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Interrelationships between Walkability, Air Pollution, Greenness, and Body Mass Index

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Abstract

Background—Recent studies have linked urban environmental factors and body mass index (BMI); however, such factors are often examined in isolation, ignoring correlations across exposures.

Methods—Using data on Nurses' Health Study participants living in the Northeastern United States in 2006, we estimated associations between neighborhood walkability (a composite of population density, street connectivity, and business access), greenness (from satellite imagery), and ambient air pollution (from satellite-based spatiotemporally resolved PM_{2.5} predictions and weighted monthly average concentrations of NO₂ from up to five nearest monitors) and self-reported BMI using generalized additive models, allowing for deviations from linearity using penalized splines.

Results—Among 23,435 women aged 60–87 years, we observed non-linear associations between walkability and BMI, and PM_{2.5} and BMI in single-exposure models adjusted for age, race, and individual- and area-level socioeconomic status. When modeling all exposures simultaneously, only the association between walkability and BMI remained non-linear and non-monotonic. Increasing walkability was associated with increasing BMI at lower levels of walkability (walkability index <1.8), while increasing walkability was linked to lower BMI in areas of higher walkability (walkability index >1.8). A 10 percentile increase in walkability right above 1.8 was

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associated with a 0.84% decrease in log BMI. The relationship between walkability and BMI existed only among younger participants (<71 years old).

Conclusions—Neighborhood walkability was non-linearly linked to lower BMI independent of air pollution and greenness. Our findings highlight the importance of accounting for non-linear confounding by interrelated urban environmental factors when investigating associations between the environment and BMI.

Keywords

Body mass index; greenness; air pollution; walkability; built environment

Introduction

Over 65% of all women in the U.S. are overweight or obese,¹ and 71.7% of women 40–59 years old report being overweight and 39.5% report being obese, placing this population at high risk of the well-characterized health effects of overweight and obesity,² including cardiovascular disease,³ cancer,⁴ and all-cause mortality.⁵ Researchers are increasingly applying an ecosocial lens to understand risk factors for obesity, investigating how individual, social, and environmental factors interact to drive health.⁶ In recent years, research has suggested that the built environment (e.g., neighborhood walkability),^{7–9} natural vegetation (i.e., greenness),¹⁰ and air pollution^{11–13} are associated with body mass index (BMI). These environmental factors are promising targets because they are ubiquitous exposures that can be modified broadly through changes to policy on development, land use, transportation, and environmental regulation.^{6,7,14,15} However, these exposures may have complex interrelationships and few studies have examined these exposures in concert to isolate independent associations of each exposure with BMI.

The literature on environmental determinants of BMI is rapidly growing. Over the past decade, there has been a dramatic increase in studies examining how factors of the built environment, such as nearby destinations to walk to, may create opportunities for higher levels of walking and subsequent lower levels of obesity.⁸ Alternatively, there has been a growing interest in how natural environments might affect health behaviors and outcomes, including obesity. Greenness is an ecologic exposure that is thought to decrease BMI by providing a location for physical activity.¹⁶ Studies show that, in general, greater neighborhood greenness is associated with lower likelihood of overweight or obesity.^{10,17} Recent studies in children have also implicated air pollution as a risk factor for obesity.^{11,12} In research focusing on adults, one study observed elevated findings.¹³ Another study in adults showed a positive association between roadway proximity and adiposity, but no association between particulate air pollution exposure and BMI.¹⁸

While evidence builds regarding the associations between BMI and exposure to neighborhood walkability, greenness, and air pollution, few studies have examined all of these factors simultaneously. Spatial features associated with walkability may be correlated with spatial patterns in air pollution levels. In addition, greenness may buffer exposure to air pollution, but greenness may be lower in more walkable places. Research has highlighted these correlations,^{19–22} but no study has examined the joint and independent associations

between these exposures and BMI. Moreover, previous studies have not examined whether the assumption of linearity holds when evaluating these associations. If this is not the case, and the association between BMI and these exposures changes across the distribution of the exposures, then previously observed and reported effect estimates might be biased.

In this study, we examine environmental correlates of BMI using data from a subset of the Nurses' Health Study, a cohort study of adult women, a population that is likely particularly susceptible to obesity-related health effects.² Our primary objective was to examine the joint, potentially non-linear, relationships between greenness, neighborhood walkability, and air pollution, and BMI across the northeastern U.S.

Methods

Study Population

We used data from the Nurses' Health Study, a nationwide prospective cohort assessing a wide variety of risk factors for chronic disease among women. In 1976, 121,701 female registered nurses aged 30–55 years from 11 states returned an initial questionnaire ascertaining a variety of health-related exposures. The cohort has been continuously followed with biennial questionnaires. Response rates over follow-up have been ~90%. Data for this analysis were taken from 2006, the most recent year for which air pollution and walkability data were available at the time of analysis. All available residential addresses in 2006 were geocoded to obtain latitude and longitude. Approximately 90% were successfully matched to the street address. For the current analyses we included all women who completed the 2006 questionnaire, lived in the northeastern US (Figure 1) where satellite air pollution predictions were available, and had an address geocoded to the street level. The study was approved by the Institutional Review Board of Brigham and Women's Hospital, Boston, MA, and informed consent was implied through return of the questionnaires.

Outcome Assessment: Body Mass Index (BMI)

The study participants were asked about their weight at the 2006 questionnaire. We used information on self-reported height, collected at enrollment, and weight in 2006 to calculate BMI as weight/height^2 (kg/m^2). A validation study of 184 Nurses' Health Study participants showed that self-reported weights were highly correlated with measured weights ($r=0.96$; mean difference, 1.5 kg).²³

Exposure Assessment

Walkability—Neighborhood walkability is often defined based on land use patterns, transportation systems, and urban design.²⁴ Although measures of neighborhood walkability have not been standardized, the measures of population density, land-use mix, and street connectivity have commonly been linked to health outcomes.^{7,8} We created a consolidated walkability index using Z-scores for these neighborhood components. This index reflects the built environment as a latent construct comprising information from various correlated individual factors. Using US Census²⁵ and commercially available GIS data, we created residence-level measures of population density, business counts (as a proxy for accessibility), and intersection counts (as a proxy for street connectivity) linked to the

participants' geocoded 2006 mailing addresses. Population density was calculated based on the 2000 Census population density in the tract of residence in 2006. To develop business count and intersection count measures, we created 1200m line-based network buffers around each home address; we previously identified this buffer as the most relevant to BMI-related associations within nurses living in the United States.²⁶ Briefly, we used ArcGIS software to identify the street network within 1200m from each participant's mailing address, and included a 50m buffer on either side of the road. Interstates and ramps were excluded from the networks, as we were interested in walkable streets only. We used this line-based network buffer to focus on areas people can access by walking²⁷ (eFigure 1). Destination counts were measured as the counts of all stores, facilities, and services in a participant's buffer using the commercially available 2009 *infoUSA* spatial database on "points of interest," which includes grocery stores, restaurants, banks, hotels, hospitals, libraries, etc. (ESRI 2008). Intersection counts were quantified as the number of 3-way intersections within each buffer. Higher intersection count increases the efficiency of walking to destinations.²⁸ For the intersection count and road network information, we used ArcGIS 8.3 StreetMap® USA from ESRI, which is based on 2007 US Census TIGER (www.census.gov/geo/www/tiger) and TeleAtlas data (www.teleatlas.com).

Finally, Z-scores were created to standardize each individual component of the built environment, namely population density, business count, and street connectivity. These scores had a mean of 0 and a standard deviation of 1, which we summed to create a walkability index combining these three built environment components. The final walkability index had a mean of 0 (range: -1.7, 34.1), with higher values indicating higher levels of neighborhood walkability. Similar indices have been used previously.^{29–31}

Neighborhood Greenness—Exposure to green, natural areas around each participant's home address was estimated using a satellite-image based vegetation index. Chlorophyll in plants strongly absorbs visible light (0.4–0.7 μm) for use in photosynthesis, while leaves reflect near-infrared light (0.7–1.1 μm). The Normalized Difference Vegetation Index (NDVI) calculates the ratio of the difference between the near-infrared region and red reflectance to the sum of these two measures, ranging from -1.0 to 1.0, with larger values indicating higher levels of vegetative density.³² For this study, we used data from the Moderate-resolution Imaging Spectroradiometer (MODIS) from NASA's Terra satellite. MODIS provides images every 16 days at a 250m resolution.³³ We used ArcGIS software to link summertime (July 2006) NDVI data to each participant's geocoded address as a measure of greenness directly accessible outside the home. Summertime NDVI was chosen as it provides the peak variation for greenness in the northeastern US. We used the 250m resolution as a measure of greenness directly accessible outside each home. In sensitivity analyses, we also modeled greenness using mean NDVI data in the 1250m area surrounding each address to capture greenness within a 10–15 minute walk of the home.³⁴

Air Pollution—We assessed particulate air pollution exposure using a satellite-based spatiotemporal model that predicts daily ambient concentrations of particulate matter with an aerodynamic diameter less than 2.5 μm (PM_{2.5}) specific to each participant's residence.

The exposure assessment was based on a hybrid model incorporating daily satellite remote sensing data at 1 km spatial resolution.³⁵ The model makes use of NASA's MAIAC (Multi-Angle Implementation to Atmospheric Correction) algorithm³⁶ providing 1km resolution aerosol optical depth data. We used a mixed model approach to regress daily PM_{2.5} mass concentrations from U.S. Environmental Protection Agency (EPA) Air Quality System (AQS) and Interagency Monitoring of Protected Visual Environments (IMPROVE) network locations on AOD, spatial and temporal predictors. For days when aerosol optical depth data were not available for some grid cells, we fit a generalized additive model with a thin plate spline term of latitude and longitude to interpolate PM_{2.5}. The mean out-of-sample R² from 10-fold cross validation was 0.88, and the slope of the predicted vs. withheld observations was 0.99, showing excellent prediction ability and no bias. We assigned each participant a PM_{2.5} exposure calculated as the calendar-year average of daily model predictions for 2006 based on the 1km cell in which their address was located.

We estimated exposure to nitrogen dioxide (NO₂) from the U.S EPA Air Quality System database (<http://www.epa.gov/ttn/airs/airsaqs/detaildata/downloadaqsdta.htm>) and estimated monthly averages for 2006 at each monitoring location across the northeastern U.S., for months during which at least 75% of the observations were available at each monitor. We assigned the weighted monthly average concentration of NO₂ from the five nearest monitors to each participant's residence, excluding participants who did not live within at least 50 km of a monitor. We used the inverse of the square of the distance between residences and monitors as the weights.³⁷ We allowed different monitors to be selected for each month, depending on data availability. We then calculated an annual average for 2006 at each participant's residence.

Covariates

Information on factors related to both environmental measures and BMI that could be potential confounders was available. We adjusted for age (continuous), race (White/Black/Asian/Other), and smoking status (current/former/never). To adjust for individual-level socioeconomic status (SES), we included information on husband's education. To adjust for area-level SES, we used information from the 2000 Census on tract-level median household income (P053001) and home value (H085001), as well as the proportion of Census tract residents without a high school diploma (P037001).²⁵ All reported results refer to models adjusting for the above covariates, unless otherwise specified.

Statistical Analysis

We first examined the means and distributions of each environmental measure and estimated Spearman correlation coefficients between each measure. Because these correlation coefficients do not capture potentially non-linear relationships, we also fit a generalized additive model using walkability as the dependent variable and greenness, NO₂ and PM_{2.5} as the independent variables and fit penalized splines to detect any potential deviations from linearity.

We then employed generalized additive models to assess the association between each exposure of interest (NO₂, PM_{2.5}, greenness, and walkability) and BMI separately, allowing

for deviations from linearity using penalized splines. If the generalized cross-validation criterion indicated that a linear association was a better fit for any of these exposures, these were included in the model as linear terms, otherwise we used the generalized cross-validation-selected number of degrees of freedom (df). When we included untransformed BMI as the dependent variable in the models, the regression diagnostics showed a poor fit and violated assumptions of normally distributed residuals and homoscedasticity. We therefore used the natural logarithm of BMI as the dependent variable, resulting in no violations. To assess independent associations between these correlated exposures and BMI, we also included all four exposures in the same generalized additive model simultaneously.

We assessed potential interactions between pairs of exposures of interest. If both exposures (main associations) were linearly associated with BMI, we included an interaction term between the two in the model. If at least one exposure was non-linearly associated with BMI then we included a penalized spline surface in the model. In this case, we compared Akaike's Information Criterion between the model with separate splines for each exposure vs. the model with the spline surface to assess better fit. If the model with the surface spline was a better fit, that would suggest an interaction between the two variables in the surface spline.

Based on prior studies showing differential relationships between walkability and health by neighborhood SES,^{38,39} we also assessed whether age, census tract median household income, median home value, proportion of residents without a high school diploma, or urbanicity modified the walkability—BMI association. Urbanicity was defined by the participant's residence in an urban (urban area > 50,000 people) versus non-urban (suburban, i.e., urban cluster of 10,000–49,999; or small town / rural, i.e., urban cluster of <10,000) census tract.⁴⁰

If linear, results are presented as percent lower or higher BMI per interquartile range width increase in exposure; otherwise we present plots depicting the non-linear dose-response curves. All statistical analyses were conducted using SAS, version 9.3 (SAS Institute Inc., Cary, NC, U.S.A), and R, version 3.2.0 (Foundation for Statistical Computing, Vienna, Austria).

Results

There were a total of 23,435 women eligible for this study (Table 1). The mean age among participants was 72 years and the average participant was normal weight (mean BMI 27). The majority of participants were white, lived in metropolitan areas, were past smokers, and had husbands with more than a high school education. We also show participant characteristics by BMI cut-points for overweight and obese.⁴¹ Obese participants were more likely to live in areas with a higher walkability index, with higher PM_{2.5}, and lower area-level socioeconomic status, were less likely to be white, and had husbands with lower educational attainment.

The correlation structure across the exposures of interest, as well as the census tract variables, is presented in eFigure 2. PM_{2.5} and NO₂ were moderately positively correlated

with each other, and were also moderately correlated with walkability. Greenness was negatively correlated with all other exposures. These relationships, however, were not linear (eFigure 3).

Due to the skewed distribution of the walkability index (eFigure 4), 99% of participants lived in an area with a walkability index below 10. Thus, Figures 2A.D and 2B.D present the association between walkability and BMI at walkability index levels below 10. eFigure 5 shows the association across the entire distribution of walkability index.

When assessing the association of each exposure of interest with BMI in separate models, we observed non-linear associations with $PM_{2.5}$ and walkability, a marginal non-linear association with greenness (Figures 2A.B–D), and no association with NO_2 (Figure 2A.A). Specifically, at lower levels of $PM_{2.5}$ ($<10 \mu g/m^3$), increases in particle concentrations were associated with increased BMI, while this association reached a plateau at higher particle concentrations (Figure 2A.B). We observed an inverse U-shaped association with greenness; at lower greenness levels, increases in greenness were associated with increased BMI, while at higher greenness levels, increases in greenness were associated with lower BMI (Figure 2A.C). Finally, we observed a non-linear association between the walkability index and BMI (Figure 2A.D).

When we included all four exposures of interest together in the same model, however, the observed associations between BMI and NO_2 , $PM_{2.5}$, and greenness changed. We observed no change in BMI (0.01%; 95%CI: $-0.36, 0.37\%$) per interquartile range width (IQR_w) increase in NO_2 (5.3 ppb), 0.30% higher BMI (95%CI: $-0.13, 0.73\%$) per IQR_w increase in $PM_{2.5}$ ($2.0 \mu g/m^3$) and 0.15% lower BMI (95%CI: $-0.53, 0.23\%$) per IQR_w increase in greenness (0.14) (Figures 2B.A–C). However, the non-linear association between walkability and BMI remained consistent after adjusting for NO_2 , $PM_{2.5}$ and greenness, with an estimated $df=3.78$ (Figure 2B.D). At low levels of walkability (walkability index below 1.8, representing the lower 89th percentile of our population) we observed a positive association between walkability and BMI where a 10 percentile increase in walkability right before this level (i.e. an increase from the 79th to the 89th percentile of the walkability index), was associated with a 0.03% increase in log BMI. However, walkability was negatively associated with BMI at high walkability levels (walkability index above 1.8, representing the top 11th percentile of our population), where a 10 percentile increase in walkability right after this level was associated with a 0.84% decrease in log BMI. Results were consistent when considering greenness at a 1250m buffer size (eFigure 6).

We observed no interactions between the exposures of interest, with the exception of a potential interaction between $PM_{2.5}$ and walkability. The model containing a surface spline for $PM_{2.5}$ and walkability yielded a slightly better fit based on Akaike Information Criterion values. We observed that at low $PM_{2.5}$ levels, higher walkability held a moderate non-linear association with lower BMI; however, at higher levels of $PM_{2.5}$, this non-linear relationship was stronger, suggesting a likely moderate interaction (eFigure 7).

Finally, we did not observe any interactions by area-level SES variables. In analyses stratified by urbanicity, the shape of the curve between walkability and BMI for urban

participants was unchanged (eFigure 8). In the non-urban participants, we observed no relationship between walkability and BMI. We did detect an interaction by participant age. Specifically we observed that among participants at the lower end of the age range, there was a non-linear association between walkability and BMI, but this relationship was not observed in the oldest participants (greater than approximately 71 years) (eFigure 9). To clarify the differences across age, we show results in eFigure 10 stratified by age quartiles.

Discussion

We conducted a study in the northeastern U.S. to assess independent associations between air pollution, walkability, and greenness, and BMI in a cohort of female nurses. Although in individual models we observed non-linear associations with PM_{2.5}, greenness, and walkability, when we simultaneously assessed all exposures only the association between walkability and BMI remained. We observed a threshold for the relationship between walkability and BMI; increasing walkability was associated with increasing BMI at lower levels of walkability, while increasing walkability was linked to lower BMI in areas of higher walkability. We also observed a suggestive interaction between PM_{2.5} and walkability, where the relationship between walkability and BMI was stronger at higher levels of PM_{2.5}. Finally, the non-linear relationship between walkability and BMI existed only among younger participants.

We observed a threshold relationship for walkability, where increasing walkability below a walkability index of 1.8 was associated with increasing BMI, while above a walkability index of 1.8, increasing walkability was associated with lower BMI. About 11% of our sample lived in areas with a walkability index of 1.8 or higher, which ranged from smaller towns such as Allentown, PA (579.2 people per square mile), to larger cities such as Boston, MA (1,685.1 people per square mile), Philadelphia, PA (1,323.1 people per square mile), and New York City, NY (8,158.7 people per square mile).²⁵ The concept of a threshold is consistent with the theory that when the built environment reaches a certain density and connectivity with sufficient land-use mix, it becomes more convenient to walk or take transit than to drive.⁴² Subsequently, residents may be more physically active and may maintain lower BMI. Indeed, these thresholds have been demonstrated in previous empirical analyses of the built environment and physical activity.⁴³

There was no association between walkability and BMI in analyses restricted to participants living in non-urban areas. This is likely due to the narrow range of walkability in non-urban areas, as well as the small number of participants living in non-urban areas. We found that the non-linear relationship between walkability and BMI was limited to younger participants. This finding is consistent with the idea that BMI represents adiposity in younger adults, but BMI may incorporate sarcopenia, or decreased muscle mass, and have lower validity in older adult populations.⁴⁴

Previous studies have investigated environmental influences on BMI, with diverse findings. There is an extensive body of literature examining the relationship between neighborhood walkability and BMI.⁷ Consistent with our findings, a recent review of natural experiments, longitudinal studies, and studies applying advanced analytical techniques to examine the

built environment and BMI concluded that the evidence supports altering the design of neighborhoods to combat obesity.⁹

Less consensus exists regarding natural environments and BMI. Results suggest that there may be an inverse association between greenness and overweight/obesity;^{45–47} however, gender-specific estimates have been shown to vary across studies.^{17,48} Other studies have observed either no association between greenness and BMI,^{49–51} or, contrary to *a priori* hypotheses, that greenness was associated with increased odds of overweight and obesity.⁵² Particle exposure has also been associated with elevated central obesity in adults.¹³ Most of these analyses controlled for a range of potential confounders, but rarely adjusted for neighborhood walkability, greenness, or air pollution exposure.

Although there is evidence for associations between air pollution, walkability, and greenness, and BMI,^{7,10–13} previous studies have assessed these associations either linearly or using categorical variables. These approaches either ignore any potential deviations from linearity in the dose–response curve or lack efficiency. Moreover, previous studies have ignored the correlations across environmental factors potentially associated with BMI. In this study we accounted for these interrelationships and were able to assess independent non-linear associations between these factors and BMI. Furthermore, we showed that because the relationship across these exposures is not linear (eFigure 2), failure to adjust for some of these environmental factors would lead to non-linear confounding and result in biased observed associations. For instance, when we assessed the PM_{2.5}-BMI association without adjusting for walkability, NO₂ and greenness, we observed a non-linearly increasing dose-response curve (Figure 2A.B). When we included these factors in the same model simultaneously, however, the association between PM_{2.5} and BMI was no longer evident (Figure 2B.B).

Our study has some limitations. In this cross-sectional study, we were unable to assess the association with incidence of obesity, but only with current BMI. Even though reverse causation is a concern in cross-sectional studies, such a scenario is not likely in this analysis, as we have shown in previous analyses in this cohort that BMI does not predict neighborhood choice.⁵³ Moreover, a recent review of prospective studies found that the use of prospective study designs and advanced methods of analysis show similar associations between walkability and obesity when compared to cross-sectional analyses.⁹ We used self-reported weight and height information to calculate BMI, which might have resulted in outcome misclassification. Self-reported weights, nevertheless, have been found to be highly reliable,²³ and any misclassification is likely non-differential with respect to exposure. Exposure measurement error is also likely for all examined exposures. For example, while many studies have examined measures of the neighborhood built environment, there is no consensus on what metrics best represent neighborhood walkability. In addition, NO₂ exposures were assessed using a weighted average of concentrations measured at monitors, which is expected to bias the estimated effects towards the null,⁵⁴ and could be one reason why we observed no association between NO₂ and BMI. Nevertheless, in our study exposure measurement error is expected to be non-differential because all exposures were assessed independent of BMI. For exposures with linear relationships, any resulting bias would likely be toward the null.⁵⁴ However, the behavior of such error in non-linear settings, and

especially in the presence of non-linear confounding measured with error, has not been widely explored. Because participants were only asked about recreational physical activity, and not routine travel-related activity that might be linked to neighborhood walkability, we were unable to assess potential mediation by physical activity. Participants in this study were nurses at the time of recruitment, were over 90% white, and were all female. While this might restrict the generalizability of these results to the general population, it also limits the potential for confounding by SES, race, and sex. Finally, the correlation structure across environmental factors is likely to vary across locations and, therefore, our results should be replicated in other parts of the country, as well as other parts of the world with a different urban design and among populations of different ages (for instance, children, who are under development).

Our study has several strengths. We used data from a large population of medical professionals with detailed information on potentially important confounders, including lifestyle, individual- and area-level factors. We used sophisticated methods to obtain exposure estimates at the residential addresses of the study participants, reducing potential exposure measurement error. We were also able to simultaneously examine the association with all four exposures of interest (NO₂, PM_{2.5}, greenness, and walkability) while allowing for non-linear dose-response curves. We were also able to observe a non-linear interaction between age and the walkability-BMI association. To our knowledge, no other study has assessed these correlated exposures simultaneously, nor allowed for non-linear interactions, when examining the association between environmental factors and BMI.

In conclusion, we conducted a large cross-sectional study across the northeastern U.S. We observed a robust non-linear association between walkability and BMI, independent of air pollution and greenness. Our findings can help to clarify the relationship between environmental factors and BMI, and highlights the importance of accounting for nonlinear confounding by interrelated environmental factors in studies of the environment and BMI.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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Figure 1. Maps of a) PM_{2.5} levels, b) NO₂ levels, c) greenness, d) neighborhood walkability, e) BMI, and f) Census tract median home values for the addresses of Nurses' Health Study participants in 2006.

Figure 2.

A. Relationship between BMI and A) NO₂, B) PM_{2.5}, C) normalized difference vegetation index (NDVI, a measure of greenness), and D) Walkability adjusted for age, race, smoking status, husband's education, and Census tract-level median household income, median home value, and proportion of residents without a high school diploma. Figure 2B. Relationship between BMI and A) NO₂, B) PM_{2.5}, C) NDVI (greenness), and D) Walkability in models adjusting for the above covariates, as well as all other environmental measures. Please note that Figures 2A.D and 2B.D present only the association at walkability index levels below 10. The vertical lines in Figures 2A.D and 2B.D represent different points in the walkability index distribution: red represents the 10th and 90th percentile, green the 25th and 75th, and yellow the median.

Table

Characteristics of Nurses' Health Study participants in 2006 overall and by BMI categories (N=23,435)

Variable	Overall N=23,435	Normal BMI (BMI<25) N=10,500	Overweight (BMI 25– 29.9) N=7,824	Obese (BMI ≥30) N=5,111
Age, years, mean (SD)	72 (7.0)	72 (7.1)	72 (7.0)	71 (6.9)
BMI, kg/m ² , mean (SD)	27 (5.2)	22 (1.8)	27 (1.4)	34.3 (4.1)
Walkability Index, mean (SD)	0.00 (2.5)	−0.02 (2.6)	0.00 (2.4)	0.05 (2.1)
Greenness, mean (SD)	0.71 (0.12)	0.71 (0.12)	0.70 (0.12)	0.70 (0.12)
PM _{2.5} , µg/m ³ , mean (SD)	10 (1.3)	10 (1.3)	10 (1.3)	10 (1.3)
NO ₂ , ppb, mean (SD)	16 (4.5)	16 (4.4)	16 (4.5)	16 (4.4)
Census Tract Median Home Value, \$1,000, ^a mean (SD)	206 (120)	219 (130)	201 (109)	189 (100)
Census Tract Median Income, \$1,000, ^a mean (SD)	75 (25)	78 (27)	74 (24)	71 (23)
Census Tract Percent No High School, ^a mean (SD)	12 (7.5)	12 (7.4)	12 (7.5)	14 (7.8)
Husband's Education, No. (%)				
Less than High School	1002 (4)	340 (3)	344 (4)	318 (6)
High School	5969 (26)	2487 (24)	2007 (26)	1475 (29)
More than High School	8634 (37)	4271 (41)	2868 (37)	1495 (29)
Missing or not Married	7830 (33)	3402 (32)	2605 (33)	1823 (36)
Race, No. (%)				
White	21843 (93)	9903 (94)	7243 (93)	4697 (92)
Black	441 (1.9)	111 (1.1)	171 (2.2)	159 (3.1)
Asian	75 (0.3)	47 (0.5)	24 (0.3)	4 (0.1)
Other	1076 (4.6)	439 (4.2)	386 (5.0)	251 (5.0)
Smoking, No. (%)				
Never Smoker	9338 (40)	4048 (39)	3152 (40)	2138 (42)
Past Smoker	11849 (51)	5217 (50)	3994 (51)	2638 (52)
Current Smoker	1712 (7.3)	958 (9.1)	505 (6.6)	249 (5.0)
Missing	536 (2.3)	277 (2.6)	173 (2.2)	86 (1.7)
Urbanicity, No. (%)				
Metropolitan, ≥50,000 people	22776 (97)	10199 (97)	7612 (97)	4965 (97)
Metropolitan, 10,000–49,999 people	414 (1.8)	194 (1.9)	128 (1.6)	92 (1.8)
Small Town / Rural, <10,000 people	245 (1.1)	107 (1.0)	84 (1.1)	54 (1.1)

^aValues are based on the 2000 Census at the participant's 2006 address.

NOTE: BMI, body mass index; SD, standard deviation.