Pedestrian Supportive Neighborhood Environments and Childhood Obesity in the Fragile Families and Child Wellbeing Study: Using Virtual Audits to Study Neighborhoods

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Abstract

Background: The rising prevalence of childhood overweight and obesity has added to early elevations in cardiovascular risk factors. One strategy to prevent children from becoming overweight or obese is to modify the local residential environment to better support physical activity. In particular, structural approaches to improve pedestrian safety from traffic may have additional benefits of encouraging physical activity and healthy weight trajectories for children.

Methods: We used data from the Fragile Families and Child Wellbeing Study, which recruited 4,898 families from 20 large US cities in the years 1998-2000. Google Street View virtual audits were conducted to characterize neighborhoods around home addresses for children living in three cities (Philadelphia, New York, and San Jose). Previous research suggests that pedestrian safety features can be reliably assessed from Google Street View. A pedestrian safety summary index has been constructed using 17 dichotomized items; items had kappas for inter-rater reliability ranging from 0.4 to 1.0, and city-specific Cronbach's α values were calculated as 0.4, 0.5, and 0.7. Kriging was used to spatially interpolate pedestrian safety values, which were then used to characterize neighborhoods (operationalized using 1 km and 0.25 km radial buffers). Linear regression models were used to evaluate the association of neighborhood pedestrian safety with childhood BMI z-scores at ages 3, 5 and 9 years, collected during home visits.

Results: There was no evidence to support the hypothesized inverse association between pedestrian safety and childhood BMI z-score (all $p > 0.1$) in models adjusting for city of residence, child's sex, race/ethnicity, low birth weight, maternal education, maternal marital status, maternal obesity, receipt of public assistance income, and Census tract percent of residents living in poverty, Hispanic residents, and non-Hispanic African American residents.

Conclusions: Using a novel approach to neighborhood data collection using virtual street audits.we did not find evidence that pedestrian safety features are associated with childhood BMI z-score as has been hypothesized.

Introduction

The rising prevalence of childhood overweight and obesity,[1] along with related health behaviors, has led to disturbing trends in childhood onset of Type II diabetes and early elevations in cardiovascular risk factors,[2-4] and possibly to other conditions including asthma[5] and social isolation.[6] Although medical treatments are available for childhood obesity, their high costs and limited long-term effectiveness make these treatments a poor substitute for prevention.[2] The current high prevalence of childhood obesity reflects a dramatic increase during recent decades that cannot readily be explained by genetics or other stable characteristics and likely reflects an increasingly "obesogenic" environment.[7]

One promising strategy to prevent children from developing unhealthy behavior patterns and becoming overweight or obese is to create health-supporting local neighborhood environments. Built environment components (e.g., buildings, transportation systems, architectural and urban design features, landscape elements, and green spaces) are continually built and rebuilt over generations, making even these relatively durable aspects of the local environment potentially modifiable. Attractive and less threatening environments are thought to promote walking and playing outdoors, resulting in increased total physical activity. Social influence may amplify any such association if the presence of pedestrians or children outside draws out others, who might not have been initially responsive to the built environment. Such processes could ultimately shift norms around physical activity and weight, or affect residential selection into and out of neighborhoods.

Previous studies have found built environment characteristics to be associated with the health behaviors and weight of children and adults,[8-11] and this initial research has generated considerable interest and momentum. As concepts such as neighborhood walkability[12-14] and food deserts[15-17] have become more prominent, they have increasing power to shape policy discussions and the environment.[18,19] Reviews of the published literature have noted some inconsistencies among these early studies.[8,9,20] Commonly measured built environment characteristics such as residential density and land use mix have been used as indicators of walkable urban form, but do not fully capture how well a neighborhood supports pedestrians. In particular, even neighborhoods with walkable urban form may have problems related to safety and aesthetics that impede pedestrian activity, particularly in economically deprived urban areas.[21,22] Yet secondary GIS data, which have the advantage of being independent of behavior or health assessments, are often limited in their coverage of features relevant to pedestrian comfort and safety. Associations of self-reported neighborhood safety or aesthetics as predictors of physical activity or adiposity may not reflect the true causal association if environment and outcome measurement errors are correlated.[23] Safety-related features of streets, such as the presence of a buffer between the sidewalk and vehicle traffic, are generally not included in large-scale GIS datasets and may be subject to information bias if reported by study subjects. However, virtual audits offer a feasible option for independent assessment of the local environment, tailored to the research questions of interest.[24] Here, we assess the association between neighborhood pedestrian safety as assessed by virtual audit and childhood adiposity.

Methods

Subjects and Setting

Longitudinal data on geographic and social environments as predictors of childhood health were from a birth cohort of children born between 1998 and 2000. The Fragile Families and Child Wellbeing Study (hereafter shortened to Fragile Families) recruited 4,898 families at the time of the birth, from 20 large US cities.[25] Core survey data collected at each visit (at birth and ages 1, 3, 5, and 9) include measures of the social environment such as household composition, food security, and perceptions of neighborhood social context, as well as parental reports of childhood health problems. Hospital record data has also been abstracted at baseline to assess indicators of perinatal health including birth weight.

Outcome measurement

Assessments of weight and body mass index

Home visits were conducted at the year 3, 5, and 9 assessments as part of the supplemental In-Home Longitudinal Study of Preschool-Aged Children to complement the survey data, and these visits included measurement of the mother's and child's weight and height. The childhood and maternal weight data have been used previously in this cohort to examine correlations with reported parental behaviors and socioeconomic status.[26,27]

The primary outcome is child adiposity at ages 3, 5, and 9 years, as indicated by BMI z-score. Child BMI z-scores and percentiles were calculated according the Center for Disease Control and Prevention age and sex-specific growth chart guidelines.[28] Overweight and obesity measures are based on the BMI percentile for children (at or above the 85^{th} or 95^{th} percentiles, respectively). Trained interviewers used electronic scales (SECA 840 Bella Digital Scale, Hanover, MD) and portable stadiometers (SECA 214 Road Rod Stadiometer) to measure weight and height during in-person study visits. Two measurements for height and weight were taken for each child, and a third measure was taken if the first two measurements deviated by 2 or more units (centimeters for height; pounds for weight). Flag variables for each follow-up period were created to indicate whether there was a potential measurement error with the child's anthropometric measures.

Maternal obesity was calculated based on height and weight measurements taken during the year 3 and year 5 in-home assessments using the same measurement tools as mentioned previously. Mothers were asked to self-report their weight if they declined to be weighed, were pregnant, or exceeded the 140kg capacity of the scales. Maternal BMI from year 3 was used as the default value, but if the mother was pregnant at the time of the measurement or was flagged as a potential measurement error, the mother's BMI from the year 5 assessment was used (excluding mothers who were flagged or pregnant at year 5 as well).

Defining and linking neighborhoods to geographic data

Home addresses provided at age 1, 5, and 9-year follow-ups were used for this study. For measurement purposes, the neighborhood around each home address is defined as a circular buffer surrounding the mother's or father's primary address, with a radius of 1 km. To test the sensitivity of study results to this definition, secondary analyses were conducted using smaller 0.25 km radius buffer areas as the neighborhood definition for exposure measurement.

Geographic context measurement using Google Street View audits

Google Street View has been used to characterize the area near homes for participants living in 3 of the 20 study cities (currently completed for three cities: Philadelphia, PA; New York City, NY; and San Jose, CA). For each of these cities a grid of street segments was selected for observation, drawn to oversample areas with a higher density of Fragile Families respondents. This approach, as compared with characterizing the street segment on which each participant lived, limited any confidentiality risk to respondents while also allowing flexibility to estimate characteristics of broader neighborhoods surrounding address points.

Item testing and field verification indicate that some measures of physical disorder and of the pedestrian environment can be reliably assessed from Google Street View, with results comparable to those obtained using in-person raters.[29,30] Selected street segments were observed by trained raters using a web application, the Computer Assisted Neighborhood Visual Assessment System (CANVAS). A subset of street segments was viewed by more than one member of our research team to allow for assessment of inter-rater reliability.

This analysis focuses on the pedestrian safety features in Table 1, which may be relevant to childhood obesity but inadequately captured by spatially aligned administrative data commonly used in studies of neighborhood walkability. Items were adapted from the Pedestrian Environment Data Scan[31] and the Irvine-Minnesota Inventory to measure built environments.[32,33] We had 6-12% of the selected segments in each city excluded from our analyses due to missing or pending data on these items. A pedestrian safety summary index was constructed using 17 dichotomized items (Tables 1 & 2); items had kappas for inter-rater reliability ranging from 0.4 to 1.0, and city-specific Cronbach's α values were calculated as 0.4, 0.5, and 0.7.

The pedestrian safety summary scores calculated for sampled street segments were used to generate a kriged surface spatially interpolating our estimate of pedestrian safety across each city. Kriging, a method of spatial interpolation, allows values of measures to be estimated for all blocks in the city, which in turn allows for the flexible definition of neighborhood boundaries. Kriging uses data on attributes from observed locations, and the spatial autocorrelation structures of those data, to estimate attribute values at non-observed locations.[34-36] Parameters include the sill, defined as the maximum dissimilarity approached asymptotically at large distances; phi is a component of the shape the Gaussian correlation function fitted to the semivariogram; and nugget is the minimum dissimilarity approached as distance approaches zero. Kriging parameters (sill, phi, and nugget) were chosen for each city based on visual fit:

Philadelphia: sill=1.1, phi=2000, nugget=2.0

NYC: sill=2.14, phi=2000, nugget=2.85

San Jose: sill=3.0, phi=1000, nugget=1.31

The kriged surfaces for each city were intersected with the study subject's neighborhood boundaries to estimate pedestrian safety summary scores for each neighborhood using ArcGIS version 10.0.

Additional Neighborhood Exposures

Several additional contextual neighborhood measures from the Fragile Families Census tract and maternal questionnaire data at the 3 year assessment were included. Random noise was introduced into the Census tract data to ensure that individual study participants' Census tracts could not be identified, but this noise should not impact the analyses.

Neighborhood composition and social context variables were derived from US Census data from the year 2000. Buffer neighborhoods from the mother's address at the year 3 follow-up have been characterized through a spatial overlay with polygon data at the census block group level. Variables constructed included percentage of residents living below the federal poverty line, the percentage of Hispanic residents, the percentage of non-Hispanic African American residents, percent of vacant housing units, and percent of housing units built before 1940. All continuous neighborhood measures based on Census tract data were rescaled to have a minimum value of 0 and an interquartile range of 1 for ease of comparison. The model coefficients for these variables may thus be interpreted as the difference in BMI z-score for a child at the 75^{th} percentile of neighborhood exposure compared to a child at the 25^{th} percentile of neighborhood exposure.

Maternal perceptions of neighborhood context were measured by survey questions on perceived social disorder and collective efficacy, as described for a previous Fragile Families analysis.[37] Social disorder was based on 8 items asking how often the mother saw 'disorderly' activities in her neighborhood, such as gang activity, drug dealers loitering, or groups of people misbehaving. Averages were computed for mothers who answered at least 6 out of the 8 items in the index, and scores were divided into tertiles. Maternal perception of neighborhood collective efficacy was comprised of two components: 1)social cohesion and trust and 2) informal social control. Social cohesion and trust consisted of 5 questions, and an average score was computed if mothers answered at least 4 out of the 5 items in the index. Similarly, informal social control (i.e. perceived likelihood of neighbors intervening in unpleasant situations) was asked in a 5-item index, and mothers with at least 4 out of 5 items answered received an average score. Values from the social cohesion and informal control index averages were combined for the collective efficacy index, which was then divided into tertiles of high, medium, and low collective efficacy.

Statistical analysis

The statistical analysis includes descriptive statistics and generalized linear regression models. Because some children had pedestrian safety index values observed for both mother's and father's address at a given time point, cluster-robust standard errors were used to account for non-independence. All adjust for city of residence and a set of covariates informed by previous experience and determined a priori—the child's sex, race/ethnicity (based on maternal report as

White, African American, or Hispanic/Other), low birth weight (less than 2500 grams), mother's marital status at time of birth, maternal education (less than high school, high school graduate, or some college/college graduate), maternal receipt of public assistance income (public assistance/welfare/food stamps reported in past year at baseline), maternal obesity (BMI at 30 or above),and Census tract percent of residents living in poverty, Hispanic residents, and non-Hispanic African American residents. Adjustment for additional neighborhood characteristics (neighborhood social disorder and collective efficacy based on maternal self-report; percent of vacant housing units and percent of housing units built before 1940 based on Census tract data) was considered as a sensitivity analysis. Statistical analyses were conducted using Stata 12.0,SAS 9.3, and R 2.15.3.

Results

At ages 3, 5, and 9 years old, 36%, 31%, and 40% of the Fragile Families cohort had completed home visits and had a plausible BMI z-score and all covariates available for analysis. Of the children available for BMI z-score analyses at one or more of these follow-up times, 22%, 19%, and 17% had geocoded maternal or paternal home addresses within the three cities for which we have assembled virtual audit data. Our analytic data set thus included 449 children who were eligible for inclusion in one or more of our analyses linking pedestrian safety with BMI z-score across time (Table 3). For this analytic sample, 49% of children in the children were African American, 45% were Hispanic, and 50% were male. Thirty-four percent of mothers in the sample did not graduate high school, 20% were receiving some income from public assistance at baseline, and 40% of mothers with observed BMI were classified as obese.

A pedestrian safety summary index has been constructed using 17 dichotomized items (Table 1) and spatially interpolated to characterize neighborhoods (operationalized using 1 km and 0.25

km radial buffers). The mean pedestrian summary index score among observed street segments ranged from 0.60 to 0.67 across the three selected cities (Table 2).

There was no evidence to support the hypothesized inverse association between pedestrian safety within 1 km of the home and childhood BMI z-score across time (all $p > 0.1$) (Table 3). Table 3 uses a rescaled mean value measure of pedestrian safety based on the child's age 1, 5, or 9 home address as a predictor of BMI z-score. The 95% confidence intervals exclude any associations greater than 0.6 units difference in BMI z-score per standard deviation in the pedestrian safety summary score.

Further adjustment for additional neighborhood characteristics (Table 4) or modification of the neighborhood definition to be a smaller 0.25 km buffer (Table 5) did not substantially alter these results. Other sensitivity analyses examined, including sex stratification and restriction to characterizing the pedestrian safety around maternal addresses only, both of which yielded similarly null results (data not shown).

Discussion

Although moderate to high inter-rater reliability was achieved using virtual audits to assess features related to pedestrian safety, the spatially interpolated pedestrian safety summary score around home addresses for ages 1-9 years were not strongly associated with childhood BMI z-score for ages 3 to 9 years.

(Discuss previous literature relevant to social context in this and other studies)

Previous analyses in the Fragile Families cohort indicate that interviewer ratings of building and neighborhood deterioration are associated with maternal obesity[38] and that cumulative social stress within the household is associated with childhood obesity for girls only.[39] Although pedestrian safety as indicated by pedestrian auto fatalities was shown to predict childhood physical activity and adiposity based on skinfold thicknesses previously, null results were observed in the same study using the outcome of BMI z-score.[40] This measure of adiposity may be less sensitive to the effects of the local environment than physical activity patterns themselves, or alternative measures of adiposity such as skinfold thicknesses or body fat percent.

Virtual audits have begun to emerge as a tool for examining the neighborhood context relevant to health.[24,30,41-46] Evaluations of validity,[24,41,46] reliability, [43-45] and perceived utility[42] of virtual audits have generally concluded that this data collection strategy may be a useful complement to other available tools. One previous study has linked physical disorder measures from virtual audits to childhood weight.[45] Although we did not find that traffic safety features and qualities along street segments were associated with lower childhood BMI z-score in this disadvantaged urban population, future studies are needed to investigate whether this metric could be relevant to other demographic groups.

Strengths and limitations

Key strengths of this study were the deployment of a novel method for assessing pedestrian safety features across three US cities. Longitudinal assessment of both home addresses and BMI z-scores allows for examination of the temporal association between neighborhood context and BMI z-scores. In addition, the rich datasets available on individual covariates, parental health, and attitudes/beliefs address collected in this birth cohort study allowed us to address the possibility of confounding by a common prior cause and to investigate potential interactions.

Key limitations included the observational nature of the study design and restriction to urban settings. There was potential for selection bias and differential loss to follow-up to distort the associations between neighborhood context and health. In addition, for our pedestrian safety summary index, the index reliability as indicated by Cronbach's alpha was only moderate, and the spatial auto-correlation was relatively low. Other neighborhood characteristics such as physical disorder may be more amenable to this approach (analyses in progress).

Next Steps

Next steps include: (1) add a fourth city (currently being audited) to the analysis; (2) explore measurement models ("ecometrics" version proposed by Raudenbush and Sampson) for scale creation that draw on item response theory, (3) conduct kriging at a more detailed spatial scale such as the block face, (4) generate conditional realizations rather than smoothed estimates from kriging and combine these using multiple imputation software tools to reflect uncertainty arising during interpolation, (5) conduct sensitivity analyses combining address information from both parents over time (maternal and paternal addresses were not necessarily identical or adjacent, but the corresponding residential context data can be combined into a weighted average to characterize the child's home environment by using survey reports of time spent at each location), and (6) explore patterns of effect modification through examining within-level and cross-level statistical interactions (including by area-based poverty and residential stability measures).

Conclusions

This project advances research on the complementary and intersecting roles of the built environment and social context in shaping childhood obesity and physical activity. Novel contextual data allowed previously untestable hypotheses to be tested. Although we did not find a statistically significant association between pedestrian safety features and childhood BMI z-score, future research using virtual street audits may elucidate the neighborhood features most relevant to childhood obesity and other health and social outcomes.

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Table 1. Virtual audit items, source, and reliability

Characteristic or feature	Full Question	Categorization	Source	Inter-rater reliability
Traffic signal	What kind of traffic signal is provided?	Any (1) vs none (0)	IMI	0.88
Pedestrian signal	Is there a pedestrian signal?	Yes (1) vs no (0)	PEDS	0.97
Marked pedestrian crossing	Consider the places that are intended for pedestrians to cross the street. Are these places marked for pedestrian crossing?	All or some (1) vs no (0)	IMI	0.89
Marked crosswalks of some type	How is the road marked at crosswalks?	Any (1) vs not marked at all (0)	IMI	0.87
Traffic island	Is there a median/traffic island large enough for a pedestrian to stand on?	Yes (1) vs no (0)	PEDS	0.50
Curb cuts	Do you see any curb cuts on the block face?	Yes (1) vs no (0)	IMI	0.67
Convenient to cross street	For an individual on this segment, how convenient (traffic-wise) do you think it is to cross the street from this segment?	Very or pretty convenient (1) vs not very or inconvenient (0)	IMI	0.60
Traffic calming device	Is there any kind of traffic calming device (curb extension, chicane, choker, speed bump, rumble strip, dimple, etc)	Yes (1) vs no (0)	PEDS	0.43
Slope flat or slight hill	What is the maximum slope of the segment?	Flat or slight hill (1) vs steep hill (0)	PEDS	0.52
≤ 2 traffic lanes	How many lanes are there for cars (include turning lanes but not including parking lanes)?	One or two (1) vs three or more (0)	IMI	0.66
Good road condition	What is the condition of the road?	Good (1) vs fair or poor (0)	PEDS	0.44
On street parking	What kind of on-street parking is there?	Any (1) vs none (0)	IMI	0.64

Sidewalk or pedestrian path	What type of sidewalk or path (paved or unpaved) is there?	Any (1) vs none (0)	PEDS	0.97
Continuous sidewalk	Is the sidewalk complete/continuous?	Complete (1) vs incomplete or no sidewalk (0)	PEDS	0.69
Sidewalk in good condition	In what condition is the sidewalk or pedestrian path?	Good (1) vs fair, poor, or none (0)	PEDS	0.51
Sidewalk away from curb	Is the sidewalk right next to the curb?	No (1) vs yes (0)	PEDS	0.7
Trees between road and sidewalk	Are there trees between the road and the path/sidewalk?	Yes (1) vs no (0)	PEDS	0.63

Note: MII indicates Irvine-Minnesota Inventory; PEDS indicates Pedestrian Environment Data Scan. Inter-rater reliability calculated on average pairwise kappas.

Table 2. Virtual audit measures related to pedestrian safety across three US cities

Characteristic or feature	Philadelphia, PA (471 segments)	New York City, NY (500 segments)	San Jose, CA (249 segments)
Traffic signal	50	62	39
Pedestrian signal	2	48	12
Any marked pedestrian crossing	83	75	22
Marked crosswalks of some type	83	75	22
Traffic island	9	15	9
Curb cuts	90	95	62
Convenient to cross street	68	72	69
Traffic calming device	1	3	2
Slope flat or slight hill	97	90	97
≤ 2 traffic lanes	90	83	81
Good road condition	39	24	33
On street parking	91	96	86
Sidewalk or pedestrian path	96	100	100
Continuous sidewalk	89	95	88
Sidewalk in good condition	16	28	54
Sidewalk away from curb	23	16	49
Trees between road and sidewalk	37	77	65
Pedestrian safety summary index	9.6 (1.9)	10.5 (2.0)	8.9 (1.9)
Cronbach's α	0.65	0.58	0.73

Note: Values shown for each item are percent of observed street segments with the given features or qualities and mean (SD) for the safety summary index calculated by adding one point per item.

Table 3. Associations of pedestrian safety within 1 km of home address and childhood BMI z-score across time

	Age 3 BMI z-score[a] **β (95% CI)**	Age 5 BMI z-score[a] **β (95% CI)**	Age 9 BMI z-score[a] **β (95% CI)**
Pedestrian safety, age 1 address with 1km buffer[b]	0.20 (-0.17, 0.57) p=0.284	0.07 (-0.43, 0.28) p=0.682	0.01 (-0.27, 0.28) p=0.965
Pedestrian safety, age 5 address with 1km buffer[b]		-0.14 (-0.50, 0.21) p=0.428	-0.03 (-0.33, 0.27) p=0.847
Pedestrian safety, age 9 address with 1km buffer[b]			0.08 (-0.23, 0.39) p=0.628

Note: Values shown are the estimated difference in BMI z-score for a 1 SD increase in pedestrian safety followed by corresponding 95% confidence intervals, with adjustment for city of residence, child's sex, race/ethnicity, low birth weight, maternal education, maternal marital status, maternal obesity, receipt of public assistance income, and Census tract percent of residents living in poverty, Hispanic residents, and non-Hispanic African American residents; N varied from 374 to 415 children with complete data across time points.

[a]BMI z-scores measured by trained interviewers during in-home visits. All measures of child height and/or weight that were flagged as a potential measurement error were set to missing.

[b]Pedestrian safety is measured by the mean value of all pedestrian safety grid points intersected by a 1-km neighborhood radial buffer. Each time point incorporates address data from the mother and father's home addresses at the specified age of the child.

Table 4. Associations of pedestrian safety and other neighborhood characteristics within 1 km of home address and childhood BMI z-score across time

	Age 3 BMI z-score[a] **β (95% CI)**	**Age 5 BMI z-score[a]** **β (95% CI)**	**Age 9 BMI z-score[a]** **β (95% CI)**
Pedestrian safety, age 1[b]	0.19 (-0.19, 0.56)	-0.03 (-0.39, 0.33)	0.04 (-0.24 0.32)
Neighborhood collective efficacy[c]			
High	(reference)	(reference)	(reference)
Medium	0.01 (-0.33, 0.35)	-0.26 (-0.59, 0.06)	-0.02 (-0.28, 0.25)
Low	0.29 (-0.06, 0.65)	-0.15 (-0.48, 0.17)	0.02 (-0.25, 0.29)
Neighborhood disorder[c]			
High	-0.08 (-0.42, 0.26)	0.24 (-0.09, 0.58)	0.20 (-0.09, 0.48)
Medium	0.14 (-0.22, 0.51)	0.01 (-0.32, 0.33)	0.10 (-0.18, 0.38)
Low	(reference)	(reference)	(reference)
Neighborhood vacant housing	**0.19 (0.01, 0.37)**	0.06 (-0.10, 0.21)	0.12 (-0.03, 0.26)
Neighborhood pre-1940 housing	0.04 (-0.30, 0.39)	-0.10 (-0.43, 0.22)	-0.11 (-0.38, 0.15)
Pedestrian safety, age 5[b]		-0.13 (-0.50, 0.24)	-0.02 (-0.33, 0.28)
Neighborhood collective efficacy[c]			
High		(reference)	(reference)
Medium		-0.20 (-0.54, 0.14)	0.06 (-0.22, 0.33)
Low		-0.11 (-0.45, 0.22)	0.02 (-0.25, 0.29)
Neighborhood disorder[c]			
High		0.23 (-0.12, 0.57)	0.21 (-0.08, 0.51)

Medium	0.11 (-0.24, 0.46)	0.19 (-0.11, 0.48)
Low	(reference)	(reference)
Neighborhood vacant housing	0.03 (-0.14, 0.20)	0.09 (-0.07, 0.24)
Neighborhood pre-1940 housing units	-0.01 (-0.38, 0.36)	-0.07 (-0.37, 0.23)
Pedestrian safety, age 9 address with 1km buffer[b]		0.13 (-0.18, 0.44)
Neighborhood collective efficacy[c]		
High		(reference)
Medium		0.04 (-0.25, 0.33)
Low		-0.06 (-0.34, 0.22)
Neighborhood disorder[c]		
High		**0.36 (0.06, 0.66)**
Medium		0.24 (-0.08, 0.55)
Low		(reference)
Neighborhood vacant housing		0.12 (-0.04, 0.29)
Neighborhood pre-1940 housing units		-0.12 (-0.42, 0.19)

Note: Values shown are the estimated difference in BMI z-score for a 1 SD increase in pedestrian safety followed by corresponding 95% confidence intervals, with adjustment for city of residence, child's sex, race/ethnicity, low birth weight, maternal education, maternal marital status, maternal obesity, receipt of public assistance income, and Census tract percent of residents living in poverty, Hispanic residents, and non-Hispanic African American residents.

[a]BMI z-scores measured by trained interviewers during in-home visits. All measures of child height and/or weight that were flagged as a potential measurement error were set to missing.

[b]Pedestrian safety is measured by the mean value of all pedestrian safety grid points intersected by a 1-km neighborhood radial buffer. Each time point incorporates address data from the mother and father's home addresses at the specified age of the child.

[c]Measured at year 3 maternal questionnaire follow-up.

[d]Based on mother's home address at year 3; in order to standardize units and interpretation of Census neighborhood characteristics, all Census variables were rescaled to have a minimum value of 0 and an interquartile range of 1; this allows BMI z-score children comparisons of with a typical 'high' level of exposure to a child with a typical 'low' exposure level.

Table 5. Associations of pedestrian safety within 0.25 km of home address and childhood BMI z-score across time

	Age 3 BMI z-score[a] **β (95% CI)**	Age 5 BMI z-score[a] **β (95% CI)**	Age 9 BMI z-score[a] **β (95% CI)**
Pedestrian safety, age 1 address with 0.25km buffer[b]	0.09 (-0.18, 0.36) p=0.505	-0.02 (-0.30, 0.25) p=0.857	0.05 (-0.14, 0.25) p=0.596
Pedestrian safety, age 5 address with 0.25km buffer[b]		-0.00 (-0.25, 0.24) p=0.987	-0.03 (-0.23, 0.17) p=0.777
Pedestrian safety, age 9 address with 0.25km buffer[b]			0.08 (-0.12, 0.27) p=0.457

Note: Values shown are the estimated difference in BMI z-score for a 1 SD increase in pedestrian safety followed by corresponding 95% confidence intervals, with adjustment for city of residence, child's sex, race/ethnicity, low birth weight, maternal education, maternal marital status, maternal obesity, receipt of public assistance income, and Census tract percent of residents living in poverty, Hispanic residents, and non-Hispanic African American residents.

[a]BMI z-scores measured by trained interviewers during in-home visits. All measures of child height and/or weight that were flagged as a potential measurement error were set to missing.

[b]Pedestrian safety is measured by the mean value of all pedestrian safety grid points intersected by a 0.25-km neighborhood radial buffer. Each time point incorporates address data from the mother and father's home addresses at the specified age of the child.