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Exposures to Walkability and Particulate Air Pollution in a Nationwide Cohort of Women

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Abstract

Background—Features of neighborhoods associated with walkability (i.e., connectivity, accessibility, and density) may also be correlated with levels of ambient air pollution, which would attenuate the health benefits of walkability.

Objectives—We examined the relationship between neighborhood walkability and ambient air pollution in a cross-sectional analysis of a cohort study spanning the entire United States using residence-level exposure assessment for ambient air pollution and the built environment.

Methods—Using data from the Nurses' Health Study, we used linear regression to estimate the association between a neighborhood walkability index, combining neighborhood intersection count, business count, and population density (defined from Census data, *infoUSA* business data, and StreetMap USA data), and air pollution, defined from a GIS-based spatiotemporal PM_{2.5} model.

Results—After adjustment for Census tract median income, median home value, and percent with no high school education, the highest tertile of walkability index, intersection count, business count, and population density was associated with a with 1.58 (95% CI 1.54, 1.62), 1.20 (95% CI 1.16, 1.24), 1.31 (95% CI 1.27, 1.35), and 1.84 (95% CI 1.80, 1.88) $\mu\text{g}/\text{m}^3$ higher level of PM_{2.5} respectively, compared to the lowest tertile. Results varied somewhat by neighborhood socioeconomic status and greatly by region.

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Conclusions—This nationwide analysis showed a positive relationship between neighborhood walkability and modeled air pollution levels, which were consistent after adjustment for neighborhood-level socioeconomic status. Regional differences in the air pollution-walkability relationship demonstrate that there are factors that vary across region that allow for walkable neighborhoods with low levels of air pollution.

Keywords

Built environment; air pollution; particulate matter; geographic information systems; neighborhood socioeconomic status

1. Introduction

The complex built environments in which we live create a dynamic interplay between factors that create both opportunities and barriers to health. Research on the built environment and health is growing, with a majority of the focus on its influence on walking (Saelens et al. 2003; Saelens and Handy 2008). Walking presents a low-cost, low-impact source of routine physical activity that can be undertaken by individuals at any life stage and at all levels of socioeconomic status. The health benefits of physical activity have been well documented, yet less than half (48%) of all adults meet the Surgeon General's recommended 30 minutes of moderate intensity physical activity on most days of the week (Centers for Disease Control and Prevention 2010; Besser and Dannenberg 2005; Freeland et al. 2013). A recent study by Lee et al. (2012) estimates that physical inactivity contributes to 6% of the global burden of disease from coronary heart disease, 7% of type 2 diabetes, 10% of breast cancer, 10% of colon cancer, 9% of premature mortality. If inactivity were decreased by 10% to 25%, between 533,000 and 1.3 million deaths could be averted every year.

Although many environmental factors have been explored, population density, access to facilities, and street connectivity are geographic information systems (GIS)-based measures of the built environment measure that are consistently associated with walking (Brownson et al. 2009; McCormack and Shiell 2011; Sallis et al. 2012). These associations have been observed in numerous settings across the US and abroad, as well as in urban (Sallis et al. 2009) and rural settings (Frost et al. 2010). We have examined associations between these measures and walking within the Nurses' Health Studies cohorts and found that levels of recreational walking were higher in more accessible neighborhoods with more connected streets (James et al. 2014). While numerous studies have demonstrated that individuals living in areas with higher residential density, many destinations in close proximity, and more connected street networks tend to walk more (Sallis et al. 2012), research in the area of the built environment rarely addresses concurrent air pollution exposures. Particulate air pollution has been well-characterized as a risk factor for chronic disease and mortality (Hoek et al. 2013; Lee et al. 2014; Pope and Dockery 2006). While there are multiple sources of particulate air pollution, such as long range transport from power plants, source apportionment studies demonstrate that vehicular emissions are a source of particulate matter concentrations (Hasheminassab et al. 2014). Features of neighborhoods that are associated with walkability (e.g. density, accessibility, and connectivity) are also predictors of vehicular air pollution levels, including particulate matter and NO₂ (Ryan and LeMasters

2007). While these neighborhood features do not explain all variability in vehicular or particulate air pollution concentrations, they may contribute to important differences in exposure across populations. Although per capita emissions may be lower in more walkable neighborhoods due to lower levels of individual vehicle use, a higher density of individuals and vehicles in a walkable neighborhood may lead to higher concentrations of traffic-related air pollution. Therefore, while levels of walking may be higher among residents of more walkable neighborhoods, increased air pollution exposure for these individuals could attenuate the health benefits of this increased physical activity.

A recent set of studies has begun to explore the potential tradeoffs between walkability and air pollution and researchers have adopted an array of approaches to tackle this complex issue. (de Nazelle et al. 2011; Hankey et al. 2012; Marshall et al. 2009). For instance, Hankey et al. (2012) showed that $PM_{2.5}$ was on average $3 \mu g/m^3$ higher in high walkability neighborhoods compared to low walkability neighborhoods in southern California. They then applied a risk assessment framework that predicted while physical activity benefits of walkable neighborhoods would produce a health benefit (7 fewer ischemic heart disease deaths/100,000/year in high vs low walkability neighborhoods), this benefit would be counteracted by higher exposure to air pollution (9 more ischemic heart disease deaths/100,000/year in high vs low walkability neighborhoods). These studies have also demonstrated that the relationship between walkability and air pollution differed according to neighborhood socioeconomic status, showing that the proportion of postal codes with low walkability and low air pollution was six times greater for the highest-income versus lowest income postal codes (Marshall et al. 2009). Although a comprehensive understanding of the tradeoffs between air pollution exposure and walkability is unclear, these studies have demonstrated a relationship between air pollution and neighborhood walkability measures with potential implications for chronic disease. However, studies on this topic have been limited to specific geographic areas, such as a single city or region, and have not investigated potentially important variations in the relationship between air pollution and the built environment between regions.

In the current study we built on the literature examining the relationship between neighborhood walkability and ambient air pollution in a nationwide cross-sectional analysis of a cohort study. Our primary objective was to investigate the relation between walkability and air pollution data using residence-level exposure assessment for ambient air pollution and the built environment. Our secondary objectives were to examine whether these relationships varied according to neighborhood-level socioeconomic status and region.

2. Methods

2.1 Population

We used data from the Nurses' Health Study (NHS), a nationwide prospective cohort assessing a wide variety of risk factors for chronic disease among women. In 1976, 121,700 female registered nurses ages 30-55 years from 11 states (New York, California, Pennsylvania, Ohio, Massachusetts, New Jersey, Michigan, Texas, Florida, Connecticut, and Maryland) returned an initial questionnaire that ascertained a variety of health-related exposures and medical diagnoses. The cohort has been continuously followed with biennial

questionnaires as participants changed addresses and moved throughout the country. Response rates at each two-year questionnaire cycle have consistently been ~90%. Data for this cross-sectional analysis were taken from 2006, the most recent year for which air pollution and walkability data are available. All available residential addresses in 2006 were geocoded to obtain latitude and longitude. Approximately 90% were successfully matched to the street address or zip plus 4 centroid (typically encompassing one side of a street segment) level. For the current analyses we included all women who completed the 2006 questionnaire, lived in the continental US, and had a street segment or zip code plus-4 level geocoding match.

2.2 Built Environment

Using Census data and commercially available geographic information systems (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 US Census reported population density in the US Census tract of residence in 2006.

To develop business count and intersection count measures, we created 1200 meter line-based network buffers around each home address. For line-based network buffers, we drew lines along the road network up 1200m, then created a 50 m polygon around each line. An example of a network buffer is shown in Figure 1 (For more information, see (James et al. 2014)).

Briefly, we used ArcGIS software (Redlands, CA) to identify the street network within 1200m from each participant's mailing address and then 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. The rationale for using a line-based network buffer versus a polygon-based network buffer was to restrict the analysis to areas close to roads that people can access by walking (Oliver et al. 2007). We then constructed the following measures:

Business counts were measured by the counts of all stores, facilities, and services in a participant's network buffer using the commercially available 2009 *infoUSA* spatial database on "points of interest", which includes grocery stores, restaurants, banks, hotels, hospitals, libraries, etc. (Figure 2). *infoUSA* maintains and adds to their database by referencing several sources including directory listings such as Yellow Pages 10Ks and Securities and Exchange Commission information; federal, state, and municipal government data; and information from the US Postal Service. After telephone verification, these addresses were geocoded. The quality of the local address system varies; address matching is better in urban areas that use street-level address systems than in rural areas. Overall, 84.3% of the points of interest were geocoded at the address level (ESRI 2008), and we restricted analyses to these points. Our research team performed a small validation study of over 400 facilities listed in the *infoUSA* database in two US counties and found that 86% of the facilities were located on the exact street segment or on an adjacent segment. These findings are comparable to three recent studies that assessed the validity of commercial facility databases using GIS

techniques and field audits and found good to moderate percentage agreement and sensitivity for correctly identifying and locating existing facilities (Bader et al. 2010; Boone et al. 2008; Paquet et al. 2008).

Intersection counts were quantified by the number of intersections that were 3-way or greater within each network buffer (Figure 2). A greater intersection count increases the efficiency of walking to destinations. For the road network, we used ArcGIS 8.3 StreetMap® USA from ESRI, which is based on 2007 US Census TIGER (Topologically Integrated Geographic Encoding and Referencing; www.census.gov/geo/www/tiger) Map data and TeleAtlas data (www.teleatlas.com).

Because neighborhood walkability is a latent construct comprising information from various neighborhood factors that are correlated, we created a walkability index by z-transforming and summing neighborhood intersection count, business count, and population density measures described above.

2.3 Air Pollution

We assessed particulate air pollution exposure using a GIS-based spatiotemporal model that predicts monthly outdoor concentrations of particulate matter with an aerodynamic diameter less than 2.5 microns ($PM_{2.5}$) specific to each participant's biennially updated residence. This generalized additive mixed model (detailed in Yanosky et al. (2009; 2014)) uses monitoring data from sites in the US Environmental Protection Agency's Air Quality System, the IMPROVE network, CASTNET data and Harvard research studies to estimate monthly smooth spatial terms and penalized regression terms of GIS-based and meteorologic covariates. These covariates include population density (at tract and county level); distance to nearest road by Census Feature Class Code A1-4; elevation; urban land use (consolidation of three variables: proportion of high intensity residential, low intensity residential, and industrial / commercial / transportation in a 1-km radius, (1km buffer, 30×30m blocks, proportion of blocks that are that type)); point- and area-source emissions; wind speed and precipitation. The $PM_{2.5}$ model was validated using 10-fold out-of-sample cross-validation to evaluate model predictive accuracy. The model performance was strong, with a cross-validation R^2 of 0.77 (Yanosky et al. 2014). We then used the average of the 12 monthly values for 2006 to assign each address an annual average $PM_{2.5}$ exposure.

2.4 Statistical Analysis

We conducted linear regression to examine the relationship between the walkability index, as well as each measure of walkability (intersection count, business count, and population density), and air pollution in separate models. Predicted average $PM_{2.5}$ levels were reported by tertile of each walkability measure. In sensitivity analyses, we also examined differences across deciles of each neighborhood walkability metric. Models included covariates for neighborhood socioeconomic status (SES) (US Census 2000 tract median household income, median home value, and percent of population with no high school education based on the 2006 residence) to estimate the relationship between air pollution and walkability independent of neighborhood SES. Models were stratified by tertile of Census SES variables to see if relationships differed according to neighborhood SES. We also ran stratified

analyses and used interaction terms to examine whether the relationship between air pollution and walkability varied by region of the US, or by urbanicity. Urbanicity was determined by the participant's residence in a metropolitan (urban area ≥ 50,000 people), micropolitan (urban cluster of 10,000-49,999), or small town/ rural (urban cluster of <10,000) Census tract (Morrill et al. 1999).

Based on prior work in this cohort, we considered the tradeoffs between walkability and air pollution for chronic disease outcomes. We applied dose-response functions for the ambient air pollution-chronic disease relationship from Puett et al. (2009), which employed the same PM_{2.5} model used in this study, to point estimates for the predicted differences in air pollution levels by walkability tertile. We chose fully adjusted coefficients for this calculation, to produce estimates independent of other factors, including SES and physical activity. This allowed for a prediction of the chronic disease attributable to air pollution levels across different levels of neighborhood walkability.

3. Results

We identified 62,588 addresses from the 48 continental United States and the District of Columbia with data eligible for analysis, with at least 6 addresses in each state. Table 1 shows built environment and socioeconomic status measures overall and by air pollution tertiles. Intersection counts, business counts, and population density increased with increasing PM_{2.5} tertiles, while Census tract median home value and median income were highest in the middle tertile. Participants were most likely to live in urban areas (86% urban area; 9% urban cluster; 5% small town/rural). The majority of participants lived in the northeast (48%), while 20% lived in the South, 17% in the Midwest, and 14% lived in the West. Figure 2 displays built environment features and air pollution together on the same map. The height of each bar represents residence-level business count, intersection count, or population density for each participant, while the color represents particulate air pollution exposure at each participant's address. In general, higher levels of walkability measures were correlated with higher particulate air pollution. Figure 3 shows the crude and neighborhood SES-adjusted PM_{2.5} levels by tertiles of walkability measures. Results for crude and adjusted models were similar, indicating a consistent positive relationship between modeled PM_{2.5} levels and intersection count, business count, and population density. After adjustment for Census tract median income, median home value, and percent with no high school education, the highest tertiles of walkability index, intersection count, business count, and population density were associated with 1.58 (95% CI 1.54, 1.62), 1.20 (95% CI 1.16, 1.24), 1.31 (95% CI 1.27, 1.35), and 1.84 (95% CI 1.80, 1.88) $\mu\text{g}/\text{m}^3$ higher levels of PM_{2.5} respectively, compared to the lowest tertile. Analyses by decile (Supplemental Table 1) showed steady increases in PM_{2.5} with higher levels of each walkability measure. The relation between air pollution and the built environment appeared to vary according to neighborhood socioeconomic status. At lower levels of Census tract median income, the relation between air pollution and intersection count was somewhat stronger compared to higher median income tracts (p for interaction <0.0001), business count (p <0.0001), and population density (p <0.0001) (Table 2). Similar effects were seen for Census tract median home value and percent with no high school education (Table 2). While these interactions are statistically significant, there were minor absolute differences in the relationship between

measures of neighborhood walkability and air pollution by Census tract SES. For instance, the difference in the mean air pollution levels between the highest and lowest tertile of intersection count was $1.58 \mu\text{g}/\text{m}^3$ (95% CI 1.50, 1.65) in the lowest income tertile, and $0.79 \mu\text{g}/\text{m}^3$ (95% CI 0.72, 0.86) in the highest income tertile.

The relationship between walkability and air pollution varied greatly by region (Table 3). In general, the highest levels of $\text{PM}_{2.5}$ were seen in the Midwest, regardless of the built environment measure, potentially due to power plant emissions. We observed strong and consistent relationships between all built environment measures and air pollution in Midwestern and Northeastern addresses. In the South, the magnitude of the relation between air pollution and walkability was statistically significantly smaller for all three measures of the built environment. For example, the difference in the mean air pollution levels between the highest and lowest tertile of business count was $0.60 \mu\text{g}/\text{m}^3$ (95% CI 0.52, 0.69) in the South, while this difference was $2.03 \mu\text{g}/\text{m}^3$ (95% CI 1.98, 2.08) in the Northeast. Additionally, the association between air pollution and both intersection count and business count was weaker in the Western states compared to the Northeast and Midwest. The difference in the mean air pollution levels between the highest and lowest tertile of intersection count was $0.09 \mu\text{g}/\text{m}^3$ (95% CI -0.07, 0.25) in the West, and $1.93 \mu\text{g}/\text{m}^3$ (95% CI 1.88, 1.98) in the Northeast.

Analyses stratified by Census tract urban areas, urban clusters, and small town / rural areas showed that higher levels of walkability were associated with higher levels of $\text{PM}_{2.5}$ regardless of urbanicity, although absolute $\text{PM}_{2.5}$ levels were highest in urban areas (Supplemental Table 2).

Results for predicted chronic disease outcomes for the differences in air pollution levels by walkability tertiles are shown in Table 4. We found that, for example, differences in air pollution levels in neighborhoods with the highest levels of population density would translate to a 4.3% (95% CI 0.4%, 8.3%) increase in all-cause mortality and a 13.8% (95% CI 1.3%, 27.7%) increase in fatal coronary heart disease.

4. Discussion

In this analysis of a nationwide cohort, we found positive relationships between neighborhood walkability measures and modeled air pollution levels which were consistent after adjustment for neighborhood-level SES. The association between walkability and air pollution varied by neighborhood SES; however, the magnitude of this variation was relatively minor. Effects varied greatly by region, with strong positive relationships between walkability and air pollution in the Northeast and Midwest, and weaker associations in the Southern and Western states.

These findings support earlier studies on the positive relationship between the built environment and air pollution (de Nazelle et al. 2011; Hankey et al. 2012; Marshall et al. 2009), and provide new perspectives on how neighborhood SES can slightly modify these relationships across the nation, as well as for regional differences in the relationship between walkability and the built environment. In one of the first studies to quantitatively assess

walkability and air pollution, Marshall et al. (2009) modeled nitric oxide through land-use regression and ozone through spatial interpolation, monitoring data at the postal code level for much of Metro Vancouver, Canada. The authors also modeled residential density, intersection density, and land-use mix in a 1-km network buffer around each postal code. They found that high walkability areas had low concentrations of ozone and high levels of nitric oxide. This reflects the status of nitric oxide as a local pollutant with large spatial heterogeneity, while ozone acts as a regional pollutant with low spatial heterogeneity. Neighborhood socioeconomic status modified these relationships, and neighborhoods with low pollution and high walkability were almost exclusively higher income.

Using a risk assessment approach, de Nazelle (2009) simulated people's movements within a spatial-temporal air pollution field in Orange County, North Carolina using a combination of an activity database and transportation models. After incorporating different built environment scenarios, the modeled physical activity and air pollution dose were compared for an analysis of competing risks. The results were unclear, as pedestrian-friendly designs did not show a straightforward benefit in terms of regular physical activity through active travel, nor were there substantial negative effects due to chronic exposure to air pollution. Overall, there was a net decrease in inhalation dose and a net increase in energy expenditure in models analyzing a shift toward a pedestrian-friendly environment. Nevertheless the authors noted that although overall air pollution exposures may decline for the population switching to a pedestrian-friendly built environment, inhalation doses of air pollution for some individuals in this type of built environment may increase by more than 10% on high exposure days.

Hankey et al. (2012) used a similar risk-assessment approach based on cross-sectional data to model the effect of the built environment on air pollution and physical activity on cardiovascular disease risk in 30,007 participants in southern California. The authors estimated ischemic heart disease (IHD) mortality risk based on a geocoded self-report travel diary to indicate physical activity levels; inverse distance interpolated estimates of outdoor PM_{2.5}, NO_x, and ozone concentrations; literature-derived estimates relating ischemic heart disease rates to physical inactivity and exposure to air pollution; and GIS variables related to walkability. Neighborhood walkability was defined by 1-km network buffers for intersection density and land use mix, and population density determined by Census tracts. Mean NO_x and PM_{2.5} levels were higher and O₃ levels were lower in high walkability neighborhoods. Physical activity levels, however, were about five times greater in high walkability neighborhoods than low walkability neighborhoods. When comparing high- and low-walkability neighborhoods for modeled IHD mortality risk, between-neighborhood variability in estimated IHD mortality attributable to physical inactivity was modest (7 fewer IHD deaths/100,000/year in high- vs. low-walkability neighborhoods) while between-neighborhood air pollution effects had similar magnitude (9 more IHD deaths/100,000/year for PM_{2.5} and 3 fewer IHD deaths for O₃ in high- vs. low-walkability neighborhoods). The authors concluded that population health benefits from increased physical activity in high-walkability neighborhoods may be offset by adverse effects of air pollution exposure.

While we observed that residences with higher levels of walkability had higher levels of predicted air pollution, contrary to Marshall et al. (2009) we did not find trends for high

walkability, low air pollution neighborhoods that were almost exclusively higher income. Instead, we observed that regardless of Census tract median home value or household income, residences with higher walkability measures had higher levels of air pollution. This discrepancy may be because the study was conducted in Vancouver, Canada, and the distribution and determinants of both air pollution and built environment features differ between the United States and Canada. In addition, their analysis focused on intra-city differences in air pollution, walkability, and neighborhood SES, while ours took a nationwide approach and compared data between cities. We did, however, observe that the association between walkability and air pollution was slightly stronger in low SES neighborhoods, which is consistent with the results seen by Marshall et al. Regional differences in the walkability-air pollution relationship are particularly noteworthy. Lower magnitude relationships observed in the South and West could be a result of regional differences in urban design and transportation planning approaches, which may concentrate major sources of air pollution farther from urban areas. Alternatively, meteorological phenomena may play a stronger role in distributing air pollution in these regions. Point and mobile sources of air pollution also vary by region, which could lead to different relationships between walkability and air pollution between regions. Despite our large sample size, we had insufficient numbers to examine intra-urban relationships within regions, and therefore our region-specific analyses may still be comparing values between cities. However, regional differences in the observed relationships between walkability and air pollution indicate that living in walkable neighborhoods does not inevitably lead to higher exposures to air pollution. Structural factors that vary by region may allow for neighborhoods that have positive amenities for walking without subsequent high levels of air pollution.

Finally, our predictions of chronic disease outcomes attributable to air pollution across walkability tertiles demonstrate the clinical significance due to differences in $PM_{2.5}$. To balance the tradeoff in chronic disease risk, these non-trivial differences in risk due to air pollution exposure between neighborhoods would need to be overcome by large differences in physical activity between neighborhood types. Recent analyses in this same cohort indicate that participants obtain about 12.9 metabolic equivalent (MET) Hrs/Wk of physical activity on average (SD 14.5), and an increase of one MET Hr/Wk of physical activity translates into a 0.42% decrease in all-cause mortality risk (95% CI 0.12%, 0.64%) and a 1.27% decrease in cardiovascular disease mortality risk (95% CI -0.30%, 2.84%) (Baer et al. 2011). Therefore, a tertile increase in walkability measures would need to increase physical activity by approximately 10 MET Hrs/Wk to offset the adverse effects of air pollution observed in this study. Effect sizes for studies of the built environment on physical activity are modest (Feng et al. 2010), making increases in air pollution exposure for residents of walkable communities relevant to overall chronic disease risk. Future studies in this cohort will address whether there is a relation between the built environment and chronic disease risk, measuring levels of walking by neighborhood type, considering both walkability and air pollution exposure.

While the scale of our analysis contributes to a generalizable understanding of how air pollution and walkability are related across the country, we may have missed important within-city differences by neighborhood SES that are masked by this large-scale approach.

In addition, because we are examining nationwide data, we were unable to measure microscale features of neighborhoods that may provide opportunities for walking, including walking paths, sidewalks, lighting, noise, and crime. Spatial datasets on these microscale features have not been collected uniformly across different municipalities, which is a limitation to this analysis. Additionally, participants in this cohort were drawn from nursing registries. Thus, since they were at one time nurses, they tended to live in moderate to high SES neighborhoods, and low SES neighborhoods, where PM_{2.5} concentrations may be highest, are not well-represented in this sample. One limitation of this analysis is the potential correlation between the model for estimating air pollution exposure and the walkability measures, as the GIS covariates for air pollution model include population density, distance to road, elevation, urban land use in a 1-km radius, point- and area-source emissions, wind speed, and precipitation. While there is some overlap in these measures and the walkability indicators used in this analysis, the variables are not strongly correlated because of the different scale of land use measure (1-km radius), different land use information source (e.g., US Geological Survey National Land Cover Dataset), and different scales of population density measure (overlapping tract and county) (Supplemental Table 3). The distance-to-road estimate for the air pollution model used highways as major predictors of PM_{2.5}, while the built environment measures excluded highways. Important predictors, such as point-source emissions, were not included in calculating the walkability parameters. However, we do acknowledge that associations between the walkability index and predicted PM_{2.5} concentrations could be explained by correlations between the land use data used to build the PM_{2.5} model and our walkability measures. Another shortcoming of this analysis is that, while we account for exposure to air pollution through a PM_{2.5} model, we did not measure potentially important near-roadway pollutants, including ultrafine particles and NO₂ (Delfino et al. 2005; Karner et al. 2010), that may be stronger measures of traffic-related air pollution. We were unable to model these exposures at the national scale, although these methods are under development.

This study has numerous strengths. It is the first to use nationwide data to study the built environment and air pollution, which allowed for assessment of differences in associations across regions of the US. The assessment of the built environment capitalized on objectively defined GIS-based measures at the residence level, and the PM_{2.5} model has been validated in prior studies and allowed for fine-resolution predictions of air pollution exposure at the residence level.

5. Conclusions

Neighborhood walkability was positively correlated with modeled PM_{2.5} air pollution concentrations. Effects varied somewhat by neighborhood SES, and greatly by region. Regional differences in the air pollution-walkability relationship demonstrate that there are factors that vary across region that allow for walkable neighborhoods with low levels of air pollution. Policies intended to increase neighborhood walkability should aim to increase physical activity while minimizing exposure to the harmful effects of air pollution, thereby minimizing chronic disease risk.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements

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Abbreviations

CI	confidence interval
GIS	geographic information systems
HS	high school
IHD	ischemic heart disease
NHS	Nurses' Health Study
PM_{2.5}	particulate matter with an aerodynamic diameter less than 2.5 microns
SD	standard deviation
SES	socioeconomic status

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Highlights

- Dense, walkable neighborhoods may have higher levels of air pollution.
- We examined walkability and air pollution in a nationwide cohort study.
- More walkable neighborhoods had higher levels of air pollution.
- Results varied somewhat by neighborhood socioeconomic status and greatly by region.

Figure 1.
An example of a line-based network buffer with business data overlay

Figure 2.

Maps of walkability variables and annual average air pollution levels for the addresses of NHS participants in 2006. The height of each bar represents business count, intersection count, or population density for each participant, while the color represents particulate air pollution exposure for each participant.

Figure 3.

Crude and adjusted predicted annual average PM_{2.5} (µg/m³) values by walkability tertiles. Tertile ranges are in parentheses. Dark bars represent crude values, light bars represent values adjusted for census tract median income and home value Table 2. Crude predicted average PM_{2.5} (µg/m³) values and 95% confidence intervals by walkability tertiles stratified by Census tract socioeconomic status.

Table 1

Characteristics of addresses of NHS participants in 2006 across the United States and by Annual Average PM_{2.5} tertile.

Variable	Overall N= 61,933 Mean ± SD	PM _{2.5} Tertile 1 (2.4-9.5 µg/m ³) N= 20,437 Mean ± SD	PM _{2.5} Tertile 2 (9.5-11.7 µg/m ³) N=21,059 Mean ± SD	PM _{2.5} Tertile 3 (11.7-18.3 µg/m ³) N=20,437 Mean ± SD
Walkability Index	0.2 ± 2.1	-0.3 ± 1.2	0.0 ± 1.4	0.8 ± 3.0
Intersection Count	57.9 ± 61.4	44.4 ± 51.6	54.6 ± 56.4	74.6 ± 70.8
Business Count	92.4 ± 318.3	53.8 ± 160.4	76.1 ± 208.7	147.8 ± 481.1
Population Density (persons per sq mi)	3197.3 ± 7576.4	1766.6 ± 2662.2	2693.9 ± 3489.3	5146.7 ± 12174.4
Census Tract Median Home Value (\$) ^a	\$174,104 ± \$125,013	\$178,604 ± \$130,830	\$182,168 ± \$128,612	\$161,296 ± \$113,798
Census Tract Median Income (\$) ^a	\$64,786 ± \$24,262	\$63,552 ± \$23,456	\$67,227 ± \$25,539	\$63,506 ± \$23,503
Census Tract Percent No HS ^a	13.1% ± 8.2%	12.5% ± 7.7%	13.0% ± 7.9%	14.0% ± 8.9%
Predicted Ambient PM _{2.5} (µg/m ³)	10.7 ± 2.2	8.3 ± 1.1	10.6 ± 0.6	13.1 ± 1.2

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

Table 2

Crude predicted annual average PM_{2.5} (µg/m³) values and 95% confidence intervals by walkability tertiles stratified by Census tract socioeconomic status.

Variable	Income Predicted PM _{2.5} (µg/m ³) and 95% CI			Home Value Predicted PM _{2.5} (µg/m ³) and 95% CI			Percent No High School Predicted PM _{2.5} (µg/m ³) and 95% CI		
	Tertile 1 (\$0, \$52K)	Tertile 2 (\$52K, \$70K)	Tertile 3 (\$70K, \$200K+)	Tertile 1 (\$0, \$112K)	Tertile 2 (\$113K, \$175K)	Tertile 3 (\$175K, \$1,000K)	Tertile 1 (0.0, 8.6)	Tertile 2 (8.7, 15.2)	Tertile 3 (15.3, 75.5)
Walkability Index									
Tertile 1 (-1.3, -0.8)	9.55 (9.50, 9.60)	9.86 (9.81, 9.91)	10.01 (9.96, 10.06)	9.65 (9.60, 9.69)	9.93 (9.89, 9.98)	9.80 (9.75, 9.86)	9.74 (9.69, 9.79)	9.74 (9.69, 9.78)	9.91 (9.86, 9.96)
Tertile 2 (-0.8, 0.3)	10.68 (10.62, 10.74)	10.92 (10.88, 10.97)	10.94 (10.90, 10.98)	10.99 (10.94, 11.04)	10.93 (10.89, 10.98)	10.69 (10.64, 10.74)	10.75 (10.71, 10.80)	10.88 (10.83, 10.92)	11.02 (10.97, 11.08)
Tertile 3 (0.3, 42.2)	11.46 (11.41, 11.51)	11.31 (11.25, 11.36)	11.15 (11.10, 11.20)	11.54 (11.50, 11.59)	11.20 (11.15, 11.26)	11.17 (11.12, 11.22)	11.04 (10.99, 11.09)	11.24 (11.19, 11.29)	11.59 (11.54, 11.63)
Intersection Count									
Tertile 1 (0, 20)	9.74 (9.68, 9.79)	10.06 (10.02, 10.11)	10.27 (10.23, 10.32)	9.72 (9.68, 9.77)	10.07 (10.03, 10.12)	10.27 (10.21, 10.32)	10.05 (9.99, 10.10)	9.88 (9.83, 9.93)	10.13 (10.08, 10.18)
Tertile 2 (21, 67)	10.62 (10.56, 10.68)	10.83 (10.78, 10.88)	10.81 (10.77, 10.85)	10.88 (10.83, 10.93)	10.86 (10.81, 10.91)	10.57 (10.51, 10.62)	10.64 (10.59, 10.68)	10.80 (10.75, 10.85)	10.93 (10.87, 10.99)
Tertile 3 (68, 797)	11.31 (11.26, 11.36)	11.17 (11.12, 11.22)	11.06 (11.01, 11.11)	11.49 (11.45, 11.54)	11.04 (10.98, 11.09)	10.98 (10.93, 11.03)	10.89 (10.84, 10.95)	11.14 (11.09, 11.19)	11.46 (11.41, 11.51)
Business Count									
Tertile 1 (0, 6)	9.67 (9.62, 9.72)	10.01 (9.96, 10.06)	10.25 (10.20, 10.30)	9.69 (9.64, 9.73)	9.98 (9.94, 10.03)	10.25 (10.20, 10.31)	9.98 (9.93, 10.03)	9.82 (9.77, 9.87)	10.08 (10.03, 10.13)
Tertile 2 (7, 58)	10.78 (10.72, 10.84)	10.76 (10.72, 10.81)	10.74 (10.70, 10.78)	11.02 (10.97, 11.07)	10.78 (10.74, 10.83)	10.51 (10.46, 10.56)	10.57 (10.53, 10.62)	10.76 (10.72, 10.81)	11.03 (10.98, 11.09)
Tertile 3 (59, 9921)	11.37 (11.32, 11.42)	11.28 (11.23, 11.33)	11.13 (11.08, 11.18)	11.50 (11.45, 11.54)	11.27 (11.22, 11.32)	11.03 (10.98, 11.08)	11.04 (10.98, 11.09)	11.23 (11.18, 11.28)	11.47 (11.42, 11.52)
Population Density (persons per sq mi)									
Tertile 1 (0, 752)	9.71 (9.66, 9.76)	9.80 (9.75, 9.85)	9.62 (9.57, 9.67)	9.85 (9.81, 9.90)	9.83 (9.79, 9.88)	9.32 (9.27, 9.38)	9.25 (9.20, 9.31)	9.66 (9.62, 9.71)	10.06 (10.01, 10.10)
Tertile 2 (752, 3K)	10.65 (10.58, 10.71)	10.79 (10.75, 10.84)	10.81 (10.77, 10.84)	10.99 (10.94, 11.05)	10.86 (10.82, 10.91)	10.50 (10.46, 10.55)	10.69 (10.65, 10.73)	10.80 (10.75, 10.84)	10.86 (10.80, 10.92)
Tertile 3 (3K, 204K)	11.58 (11.53, 11.63)	11.50 (11.45, 11.55)	11.42 (11.37, 11.46)	11.58 (11.53, 11.62)	11.36 (11.31, 11.41)	11.53 (11.49, 11.58)	11.35 (11.30, 11.40)	11.39 (11.34, 11.44)	11.71 (11.67, 11.76)

Table 3

Predicted annual average PM_{2.5} (µg/m³) values and 95% confidence intervals, adjusted for Census tract socioeconomic status, by walkability tertiles stratified by Census regions.

Variable	Northeast (n=30,318) Predicted PM _{2.5} (µg/m ³) and 95% CI	Midwest (n=10,557) Predicted PM _{2.5} (µg/m ³) and 95% CI	West (n=8,770) Predicted PM _{2.5} (µg/m ³) and 95% CI	South (n=12,288) Predicted PM _{2.5} (µg/m ³) and 95% CI
Walkability Index				
Tertile 1 (-1.3, -0.8)	9.40 (9.36, 9.43)	10.48 (10.44, 10.52)	8.76 (8.60, 8.92)	10.32 (10.27, 10.37)
Tertile 2 (-0.8, 0.3)	10.58 (10.55, 10.62)	11.89 (11.85, 11.93)	10.57 (10.46, 10.69)	10.78 (10.72, 10.83)
Tertile 3 (0.3, 42.2)	11.38 (11.35, 11.42)	12.15 (12.10, 12.21)	11.10 (11.01, 11.19)	10.81 (10.75, 10.87)
Intersection Count				
Tertile 1 (0, 20)	9.39 (9.35, 9.43)	10.68 (10.64, 10.73)	10.60 (10.47, 10.73)	10.25 (10.20, 10.30)
Tertile 2 (21, 67)	10.52 (10.48, 10.55)	11.73 (11.69, 11.78)	10.22 (10.09, 10.35)	10.87 (10.81, 10.92)
Tertile 3 (68, 797)	11.32 (11.29, 11.36)	12.02 (11.96, 12.07)	10.69 (10.59, 10.79)	10.75 (10.69, 10.82)
Business Count				
Tertile 1 (0, 6)	9.27 (9.23, 9.31)	10.56 (10.52, 10.59)	10.45 (10.33, 10.58)	10.28 (10.23, 10.33)
Tertile 2 (7, 58)	10.52 (10.49, 10.56)	11.89 (11.85, 11.94)	10.27 (10.15, 10.40)	10.76 (10.71, 10.82)
Tertile 3 (59, 9921)	11.30 (11.27, 11.33)	12.28 (12.23, 12.33)	10.79 (10.69, 10.90)	10.89 (10.82, 10.95)
Population Density (persons per sq mi)				
Tertile 1 (0, 765)	9.49 (9.45, 9.52)	10.32 (10.28, 10.35)	7.88 (7.75, 8.00)	10.49 (10.44, 10.55)
Tertile 2 (765, 3K)	10.63 (10.60, 10.67)	11.84 (11.80, 11.88)	9.93 (9.81, 10.05)	10.60 (10.55, 10.66)
Tertile 3 (3K, 204K)	11.36 (11.33, 11.40)	12.31 (12.26, 12.36)	11.82 (11.75, 11.90)	10.76 (10.70, 10.82)

Table 4

Percent Increase in Chronic Disease Outcomes based on Predicted annual average PM_{2.5} concentrations by Tertile of Walkability Measures using Dose-Response Relationships from Puett et al. (2009)

	All-Cause Mortality Percent Increase (95% CI)	Fatal Coronary Heart Disease Percent Increase (95% CI)	First Coronary Heart Disease Percent Increase (95% CI)	Nonfatal Myocardial Infarction Percent Increase (95% CI)
Walkability Index Tertile 3 v 1	3.72% (0.31%, 7.06%)	11.74% (1.07%, 23.37%)	1.66% (−3.65%, 7.17%)	−4.85% (−10.94%, 1.81%)
Intersection Count Tertile 3 v 1	2.80% (0.24%, 5.30%)	8.77% (0.81%, 17.23%)	1.26% (−2.78%, 5.38%)	−3.69% (−8.40%, 1.36%)
Business Count Tertile 3 v 1	3.08% (0.26%, 5.83%)	9.67% (0.89%, 19.07%)	1.38% (−3.05%, 5.92%)	−4.05% (−9.18%, 1.50%)
Population Density Tertile 3 v 1	4.34% (0.36%, 8.26%)	13.79% (1.25%, 27.68%)	1.94% (−4.24%, 8.39%)	−5.62% (−12.62%, 2.10%)