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Life Expectancy and Built Environments in the U.S.: A Multilevel Analysis

Byoungjun Kim, PhD, MUP[1], **Ben R. Spoer, PhD**[1], **Andrea R. Titus, PhD, MPP**[1], **Alexander Chen, MPH**[1], **George D. Thurston, ScD**[2], **Marc N. Gourevitch, MD, MPH**[1], **Lorna E. Thorpe, PhD**[1]

[1]Department of Population Health, New York University Grossman School of Medicine, New York, New York

[2]Department of Environmental Medicine, New York University Grossman School of Medicine, New York, New York

Abstract

Introduction: The purpose of this study is to examine the associations between built environments and life expectancy across a gradient of urbanicity in the U.S.

Methods: Census tract–level estimates of life expectancy between 2010 and 2015, except for Maine and Wisconsin, from the U.S. Small-Area Life Expectancy Estimates Project were analyzed in 2022. Tract-level measures of the built environment included: food, alcohol, and tobacco outlets; walkability; park and green space; housing characteristics; and air pollution. Multilevel linear models for each of the 4 urbanicity types were fitted to evaluate the associations, adjusting for population and social characteristics.

Results: Old housing (built before 1979) and air pollution were important built environment predictors of life expectancy disparities across all gradients of urbanicity. Convenience stores were negatively associated with life expectancy in all urbanicity types. Healthy food options were a positive predictor of life expectancy only in high-density urban areas. Park accessibility was associated with increased life expectancy in all areas, except rural areas. Green space in neighborhoods was positively associated with life expectancy in urban areas but showed an opposite association in rural areas.

Conclusions: After adjusting for key social characteristics, several built environment characteristics were salient risk factors for decreased life expectancy in the U.S., with some measures showing differential effects by urbanicity. Planning and policy efforts should be tailored to local contexts.

Address correspondence to: Byoungjun Kim, PhD, MUP, Department of Population Health, New York University Grossman School of Medicine, 180 Madison Avenue, 5th Floor, New York NY 10016 byoungjun.kim@nyulangone.org.

CREDIT AUTHOR STATEMENT

Byoungjun Kim: Conceptualization, Methodology, Writing - original draft, Writing review & editing. Ben Spoer: Data curation, Writing - reviewing & editing. Andrea R. Titus: Conceptualization, Writing - review & editing. Alex Chen: Data curation, Writing - review & editing. George D. Thurston: Writing - review & editing. Marc N. Gourevitch: Writing - review & editing. Lorna E. Thorpe: Conceptualization, Supervision, Writing - review & editing.

SUPPLEMENTAL MATERIAL

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INTRODUCTION

Disparities in life expectancy (LE) in the U.S. are well documented.[1] Between 2001 and 2014, LE for men and women in the top 5% of the income distribution increased by 2.34 and 2.91 years, respectively, but increased by only 0.32 and 0.04 years, respectively, for the bottom 5%.[2] Between 2010 and 2017, persons with a high-school degree or less experienced decreased LE up to 1.1 years, whereas college-educated persons gained up to 1.7 years.[3] In addition to income and education, race/ethnicity have been identified as important drivers of this inequality. The gains from income and education are not uniformly seen across all race/ethnicity groups, and the differences in LE persist between race/ethnic groups at high-income and high-education levels.[4] The gaps are even more striking among intersectional low-income, low-education, and racial/ethnic minority populations.[2,5] Singh and Siahpush[6] have shown striking geographic inequalities in LE gaps between urban and rural communities, suggesting that social and physical characteristics of communities, in addition to individual-level factors, may play salient roles in aggravating LE inequalities.[7,8] Indeed, a wide range of neighborhood-level social and built environment characteristics have been linked to individual-level health outcomes and health behaviors,[9] which may in turn increase mortality in a neighborhood and contribute to geographic LE inequalities.[10]

Although most studies on geographic LE disparities have utilized large administrative geographies (e.g., state and county),[7,8,11,12] recent statistical modeling efforts have yielded smaller-area LE measures that have found geographic LE disparities to be localized phenomena.[13,14] One recent paper showed that >70% of the variation in LE was attributable to census tract–level conditions, whereas only 19% and 10% of variation was explained by the state and county levels, respectively.[14] Recent studies suggest that LE at the local level is associated with a number of neighborhood social disadvantage features.[15,16] However, only a few studies have investigated the associations of built environment with LE. One study found that an index score of neighborhood characteristics, including social characteristics (e.g., race/ethnicity, employment, health insurance) and built environment features (e.g., food environments, physical activity venues, tree canopy, etc.), was associated with tract-level LE in Texas, yet the effect of each index component was not evaluated.[17]

Finally, despite widening LE gaps by sociodemographic status across the U.S., differences in LE and their associations with neighborhood characteristics may vary by the level of urbanization.[17] Neighborhood-level social and built environments across an urbanicity spectrum have distinct characteristics in multiple domains such as poverty, education, racial/ethnic composition, occupation, housing, infrastructure, and amenities,[18] in which the health outcomes and behaviors of individuals in communities substantially differ. As such, the goal of this analysis is to examine the associations between built environment attributes and neighborhood-level LE across diverse U.S. communities, using appropriate multilevel modeling approaches.

METHODS

Study Sample

Census tract–level LE estimates from 2010 to 2015 were obtained from U.S. Small-Area Life Expectancy Estimates Project (USA-LEEP), provided by National Center for Health Statistics.[19] Death records of all U.S. residents between 2010 and 2015 were geocoded by National Center for Health Statistics (6-year period), and census tract abridged life tables as well as age-specific death rates were calculated on the basis of the 2010 decennial Census and 2011–2015 American Community Survey 5-year estimates. Maine and Wisconsin were excluded from USALEEP because the 2 states had only 5 years of geocoded death records (2011–2015), not 6 (2010–2015). To address the problem of small populations and missing death records, statistical modeling strategies were developed by USALEEP on the basis of selected census tracts with >5,000 residents over the 6-year period (2010–2015) and no missing age-specific death counts. Sociodemographic variables in the modeling process included the median household income, population density, proportions of non-Hispanic Black, proportions of Hispanic, and residents with a 4-year college degree or higher. The negative binomial model based on selected census tracts predicted missing death records to complete age-specific death rates.[20] Because several sociodemographic characteristics were already utilized to predict LE, these variables were included as covariates. The covariates are potential confounders for tracts without missingness, and adjusting for imputation covariates in regression models does not bias the results.[21] All census tracts were classified into 1 of 4 urbanicity types on the basis of a previously derived typology.[22] This classification modified the original 2010 Rural-Urban Commuting Area (RUCA) Codes defined by the U.S. Department of Agriculture, which had 3 categories: metropolitan core, micropolitan core, and small town core. The modified RUCA further divided the metropolitan core into 2 subcategories (high- and low-density urban) on the basis of the distribution of the land area and collapsed micropolitan/small town cores into 1 group (i.e., suburban/small town). The *rest of the areas* were defined as rural. The modified RUCA classification provides clearer geographic delineations of community types within urban areas than within other methodologies.[22]

Measures

Census tract–level built environment measures of interest were based on previous literature (Table 1).[10] The proportions of the population living more than half a mile (urban areas), 1 mile (suburban or small-town areas), or 10 miles (rural areas) from the nearest supermarket or large grocery store were classified as having limited access to healthy food.[23–25] The data were accessed from the U.S. Department of Agriculture Economic Research Service Food Access Research Atlas.[26]

The number of alcohol outlets (off-premise, e.g., liquor stores), tobacco outlets, and convenience stores with sales >$0 were normalized to 1,000 population. Convenience stores have been identified as a major channel for sales of cigarettes, alcohol, and unhealthy food, such as sugar-sweetened beverages and energy-dense snacks.[27] The businesses were identified from the North American Industry Classification System Code accessed from the National Neighborhood Data Archive.[28]

The number of fast-food restaurants and drinking establishments defined by the North American Industry Classification System with sales >$0 were normalized to 1,000 population. The data were processed and accessed from the National Neighborhood Data Archive.[29]

Two constructs of walkability were employed in this analysis: pedestrian intersection density that facilitates walking and transit stop coverage that can promote transit ridership and walking.[30,31] The density intersections were calculated on the basis of the 2011 NAVSTREETS Street Data. The proportion of census tract area within half mile of a fixed-guideway transit stop, referred to as transit stop coverage, was calculated on the basis of the 2011 Transit Oriented Development a Database. These variables were accessed through the Smart Location Database, Version 2.0.[32]

The number of open parks was assessed per census tract using 2018 ParkServe data. The database, which includes parks in 14,000 communities across the U.S., was consolidated with the U. S. Geological Survey Protected Areas Database, Version 2.1.

The proportion (%) of green space in each census tract was assessed on the basis of the U.S. Geological Survey National Land Cover Database 2011 satellite imagery. Land covers of contiguous U.S. classified as deciduous forest, evergreen forest, mixed forest, shrub/scrub, and herbaceous were summed and divided by the area of census tract.[33,34]

Annual average estimates of outdoor concentrations at tract level for 6 pollutants throughout the contiguous U.S. (ozone, carbon monoxide, sulfur dioxide, nitrogen dioxide [NO_2], particulate matter smaller than 10 μm, and particulate matter smaller than 2.5 μm). The concentration estimates were developed by the Center for Air, Climate and Energy Solutions using v1 empirical models as described by Kim and colleagues,[35] which were based on multiple sources of data, including U.S. Environmental Protection Agency regulatory monitors, United States National Aeronautics and Space Administration air pollution estimates from satellite image, and land use information for empirical land use regression models. Alaska and Hawaii were excluded from the data set.

Housing characteristics by census tract were assessed through the 2015 American Community Survey 5-year estimates. Housing built before 1979 was identified as a risk factor for multiple potential housing-related health hazards, including lead exposure[36] and dilapidated housing conditions (measured as before 1979) such as problems with kitchen and plumbing systems.[37] *Crowding* was defined as >1 person per room.[38] Excessive housing cost was the percentage of households spending ≥30% of their income on housing costs. Each measure was calculated as proportions per all households in each census tract.

Statistical Analysis

All data sets were linked using the 2010 Federal Information Processing Standards code, and a total of 65,232 tracts, except in Wisconsin, Maine, Alaska, and Hawaii, were included in the analysis. Other census tract–level sociodemographic characteristic distributions were included, such as age group (ages under 18, 18–34, 35–64, ≥65 years), unemployment rate, the proportion of foreign-born residents, and the proportions of households with children and without vehicles as potential confounders, on the basis of previous literature.[15–17] Collinearity analyses were performed among the variables and did not find a significant correlation, except between carbon monoxide and NO_2 measures. Descriptive analyses were performed by 4 urbanicity types, and binary Pearson correlation tests were conducted for each variable. Hierarchical multilevel linear regression models were fitted on LE, with all built environment characteristics for each of the 4 urbanicity types. The hierarchical geographic boundaries included county, state, census division, and region, allowing random intercepts for each geographic unit. By including random intercepts for county, state, division, and region, the hierarchical multilevel model relaxes the independent assumption for tract-level LE and allows the associations to vary across different geographies. Conditional intraclass correlation coefficients (ICCs) and marginal R^2 for linear mixed-effects models were calculated, indicating the proportions of variance explained by random effects and by fixed effects, respectively.[39] The sum of conditional ICCs and the marginal R^2, known as the conditional R^2, was also provided. All exposure variables were normalized as z-scores to facilitate comparison within each model, and 95% CIs were calculated. Statistical analyses were conducted using R software, Version 4.1.3, and package lme4. IRB approval was not required because all data sets are publicly available for use in secondary analysis.

RESULTS

Table 2 displays the descriptive statistics by urbanicity types. Average LE was similar across the 4 urbanicity types: high-density urban (15,120 census tracts), low-density urban (23,480), suburban/small town (10,680), and rural areas (15,592). Conditional R^2, the proportion of variance explained by fixed and random effects, ranged from 0.49 to 0.67. The conditional ICC of each model increased from high-density urban areas to rural areas, suggesting increasing homogeneity of neighborhood characteristics by urbanicity within a county, state, census division, and region. Marginal R^2, variance explained by fixed effects only, ranged from 0.30 to 0.60, with the lowest values in rural areas. Table 3 (high- and low-density urban areas) and Table 4 (suburban/small town and rural areas) display binary Pearson correlation tests and multilevel regression modeling results.

The percentage of renters was one of the strongest predictors of LE across urbanicity types (Tables 3 and 4, multivariable columns). In high-density urban areas, a 1 SD increase in the proportion of renters (23%) was negatively associated with LE at birth by 0.43 years (95% CI= −0.51, −0.34). The proportion of housing built before 1979 was strongly associated with lower LE in low-density urban and suburban/small town areas (−0.33 years, 95% CI= −0.37, −0.28 and −0.40 years, 95% CI= −0.48, −0.32, respectively) but had relatively small associations in high-density urban and rural areas (−0.08 years, 95% CI= −0.14, −0.03 and −0.11 years, 95% CI= −0.18, −0.05, respectively). Excessive housing cost was a risk factor for low LE in all urbanicity types (−0.12 to −0.22 years), except in high-density urban areas. Housing overcrowding was associated with LE only in high-density urban areas: a 1 SD increase in the percentage of housing crowding (8%) was associated with 0.16 years lower LE (95% CI= −0.24, −0.08).

A 1 SD increase in the population proportion who had limited access to healthy food in a neighborhood (0.37%) was associated with −0.06 years in LE, whereas an association was not detected in low-density urban and suburban/small town areas. The number of fast-food restaurants was a risk factor for LE in suburban/small towns and rural areas (−0.06 and −0.09 years, respectively). A 1 SD increase in convenience stores was associated with decreased LE in all urbanicity types (−0.10 to −0.18 years).

A 1 SD increase in pedestrian intersection density was negatively associated with LE by 0.15–0.2 years across all urbanicity types except in high-density urban areas. In high-density urban areas, sulfur dioxide was the strongest predictor of decreased LE (−0.32 years, 95% CI= −0.43, −0.22), whereas particulate matter smaller than 2.5 μm showed the strongest association with LE in rural areas (−0.35 years, 95% CI= −0.48, −0.22).

DISCUSSION

This findings suggest that many environmental characteristics, particularly neighborhood-level housing characteristics, are associated with LE across urbanicity types, whereas associations with some other factors, such as access to healthy foods and park/green space access, were only salient in specific settings. This finding suggests that built environment characteristics may influence health outcomes and health behaviors through different mechanisms, contingent on the level of urbanization. Findings confirm a previous study examining differential impacts of environmental factors by urban and rural areas.[17]

In the present analyses, housing measures emerged as important built environment predictors of LE disparities. First, LE levels were lowest in neighborhoods with high proportions of rental housing, even after adjusting for income, excessive housing cost, and other social and built environment covariates. Although this may reflect some combination of greater residential instability and lower social capital or social cohesion,[40] it may also reflect direct built environment influences of worse housing conditions in rental units than in owned homes.[41] Housing affordability, another salient risk factor in all urbanicity types except high-density urban areas, may directly and indirectly affect health because it suggests reduced resources for health care and amenities and increased psychological stress.[42] The strength of association with housing tenure increased in denser urbanicity categories, whereas associations with housing affordability were larger in less dense settings. Old housing, measured as the percentage of housing built before 1979, was also a risk factor across urbanicity types, confirming previous literature.[43] The associations were larger in low-dense urban and suburban areas. Although living in older housing may expose individuals to various conditions that may impact health, one clear plausible mechanism is poor ventilation and poor indoor air quality. U.S. Environmental Protection Agency identified indoor air pollution as one of the country's top 4 environmental health risks,[44,45] which may contribute to respiratory and cardiovascular inequities.[46] Taken together, these findings stress the importance of sharpening the understanding of the influence of housing conditions on health.

Park access was protective in all urbanicity categories except in the rural category, and the association was more salient in denser urban settings in which available park space may be limited. Similarly, the positive associations of green space with LE diminished in less urban settings, and in rural areas, it was associated with lower LE. This finding is consistent with previous literature, which finds that the positive effect of green space is primarily limited to urban settings.[47] This may reflect a context in which census tracts with higher green space in rural areas may be isolated from health-promoting resources, resulting in the observed negative association.

Some of the findings were contrary to existing literature. Outdoor concentrations of NO_2 in high-density urban areas were associated with higher LE.[48] Unmeasured confounders, such as indoor air quality and temperature, may potentially bias these estimates.[49] The observed negative association between pedestrian intersection density and LE likewise may reflect other unmeasured neighborhood characteristics linked with intersection density, such as noise and light pollution.[50] In rural areas, limited healthy food was associated with increased LE. Grocery stores and supermarkets are typically located near major highways in rural areas, and unmeasured adverse characteristics near highways, such as increased injuries and crime, as well as environmental and noise/light pollution[51–53] may pose residual confounding.

Limitations

This study is a cross-sectional ecologic analysis, which cannot distinguish causal relationships at the individual level. The unmeasured confounders correlated with examined neighborhood characteristics remain a limitation. Most of the data sets except the ParkServe data aligned with USALEEP estimate years, yet the sequential temporal consistency between the exposures and outcome is unclear. Some measures, such as tobacco and alcohol outlets, may vary substantially over short periods. It is unknown the extent to which populations within neighborhoods were residentially stable enough to be influenced by built environments, and the analysis ignores individuals' exposures across daily activities outside of residential areas. Although limited access to healthy food employed certain buffer areas from grocery stores, other business measures were simple counts within census tracts, which may increase susceptibility to spatial misclassification. In addition, aggregated data at any given geographic level are susceptible to modifiable areal unit problems. In other words, the same analyses with different spatial units or point-based measures may produce different results (i.e., the zonal effect), and spatial resolution problems from using large aggregated data (e.g., county or state) can yield distinct results (i.e., the scale effect). However, the census tract–level estimates of the exposures of interest were the most granular data available, and small-area level estimates can address these issues to some degree. The LE estimates for census tracts with missing death records were imputed using a set of covariates. Despite the common practice of adjusting for the covariates used in imputation processes,21 an additional analysis was run without the covariates (Appendix Tables 1 and 2, available online). The results showed marginally larger effect estimates than the main results, showing that the presented results (Tables 3 and 4) were more conservative estimates. The air pollution measures used in the analysis were predicted concentrations on the basis of limited numbers of monitors, thus the estimates may not align with actual air quality monitored from local locations. Four states were not able to be assessed owing to limited data availability, and this analysis may not fully represent a national-scale phenomenon. Finally, the modeling approach assumed a linear relationship between each predictor and the outcome and no interactions between predictors. Future work needs to explore alternative assumptions and modeling approaches. Longitudinal studies with accurate and granular environmental data sets are required to investigate causal mechanisms.

CONCLUSIONS

This study incorporated a comprehensive set of secondary data in this near-national-scale analysis to examine the associations between multiple built environments and LE with hierarchical geographies to address potential biases from the use of a single geographic scale.[54] Granular LE estimates were employed and found built environmental influences on LE. The built environment measures cover various access and opportunities to health-promoting resources and direct risk factors for health outcomes. Overall, this findings suggest that tailored community planning and policies are required on the basis of neighborhood spatial context: a risk factor in a metropolitan center may not have the same effect in a suburban area and vice versa. Federal- or state-level policies can focus on universal risk factors for LE, such as housing conditions and air pollution. Local governments, particularly in urban areas where there are greater variations by geographic contexts, can thereby identify community-specific determinants of health using local surveillance and granular data analysis.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1.

List of Built Environment Variables

Measures	Data sources	Data year
Limited access to healthy food	USDA food access research atlas	2010
Tobacco and alcohol outlets	National neighborhood data archive	2010
Convenience stores	National neighborhood data archive	2010
Fast-food restaurants	National neighborhood data archive	2010
Bars and taverns	National neighborhood data archive	2010
Pedestrian intersection density	U.S. EPA Smart Location Database	2011
Distance to the nearest transit stop	U.S. EPA Smart Location Database	2012
Access to park	ParkServe data	2018
Green space	USGS National Land Cover Database	2010
Air pollution	CACES land-use regression data	2010
Housing before 1979	ACS 2011–2015	2011–2015
Crowding	ACS 2011–2015	2011–2015
Housing tenure	ACS 2011–2015	2011–2015
Excessive housing cost	ACS 2011–2015	2011–2015

ACS, American Community Survey; CACES, The Center for Air, Climate, and Energy Solutions; EPA; Environmental Protection Agency; USDA, U.S. Department of Agriculture; USGS, U.S. Geological Survey.

Table 2.

Descriptive Statistics (n=65,232 Census Tracts)

Variables	Higher density urban mean (SD) *n*=15,120	Low-density urban mean (SD) *n*=23,480	Suburban/small town mean (SD) *n*=10,680	Rural mean (SD) *n*=15,952
Life expectancy (year)	77.95 (4.48)	78.67 (4.01)	78.48 (3.79)	77.89 (3.55)
Population density (/mi2)	17,017 (21,169)	3,443 (1,884)	1,070 (1,121)	145 (215)
Black[a]	0.22 (0.29)	0.14 (0.21)	0.09 (0.16)	0.07 (0.14)
Hispanic[a]	0.28 (0.27)	0.17 (0.20)	0.12 (0.17)	0.07 (0.14)
Bachelor's degree or above[a]	0.29 (0.21)	0.33 (0.19)	0.30 (0.17)	0.19 (0.10)
Annual income ($)	51,755 (27,149)	64,293 (32,309)	63,648 (30,258)	49,702 (17,026)
Age under 18 years[a]	0.23 (0.08)	0.23 (0.06)	0.24 (0.06)	0.23 (0.05)
Age 18 to 34 years[a]	0.27 (0.09)	0.23 (0.08)	0.21 (0.07)	0.19 (0.05)
Age 35 to 64 years[a]	0.38 (0.06)	0.40 (0.06)	0.40 (0.06)	0.41 (0.05)
Age over 65 years[a]	0.12 (0.06)	0.14 (0.07)	0.15 (0.07)	0.17 (0.05)
Presence of children[a]	0.33 (0.13)	0.33 (0.10)	0.34 (0.10)	0.30 (0.07)
Unemployment[a]	0.12 (0.07)	0.09 (0.06)	0.09 (0.05)	0.09 (0.05)
No vehicle available[a]	0.21 (0.19)	0.07 (0.07)	0.06 (0.06)	0.05 (0.04)
Foreign born[a]	0.24 (0.18)	0.13 (0.11)	0.08 (0.08)	0.04 (0.05)
Limited healthy food[b]	0.39 (0.37)	0.27 (0.31)	0.58 (0.34)	0.10 (0.22)
Liquor store/1,000 people	0.19 (0.33)	0.16 (0.30)	0.14 (0.27)	0.13 (0.27)
Tobacco store/1,000 people	0.04 (0.14)	0.04 (0.12)	0.03 (0.10)	0.02 (0.12)
Convenience store/1,000 people	0.22 (0.35)	0.25 (0.35)	0.29 (0.38)	0.36 (0.39)
Gas station/1,000 people	0.00 (0.01)	0.00 (0.01)	0.00 (0.02)	0.00 (0.02)
Fast food/1,000 people	0.44 (0.74)	0.59 (0.84)	0.49 (0.71)	0.32 (0.48)
Bar/1,000 people	0.35 (0.73)	0.28 (0.62)	0.25 (0.47)	0.27 (0.44)
Intersection density (/mi2)	119.9 (122.5)	60.6 (80.6)	17.5 (44.1)	39.8 (76.9)
Transit stop coverage[a]	0.23 (0.38)	0.03 (0.11)	0 (0.01)	0 (0.03)
Count of Open park	1.56 (1.89)	2.60 (3.01)	3.18 (4.43)	1.34 (2.29)
Green space[c]	0.09 (0.12)	0.32 (0.19)	0.46 (0.24)	0.52 (0.29)

Variables	Higher density urban mean (SD) n=15,120	Low-density urban mean (SD) n=23,480	Suburban/small town mean (SD) n=10,680	Rural mean (SD) n=15,952
CO (ppm)	0.37 (0.07)	0.32 (0.04)	0.29 (0.05)	0.27 (0.06)
NO_2 (ppb)	14.58 (5.48)	9.04 (3.39)	5.70 (1.90)	4.06 (1.37)
O_3 (ppb)	46.32 (5.87)	45.57 (6.89)	45.79 (5.94)	45.61 (5.09)
PM 10 (μ/m[a])	20.68 (3.87)	19.05 (4.06)	17.19 (4.23)	16.19 (4.59)
PM2.5 (μ/m^3)	10.21 (1.87)	9.59 (2.10)	9.02 (2.13)	8.43 (2.18)
SO_2 (ppb)	1.83 (0.73)	1.53 (0.63)	1.58 (0.66)	1.59 (0.59)
Renter[a]	0.54 (0.23)	0.35 (0.20)	0.28 (0.17)	0.23 (0.11)
House pre 1979[a]	0.80 (0.21)	0.59 (0.29)	0.47 (0.26)	0.53 (0.18)
Crowding[a]	0.07 (0.08)	0.03 (0.04)	0.02 (0.03)	0.02 (0.03)
Excessive housing cost[a]	0.45 (0.12)	0.36 (0.10)	0.31 (0.09)	0.27 (0.08)

CO, carbon monoxide; NO_2, nitrogen dioxide; O_3, ozone; PM10, particulate matter smaller than 10 μm; PM2.5, particulate matter smaller than 2.5 μm; ppb, parts per billion; ppm, parts per million; SO_2, sulfur dioxide.

[a]Proportion per total population.

[b]Half mile buffer for high-density urban areas, 1 mile for low-density urban and suburban/small-town areas, and 10 miles for rural areas.

[c]Proportion per total land area.

Table 3.

Bivariate Associations and Multilevel Regression Model Results, High- and Low-Density Urban Areas

Variables	High-density urban (*n*=15,120)				Low-density urban (*n*=23,480)			
	Bivariate[a]		Multivariable		Bivariate		Multivariable	
	R_s	*p*-Value	β	(95% CI)	R_s	*p*-Value	β	(95% CI)
Limited healthy food (z)[b]	−0.17	<0.01	−0.06	**(−0.11, −0.01)**	0.06	<0.01	−0.01	(−0.05, 0.02)
Liquor store/1,000 (z)	−0.04	<0.01	−0.01	(−0.06, 0.04)	−0.07	<0.01	−0.02	(−0.05, 0.02)
Tobacco store/1,000 (z)	0.00	0.77	0.02	(−0.03, 0.06)	−0.06	<0.01	−0.01	(−0.04, 0.02)
Convenience store/1,000 (z)	−0.17	<0.01	−0.10	**(−0.14, −0.05)**	−0.28	<0.01	−0.14	**(−0.17, −0.1)**
Gas station/1,000 (z)	−0.01	0.14	0.00	(−0.04, 0.04)	−0.02	<0.01	−0.04	**(−0.07, −0.01)**
Fast-food/1,000 (z)	−0.04	<0.01	−0.02	(−0.08, 0.03)	−0.12	<0.01	0.00	(−0.04, 0.04)
Bar/1,000 (z)	−0.10	<0.01	−0.12	**(−0.17, −0.07)**	−0.20	<0.01	−0.11	**(−0.15, −0.08)**
Intersection density (z)	−0.04	<0.01	0.02	(−0.02, 0.07)	−0.17	<0.01	−0.16	**(−0.19, −0.12)**
Transit stop coverage (z)	0.12	<0.01	0.06	(0, 0.12)	0.07	<0.01	0.02	(−0.02, 0.05)
Count of open parks (z)	0.02	0.02	0.08	**(0.04, 0.13)**	0.12	<0.01	0.05	**(0.02, 0.09)**
Percentage green space (z)	−0.01	0.32	0.22	**(0.16, 0.28)**	0.17	<0.01	0.10	**(0.05, 0.16)**
CO (z)	0.19	<0.01	0.09	(0, 0.19)	−0.01	0.07	−0.02	(−0.07, 0.03)
NO_2 (z)	0.19	<0.01	0.37	**(0.24, 0.5)**	−0.03	<0.01	0.07	(0, 0.15)
O_3 (z)	−0.05	<0.01	−0.03	(−0.16, 0.1)	0.00	0.61	−0.26	**(−0.37, −0.14)**
PM10 (z)	0.01	0.09	−0.13	**(−0.24, −0.02)**	−0.15	<0.01	0.00	(−0.08, 0.08)
PM2.5 (z)	−0.19	<0.01	−0.05	(−0.19, 0.08)	−0.28	<0.01	−0.09	(−0.2, 0.02)
SO_2 (z)	−0.25	<0.01	−0.32	**(−0.43, −0.22)**	−0.27	<0.01	−0.25	**(−0.32, −0.19)**
Renter (z)	−0.20	<0.01	−0.43	**(−0.51, −0.34)**	−0.46	<0.01	−0.37	**(−0.43, −0.31)**
House before 1979 (z)	−0.08	<0.01	−0.08	**(−0.14, −0.03)**	−0.24	<0.01	−0.33	**(−0.37, −0.28)**
Crowding (z)	0.08	<0.01	−0.16	**(−0.24, −0.08)**	−0.20	<0.01	0.00	(−0.05, 0.04)
Excessive housing cost (z)	−0.16	<0.01	−0.02	(−0.09, 0.05)	−0.31	<0.01	−0.12	**(−0.17, −0.07)**
Null-model ICC				0.411				0.355
Conditional ICC				0.070				0.076
Marginal R^2				0.571				0.596
Conditional R^2				0.641				0.672

Note: Boldface indicates statistical significance (p<0.05) in multivariable models.

R_S were calculated from Pearson correlation test.

CO, carbon monoxide; ICC, intraclass correlation coefficient; NO_2, nitrogen dioxide; O_3, ozone; PM10, particulate matter smaller than 10 μm; PM2.5, particulate matter smaller than 2.5 μm; SO_2, sulfur dioxide.

[a]Four hierarchical geographic boundaries, county, state, census division, and region were included as random effects. Multivariable models adjusted for median household income; population density; proportions of non-Hispanic Black, Hispanic, and residents with a 4-year college degree or higher; as well as age groups, unemployment rate, the proportion of foreign-born residents, and the proportions of households with children and without vehicles.

[b]Half mile buffer for high-density urban areas, and 1 mile for low-density urban areas.

Table 4.

Bivariate Associations and Multilevel Regression Model Results, Suburban/Small Town and Rural Areas

Variables	Suburban/small town (n=10,680)				Rural (n=15,952)			
	Bivariate[a]		Multivariable		Bivariate		Multivariable	
	R_s	*p*-Value	β	(95% CI)	R_s	*p*-Value	β	(95% CI)
Limited healthy food (z)	0.25	<0.01	0.05	(−0.01, 0.11)	0.11	<0.01	0.26	**(0.22,0.31)**
Liquor store/1,000 (z)	−0.06	<0.01	0.00	(−0.05, 0.05)	0.04	<0.01	−0.04	(−0.08, 0.01)
Tobacco store/1,000 (z)	−0.13	<0.01	−0.03	(−0.08, 0.01)	−0.09	<0.01	−0.05	**(−0.09, −0.01)**
Convenience store/1,000 (z)	−0.34	<0.01	−0.18	**(−0.23, −0.12)**	−0.22	<0.01	−0.16	**(−0.21, −0.12)**
Gas station/1,000 (z)	−0.02	0.02	−0.01	(−0.06, 0.03)	0.01	0.20	0.02	(−0.02, 0.06)
Fast-food/1,000 (z)	−0.20	<0.01	−0.09	**(−0.15, −0.04)**	−0.12	<0.01	−0.07	**(−0.11, −0.02)**
Bar/1,000 (z)	−0.20	<0.01	−0.11	**(−0.16, −0.05)**	0.11	<0.01	−0.01	(−0.06, 0.03)
Intersection density (z)	−0.27	<0.01	−0.15	**(−0.21, −0.08)**	−0.14	<0.01	−0.20	**(−0.25, −0.15)**
Transit stop coverage (z)	0.04	<0.01	0.01	(−0.04, 0.05)	0.02	0.01	0.00	(−0.04, 0.04)
Count of Open parks (z)	0.22	<0.01	0.06	**(0.01, 0.12)**	0.07	<0.01	0.00	(−0.04, 0.05)
Percentage green space (z)	0.17	<0.01	0.00	(−0.07, 0.07)	−0.03	<0.01	−0.17	**(−0.25, −0.09)**
CO (z)	−0.01	0.20	−0.08	(−0.14, −0.01)	0.11	<0.01	−0.04	(−0.11, 0.03)
NO_2 (z)	−0.05	<0.01	0.02	(−0.06, 0.11)	0.01	0.43	0.06	(−0.03, 0.15)
O_3 (z)	−0.01	0.36	−0.16	**(−0.27, −0.04)**	−0.10	<0.01	−0.02	(−0.12, 0.08)
PM10 (z)	−0.20	<0.01	0.02	(−0.08, 0.13)	−0.04	<0.01	0.04	(−0.07, 0.16)
PM2.5 (z)	−0.34	<0.01	−0.03	(−0.16, 0.1)	−0.34	<0.01	−0.35	**(−0.48, −0.22)**
SO_2 (z)	−0.23	<0.01	−0.23	**(−0.32, −0.14)**	−0.17	<0.01	−0.16	**(−0.24, −0.08)**
Renter (z)	−0.48	<0.01	−0.36	**(−0.46, −0.27)**	−0.31	<0.01	−0.33	**(−0.4, −0.26)**
House before 1979 (z)	−0.33	<0.01	−0.40	**(−0.48, −0.32)**	0.02	0.03	−0.11	**(−0.18, −0.05)**
Crowding (z)	−0.18	<0.01	−0.03	(−0.1, 0.04)	−0.09	<0.01	0.02	(−0.04, 0.08)
Excessive housing cost (z)	−0.18	<0.01	−0.16	**(−0.22, −0.09)**	−0.05	<0.01	−0.14	**(−0.2, −0.09)**
Null-model ICC				0.466				0.449
Conditional ICC				0.113				0.194
Marginal R^2				0.522				0.297
Conditional R^2				0.635				0.492

Note: Bold indicates statistical significance (p<0.05) in multivariable models.

R_S were calculated from Pearson correlation test. Four hierarchical geographic boundaries, county, state, census division, and region were included as random effects. Multivariable models adjusted for median household income; population density; proportions of non-Hispanic Black, Hispanic, and residents with a 4-year college degree or higher; as well as age groups, unemployment rate, the proportion of foreign-born residents, and the proportions of households with children and without vehicles.

CO, carbon monoxide; ICC, intraclass correlation coefficient; NO_2, nitrogen dioxide; O_3, ozone; PM10, particulate matter smaller than 10 μm; PM2.5, particulate matter smaller than 2.5 μm; SO_2, sulfur dioxide.

[a]Half mile buffer for high-density urban areas, and 1 mile for low-density urban areas.