Health Impacts of the Built Environment: Within-Urban Variability in Physical Inactivity, Air Pollution, and Ischemic Heart Disease Mortality

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Background: Physical inactivity and exposure to air pollution are important risk factors for death and disease globally. The built environment may influence exposures to these risk factors in different ways and thus differentially affect the health of urban populations.

Objective: We investigated the built environment's association with air pollution and physical inactivity, and estimated attributable health risks.

Methods: We used a regional travel survey to estimate within-urban variability in physical inactivity and home-based air pollution exposure [particulate matter with aerodynamic diameter ≤ 2.5 µm ($PM_{2.5}$), nitrogen oxides (NO_x), and ozone (O_3)] for 30,007 individuals in southern California. We then estimated the resulting risk for ischemic heart disease (IHD) using literature-derived dose–response values. Using a cross-sectional approach, we compared estimated IHD mortality risks among neighborhoods based on "walkability" scores.

Results: The proportion of physically active individuals was higher in high- versus low-walkability neighborhoods (24.9% vs. 12.5%); however, only a small proportion of the population was physically active, and 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). Between-neighborhood differences in estimated IHD mortality from air pollution were comparable in magnitude (9 more IHD deaths/100,000/year for $PM_{2.5}$ and 3 fewer IHD deaths for O_3 in high- vs. low-walkability neighborhoods), suggesting that population health benefits from increased physical activity in high-walkability neighborhoods may be offset by adverse effects of air pollution exposure.

Policy implications: Currently, planning efforts mainly focus on increasing physical activity through neighborhood design. Our results suggest that differences in population health impacts among neighborhoods are similar in magnitude for air pollution and physical activity. Thus, physical activity and exposure to air pollution are critical aspects of planning for cleaner, health-promoting cities.

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Physical inactivity is associated with increased risk of several adverse health outcomes including heart disease, type 2 diabetes, colon cancer, breast cancer, and mortality (Colditz et al. 1997; Kelley and Goodpaster 2001; Kohl 2001; Verloop et al. 2000). Active commuting, such as walking or biking to work on a daily basis, has been shown to decrease risk of all-cause mortality and cardiovascular disease (Andersen et al. 2000; Hamer and Chida 2008; Zheng et al. 2009). Various attributes of the built environment (e.g., population density, street connectivity, land use mix) have been associated with rates of physical activity at the neighborhood level (Ewing et al. 2003; Frank et al. 2005; Saelens et al. 2003a; Sallis et al. 2009). Furthermore, the type of transportation mode used (public transit vs. car) affects personal energy expenditure (Morabia et al. 2010). Thus, an important research question is whether urban planning can reduce physical inactivity and improve health.

Exposure to outdoor urban air pollution is associated with various adverse health outcomes including heart disease, respiratory disease, lung cancer, asthma, and mortality (Brunekreef and Holgate 2002; Gent et al. 2003; Pope and Dockery 2006; Pope et al. 2002). Chronic exposures vary at similar magnitudes within-cities as between-cities (Jerrett et al. 2005; Miller et al. 2007), suggesting that neighborhood location, urban design, and proximity to roads can affect exposures (Health Effects Institute 2009; Marshall et al. 2005).

Recently, the World Health Organization (WHO) cited physical inactivity (4th) and exposure to outdoor urban air pollution (14th) among the top 15 risk factors for the Global Burden of Disease (WHO 2009); for high-income countries, these ranks are 4th (physical inactivity) and 8th (outdoor air pollution). Urban planning and the built environment may differentially influence exposures to those two risk factors (Marshall et al. 2009). A small number of studies have investigated the effects of exercise while controlling for air pollution exposure (de Nazelle et al. 2009; Wong et al. 2007) or explored regional- or national-scale theoretical shifts to active travel (de Hartog et al. 2010; Grabow et al. 2011); however, accounting for health outcomes from exposure to air pollution and physical inactivity among neighborhood types is a little-studied area.

We used risk assessment to explore urban-scale spatial patterns in exposures associated with the built environment. We investigated differences in urban form that have been associated with physical inactivity and air pollution [specifically, particulate matter with aerodynamic diameter ≤ 2.5 µm ($PM_{2.5}$), nitrogen oxides (NO_x), and ozone (O_3)] to assess relationships between urban form and public health.

Methods

Our approach combined four primary sources of information: a geocoded, self-report travel diary to indicate home location and physical activity levels for a specific cohort (n = 30,007); modeled and measured estimates of outdoor air pollution concentrations and their variability in space and time; literature-derived estimates relating ischemic heart disease (IHD) rates with physical inactivity and exposure to air pollution; and geographic information system (GIS) land use variables related to walkability. Our method is descriptive (i.e., cross-sectional) and aims to explore long-term health effects of neighborhood characteristics and location. Figure 1 illustrates our risk assessment approach.

Physical inactivity and air pollution exposures. We used the year 2001 Post-Census Regional Travel Survey to estimate exposure to physical inactivity and home-based exposure to outdoor air pollution. This survey, which covers southern California communities such as Orange County and Los Angeles, included a geocoded time–activity

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diary that captured self-reported activities and travel during fall 2001 and spring 2002. The survey population consisted of a random sample of residents, recruited by telephone in six southern California counties [Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura; for survey details, see Southern California Association of Governments (SCAG 2003)]. To our knowledge, no other metropolitan-scale travel survey has been used to estimate physical activity and exposure to air pollution (Marshall et al. 2006); in addition, this survey represents one of the largest exposure-relevant surveys available for any urban area in the world.

Of the 40,376 survey respondents, 30,007 (74%) met our inclusion criteria: *a*) geocoded home location [2,346 respondents excluded (5.8%)], *b*) home location within the air pollution modeling domain—the South Coast Air Basin [4,491 respondents excluded (11.1%)], and *c*) complete demographic information [age, sex, and ethnicity; 3,532 respondents excluded (8.7%)]. The survey generally covered 1 weekday per participant. We multiplied each participant's 1-day physical activity record by 7 to obtain an estimate of weekly minutes of physical activity. This approach assumed that physical activity was constant across all days of the week. Population-average levels of physical activity were similar (< 15% difference) between weekdays and weekends (11 vs. 12 min/day, respectively) based on data from a small number of respondents (13%, n = 5,104) who participated in an additional weekend survey supplement (see sensitivity analysis 1, below). The survey recorded total physical activity and separately disaggregated that total into active transport (e.g., walking, bicycling) versus recreational activities (e.g., sports, working out at a gym).

Our primary estimates for air pollution exposure were based on monitoring data [U.S. Environmental Protection Agency (EPA) 2010] for $PM_{2.5}$, NO_x, and O_3 in 2001. We interpolated concentrations [inverse-distance weighted average of the nearest three monitors (Marshall et al. 2008)] to each survey participant's home location. Each pollutant had several monitoring stations ($PM_{2.5}$, 27; NO_x, 42; O_3, 52), providing good spatial coverage for the 36,000-km^2 study area. We estimated the annual average of daily 1-hr maximum concentrations for O_3 and annual-average concentrations for $PM_{2.5}$ and NO_x at each survey participant's residence to match the metrics used in the epidemiological studies that we used to estimate IHD risks. We used spatial interpolation for the base case because it can be used for all three pollutants and is easily transferable to other urban areas.

Neighborhood walkability. We calculated three built environment variables to represent neighborhood type: *a*) population density, *b*) intersection density, and *c*) land use mix. Neighborhoods that were in the upper (lower) tertile of all three built environment variables were defined as high- (low-) walkability neighborhoods. This approach classified 12% of the survey population as living in a high-walkability neighborhood and 18% as living in a low-walkability neighborhood. We used objective measurements of the built environment rather than geographical overlays to match methods commonly used in the urban planning literature. Although no standard measure of walkability exists, most indices include measures of density, connectivity, and land use mix (Ewing and Cervero 2001). As a sensitivity analysis, based on prior research (Marshall et al. 2009) we implemented a second definition that classified 33% of survey participants in high- and 33% in low-walkability neighborhoods [for methods, see Supplemental Material, p. 2 (http://dx.doi.org/10.1289/ehp.1103806)]. Results were similar for both definitions; therefore, we report results using the first definition only.

Population density. We used U.S. Census data from the year 2000 to calculate population density at the tract level for each household (U.S. Census Bureau 2000). Population density has been shown to be a predictor of per capita automobile travel (Holtzclaw et al. 2002; Marshall 2008) and trip length (Ewing and Cervero 2001), both of which are predictors of bicycling and walking (Handy et al. 2002).

Intersection density. Intersection density was calculated using road TIGER/Line data (U.S. Census Bureau 2000). A 1-km non-freeway network buffer was generated for each household using ArcGIS (version: 9.3.1, ESRI; Redlands, CA, USA). Intersections (more than two road segments) were summed within the buffer, yielding a measure of street connectivity. Previous studies show that street connectivity may reduce vehicle travel and increase walking (Ewing and Cervero 2001; Forsyth et al. 2008).

Land use mix. Following Frank et al. (2004), we calculated a land use mix index for each household location. Aerial land use data was obtained from SCAG for the year 2001 (SCAG 2010). The index [see Supplemental Material, pp. 2–3 (http://dx.doi.org/10.1289/ehp.1103806)] is a normalized ratio of the mix of four primary land uses (residential, commercial, retail, and institutional) to total land area within the 1-km network buffer. The index ranges from 0 to 1: A value of 1 represents an equal mixture of the four land uses; a value of 0 indicates 100% of land is a single land use. Impacts of land use mix on health include reducing obesity (Frank et al. 2005) and increasing physical activity (Saelens et al. 2003b).

Dose–response and relative risk estimates. For each survey participant (i.e., at the individual level), we estimated relative risks (RRs) attributable to outdoor air pollution and physical inactivity for one important health outcome: IHD. IHD is consistently associated with outdoor air pollution and physical inactivity (WHO 2009), is responsible for a large proportion of deaths in the United States (~ 18% of all deaths and 67% of heart disease deaths in 2006) [Centers for Disease Control and Prevention (CDC) 2009], and has been shown to be an important health outcome for both risk factors when considering large-scale shifts to active travel (Woodcock et al. 2009). Because our exposure estimates for air pollution are continuous, we estimated an RR for each survey participant based on a linear dose–response [see Supplemental Material, Figure S2 (http://dx.doi.org/10.1289/ehp.1103806)] for the range of observed air pollutant concentrations and the referent exposure levels described below. In contrast, WHO (2004) suggests a three-tier dose–response for physical activity: *a*) active (exercise for > 150 min/week; RR = 1), *b*) insufficiently active (exercise for 1–150 min/week; RR = 1.31), and *c*) inactive (0 min exercise per week; RR = 1.47), allowing for only three possible physical activity RRs for each survey participant. We estimated

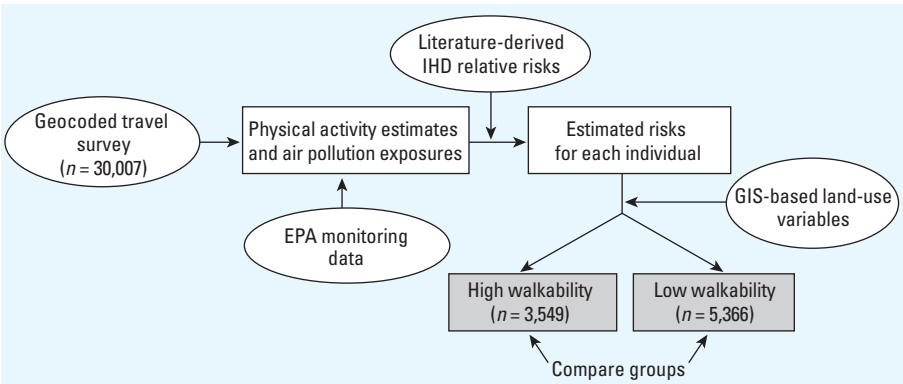

Figure 1. Conceptual framework for this risk assessment. Ovals are inputs, and boxes are midpoint calculations. Shaded boxes indicate estimated risk separated into two groups for comparison.

attributable fractions for outdoor air pollution and physical inactivity using the mean individual RR in high- or low-walkability neighborhoods.

Air pollution dose–response relationships were identified and selected as follows. We manually searched the tables of contents of four journals (*Journal of the American Medical Association*, *New England Journal of Medicine*, *British Medical Journal*, *Lancet*) for the years 2000–2010 for air pollution risk estimates. We also performed a search of key words in Google Scholar and ISI Knowledge, including (in various combinations) "air pollution," "O_3/NO_x/$PM_{2.5}$," "ischemic heart disease," "cardiovascular disease," "cardiopulmonary disease," "respiratory disease," "mortality," "health effects," "chronic/acute," and "dose–response." We used the "cited by" function in Google Scholar to explore subsequent studies related to each article. Through this process, we identified 62 articles. We then selected studies that focused on within-city variation and included IHD as a health outcome (Table 1).

Each RR for air pollution was estimated from cohort studies of long-term exposures; however, these estimates differed in important ways. For example, Nafstad et al. (2004) studied men 40–49 years of age, meaning our NO_x results cannot be generalized to other populations [RR = 1.08; 95% confidence interval (CI): 1.06, 1.11]. Jerrett et al. (2005) used a subset of the American Cancer Society (ACS) cohort (Los Angeles, CA, USA) to estimate a within-city RR of 1.25 per 10 μg/m^3 increase in $PM_{2.5}$ (95% CI: 0.99, 1.59). Jerrett et al. (2005) did not report a significant RR for $PM_{2.5}$ in Los Angeles, but the RR estimate is roughly consistent with two between-city studies that did report statistically significant RRs: Pope et al. (2004; RR = 1.18 per 10 μg/m^3 increase in $PM_{2.5}$; 95% CI: 1.14, 1.23) and Jerrett et al. (2009; RR = 1.21; 95% CI: 1.16, 1.27). The Jerrett et al. (2009) RR for a 10 μg/m^3 increase in O_3 (1.008; 95% CI: 1.002, 1.013) was based on between-city variation (ACS cohort) in 96 U.S. metropolitan statistical areas generated from a one-pollutant model. However, it is important to note that Jerrett et al. (2009) reported a protective effect for O_3 based on a two-pollutant model adjusted for $PM_{2.5}$ (RR = 0.97; 95% CI: 0.96, 0.99), and overall there is less evidence in the literature for O_3 associations with IHD compared with those for $PM_{2.5}$. A within-city study of O_3 and IHD was not available.

The referent exposure levels used to estimate individuals' RRs were "active" for physical inactivity (> 150 min of moderate-vigorous activity per week), and the 10th percentile of exposure (survey population based; values: 13.6 μg/m^3 for $PM_{2.5}$, 39.8 μg/m^3 for NO_x, 80.3 μg/80.3 μg/m^3 for O_3) for air pollution, consistent with exposures in a relatively clean neighborhood in the study area. Each survey participant's air pollution RR was estimated based on the difference between their home-location air pollution exposure and the referent exposure level. For example, for $PM_{2.5}$, an individual whose home-location exposure estimate was 23.6 μg/m^3 (10 μg/m^3 above the referent level) would be assigned an RR of 1.25.

Population-attributable fraction. We calculated population-attributable fraction (PAF) and estimated attributable IHD mortality rates for each risk factor in high- and low-walkability neighborhoods. PAF for a neighborhood was calculated based on the proportion of individuals exposed to each risk factor and average RR among all individuals in a neighborhood (Baker and Nieuwenhuijsen 2008):

$$\mathrm{PAF} = \frac{p \times (\mathrm{RR} - 1)}{[p \times (\mathrm{RR} - 1)] + 1}. \qquad [1]$$

Here, RR is the mean individual RR in each group (high- and low-walkability neighborhoods) and risk factor, and p is the proportion of individuals exposed in each group (defined by our referent exposure levels). We used the 2000–2001 age-adjusted IHD mortality rate in California (191.2 IHD deaths/100,000/year; CDC 2011) to estimate deaths within each group and subsequent attributable IHD mortality rates (except for NO_x where we used the IHD mortality rate for men in California 45–54 years of age: 81.9 IHD deaths/100,000/year). Attributable mortality due to physical inactivity, $PM_{2.5}$, NO_x, and O_3 cannot be summed because of confounding among the risk factors and overlap of at-risk populations. Therefore, we report attributable mortality due to the different factors separately.

We separately calculated PAF using a method with multiple exposure levels instead of the dichotomous exposure levels implicit in Equation 1, as described in the Supplemental Material [pp. 5–6 (http://dx.doi.org/10.1289/ehp.1103806)] Results based on this alternative method were similar to those reported below.

Sensitivity analyses. To explore the robustness of our estimates, we used three sensitivity analyses to assess *a*) different methods of scaling minutes of physical activity, *b*) alternate modeling approaches for air pollution, and *c*) stepwise versus linear dose–response for physical activity.

Sensitivity analysis 1: scaling method for minutes of physical activity. Our approach requires extrapolating weekly exercise rates based on the 1-day travel diary because most physical activity epidemiological literature employs the metric "minutes of physical activity per week." To test the limitations of this extrapolation for our analysis, we developed a Monte Carlo simulation that relaxes our base-case assumption (i.e., that individuals' physical activity rates are constant by day), by employing two alternative assumptions: that people who are nonsedentary are physically active *a*) every other day or *b*) every third day. The Monte Carlo simulation distributes total minutes of physical activity accordingly, stratifying by age, sex, and ethnicity. The resulting distributions of physical activity better approximate national estimates on the prevalence of physical inactivity (WHO 2004).

Sensitivity analysis 2: air pollution model. Our base-case analysis used spatial interpolation of U.S. EPA monitoring data, which are readily available for all three pollutants for many urban areas. We compared results using a Eulerian dispersion model [Comprehensive Air Quality Model with Extensions (CAMx); http://www.camx.com; nitrous oxide (NO), nitrogen dioxide (NO_2), O_3] and land-use regression (LUR; NO_2; Novotny et al. 2011). CAMx and LUR provide greater spatial precision than inverse-distance weighting but may or may not be available in other urban areas.

Sensitivity analysis 3: physical activity dose–response. We tested the sensitivity of our results to the dose–response curve for physical inactivity. Our base case used the stepwise dose–response from WHO (2004) (Table 1). For this sensitivity analysis, we generated three linear dose–response curves (low, medium, and high slopes) based on the same WHO values.

Results

Annual-average air pollution exposure for the survey population averaged 49 μg/m^3 for NO_2 [interquartile range (IQR), 41–60 μg/m^3), 99 μg/m^3 for O_3

Table 1. Summary of RR estimates used for IHD.

Study	Risk factor	Study details	RR (95% CI)
Nafstad et al. 2004	NO_x	Within-city; men 40–49 years of age in Oslo, Norway (n = 16,209)	1.08[a] (1.06, 1.11) per 10 μg/m^3
Jerrett et al. 2005	$PM_{2.5}$	Within-city; subset (Los Angeles, CA) of the ACS cohort (n = 22,905)	1.25[a] (0.99, 1.59) per 10 μg/m^3
Jerrett et al. 2009	O_3	Between-cities; ACS cohort (n = 448,850)	1.008[a] (1.002, 1.013) per 10 μg/m^3
WHO 2004	Physical inactivity	Meta-analysis of 20 studies from two continents (Western Europe, 8; North America, 12; total n = 327,004)	Insufficiently active:[b] 1.31 (1.21, 1.41) Inactive:[b] 1.47 (1.39, 1.56)

[a]Air pollution risk estimates used here were based on long-term cohort studies and chronic health effects. [b]Referent, > 150 min/week; insufficiently active, 1–150 min/week; inactive, 0 min/week.

(86–112 μg/m^3; annual average of 1-hr daily maximums), and 22 μg/m^3 for $PM_{2.5}$ (20–24 μg/m^3; Table 2). Mean NO_2 exposures were below current ambient-air standards [U.S. EPA and California Environmental Protection Agency (CalEPA) standards, respectively: 100 and 57 μg/m^3]. $PM_{2.5}$ exposures were approximately 1.5 and 2 times higher than U.S. EPA (15 μg/m^3) and CalEPA (12 μg/m^3) long-term standards (annual arithmetic mean), respectively (California Air Resources Board 2010).

Table 2. Descriptive statistics by neighborhood type [mean (IQR)].

Variable	All (n = 30,007)	Low walkability (n = 5,366)	High walkability (n = 3,549)
Age (years)	38 (21–54)	41 (23–58)	34 (20–47)
Nonwhite (%)	40	23	65
Male (%)	50	49	50
Income > $50,000 per year (%)	48	57	31
College or more (%)	46	52	40
NO_x (μg/m^3)[a]	85 (68–103)	67 (50–88)	106 (89–130)
O_3 (μg/m^3)[b]	99 (86–112)	111 (97–124)	86 (82–92)
$PM_{2.5}$ (μg/m^3)[a]	22 (20–24)	20 (14–25)	23 (22–24)
Physical activity (min/week)	77 (0–0)	68 (0–0)	102 (0–0)
Population density in Census tract (people/km^2)[c]	22,400 (7,800–28,400)	3,100 (600–5,200)	53,500 (31,900–61,600)
Intersection density (1-km network buffer)[c]	57 (27–82)	11 (2–20)	109 (86–114)
Land use mix (1-km network buffer)[c]	0.37 (0.25–0.49)	0.13 (0–0.23)	0.59 (0.50–0.66)

All continuous variables in high-walkability neighborhoods have statistically significant differences (for all variables $p < 0.001$) compared with low-walkability neighborhoods (two-tailed t-test).
[a]Home-location annual-average concentrations. [b]Home-location annual average of daily 1-hr maximum concentrations.
[c]This land use variable was used to define walkability.

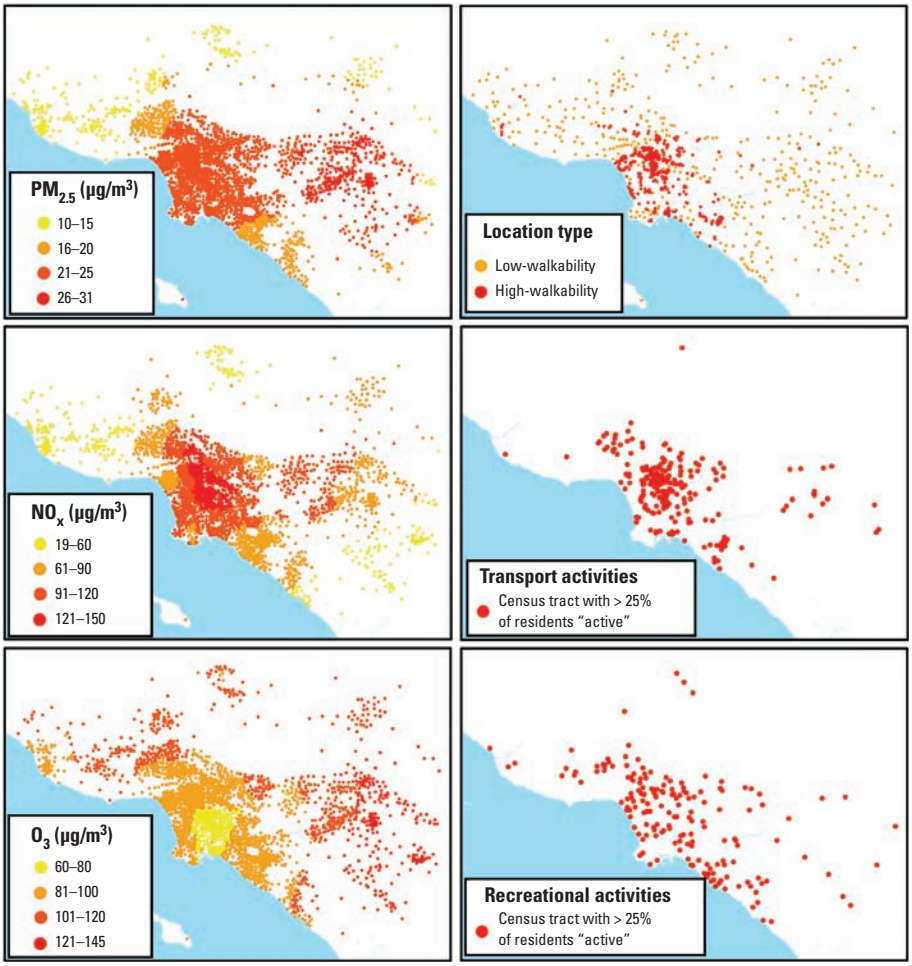

Figure 2. Spatial variation of air pollution exposure and physical inactivity. Physical activity estimates were derived from time–activity diaries, air pollution exposures were calculated from U.S. EPA monitoring data, and walkability was defined using publicly available land use variables. Icons for transport and recreational activities represent census tracts where > 25% of the survey respondents reported > 150 min/week of that activity type.

Self-reported physical activity levels averaged 77 min/week (IQR, 0–0 min/week; i.e., the 25th and 75th values are 0 min/week; Table 2). Most (83.5%) of the survey participants reported being inactive (0 min/week), 5.6% reported being insufficiently active (1–150 min/week), and 10.9% reported being active (> 150 min/week; physical activity recommendations; U.S. Department of Health and Human Services 1996). Activity levels were notably lower than national averages (U.S. averages: inactive, 29%; insufficiently active, 45%; active, 26%; WHO 2004). Sensitivity analysis 1 addresses this difference in activity levels.

NO_x and $PM_{2.5}$ concentrations were highest near the city center and major roadways, whereas O_3 concentrations were higher in the outer-lying areas (Figure 2). Because of this spatial pattern, few locations experienced low exposure to all three pollutants. Spatial patterns for physical activity were dependent on the purpose of the activity; there was no discernable spatial pattern for recreational activities, but active transport was clustered near high-walkability neighborhoods (Figure 2).

Average per capita physical activity was 50% higher in high- than in low-walkability neighborhoods (102 vs. 68 min/week; Figure 3). The number of nonsedentary individuals (people with > 0 min/week physical activity) was two times higher in high- versus low-walkability neighborhoods (24.9% and 12.5%, respectively; $p < 0.001$). However, considering nonsedentary individuals only, average physical activity was 24% lower in high- than in low-walkability neighborhoods (410 vs. 543 min/week). This finding suggests that neighborhood type may have differing impacts on the number of people participating in physical activities, average physical activity among all individuals, and average physical activity among nonsedentary individuals.

The self-reported purpose of physical activity differs by neighborhood (Figure 3). For example, active transport accounts for about half of physical activity in the high-walkability neighborhoods but only 20% in low-walkability neighborhoods. Active transport is 3.6 times higher in high- versus low-walkability neighborhoods (a finding that partially corroborates our GIS estimates of walkability), whereas nontravel activity is similar (< 10% difference) in low- versus high-walkability neighborhoods. Activity level and purpose exhibited greater weekend/weekday differences in low-walkability areas than in high-walkability areas [see Supplemental Material, Table S2, Figure S4 (http://dx.doi.org/10.1289/ehp.1103806)].

Figure 4 shows estimated attributable IHD mortality rates for each neighborhood type

and risk factor. Physical inactivity was more strongly associated with IHD mortality (51 additional deaths/100,000/year overall) than were the other exposures, but IHD mortality attributable to physical inactivity was only slightly different between high- and low-walkability neighborhoods (7 fewer IHD deaths/100,000/year in high- vs. low-walkability). Conversely, overall estimated attributable IHD mortality due to exposure to $PM_{2.5}$ was smaller (30 deaths/100,000/year), but the difference between neighborhoods was slightly larger than for physical inactivity (9 more IHD deaths/100,000/year in high- vs. low-walkability). O_3 shows the reverse spatial pattern as $PM_{2.5}$ (i.e., O_3 exposure is higher in low-walkability neighborhoods, whereas $PM_{2.5}$ is lower) but a smaller difference in mortality between neighborhoods (3 fewer IHD deaths/100,000/year in high- vs. low-walkability). Attributable IHD mortality rates for NO_x (represented by risk estimates for men 40–49 years of age; not shown in Figure 4) were 13 (28) IHD deaths/100,000/year for low- (high-) walkability neighborhoods. Attributable risk estimates for physical inactivity, $PM_{2.5}$, and O_3 showed similar patterns when neighborhoods were classified according to deciles of walkability scores [Supplemental Material, Figure S5 (http://dx.doi.org/10.1289/ehp.1103806)].

Sensitivity analysis 1: scaling method for minutes of physical activity. Results [see Supplemental Material, pp. 8–9 (http://dx.doi.org/10.1289/ehp.1103806)] indicate that our alternative assumptions reduce the variability in physical activity among neighborhoods. Specifically, the Monte Carlo simulation increases the share of nonsedentary individuals (subsequently reducing average risks from physical inactivity) but also yields reductions in estimated IHD mortality differences among neighborhoods. Our core conclusions are similar among the Monte Carlo simulations.

Sensitivity analysis 2: air pollution model. Central tendencies varied by pollutant and model; however, trends in the core conclusions (i.e., shifts in exposure and risk by neighborhood type) were similar where it was possible to compare [see Supplemental Material, pp. 9–10 (http://dx.doi.org/10.1289/ehp.1103806)]. In general, differences in estimated IHD mortality rates between high- and low-walkability neighborhoods were larger when using the alternate models; therefore, base-case results reported above may be conservative estimates (i.e., underestimates) of air pollution spatial variability.

Sensitivity analysis 3: physical activity dose–response. Our results did not change appreciably when using the linear dose–response curves [see Supplemental Material, pp. 10–11 (http://dx.doi.org/10.1289/ehp.1103806)].

We also estimated RRs according to neighborhood type (high- or low-walkability) within strata of age (0–25 years, 26–50 years, > 50 years) and according to income and ethnicity [high income (> $75,000) and white vs. low income (< $35,000) and nonwhite]. The results reveal similar trends in risk differences between neighborhoods for each strata, suggesting that our results are robust to accounting for differences in income, ethnicity, and age. Details are in the Supplemental Material [pp. 11–14, Table S6 (http://dx.doi.org/10.1289/ehp.1103806)]. Prior literature further explores socioeconomic aspects of this topic (e.g., Ewing 2005; Frank et al. 2007; Sallis et al. 2009).

Discussion

Our analysis summarizes between-neighborhood variations in two risk factors (exposure to air pollution, physical inactivity) using a time–activity travel diary for one region. We found risks were differential when stratified by neighborhood walkability. Specifically, when comparing estimated IHD mortality rates among neighborhoods, differences attributable to physical inactivity were modest and comparable to differences attributable to individual air pollutants. Because of spatial patterns associated with each pollutant, urban residents were often highly exposed to at least one but not all pollutants (e.g., high exposure to O_3 in low-walkability neighborhoods or high exposure to $PM_{2.5}$ in high-walkability neighborhoods). This trade-off suggests that the net health impact of neighborhoods may depend in part on spatial patterns of air pollution.

Recent health comparisons between air pollution and exercise (Carlisle and Sharp 2001; de Hartog et al. 2010) emphasize the greater health importance of exercise relative to air pollution. This prior research considered only people who exercise (Carlisle and Sharp 2001; de Hartog et al. 2010); here, we consider the entire population—nonsedentary plus sedentary individuals. Only a subset of a given population is physically active, and only a subset of that physical activity is influenced by neighborhood design; here, the net result is that spatial differences in attributable IHD mortality risks are of similar magnitude for physical inactivity as for air pollution. Our results indicate a doubling in the share of nonsedentary people in high- versus low-walkability neighborhoods (24.9% vs. 12.5%); however, all individuals—inactive and active—experience changes in air pollution exposures. For this study population, physical activity rates were higher (and exercise-attributable IHD mortality rates lower) in high- than in low-walkability neighborhoods. However, because variations in air pollution risk are similar to variations in physical inactivity risks, when comparing high- versus low-walkability neighborhoods, health benefits from increased physical activity may be offset by health risks from air pollution exposure.

Our study uses self-reported rather than objectively measured physical activity. Previous studies that have used objectively-measured physical activity to investigate effects of urban form on physical activity (Table 3) have reported mixed results: two studies reported

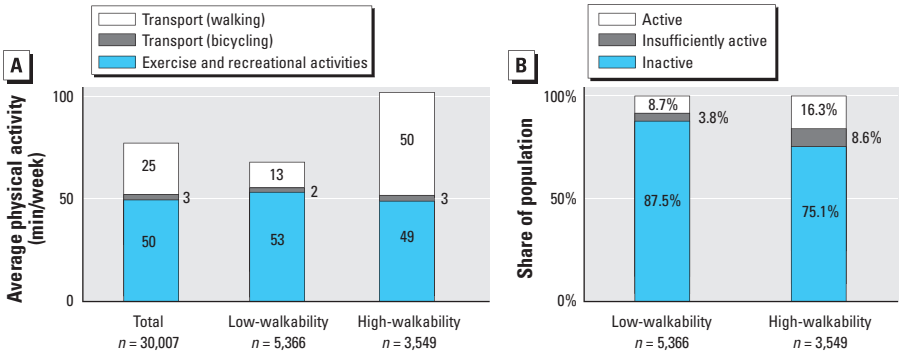

Figure 3. Differences among neighborhoods. (*A*) Average active transport (minutes walking and bicycling per person) and recreational activities. (*B*) Physical activity levels. The between-neighborhood difference in total physical activity is statistically significant ($p < 0.001$, two-tailed *t*-test).

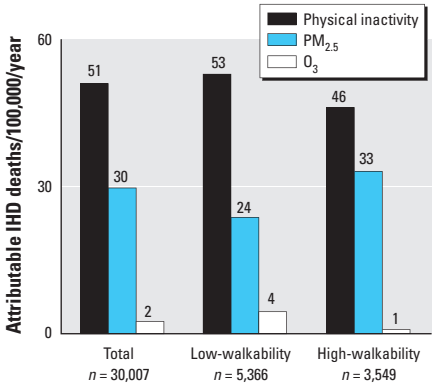

Figure 4. Estimated attributable IHD mortality rates for each risk factor and neighborhood type. Rates were calculated using means of individual RRs and prevalence of exposure within neighborhood type [referent, > 150 min/week of physical activity; 10th percentile of air pollution exposure (13.6 μg/m^3 for $PM_{2.5}$, 39.8 μg/m^3 for NO_x, and 80.3 μg/m^3 for O_3)]. The overall incidence of IHD mortality in California is 191 deaths/100,000/year (CDC 2011).

Table 3. Comparison of results from studies using objective measures of physical activity with results from the present study.

Study	Location	Measure of physical activity	Measure of urban form	Core result
Sallis et al. 2009	Seattle, WA, and Baltimore, MD	Objective: 7-day accelerometer	Walkability (net residential density, intersection density, land use mix, retail floor area ratio)	41 min/week increase in physical activity between high- vs. low-walkability neighborhoods
Frank et al. 2005	Atlanta, GA	Objective: 2-day accelerometer	Walkability (net residential density, intersection density, land use mix)	Two-fold increase in meeting physical activity recommendations in high- vs. low-walkability neighborhoods
Forsyth et al. 2008	St. Paul, MN	Objective: 7-day accelerometer	Population density, block size (street pattern)	Significant increase in transport-related physical activity (high- vs. low-walkability neighborhoods) but no difference in total physical activity
Present study	South Coast Air Basin, CA	Self-report: one-day time activity diary	Walkability (population density, intersection density, land use mix)	34 min/week increase in physical activity between high- vs. low-walkability neighborhoods (2-fold increase in meeting physical activity recommendations)

differences in physical activity by neighborhood type (Frank et al. 2005; Sallis et al. 2009), and one indicated shifts in the purpose (transport vs. fitness) but not the amount of physical activity (Forsyth et al. 2008). These findings suggest that urban-scale differences in physical activity rates are similar between objectively measured physical activity and our self-reported measures of activity. For example, differences in per capita physical activity between high- and low-walkability neighborhoods in Seattle, Washington, and Baltimore, Maryland, were similar to differences in our southern California population [41 min/week (Seattle, Baltimore) versus 34 min/week (southern California) (Sallis et al. 2009)].

Our study limitations include those associated with travel surveys and self-reported information in general. For example, travel surveys typically undercount trips by all modes (Bricka and Bhat 2006), affecting estimates of travel time (Wolf et al. 2003). The SCAG survey suggests that vehicle undercount rates may approach 20–25% but gives little information regarding nonmotorized trips (SCAG 2004). Undercount rates may be differential by trip length (SCAG 2004), mode, or neighborhood. Comparisons with studies using objectively measured physical activity (see preceding paragraph) suggest that our core findings are robust to trip undercounting and other problems with self-reported travel data.

Our work is motivated by the goal of understanding and designing clean, healthy, sustainable cities (Giles et al. 2011). Our investigation explores only one location (Los Angeles), one health outcome (IHD), one cohort, a small number of pollutants (NO_x, $PM_{2.5}$, O_3), and physical inactivity. Clearly, further analyses incorporating other risk factors (e.g., noise, transport injury) linked to the built environment are warranted. Interaction between physical activity and air pollution may vary on an even smaller scale than we have investigated in the present study (i.e., within neighborhoods). Future analyses could use age-specific risks of IHD mortality for air pollution and physical inactivity. Our analysis is descriptive (i.e., cross-sectional) in nature; more research is needed to explore causality between urban form and health risks (especially for physical activity, because ambient air pollution exposure is largely determined by geographical location).

Despite these limitations, our results are relevant to health officials, sustainability scientists, and urban planners. To our knowledge, ours is the first analysis that directly compares health risks for both air pollution and physical inactivity among neighborhoods based on activity patterns for a random sample of residents in an urban area, and thus is the first to quantify relationships between urban form and the health impacts of physical activity and air pollution. We found that attributes of the built environment were associated with both air pollution exposure and physical inactivity. These results emphasize that to be health protective, neighborhoods designed to decrease risks from one factor must avoid unintentionally increasing risks from other factors.

Conclusion

We compared the health impacts attributable to air pollution and physical inactivity among neighborhoods for one cohort (~ 30,000 individuals in Southern California). A larger proportion of our Southern California study population was classified as nonsedentary in high- versus low-walkability neighborhoods (25% vs. 13%). However, because only a small share of the total population was classified as physically active, we estimated only moderate differences in IHD mortality rates attributable to physical inactivity between neighborhood types. Spatial patterns of estimated attributable IHD mortality rates varied by pollutant: estimated mortality due to increased $PM_{2.5}$ and NO_x were greater in high- than in low-walkability neighborhoods, whereas estimated IHD mortality due to increased O_3 was greater in low- than in high-walkability neighborhoods. In general, differences in estimated IHD mortality between neighborhoods were comparable for exposure to air pollutants and physical inactivity. Our results suggest complex within-urban spatial trade-offs in health risks associated with air pollution and physical inactivity. Efforts to design healthy neighborhoods should account for many factors, including air pollution and physical inactivity, and not address one concern at the expense of others.

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Supplemental Material

Health Impacts of the Built Environment: Within-urban Variability in Physical Inactivity, Air Pollution, and Ischemic Heart Disease Mortality

S Hankey, JD Marshall, M Brauer

This document provides supporting information on the following topics:

I. Walkability scores and land use mix 2
II. Dose-response: Physical inactivity and air pollution 5
III. Population attributable fraction calculations for IHD mortality rates 5
IV. Purpose of physical activities and weekend-weekday activity patterns 6
V. Results stratified by walkability decile 8
VI. Sensitivity analysis #1: Scaling method for minutes of physical activity 8
VII. Sensitivity analysis #2: Air pollution model 9
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IX. Results stratified by age, SES, and built environment variables 11
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I. Walkability scores and land use mix

We used an alternate approach to define neighborhoods (a composite walkability index) to test the robustness of the core findings to our method for defining high- and low-walkability neighborhoods (main text method selects neighborhoods in the highest (or lowest) tertile of all three built environment variables). The composite walkability index (alternate approach) was created by first calculating z-scores for each built environment variable (population density, intersection density, land use mix). At each home location all three z-scores were summed according to equation S1 (adapted from [Marshall et al. 2009]; data on retail floor area ratio was unavailable and therefore was not included here):

$$Walkability = Z_{PD} + Z_{LUM} + 2Z_{ID} \quad \text{(S1)}$$

Where Z_{PD} is the z-score for population density, Z_{LUM} is the z-score for land use mix, and Z_{ID} is the z-score for intersection density. The coefficient for Z_{ID} reflects the greater walkability importance of intersection density relative to population density and land use mix. For our primary approach, we define high- , low- walkability as locations that fall in the upper tertile of each built environment variable. For the sensitivity analysis (alternate approach) we instead defined high- [low-] walkability neighborhoods as those in the upper [lower] tertile of the composite index (i.e., 33% of the survey population are located in high-walkability neighborhoods and 33% are located in low-walkability neighborhoods), thereby yielding an approximately equal number of people in each neighborhood type. By design, the number of people in high- and low-walkability neighborhoods is larger for the sensitivity analysis (n=9,994 and 10,008, respectively) than for the main approach (n=3,549 and 5,366, respectively). Figure S1 and Table S1 compare findings using the main and alternative approaches for identifying high- and low-walkability neighborhoods.

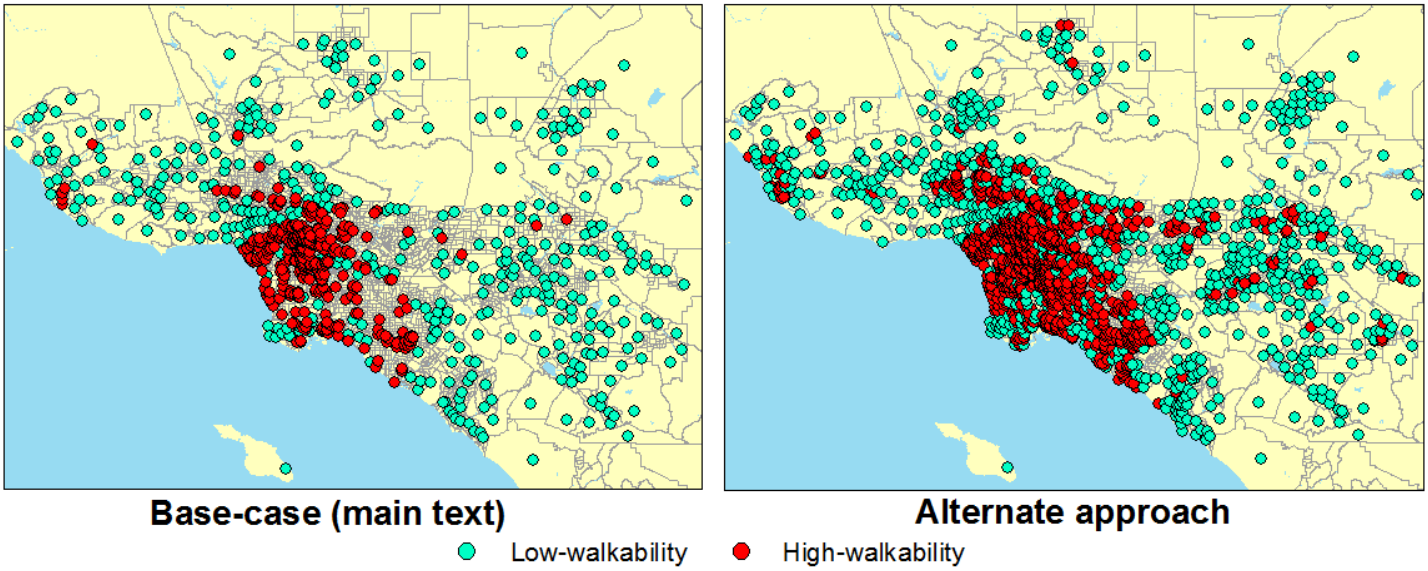


Figure S1. Home locations of survey respondents in high- and low-walkability neighborhoods, by method. By design, the number of individuals included is larger for the alternative approach than for the main approach. Core conclusions are similar between the two methods.

<u>Land use mix</u>: We used the equation in Frank et al. (2004) to calculate land use mix:

$$Land\ use\ mix = -\sum_{i=1}^{n} \frac{p_i \ln p_i}{\ln n} \tag{S2}$$

Here, p_i is the proportion of land use (by area) i and n is the number of land uses. We included four land types: residential, commercial, office, and institutional. All "other" land uses were included for estimating total land area when calculating p_i.

Table S1. Comparison of two methods to calculate walkability

		Mean RR	Proportion above 10th percentile of entire cohort	Population attributable fraction	Total estimated attributable IHD deaths per year (in each subgroup)	Estimated attributable IHD deaths per 100,000 per year[a]
Main approach	**High-walkability (n = 3,549)**					
	Physical inactivity	1.38	0.84	0.24	1.6	46.1 (39-53)
	NO_x	1.53	0.95	0.34	2.3	27.5 (22-34)
	$PM_{2.5}$	1.22	0.95	0.17	1.2	33.1 (-2-64)
	O_3	1.005	0.80	0.004	0.03	0.7 (0.2-1.2)
	Low-walkability (n = 5,366)					
	Physical inactivity	1.42	0.91	0.28	2.8	53.0 (46-60)
	NO_x	1.22	0.84	0.16	1.6	12.7 (10-16)
	$PM_{2.5}$	1.17	0.83	0.12	1.3	23.7 (-1-47)
	O_3	1.02	0.99	0.02	0.2	4.4 (1-7)
Alternate approach	**High-walkability (n = 9,994)**					
	Physical inactivity	1.39	0.86	0.25	4.8	48.0 (41-55)
	NO_x	1.49	0.95	0.32	6.0	25.9 (21-32)
	$PM_{2.5}$	1.22	0.94	0.17	3.3	33.2 (-2-63)
	O_3	1.01	0.81	0.005	0.1	0.9 (0.2-1.6)
	Low-walkability (n = 10,008)					
	Physical inactivity	1.42	0.91	0.28	5.3	53.0 (46-60)
	NO_x	1.24	0.84	0.17	3.2	13.7 (11-18)
	$PM_{2.5}$	1.18	0.84	0.13	2.5	24.5 (-1-49)
	O_3	1.02	0.99	0.02	0.4	4.1 (1-7)

[a]Incidence of IHD mortality in CA (age-adjusted): 191.2 deaths/100,000/year (CA men aged 45-54 (used for NO_x: 89.1 deaths/100,000/year). Values in parentheses are 95% confidence intervals based on the 95% CI from the risk estimates in Table 1 (main text).

II. Dose-response: Physical inactivity and air pollution

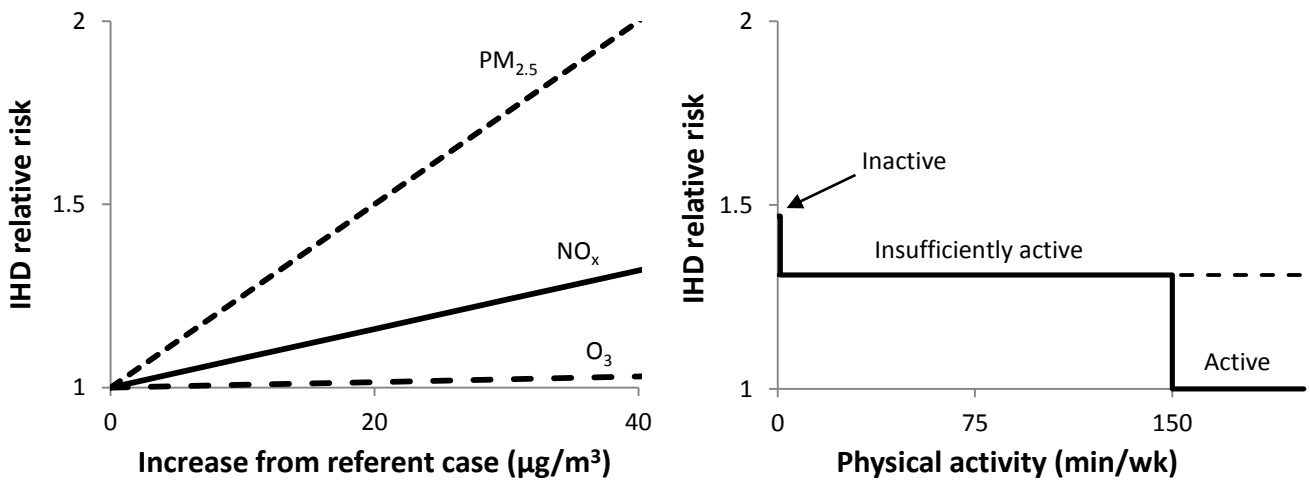


Figure S2. Dose response curves for air pollution (left panel) and physical inactivity (right panel).

III. Population attributable fraction calculations for IHD mortality rates

We also calculated PAF using an alternate disaggregate method using 10 levels of exposure for each air pollutant and 3 levels of exposure for physical inactivity. We followed the methods described in Greenland (2001) to test if our results are sensitive to assumptions associated with the equation used to calculate PAF in the main text as well as a dichotomous definition of exposure. We calculated a mean relative risk and proportion of individuals in each exposure category. We then estimate the population risk and PAF for the total survey population and the subgroup of individuals in high- and low- walkability neighborhoods according to the following equations (Greenland, 2001):

$$RR = \sum_0^k p_k RR_k \quad \text{(S3)}$$

$$PAF = \frac{(RR-1)}{RR} \quad \text{(S4)}$$

Here, *RR* is the population (or subgroup) relative risk, p_k is the proportion of individuals in each exposure level and RR_k is the relative risk at each exposure level. We used ten, equal interval levels of exposure for $PM_{2.5}$ and O_3. Since the dose-response function for physical inactivity is a three-level stepwise function we used 3 levels of exposure for physical inactivity. Figure S3 shows attributable IHD mortality rates calculated using the method from the main text and the alternate method described above. We found similar trends in risk using both methods.

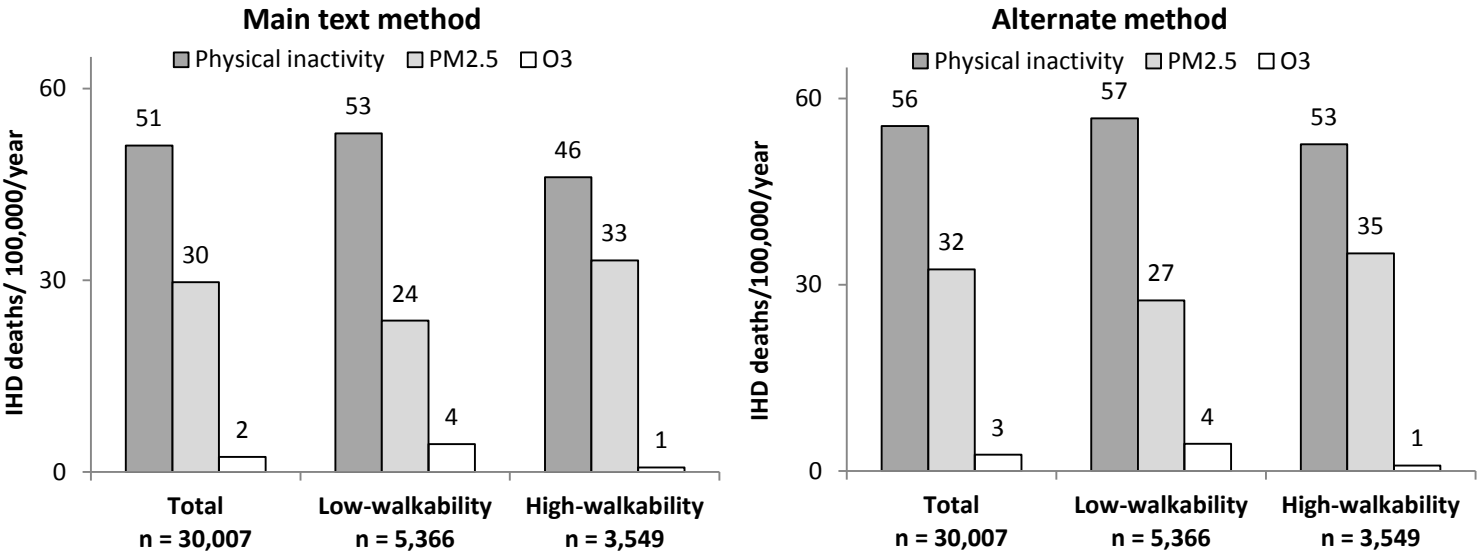


Figure S3. Comparison of the two methods used to calculate population attributable fraction. Left panel: method used in the main text (dichotomous exposure levels); Right panel: an alternate method (multiple exposure levels).

IV. Purpose of physical activities and weekend-weekday activity patterns

Two groups of people are listed in Table S2, Figure S4: (1) "Total sample" (n = 30,007) is the weekday-only sample used throughout the analysis in the main text; (2) "Weekend subsample" and "weekday subsample" refer to the subset of participants who completed a 48-hour survey (n=5,104). For the subsample (n=5,104), total physical activity is similar (<15% difference) between weekend and weekday.

Table S2. Comparison of weekend vs. weekdays and transport vs. leisure physical activity

	N	Average physical activity (min/day)			
		Walking	*Bicycling*	*Fitness*	*Total*
Total Sample					
Total	30,007	3.5	0.4	7.1	11.0
Low-walkability	5,366	1.8	0.3	7.6	9.7
High-walkability	3,549	7.2	0.4	7.0	14.6
Weekend subsample					
Total	5,104	2.4	0.2	9.8	12.4
Low-walkability	916	2.0	0.0	10.6	12.6
High-walkability	661	4.7	0.2	7.4	12.3
Weekday subsample					
Total	5,104	4.4	0.4	6.1	10.9
Low-walkability	916	1.6	0.3	7.9	9.8
High-walkability	661	8.4	0.3	2.8	11.5

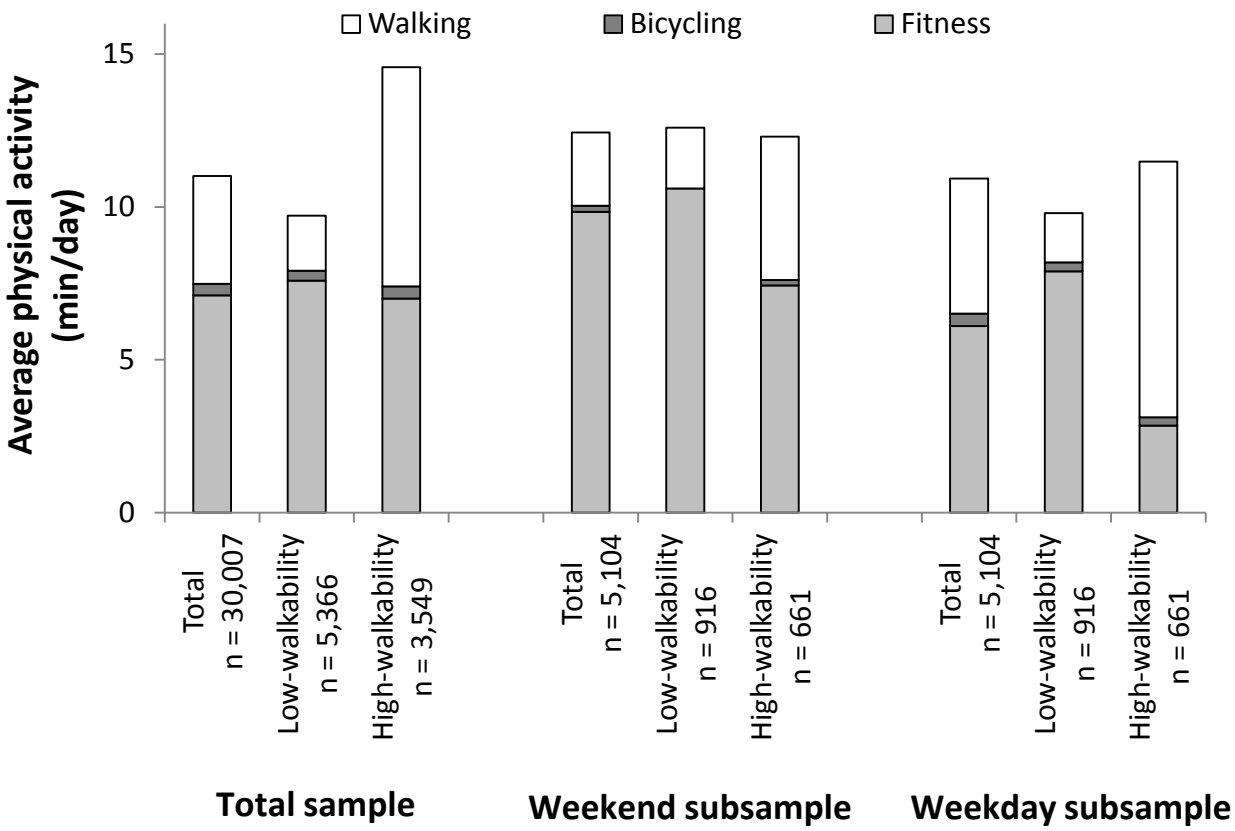


Figure S4. Minutes of physical activity by sample type and purpose.

V. Results stratified by walkability decile

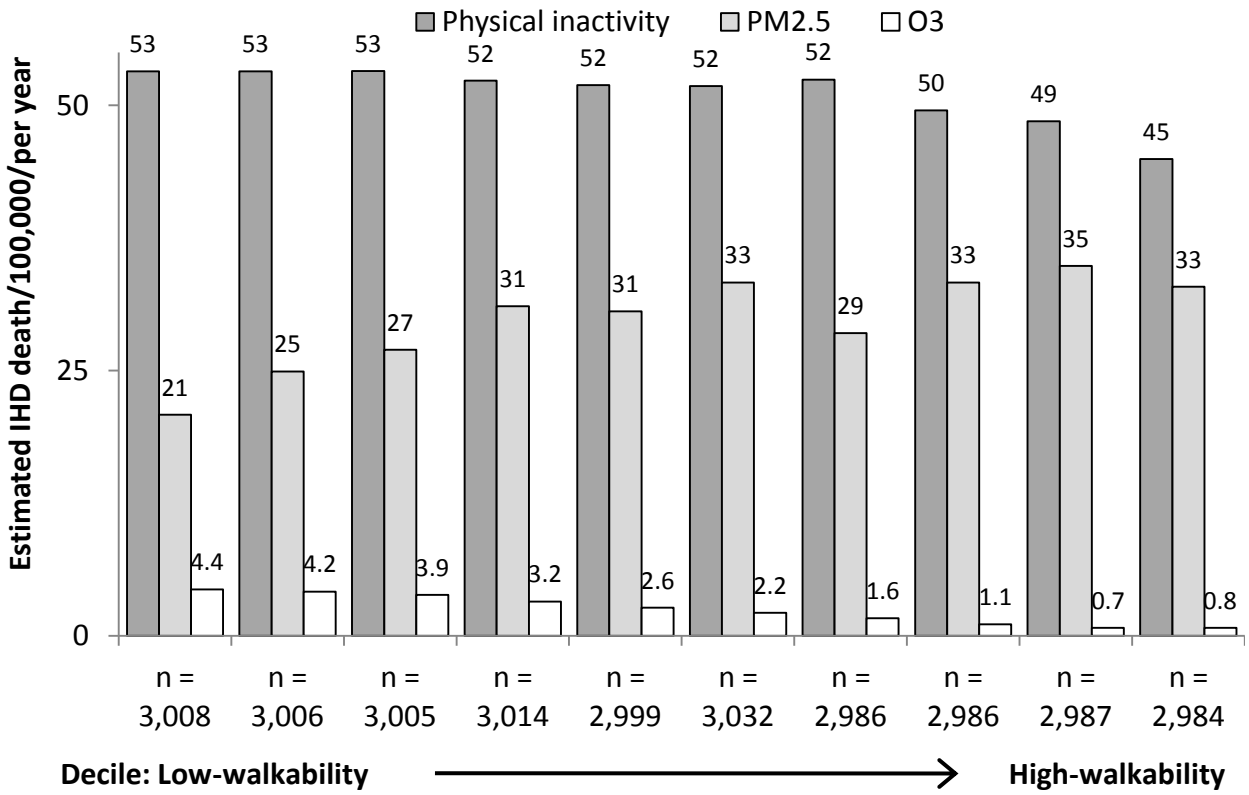


Figure S5. Estimated attributable IHD deaths stratified by walkability decile.

VI. Sensitivity analysis #1: Scaling method for minutes of physical activity

In the main paper, we assumed constant physical activity by day-of-week. To test this assumption we employed a Monte Carlo simulation that redistributed minutes of physical activity for two alternate assumptions: (1) people exercise every two days and (2) people exercise every three days. We held the total minutes of physical activity constant in the population but redistributed minutes to inactive individuals based age, ethnicity, and gender. We found that while the overall proportion of non-sedentary individuals increased, the variability between neighborhoods decreased, suggesting that our core findings are not sensitive to the

assumption that daily activity is constant during the week. Table S3 shows the results of our Monte Carlo analysis.

Table S3. Monte Carlo simulation adjusting for assumed frequency of physical activity

	Low-walkability				**High-walkability**				**Estimated IHD mortality difference per 100,000** (low-high walkability)
	Inactive	Insufficiently active	Active	Total	Inactive	Insufficiently active	Active	Total	
***Base case assumption**: non-sedentary exercise every day*	87%	4%	9%	100%	75%	9%	16%	100%	6.9
***Alternative assumption #1**: non-sedentary exercise every 2 days*	71%	14%	15%	100%	59%	23%	18%	100%	4.2
***Alternative assumption #2**: non-sedentary exercise every 3 days*	54%	30%	16%	100%	43%	39%	17%	100%	2.8

VII. Sensitivity analysis #2: Air pollution model

We compared our air pollution exposure estimates to alternate modeling methods in the South Coast Air Basin. Table S4 shows mean air pollution exposures for the survey population using data available for alternate air pollution models in southern California. We were only able to compare certain pollutants between models. Our estimates show that while central tendencies vary by model, differences in exposure (and subsequently risks) between neighborhoods are consistent in most cases. For example, average individual relative risks for O_3 using IDW [CAMx] were 1.02 [1.02] for high-walkability neighborhoods and 1.09 [1.12] for low-walkability neighborhoods. Similarly, for NO_x using IDW [CAMx] risks were 1.53 [1.55] in high-walkability neighborhoods and 1.22 [1.08] in low-walkability neighborhoods. IDW typically resulted in the smallest urban-variability among the models evaluated here, indicating

that our estimates may be conservative for differences in air pollution exposure between neighborhoods.

Table S4. Mean air pollution exposures by model type

	NO (μg/m^3)			NO_2 (μg/m^3)			O_3 (μg/m^3)			$PM_{2.5}$ (μg/m^3)		
	IDW	**CAMx**	**LUR**	**IDW**	**CAMx**	**LUR**	**IDW**	**CAMx**	**LUR**	**IDW**	**CAMx**	**LUR**
All	36	11	-	49	44	38	99	60	-	22	-	-
Low-walkability	25	3	-	42	22	25	111	78	-	20	-	-
High-walkability	48	21	-	58	63	48	86	45	-	23	-	-
Difference (high-low walkability)	23	18	-	16	41	23	-25	-33	-	3	-	-

IDW = inverse distance weighted; CAMx = comprehensive air quality model with extensions (dispersion model); LUR = land use regression. Note: For O_3 CAMx modeled annual average concentrations, IDW modeled the annual average of daily 1-hour maximum concentrations.

VIII. Sensitivity analysis #3: Physical activity dose-response

Here, we employ a linear dose-response for physical activity. See Figure S6; each curve was derived from values given by the WHO (2004) (Table 1 in the main text). The stepwise curve represents values given directly in WHO (2004). The remaining lines reflect linear dose-response relationships employed as sensitivity analyses: a lower bound, upper bound, and midpoint estimate. Table S5 is a comparison of mean relative risks and IHD mortality rates for the survey population (n = 30,007) using each dose-response curve. We found only minor differences between linear and stepwise dose-responses. We also observe only small differences between the upper and lower bound curves. Note that when comparing between dose-response curves not only the slope changes, but so does the population that is exposed. For example, the lower bound curve reaches a RR = 1 at 150 minutes while the upper bound reaches a RR = 1 at 440 minutes. We chose to employ the step-wise dose response for our main analysis as it most directly reflects current physical activity guidelines as described in WHO (2004).

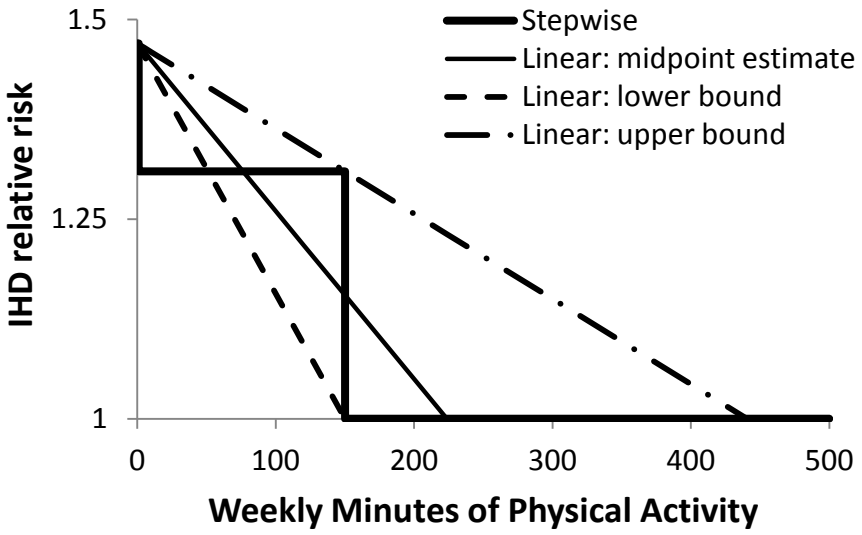


Figure S6. Dose-response curves for physical activity.

Table S5. Comparison of core results for the survey population using various dose-response curves for physical activity

Dose-response	RR physical inactivity	Proportion exposed	Population attributable fraction	IHD mortality per 100,000 per year
Stepwise (WHO 2004)	1.41	0.89	0.27	51.1
Linear: midpoint estimate	1.41	0.91	0.27	52.0
Linear: lower bound	1.40	0.89	0.26	50.6
Linear: upper bound	1.42	0.95	0.29	54.7

IX. Results stratified by age, SES, and built environment variables

Table S6 shows average survey participant relative risks (air pollution and physical inactivity) as well as descriptive statistics for weekly minutes of physical activity stratified by built environment and SES variables (i.e., we calculate a relative risk for each individual [for each risk factor] and then average those relative risks within each strata). We use the same reference case for all relative risk calculations (>150 minutes of physical activity; 10th percentile of air pollution exposure).

Table S6. Summary statistics of travel survey data by SES and built environment strata

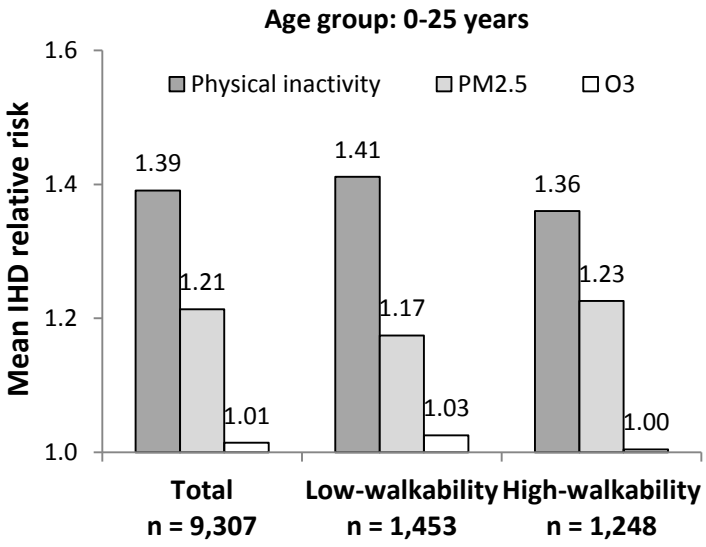
		n	Total physical activities (min/wk)	Average per capita minutes of physical activity	Number of people with >0 minutes of activity	Average physical activity: non-sedentary individuals (min/wk)	% of people > 0 minutes of activity	RR physical inactivity	Mean RR $PM_{2.5}$	Mean RR NO_x	Mean RR O_3
	All	30,007	2,312,016	77.0	4,957	466	16.5%	1.41	1.20	1.36	1.014
Population Density	*Low density*	10,001	690,291	69.0	1,319	523	13.2%	1.42	1.18	1.24	1.023
	Medium density	9,999	737,989	73.8	1,525	484	15.3%	1.41	1.21	1.34	1.014
	High density	10,007	883,736	88.3	2,113	418	21.1%	1.39	1.23	1.51	1.005
Intersection Density	*Low density*	10,072	703,689	69.9	1,354	520	13.4%	1.42	1.19	1.26	1.021
	Medium density	10,087	733,684	72.7	1,586	463	15.7%	1.41	1.21	1.36	1.014
	High density	9,848	874,643	88.8	2,017	434	20.5%	1.40	1.22	1.47	1.007
Land Use Mix	*Low LUM*	10,004	686,623	68.6	1,338	513	13.4%	1.42	1.18	1.28	1.020
	Medium LUM	10,004	732,718	73.2	1,608	456	16.1%	1.41	1.22	1.39	1.013
	High LUM	9,999	892,675	89.3	2,011	444	20.1%	1.40	1.22	1.43	1.010
Walkability (tertiles)	*Low*	5,366	364,770	68.0	672	543	12.5%	1.42	1.17	1.22	1.023
	Medium	21,092	1,585,143	75.2	3,401	466	16.1%	1.41	1.21	1.37	1.013
	High	3,549	362,103	102.0	884	410	24.9%	1.38	1.22	1.53	1.005
Walkability (z-scores)	*Low*	10,008	687,316	68.7	1,326	518	13.2%	1.42	1.18	1.24	1.022
	Medium	10,005	720,419	72.0	1,450	497	14.5%	1.42	1.22	1.36	1.014
	High	9,994	904,281	90.5	2,181	415	21.8%	1.39	1.22	1.49	1.006
Gender	*Male*	14,875	1,262,681	84.9	2,502	505	16.8%	1.41	1.20	1.36	1.014
	Female	15,132	1,049,335	69.3	2,455	427	16.2%	1.41	1.20	1.36	1.014
Ethnicity	*White*	18,094	1,448,321	80.0	2,677	541	14.8%	1.41	1.19	1.30	1.016
	Non-white	11,913	863,695	72.5	2,280	379	19.1%	1.40	1.23	1.45	1.011
Residence Type	*Detached*	20,336	1,497,265	73.6	2,983	502	14.7%	1.42	1.20	1.34	1.016
	Duplex	1,023	78,694	76.9	190	414	18.6%	1.40	1.20	1.43	1.010
	Condo/townhome	2,793	243,474	87.2	583	418	20.9%	1.39	1.20	1.38	1.010
	Apartment	4,797	435,015	90.7	1,059	411	22.1%	1.39	1.22	1.43	1.010
Age	*0-17*	6,431	550,165	85.5	1,692	325	26.3%	1.38	1.21	1.37	1.015
	18-65	19,538	1,372,350	70.2	2,713	506	13.9%	1.42	1.20	1.37	1.014
	65+	4,038	389,501	96.5	552	706	13.7%	1.42	1.19	1.33	1.014
Education	*High school or less*	15,493	1,132,397	73.1	2,841	399	18.3%	1.41	1.21	1.38	1.015
	College or more	13,861	1,153,047	83.2	2,048	563	14.8%	1.41	1.19	1.34	1.013
Income	*0-35K*	8,593	695,891	81.0	1,785	390	20.8%	1.40	1.22	1.42	1.013
	35-75K	9,819	709,737	72.3	1,431	496	14.6%	1.42	1.20	1.35	1.015
	75K+	8,221	644,805	78.4	1,212	532	14.7%	1.41	1.19	1.32	1.014
Income/ Ethnicity	*High income/white*	6,400	538,594	84.2	978	551	15.3%	1.41	1.18	1.30	1.015
	Low income/non-white	5,352	459,550	85.9	1,303	353	24.3%	1.38	1.23	1.47	1.010

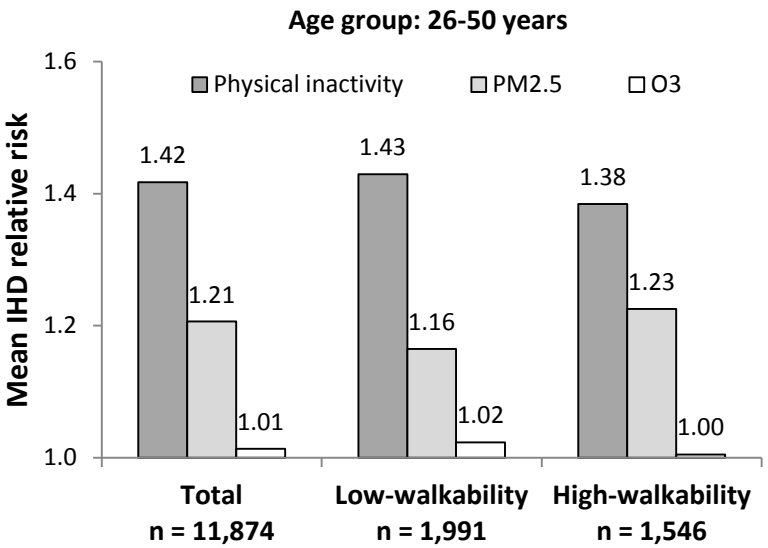
Table S7. Core results stratified by income, ethnicity, and walkability

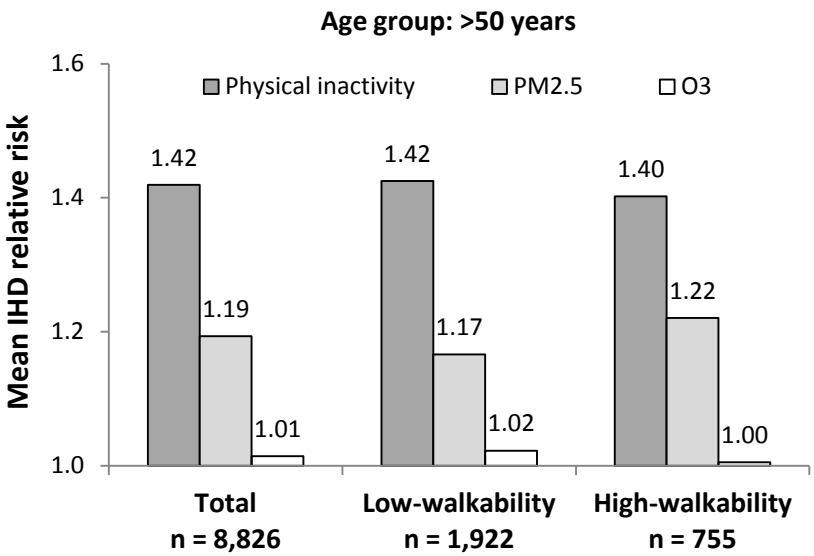
		Mean RR	Proportion above 10th percentile of entire cohort	Population attributable fraction	Total estimated attributable IHD deaths per year (in each subgroup)	Estimated attributable IHD deaths per 100,000 per year[a]
Low income non-white	**High-walkability (n = 1,327)**					
	Physical inactivity	1.37	0.82	0.23	0.59	44.4
	NO_x	1.58	0.95	0.35	0.90	29.0
	$PM_{2.5}$	1.23	0.95	0.18	0.45	34.2
	O_3	1.004	0.74	0.00	0.01	0.6
	Low-walkability (n = 440)					
	Physical inactivity	1.41	0.90	0.27	0.23	51.6
	NO_x	1.2	0.78	0.14	0.11	11.1
	$PM_{2.5}$	1.19	0.78	0.13	0.11	24.7
	O_3	1.03	0.99	0.02	0.02	4.8
High income, white	**High-walkability (n = 392)**					
	Physical inactivity	1.38	0.83	0.24	0.18	45.7
	NO_x	1.43	0.97	0.29	0.22	24.1
	$PM_{2.5}$	1.22	0.97	0.18	0.13	33.7
	O_3	1.006	0.95	0.01	0.00	1.0
	Low-walkability (n = 1,684)					
	Physical inactivity	1.42	0.90	0.27	0.88	52.4
	NO_x	1.21	0.81	0.15	0.47	12.0
	$PM_{2.5}$	1.15	0.82	0.11	0.35	21.0
	O_3	1.02	1.00	0.02	0.07	3.9

[a]Incidence of IHD mortality in CA (age-adjusted): 191.2 deaths/100,000/year (CA men aged 45-54 (used for NO_x: 89.1 deaths/100,000/year).

We also investigated differences in relative risk by age. Figures S6-S8 show mean IHD relative risks in 3 age groups: 0-25 years, 26-50 years, and >50 years. We found similar trends in risk between neighborhoods for each age group. Between-neighborhood risk differences for physical activity were largest for the youngest age group and smallest for the oldest age group. This suggests that, for physical activity, the built environment may influence younger age groups more than older age groups. We also give descriptive statistics for age stratified by level of air pollution exposure and neighborhood type in Table S8.







Figures S6-S8. Mean IHD relative risks for 3 age groups (0-25 years, 26-50 years, >50 years) for each neighborhood type (high- and low-walkability neighborhood).

Table S8. Age distribution by level of air pollution exposure and neighborhood walkability

	$PM_{2.5}$ exposure			**O_3 exposure**			**Walkability**		
	low	*medium*	*high*	*low*	*medium*	*high*	*low*	*medium*	*high*
n	10,067	9,719	10,221	10,062	10,108	9,837	5,366	21,092	3,549
Range (μg/m^3)	0-21.5	21.6-23.5	>23.5	0-88	89-105	>105	-	-	-
Mean age	39.6	38.6	35.5	37.2	39.2	37.1	40.9	37.8	34.0
Standard deviation age	22.3	21.5	21.6	21.6	21.9	22.1	22.2	22.0	20.3

References

Greenland S. 2001. Attributable fractions: Bias from broad definition of exposure. Epidemiology 12(5):518-520.