhood obesity is a significant public health concern and it carries long-term consequences that are costly in terms of health outcomes and medical expenditures.[1,2] Obese children and adolescents are at risk for heart disease and diabetes, and many begin to show early-stage manifestations of these ailments while they are still young.[3–5] Environments provide varying kinds of health opportunities and subsequent, often life long, health behaviors develop in the context of those environments.[6] This means that limited access to healthy foods or exercise opportunities may eventually be internalized as dispositions toward unhealthy eating and sedentary behavior. Because these internalized social structural limitations become more durable over time, studies of environmental impacts on child health provide an important perspective.[7]

Lovasi *et al.*[8] note that the literature on the relationship between environment, behavior and obesity was relatively scant before 2000. Since then, however, there have been numerous studies examining how environmental factors constrain or enable health.[9] Although the majority of these studies have focused on adult populations, there is a growing literature on the relationships of community and environmental factors with the health of children.[10,11] The presence of parks and other places to be active has been found to be associated with lower rates of obesity in children.[2,8,12–16] Others, however, have found no relationship between obesity and distance to parks.[11,17,18] Although most find that density of fast-food restaurants is positively correlated with body mass index (BMI) both in adults and children, one study found no such relationship for a large sample of 3- and 4-year olds.[15,18,19] Other studies have suggested that alternative factors such as school policies that impact fast-food access may be more important than availability itself.[20] Although availability of grocery stores has been found to be associated with lower BMI, some studies have found that the presence of grocery stores actually promotes higher BMI.[8,11,21–23] Of course it is not just the presence of grocery stores, but also the availability of healthy foods in them that appears to be a critical determinant of their effects on obesity.[24] One study conducted in an East Los Angeles community found that ~50% of 190 food outlets were fast-food restaurants, and of the 62 grocery stores quality fruits and vegetables were available at only 18%.[24] Similarly, the presence of convenience stores, because they typically sell relatively unhealthy foods, may promote higher BMI. At the same time, convenience store density may be related to the density of businesses overall and the mingling of retail outlets and residences, both of which are protective against high BMI.[8,11,15,16,25]

It is evident from these studies that both school environment and the surrounding neighborhoods have a complex and multifactorial relationship with childhood obesity.[26,27] Unfortunately, these mixed results, along with other several limitations, contribute to our lack of understanding about how school neighborhoods affect child health. Despite the quantity of studies

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Received 5 September 2013; revised 18 March 2014; accepted 6 April 2014; accepted article preview online 15 April 2014; advance online publication, 20 May 2014

done in this area, few have examined large samples with sufficient representation from racial/ethnic minority children, included environmental features related to physical activity, diet and obesity,[28] obtained more objective (not self-report) data on environmental features or directly measured heights and weights of children.[29] In addition, only half of the studies reviewed by Papas *et al.*[29] used multi-level modeling that is necessary when simultaneously analyzing group and individual-level data.

Recent evidence suggests that neighborhood environments surrounding schools may have specific influence on both physical activity and dietary intake. More pedestrian and cyclist-friendly school neighborhoods promote those physical activity behaviors among children.[30–34] Road connectivity and flatter topography in school neighborhoods also increase odds of walking and cycling, and even promote higher levels of physical exertion while engaged in those activities.[33,35,36] Similarly, the food environments surrounding schools intuitively bear influence on child health, but previous research results have been mixed. Fast-food restaurants appear to be clustered around schools, but the downstream consequences on child health remain unclear.[37,38] As with studies targeting more traditionally defined neighborhoods, some studies have found that the presence of fast-food restaurants near schools was associated with overweight among adolescents.[39,40] However, Seliske *et al.*[40] found no such association using a multi-level approach among a sample of Canadian children. At least two studies among younger age groups in the United States also have found no relationship between fast-food density and obesity.[19,41]

Schools are major focal points of many communities and they are places where children spend a considerable amount of time. As such, numerous studies examining associations between schools and child health have focused on the immediate school environment (for example, cafeteria and schoolyard).[35,42–44] According to Harrison and Jones,[44] we need to think about school environments and their effects on child health more broadly. In particular, they propose a multi-tiered model that includes not only the infrastructure of schools, per se, but also the neighborhoods surrounding the schools. One of the reasons is that, at least for public schools, while many children attending the school reside in the area surrounding it, even those that do not nonetheless spend a great deal of time traversing school neighborhoods. If the areas surrounding schools have significant influence on student health, they may represent anchors around which to deploy resources for environmental improvements aimed at that end. Of critical importance, this study accounted for individual-level factors such as race, gender and age to more robustly estimate the effects of park or fast-food density, population change and other community-level health indicators.[10,27] Thus, with a large sample ($n = 12\,118$) of racial/ethnically diverse elementary school children from the Kansas City metropolitan area, this study used hierarchical linear modeling to more precisely estimate the associations between objective assessments of the built environment in low-income urban school neighborhoods and measured BMI expressed as BMI percentile (BMIp).

METHODS

The sample used in this analysis was collected in the 2008–2009 academic year and initially contained 12 433 students in 46 different schools. Of the 46 schools, 39 were public (84.8%), two were charter schools (4.3%; publicly funded schools that are privately operated by a particular interest group) and five were parochial schools (10.9%; privately funded schools associated with a particular religious denomination). Some of the charter or parochial schools included middle- and high-school students ($n = 315$). However, given the developmental effects of age on BMI and the small number of 6–8th graders, these students were eliminated from the analysis. The distribution across grade levels was relatively even, ranging from 2123 students in the kindergarten cohort (17.5%) to 1894 students in the fifth-grade cohort (15.6%). The schools also were ethnically diverse (41.76% black, 33.28% Hispanic, 21.89% white and 3.07% other), with 49.07% female and 50.93% male students. Half of the schools in the data set fell into a unique zip code, wheareas the other half shared a zip code with at least one other school. Thus, where zip code-level data are used (for example, population size and change), the values are duplicated for some schools in the data set. School zip codes had a mean size of 8.69 square miles (s.d. = 8.13). Analyses with and without a positive outlier for square mileage demonstrated no significant differences in the results. Thus, the analysis presented here did not exclude any school for this reason.

Individual-level data on the students were collected as part of a non-profit program called Score 1 for Health. This program offers health screenings, education and referral for services as needed to area school children, primarily between kindergarten and fifth grade. To qualify for the Score 1 program, a school must be in the Kansas City metropolitan area (which encompasses both Kansas City, Missouri and Kansas City, Kansas). Although schools partly are chosen based on their interest in participation in the Score 1 program, the target areas for recruitment focus on those districts that have a high percentage of students on free and reduced lunch.

Health screenings were conducted by medical students trained to complete the evaluations through a series of seminars, didactics and hands-on lab activities. A pediatrician instructed these students on the proper method for conducting the portions of physical exams relevant to this study, including the measurement of height and weight. All school children who received parental consent reported to a school-based screening area at scheduled times during the day. They then rotated through various stations that include assessments of height and weight, dental caries, vision, hearing, blood pressure and other measures. Supervising physicians and other licensed health-care professionals were on hand to address any questions or issues. Parental consent is obtained in advance of the screenings that includes consent for results to be used for research purposes. The creation of the deidentified data set used in this study was subsequently approved by the institutional review board at (Kansas City University of Medicine and Biosciences).

Table 1. Descriptive statistics for dependent and independent variables

	*Mean/ percentage (*n*)*	*s.d.*	*Min.*	*Max.*
Dependent variables				
BMI percentile	69.44	26.85	0.01	99.92
Overweight[a]	20.69% (12 090)			
At risk of overweight[b]	38.97% (12 090)			
Individual-level predictors				
Age (years)	8.22	1.77	4.33	13.75
Female	49.07% (12 116)			
Race/ethnicity				
White	21.89% (11 750)			
Black	41.76% (11 750)			
Hispanic	33.28% (11 750)			
Other	3.07% (11 750)			
School/community-level predictors				
Zip code-level measures				
Population size per 1000 persons	18.93	8.12	2.68	34.22
% White	49.56	21.65	2.8	95.8
% Population change	− 3.34	8.63	− 12.8	32.89
School-level measures				
School SES (< 50%)	10.87% (46)			
School SES (50–75%)	19.57% (46)			
School SES (75–100%)	69.57% (46)			
Public school	84.78% (46)			
Convenience stores within 0.5 mile	1.09	1.28	0	4
Fast-food restaurants within 0.5 mile	0.96	1.64	0	7
Grocery stores within 0.5 mile	1.13	1.59	0	6
Fitness centers within 0.5 mile	0.22	0.55	0	2
Parks within 1 mile	1.93	1.78	0	5
Kansas	30.43% (46)			

Abbreviations: BMIp, body mass index percentiles; Max., maximum; Min., minimum; SES, socioeconomic status. [a]Overweight was defined as $\geqslant 95$ BMIp. [b]At risk of overweight was defined as $\geqslant 85$ BMIp.

Measures

Individual-level independent variables. Sex was coded based on school records as either male = 0 or female = 1. Race/ethnicity was also coded based on school records, but collapsed into major race/ethnic categories for the purposes of analysis. These final categories included 'white,' 'black,' 'Hispanic' and 'other.' The residual category for race/ethnicity was comprised largely of 'Asian' students (2.9% of the total sample), followed by 'Indian' students (at just 0.3% of the total sample). Age was measured in years and centered at 5-years-old, so that intercepts in regression analysis represent estimated BMIp for kindergarteners.

School- and neighborhood-level independent variables. School socioeconomic status (SES) was measured as the percent of students on free or reduced lunch. This variable was coded into three categories (1 = 0–50%, 2 = 51–75% and 3 = 76–100%). Although only ~ 10% of schools fall in the highest SES category, we did not combine them with other categories because of the well-established association of SES on environment and health. Using unbalanced SES groups is not uncommon in the literature (for example, Wu *et al*. and Ward *et al*.).[45,46] Population size, percent white and population change from 2000 to 2010 were measured on the basis of the zip code in which the school was situated using data from the US census. Schools were classified as either public or non-public (comprising charter and parochial schools).

The density of convenience stores, fast-food restaurants, grocery stores, fitness facilities and parks were collected by entering the school address into the Walkscore website and recording the number of locations in each category that fell within a 0.5-mile radius of the school (www.walkscore.com). The exception to this concerned the 'parks' variable for which the radial distance was set at 1 mile because of the size and nature of parks, such that they likely have a naturally lower frequency (as compared with a store or restaurant). In addition, a two-stage process was used to verify the Walkscore data. First, search results were screened to delete blatantly errant data (~2% of identified places), which was mostly a problem associated with playgrounds (for example, a playground equipment manufacturer listed as a playground). Second, a subsample of 10% of the search results was verified in-person by researchers to confirm their presence, accuracy of the classification and location (no results were altered because of this second stage, yielding confidence in the results of the procedure). Finally, because of potential state-level effects (for example, varying school policies), state of residence (Missouri = 0 and Kansas = 1) was included as a control variable.

Outcome variables. BMIp was calculated from the algorithm produced by the Centers for Disease Control and Prevention that accounts for height, weight, sex and age.[47] Balance beam scales were used to assess weight to the nearest 0.1 kg, and secured stadiometers were used to measure height to the nearest 0.1 cm. Children were instructed to remove their shoes and socks before stepping on the scale. Height was measured with the child standing with both heels and buttocks against a vertical stadiometer. Each child's height and weight were assessed twice during the screening session and the average of the two measures was used. A standardized weight was used to calibrate the scales before each screening session. BMIp was primarily used as a scale variable, but two additional analyses examined it dichotomously as overweight and above (that is, ⩾ 95th) and at risk of overweight and above (that is, ⩾ 85th).

Analytic strategy

We first examined bivariate correlations among the variables in our study as well as the partial correlations between each school/community-level variables and BMIp controlling for individual-level characteristics. In the next step, consistent with the call by Feng *et al.*[25] for multi-level analytic approaches to study the relationship between community-level environmental factors and health outcomes, we used a two-level variance components model, with a random term for school-level variance at level 2. We estimated our random effect model in two steps. In Model 1, only individual-level predictors were considered. School-level variations in BMIp that are above and beyond the effect of individual characteristics were captured by school-specific random effects. Where the variance for school-specific effects is significant, we proceeded with Model 2 to include school neighborhood-level predictors into the model.

With the same individual- and school-level predictors, we examined their effects on different measures of weight status. These include overweight and at risk of overweight. Because the two variables are dichotomous, we used a logit link function to model the expected probability of overweight or at risk of overweight.

Based on the results of these analyses, we generated predictive BMIp values by race/ethnicity and gender for hypothetical 'most obesogenic' and 'least obesogenic' school neighborhoods. This gives a more holistic picture of the contribution of school neighborhood that can be lost among in the individual variable coefficients.

RESULTS

Descriptive statistics are provided in Table 1. Notably, the sample manifests an average BMIp of 69.44 that falls to the upper side of a healthy weight range as determined by the Centers for Disease Control and Prevention. A significant portion of the sample also was overweight (20.69%) or at risk of overweight (38.97%).

Bivariate correlations demonstrated a number of significant associations (Table 2). Without controlling for other variables or accounting for the inherent hierarchical nature of the data, BMIp is positively associated with age, percent on free/reduced lunch and declining neighborhood population, and is negatively associated with gender (males higher BMIp values), the number of fitness facilities, the number of convenience stores and weakly associated with the amount of health sales. BMIp also was higher in public verse private schools and higher in Kansas school neighborhoods, relative to those on the Missouri side of the state line.

Table 2. Bivarate and partial correlations among dependent and independent variables

	Bivariate correlations												*Partial correlations*[a]
	Age	*Female*	*Public school*	*Pop. size*	*% White*	*Pop. change*	*Conv. stores, 0.5 mile*	*Fast food, 0.5 mile*	*Groc. stores, 0.5 mile*	*Fit. fac., 0.5 mile*	*Parks, 1 mile*	*KS*	*BMIp*
BMIp	0.04**	− 0.04***	0.04***	0.04***	− 0.02+	− 0.05***	− 0.03**	− 0.01	0.01	− 0.05***	− 0.02+	0.03***	—
Age		− 0.01	0.02**	0.01	0.01	0.02*	− 0.03***	− 0.04***	− 0.04***	− 0.03***	− 0.04***	0.00	—
Female			− 0.01	0.00	0.00	− 0.01	0.02*	0.02*	0.02**	0.01	0.02*	0.00	—
Public school				0.08***	− 0.18***	0.03***	− 0.45***	− 0.46***	− 0.25***	− 0.56***	− 0.27***	0.17***	0.02**
Pop. size					0.25***	− 0.12***	− 0.23***	− 0.19***	− 0.10***	− 0.17***	− 0.30***	0.23***	0.06***
% White						0.62***	− 0.12***	0.06***	− 0.18***	0.05***	− 0.30***	− 0.16***	0.00
Pop. change							− 0.15***	− 0.10***	− 0.23***	− 0.09***	− 0.17***	− 0.35***	− 0.03***
Conv. stores, 0.5 mile								0.54***	0.68***	0.50***	0.47***	0.00	− 0.04***
Fast food, 0.5 mile									0.48***	0.76***	0.47***	0.00***	− 0.02*
Groc. stores, 0.5 mile										0.29***	0.65***	0.14***	− 0.01
Fit. fac., 0.5 mile											0.38***	− 0.07***	− 0.04***
Parks, 1 mile												− 0.07***	− 0.04***

Abbreviations: BMIp, body mass index percentiles; Conv., convenience; Fit. fac., fitness facilities; Groc., grocery; KS, Kansas; Pop., population. $^+P < 0.10$; $^*P < 0.05$; $^{**}P < 0.01$; $^{***}P < 0.001$. [a]Partial correlation coefficients between school/community-level predictors and BMIp controlling for individual-level predictors.

The results of both the bivariate and partial correlation analyses, in conjunction with previous literature, informed models for hierarchical linear analysis. Shown in Table 3 are the results of Models 1 and 2. Model 1 examined only the individual-level variables showing that being older and Hispanic are significantly related to higher BMIp values, whereas being female is predictive of lower BMIp values. However, the level 2 variance for intercepts across schools (6.71, $P < 0.01$) shows that a significant amount of variance at the school neighborhood-level remains unexplained. Model 2 adds school neighborhood-level variables, demonstrating that neighborhood population as well as the number of grocery stores are directly associated with higher BMIp values, even when controlling for the individual-level predictors. Conversely, population decline and membership in the highest SES group (< 50% on free/reduced lunch), along with higher numbers of convenience stores, fitness facilities and parks predicted lower BMIp. Although Kansas school neighborhoods were positively associated with BMIp in the bivariate test, this variable was significantly negatively predictive in the hierarchical model. These neighborhood-level variables explained a great deal of the neighborhood-level variation in BMIp values, as shown by the sizable reduction in estimated level 2 residual variance. Model 2 assumptions were assessed by conducting residual analyses that uncovered no notable correlation between residuals and predictors at the same analytic level or across levels. Moreover, the correlation between level 1 and level 2 residuals is very weak ($r = 0.02$), and both level 1 and level 2 residuals are approximately normally distributed. Although the level 1 residual distribution is affected by the fact that the values of BMIp are bounded ([0,100]), such a moderate violation of normality should not bias the estimation of the level 2 coefficients.[48,49]

Table 4 presents a variation on the same analysis but with 'overweight' and 'at risk of overweight' as dependent variables. These analyses have somewhat similar results. At the community level, larger population size and the number of grocery stores increased the odds of being overweight. Significantly lower odds of being overweight were associated with membership in the highest SES group (< 50% on free/reduced lunch), along with the number of convenience stores, fitness centers and parks, as well as living in Kansas. Population decline, membership in the middle SES group (50–75% on free/reduced lunch) and the number of grocery stores were associated with greater odds of being at risk of overweight. Conversely, membership in the highest SES group (< 50% on free/reduced lunch), along with the number of convenience stores, fitness centers and parks were associated with significantly lower odds of being at risk for overweight.

Table 3. Multi-level analysis of community environments on children's BMI percentile

	Model 1[a]		*Model 2*[b]	
	Coef.	*s.e.*	*Coef.*	*s.e.*
Fixed effects				
Grand intercept	66.37***	1.06	66.46***	2.41
Individual-level predictors				
Age (years)	0.56***	0.17	0.56**	0.17
Female	− 2.28***	0.59	− 2.27***	0.58
Race/ethnicity				
Black	0.91	0.98	0.74	0.99
Hispanic	5.89***	0.95	5.83***	0.99
Other	0.79	2.11	0.80	2.10
School/community-level predictors				
Zip code-level measures				
Population size per 1000 persons			0.09+	0.05
% White			0.01	0.03
% Population change			− 0.14**	0.04
School-level measures				
School SES 1 (< 50%)			− 2.39+	1.40
School SES 2 (50–75%)			0.32	1.01
School SES 3 (75–100%; reference group)				
Public school			− 0.88	0.78
Convenience stores within 0.5 mile			− 0.84*	0.33
Fast-food restaurants within 0.5 mile			0.35	0.23
Grocery stores within 0.5 mile			0.66**	0.24
Fitness centers within 0.5 mile			− 1.42+	0.75
Parks within 1 mile			− 0.62**	0.22
Kansas			− 1.58*	0.81
Random effects				
Level 1 residual variance	704.28***	9.22	704.30***	9.22
Level 2 variance for intercepts across schools	6.38***	1.99	2.46*	1.33
Model fit				
AIC	110 232		104 300	
n (Individuals)	11 728		11 728	
k (Schools)	46		46	

Abbreviations: AIC, Akaike's information criterion; Coef., coefficient; SES, socioeconomic status. $^{+}P < 0.10$; $^{*}P < 0.05$; $^{**}P < 0.01$; $^{***}P < 0.001$; two-tailed test. [a]Random effect model on children's BMI percentile with individual-level predictors only. [b]Random effect model on children's BMI percentile with both individual-level and school/community-level predictors.

DISCUSSION

Our results resonate with previous literature that suggests both individual- and community-level factors are influential for child BMI. Specifically, the analyses provide support for the comprehensive model proposed by Harrison and Jones,[44] where the importance of school neighborhood is evidenced, though with some variability, in all of the hierarchical analyses. Our multi-level approach in which schools and their surrounding neighborhoods anchor the community-level factors suggests that school neighborhoods may indeed function as significant zones of influence. This is demonstrated by the effects of environmental features in the radial areas around schools, even when controlling for demographics at the zip code level and accounting for the multi-level nature of the data. Although further study is needed, this provides some initial evidence that school neighborhoods may be good targets for redevelopment initiatives seeking to improve health among children.

Although race, age and sex remained predictive, the presence of parks and fitness facilities nonetheless were associated with additional reductions in BMIp. Similarly, the number of fast-food restaurants predicts higher BMIp, as does population decline, that likely signals general neighborhood decay. More complex relationships manifest among some other community-level variables in the models. Although many call for increased access to grocery stores, particularly in efforts to assist 'food deserts,' our analysis shows that access does not necessarily promote health, at least among children, in light of the positive relationship between grocery stores and child BMIp. Similarly, convenience stores often are regarded as having a preponderance of unhealthy consumer products, including unhealthy food choices. That they manifest in our analysis as health promoting may suggest that this association is related to other factors in complex ways. For example, in the context of other factors such as SES and urban residence, people who make significant numbers of food purchases at convenience stores may consume more unhealthy foods but in more modest amounts, such that there is no association with BMI. In addition, the delineation between grocery stores and convenience stores may be problematic, where the latter, particularly in economically disadvantaged areas, may introduce more stock typically associated with grocery stores due based on demand caused by a relative scarcity of bonafide grocery stores. This could convolute the classification of these variables.

Differential estimates of BMIp among children based on the results of Model 2 are particularly illuminating. While the

Table 4. Multi-level analysis of community environments on children's weight status

	Overweight[a]		*At risk of overweight*[b]	
	Odds ratio	*95% CI*	*Odds ratio*	*95% CI*
Fixed effects				
Individual-level predictors				
Age (years)	1.12	(1.10, 1.15)***	1.10	(1.08, 1.12)***
Female	0.81	(0.74, 0.88)***	0.91	(0.84, 0.98)*
Race/ethnicity				
Black	1.00	(0.87, 1.15)	1.03	(0.92, 1.15)
Hispanic	1.60	(1.38, 1.85)***	1.57	(1.38, 1.76)***
Other	1.09	(0.81, 1.46)	1.04	(0.82, 1.32)
School/community-level predictors				
Zip code-level measures				
Population size per 1000 persons	1.00	(1.00, 1.00)*	1.00	(1.00, 1.00)
% White	1.00	(1.00, 1.01)	1.00	(1.00, 1.00)
% Population change	0.99	(0.98, 1.00)*	0.99	(0.98, 1.00)*
School-level measures				
School SES 1 (< 50%)	0.53	(0.37, 0.76)***	0.78	(0.58, 1.04)$^+$
School SES 2 (50–75%)	1.13	(0.93, 1.38)	1.24	(1.04, 1.47)*
School SES 3 (75–100%; reference group)				
Public school	0.89	(0.69, 1.13)	0.96	(0.78, 1.19)
Convenience stores within 0.5 mile	0.94	(0.87, 1.00)$^+$	0.94	(0.89, 1.00)$^+$
Fast-food restaurants within 0.5 mile	1.02	(0.97, 1.08)	1.02	(0.98, 1.08)
Grocery stores within 0.5 mile	1.06	(0.99, 1.12)$^+$	1.06	(1.00, 1.12)*
Fitness centers within 0.5 mile	0.86	(0.74, 1.01)$^+$	0.84	(0.74, 0.96)*
Parks within 1 mile	0.94	(0.90, 0.98)**	0.95	(0.92, 0.99)*
Kansas	0.88	(0.75, 1.02)$^+$	0.95	(0.83, 1.08)
Random effects				
Level 2 variance for intercepts across schools	0.02*		0.02**	
n (Individuals)	11 728		11 728	
k (Schools)	46		46	

Abbreviation: BMIp, body mass index percentiles. $^+P < 0.10$; $^*P < 0.05$; $^{**}P < 0.01$; $^{***}P < 0.001$; two-tailed test. [a]Overweight was defined as ⩾95 BMIp. [b]At risk of overweight was defined as ⩾85 BMIp.

preceding analyses lead one naturally to focus on individual variables, predictive models that compare the most and least obseogenic environments provide a more holistic picture of the association of school neighborhood and BMIp among children. The 'most obesogenic' neighborhoods based on the model in this study are those with a public school with lowest school SES, largest population size, most negative population change, maximum number of grocery stores, but has no convenience store, no fitness centers, no parks, the mean number of fast-food restaurants and the mean percent white residents and is in Missouri. Conversely, the 'least obesogenic' neighborhoods are those with a public school with highest school SES, smallest population size, greatest population increase, maximum number of convenience stores, fitness center and parks, but with no grocery store, the mean number of fast-food restaurants, the mean percent white residents and is in Kansas. Figure 1 contrasts the predicted BMIp at age 10 by race/ethnicity and sex for the most obeseogenic and least obeseogenic school neighborhoods using the values from our data and shows an approximate predicted 25% point difference in BMIp between the two. Although further research is needed, where redevelopment efforts have previously focused on classically defined neighborhood boundaries, improving the areas surrounding schools may be a more effective environmental strategy to reduce overweight in children by creating catchment areas that affect a greater number of them.

The hierarchical design and size of our sample at both the individual and community levels represent particularly important strengths of this study. When unable to control for clustering effects and individual-level variation, the impact of community-level factors may be under- or overestimated, which may offer one explanation as to why results of previous research are mixed. Our study provides support for the influence of school neighborhood factors on the health of children with a robust sample and design. In addition, height and weight were measured on a large sample of children from varied racial/ethnic backgrounds. These have been limitations in previous studies where heights and weights were obtained by self-reports or proxy reports and most subjects were white.

Nonetheless, this study has several limitations of its own. It was localized to a mid-sized Midwestern urban area, and it may not be generalizable to other parts of the United States or internationally. Some key phenomena were not measured, including individual student SES. Some community-level factors (for example, parks) were included in the analysis because of their presence in an environment, which may not correspond to actual usage. In addition, some of our variables are proxy measures that may not coincide fully with the phenomenon they are intended to capture. This notably pertains to the population size and change variables that serve in different ways as proxy measures for neighborhood vitality or decay. More significantly, the cross-sectional nature of this data cannot elucidate causality. Thus, we cannot conclude that school environments necessarily have a causal effect on student BMIp. Also, the data do not allow us to disentangle the contributions to BMIp from school neighborhood and other key related factors, notably student's home environment, which are included in the theoretical model by Harrison and Jones.[44] In addition, there is a possibility of misclassification of several of the environmental features used in this study (for example, see above discussion of grocery stores and convenience stores). Although our data verification procedure described above should have mitigated this issue, unlike the index measures from the

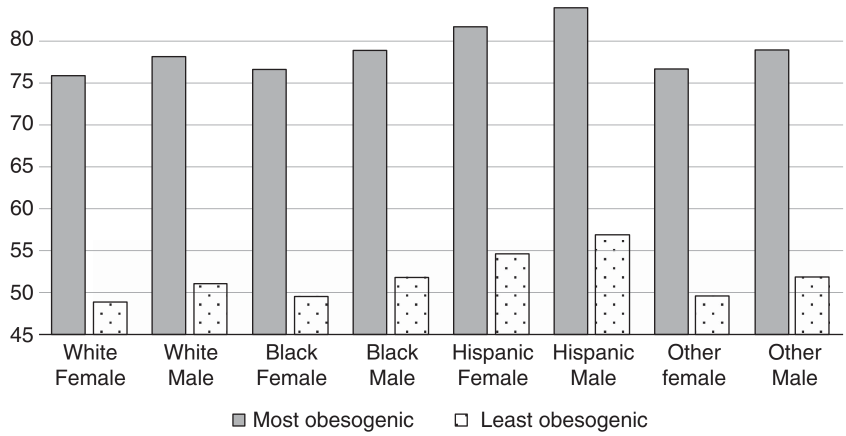

Figure 1. Predicted BMI percentiles by race and gender in the 'most obesogenic' compared with the 'least obesogenic' neighborhoods.

Walkscore website, the individual results by category, to our knowledge, have not been validated. Finally, a limitation to studies of environmental effects on health outcomes such as ours concerns the complexity and multi-faceted nature of the measures and associations. This is an inherent feature of the multi-factorial nature of environments, where facets of neighborhoods can be both simultaneously positive and negative for health. A flourishing neighborhood may simultaneously see the development of parks and the influx of business, including those with negative impacts on health such as fast-food restaurants. These complex associations are difficult to disaggregate and may complicate any analysis that seeks to disentangle particular environmental features, as our analysis does. In our analysis, several variables have bivariate associations and a factor analysis shows that parks, fast-food restaurants, grocery stores and fitness facilities have reasonably strong factor loadings, suggesting that all are associated with some underlying factor (perhaps how developed a particular environment is). However, this does not necessarily imply multicollinearity and the partial correlations (Table 2) suggest that there is enough unique contribution of each variable to reasonably include them separately in the analysis.

Future research should address a number of these limitations, including longitudinal examination of BMIp. Notably, age and sex remained significant in the models even though BMIp calculation inherently accounts for them, suggesting that changes in BMIp over time may not be equal across groups. A longitudinal analysis examining difference in BMI growth over time may elucidate additional factors that promote or mitigate overweight among children. In addition, efforts should be undertaken to improve the operational definitions of environmental features, and subsequently their measurement, in hopes of disaggregating what are likely conflicting social forces that are simultaneously both positive and negative for health, and which are currently still aggregated into single variables in most analyses, including ours. This would improve the accuracy and usefulness of models of the associations between environment and health.

Organizing child health programming around schools is not a new idea. However, recent calls for examining the extent to which schools can serve as the anchor points for zones of health influence suggest a broader conceptualization of the ways in which they impact health. Using a large sample and a multi-level approach, this paper demonstrates that aspects of the built environment in the neighborhoods surrounding schools indeed are associated with childhood BMIp. Although more research is needed, this may represent initial evidence that neighborhood redevelopment efforts by United States Department of Housing and Urban Development and other non-profits (for example, Local Initiative Support Corporation) should consider targeting the radial areas around schools, rather than traditionally defined neighborhoods. This is particularly important because improved child health manifests in healthier adults later on. Although traditional neighborhood boundaries will capture a cross-section of the public, the number of children affected by improvements to school neighborhoods ultimately may pay greater health dividends, and the full range of corollary benefits, as they age.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

ACKNOWLEDGEMENTS

We would like to thank Annette Campbell, Katherine Braunlich and Arthur Kheyfets for their support and assistance with this article.

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