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Longitudinal associations between neighborhood-level street network with walking, bicycling, and jogging: The CARDIA study

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Abstract

Objective—To investigate the differential association between neighborhood-level street network with walking, bicycling, and jogging by urbanicity and gender.

Methods—We used prospective data from 4 repeated exams on 5,115 young adults recruited in 1985–86, followed through 2000–01, with self-reported walking, bicycling, and jogging. Using a Geographic Information System, we spatially and temporally linked time-varying residential locations to street network data within a 1 Euclidean km buffer. Two-part marginal effect modeling assessed longitudinal associations between neighborhood-level street network with walking, bicycling, and jogging, by urbanicity and gender, controlling for time-varying individual- and census-level covariates.

Results—Neighborhood street density was positively associated with walking, bicycling, and jogging in low urbanicity areas, but in middle and high urbanicity areas, these associations became null (men) or inverse (women).

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Conclusion—Characteristics of neighborhood streets may influence adult residents' walking, bicycling, and jogging, particularly in less urban areas. This research may inform policy efforts to encourage physical activity.

Keywords

urbanicity; urban design; gender; built environment; physical activity; adults

Introduction

Owing to minimal impact of behavioral interventions on increasing physical activity (PA) (Ogilvie et al., 2004), recent work has turned to environmental factors, such as street network, an important dimension of urban form, as intervention targets(Owen et al., 2004). Findings in this area suggest that better street connectivity, indicated by more intersections, less dead end streets, more streets, and smaller blocks, leads to more pedestrian travel, generally by reducing travel distance and providing a wide range of possible routes (Berrigan et al., 2010; Braza et al., 2004; Forsyth et al., 2008; Frank L.D. et al., 2003; Saelens et al., 2003). However, the literature on street networks and health outcomes is dominated by cross sectional designs and yields inconsistent findings (Boer et al., 2007; Duncan and Mummery, 2005; Ewing, 2005; Frank et al., 2004; Lovasi et al., 2008; Oakes et al., 2007; Smith et al., 2008; Trost et al., 2002).,

Street networks are highly complex in terms of dimensions that might influence behavior. Following the constructs described by Jean-Paul Rodrigue et al. (Rodrigue et al., 2006), street networks can be measured in the following three dimensions: 1) intersection density, a widely used indicator of basic structural properties (Doyle et al., 2006; Frank et al., 2006; Li et al., 2005); 2) link to node ratio, an indicator of the structural properties of the network; and 3) road type/classification, which represents the hierarchy of linkages across the street network, ranging from local roads (Carver et al., 2010) to highways.

Further, the literature on street networks and behavior generally comes from studies in single metropolitan areas(Duncan and Mummery, 2005; Frank et al., 2004; Oakes et al., 2007), thus resulting in little understanding of how the relationship between neighborhood-level street network and physical activity varies across diverse environmental contexts. Urban, suburban, and rural areas may have different land use and street patterns, ranging from urban gridded streets to suburban cul-de-sacs, which may differentially impact physical activity that takes place in streets, such as walking, bicycling, and jogging. Yet, few studies have the geographic variation necessary to capture differences in walking, bicycling and jogging across different environmental settings(Riva et al., 2009). Further, some evidence suggests that such relationships may vary by gender, with economic and social environment aspects relatively more important for men, whereas built environment factors are more salient for women (Grafova et al., 2008). Others have found sprawl related to BMI among men only (Ross et al., 2007). In general, findings are mixed and all are cross-sectional (Frank et al., 2004; Frank et al., 2008).

Our objective is to investigate the relationship between neighborhood-level street network and leisure-time walking, bicycling, and jogging, and how this relationship varies across urbanicity and gender. We capitalize upon 15-year longitudinal data from the Coronary Artery Risk Development in Young Adults (CARDIA) study, including longitudinal physical activity data as well as longitudinal street network data that are spatially and temporally via a Geographic Information Systems (GIS) to time-varying residential location of study participants.

Participants and Methods

Study Sample

CARDIA is a population-based prospective epidemiologic study of the evolution of cardiovascular risk factors among young adults. At baseline (1985–6), 5,115 eligible participants, aged 18–30 years, were enrolled with balance according to race, gender, education high school or less and more than high school) and age (18–24 and 25–30) from the populations of Birmingham, AL; Chicago, IL; Minneapolis, MN; and Oakland, CA. Specific recruitment procedures were described elsewhere (Friedman et al., 1988). Seven repeated examinations were conducted. For the current study, we use data from: 1985–86 (Baseline), 1992–1993 (Year 7), 1995–1996 (Year 10), and 2000–2001 (Year 15), with retention rates of 90%, 79%, and 74%, respectively

The analysis sample includes participants with complete data and without significant physical disabilities. Among 20,460 observations across the four exam years, 19.0% (obs=3,900) were excluded from analysis, mostly due to sample attrition (obs=3,643), missing outcome data (obs=146), missing environmental data (obs=2) or statistical control variables (obs=109). A range of 5–14% of respondents moved to a new state, and 11–27% moved to a new county between exam years during follow-up. Despite starting at baseline in the four U.S. metropolitan areas, by 2000–01 the CARDIA participants were located across 48 states, 1 federal district, 1 territory, 529 Counties and 3,805 Census Tracts.

All CARDIA participants had residential street addresses recorded at each exam year, which we geocoded and temporally and spatially linked with contemporaneous data on environmental factors derived from a series of public and commercially available data.

Exposure and Outcome Measures

Main Exposure: neighborhood-level street network within 1 km Euclidean buffer —The 1 km Euclidean buffer (circle of 1 km radius) around each respondent's residential street address at each time period represents the immediate residential neighborhood to capture pedestrian activity (Hoehner et al., 2003; Lee and Moudon, 2004) and is an empirically determined easy walking distance (Jago et al., 2005; Timperio et al., 2006) of around 12–15 minute walk at 4–5 km/hour. Thus, the Euclidean buffer provides a comparable geographic area comparison as it relates to walking distance over time and across more and less urban areas, a major focus of our analysis.

Unfortunately detailed and accurate street network data were not equally available across all time points, thus necessitating use of only two time periods for street data, which were spatially and temporally linked to residential locations: StreetMap 2000 data for exam years 0, 7, and 10 and from the enhanced product StreetMap Pro 2003 data for exam year 15, both from ESRI, Redlands, CA. StreetMap data were the highest quality data available and provided comparability over the full study, albeit with the limitation of only 2000 and 2003 time periods and the fortune that the CARDIA cities were fairly established with little changes in street network over time. Road type/classification was extracted from TIGER/line™ files.

Following Rodrigue et al. (Rodrigue et al., 2006), we used three measures of street network: 1) intersection density, as a basic structural property, 2) link-node ratio as a derived structural property, and 3) road type/classification, which represents the hierarchy of linkages across the street network. We describe these measures below and provide examples in Figure 1.

Street connectivity: Higher street connectivity is defined as high number of intersections, few dead end streets, more streets, and smaller blocks. We hypothesized greater walking, bicycling, and jogging in areas with greater street connectivity. Using the StreetMap data, we identified

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intersections and based connectivity on the number of unique street connections at each intersection. We measured two dimensions of street connectivity: 1) *intersection density* is calculated as number of intersections with 3 or more unique intersecting streets (true intersections) in buffer divided by buffer area (3.14km^2 across all participants), yielding a comparable measure to other studies. 2) *link-node ratio* (also known as beta index) is an index of connectivity and equals to the number of links divided by the number of nodes in buffer, where links = street segments (continuous street without interruption of intersection or cul-de-sac); nodes = intersections or cul-de-sacs (Figure 1). Higher values of intersection density and link-node ratio reflect higher level of street connectivity, largely through the provision of many possible direct routes (links) across the possible intersections (nodes) within the 1 km buffer.

Characteristics of local roads were derived from TIGER/line™ files road classifications. Detailed descriptions can be accessed at http://www.census.gov/geo/www/tiger/appendxe.asc. We measure more walkable, local roads using the A4x category 'local, neighborhood, and rural roads' relative to highways and other vehicle-friendly roads (A0x: roads with major category unknown, A1x,interstate highways: A2x, U.S. and State highways; A3x; State and county highways; A5x vehicular trails; and A6x traffic circles and access ramps). We characterized local roads in two dimensions: 1) *density of local roads*: as total length of local roads within the 1km buffer, and 2) *proportion of local relative to total roads*: as the proportion of local road length relative to total road length in the 1km buffer. We hypothesized that higher density of local roads and higher proportion of local relative to total roads would be positively associated with higher walking, bicycling, and jogging.

In models using density of local roads as the main exposure, the density of nonlocal roads served as a control variable, and in models using the proportion of local relative to total roads as an exposure, total roads were used as a control, because local and non-local roads are each related to behavior and non-local roads may confound the association between local roads and PA. This is analogous to what is done in energy partitioning and nutrient density models (Willett, 1998)

In Figure 1, we provide examples of each of the connectivity (Panels A B) and road type (Panels C D) measures. For illustrative purposes, a low connectivity area would have <15, 3 or more-way intersections per km^2 and <1.5 link-node ratio, which would be typical of a rural isolated area, whereas, a high connectivity area would have >50 3 or more-way intersections per km^2 and ~2.0 link-node ratio, typical of a dense city with a system of gridded streets (for illustrative purposes we include a small number of 3 or more-way intersections so as to not clutter space). A typical rural area might have less than 15 km of local roads within a 1km buffer and local roads might account for 60–100% of total roads. A typical urban area might have more than 30 km of local roads within a 1km buffer and local roads might account for 70–90% of total roads.

Outcome: Physical activity—At each examination, self-reported physical activity was ascertained by an interviewer-administered questionnaire designed for CARDIA. Study participants were asked about the frequency of participation in 13 different activity categories (eight vigorous and five moderate) of recreational sports, exercise, leisure, and occupational activities over the previous 12 months. Of central interest are activities conceptually linked to neighborhood street settings (walking, bicycling, and jogging), assessed in the following format: "Did you take walks or hikes or walk to work in the past 12 months for at least one hour total time in any month? How many months did you do this activity? How many of these months were for at least 4 hours per week?" The reliability and validity of the instrument is comparable to other activity questionnaires (Jacobs et al., 1989).

We calculated total frequency of participation in walking, bicycling, and jogging, summarized as $\Sigma(m_i+3n_i)$, where i is each of the activity categories (walking, bicycling and jogging), m_i is the number of months of less frequent participation, and n_i is the number of months of more frequent participation, with an arbitrarily assigned weight of 3. The frequency for each activity ranged from 0–36 units, with 36 representing more frequent participation of the activity for every month of a year (3×12month). The cut-point for more vs. less frequent participation varies by activity, e.g. walking ≥4 hour/week, and bicycling or jogging ≥2 hour/week.

Effect Measure Modifiers—Given our primary hypothesis that the association between street network and walking, bicycling, and jogging varies by level of **urbanicity**, we tested effect measure modification by urbanicity, which we defined using a combination of urban boundary data (using census urbanized areas) and population density (census population adjusted proportional to the percent of the census area that fell within the 1 km respondent buffer for each participant using census data contemporaneous to each location at each exam period).

As CARDIA participants were originally recruited from four U.S. major cities, most of them resided in urbanized areas, with only ~5% from rural areas. To refine our measure of urbanicity, we categorized Census tract-level population density in tertiles among participants living in an urbanized area, representing low (including rural), middle, and high urbanicity. The average population density in low urbanicity areas was 1,087/km^2 (e.g., low population-dense states such as South Dakota or New Mexico); middle urbanicity areas: 2,893/km^2 (e.g., Staten Island, New York City's most suburban borough); and high urbanicity areas: 7,348/km^2 (e.g., Queens, one of the most populous area in NYC).

Our secondary hypothesis is that the association between neighborhood-level street network and walking, bicycling, and jogging varies by **gender** across level of urbanicity. We hypothesized that men and women may respond differently to the street network, perhaps for safety or other reasons, Investigation of differences in street network in predicting physical activity across urbanicity has not been well addressed in the literature. While we included urbanicity and gender as effect modifiers, we did not consider effect modification by race for conceptual reasons. Our rationale was that in terms of potential policy efforts targeting environmental changes in street network, our findings would inform whether such changes would be relatively more or less important in rural versus urban settings, for example, and such efforts would target the full population in those areas, regardless of race. Nonetheless, we tested race for effect measure modification, purely for empirical purposes.

Covariates (control variables)—Individual-level covariates included age, gender, race, educational attainment, marital status, and baseline study center

Census-tract level covariates: Using U.S. Census data (1980, 1990, and 2000) contemporaneous to CARDIA exam years, we linked tract-level variables that reflected neighborhood characteristics where the individual participants resided: 1) proportion of residents in the tract who walk to work, i.e. in participant's residential tract, % workers (≥16 years of age) travel to work by walking. This variable should indicate if neighborhoods have a sufficient mix of residential and employment land uses to make walking feasible and attractive (Smith et al., 2008), and it was reported to be inversely associated with BMI and risks of overweight/obesity (Brown et al., 2009); 2) Median age of houses in the residential tract. Residents of older neighborhoods generally report more walking (Berrigan and Troiano, 2002). 3) Proportion of white residents in the residential tract, reflecting racial composition in neighborhood. 4) Median household income in the residential tract, as a proxy of neighborhood socioeconomic status and was inflation-adjusted using Bureau of Labor Statistics Consumer Price Index, for comparability across time.

Statistical Analysis

We conducted all statistical analyses using Stata (version 10.1, College Station, TX). We computed descriptive statistics for the four street network main exposures (intersection density, link-node ratio, density of local roads, and proportion of local relative to total roads), the outcome measure of walking, bicycling, and jogging frequency, and all covariates. We performed separate models for each of the four street network main exposures to estimate the association between each street network main exposure and walking, bicycling, and jogging frequency.

A considerable proportion of participants reported no walking, bicycling, and jogging, resulting in positively skewed distributions on the outcome variable (12.4% zero values, the remainder positive and continuous). The type of outcome distribution is common in the public health and health economics literature (Haines et al., 1988; Hu et al., 2009; Ng et al., 2008; Pendergast et al., 2010; Walls et al., 2009). The prevailing strategy where the proportion of zero outcomes is ≥ 5% is to use the two-part marginal effect model to properly analyze these data (Duan, 1983; Liu et al., 2010; Madden, 2008). The two-part model allows flexibility by allowing for two separate decisions (the decision to engage in any walking, bicycling, and jogging, and second, the conditional frequency of such activity). This is in contrast to two other frequently used models for data with a mass of zero observations, Poisson and Tobit. Poisson is inappropriate for this case since the non-zero observations are continuous rather than ordinal. The Tobit model assumes a single decision and estimates a single set of coefficients (a test to determine if the two-part model simplifies to a Tobit model was strongly rejected with a p value of less than 0.001). We hypothesize that factors associated with participation in these given activities differ from those that determine frequency or minutes of physical activity. Thus, the two-step model includes: (1) a probit model using maximum likelihood estimation to estimate the probability of engaging in walking, bicycling, and jogging, and (2) an ordinary least squares regression model for those individuals who had non-zero amounts of walking, bicycling, and jogging. The two parts have the same specifications and the equations are demonstrated below:

$$\begin{aligned}
&\mathrm{Pr}(\text{Conduct walking, bicycling, and jogging}_{it}) \\
&\quad = \gamma_0 + \gamma_1\,\text{StreetNetwork}_{it} \\
&\quad + \gamma_2\text{StreetNetwork} \\
&\quad \times \text{Urbanicity}_{it} \\
&\quad + \gamma_3\text{Urbanicity}_{it} \\
&\quad + \sum \gamma_x \text{Covar}_{it} \\
&\quad + \mu_i + \nu_{it}
\end{aligned}$$

$$\begin{aligned}
&(\text{walking, bicycling, and jogging freq})_{it} | (\text{Conduct walking, bicycling, and jogging}) \\
&\quad = \theta_0 + \theta_1\text{StreetNetwork}_{it} \\
&\quad + \theta_2\text{StreetNetwork} \\
&\quad \times \text{Urbanicity}_{it} \\
&\quad + \theta_3\text{Urbanicity}_{it} \\
&\quad + \theta_x\text{Covar}_{it} \\
&\quad + \mu_i + \nu_{it}
\end{aligned} \tag{1}$$

Where the subscript *i* denotes an individual and *t* denotes time.

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We pooled data across four exam years and robust standard errors were used to correct for multiple observations on individuals. The two parts were estimated separately and unconditional estimates were obtained by calculating a weighted mean from the two estimations. Bootstrapped standard errors were then obtained using 1000 replications, each clustered at the individual level. We present the bootstrapped joint effect as well as results from both model parts.

In the two part models, we controlled for individual- and Census tract-level covariates and included density of non-local roads as an additional control when density of local roads served as main exposure, and density of total roads when proportion of local relative to total roads served as main exposure. We tested gender and urbanicity separately for effect measure modification by including appropriate cross-product terms (e.g., urbanicity by intersection density) and likelihood ratio testing at $p<0.05$. Both were statistically significant modifiers. Therefore we stratified all regression models by gender, and in each gender group we entered a product term of urbanicity with each main exposure variable. In addition, we tested effect modification by race by including a cross-product term of race by each main exposure, within each gender strata with urbanicity interactions, and followed by a likelihood ratio test. Race did not modify the association between street network and walking, bicycling, and jogging in men ($p>0.05$), but did in women ($p<0.001$). However, results from the race-stratified models in women were remarkably similar in effect and direction, albeit with reduced power, thus we present results not race- stratified for women. We also conducted a sensitivity analysis comparing our models with frequency of non-walking, non-bicycling, and non-jogging forms of PA as an additional control variable. Another sensitivity analysis compared individual effects for walking, bicycling, and jogging separately, finding similar patterns of association using each separate measure. Ultimately, despite different contributions to health given intensity differences, we combined all three measures into a single outcome measure since our modeling involved physical activity outcomes only (i.e., we did not model broader health outcomes). A final sensitivity analysis using residential mobility as an additional control showed similar results (although descriptive results show that movers were less likely to engage walking, bicycling, and jogging).

As the four main exposures have very different values and distributions, a1 unit change in value can vary greatly across measures. Thus, we present model estimations associated with a 1 SD change in each main exposure. For example, in low urbanicity areas, a 1 SD change in intersection density was 14.7 intersections per km^2; a 1 SD change in link-node ratio was 0.2; a 1 SD change in local road density was 8.3 km local roads in the 1 km buffer; and a 1 SD change in proportion of local relative to total roads was 11.0%.

Results

Descriptive Characteristics

The analysis sample reflects CARDIA sampling to achieve a race (black and white), gender, and education balanced mix of young to mid-aged adults as shown in Table 1. Walking, bicycling, and jogging frequency was significantly higher at baseline, while remaining relatively stable across years 7, 10, and 15. There was also temporal variation across the environment exposures, street connectivity and road density. Neither street connectivity nor road density differed significantly by gender for any exam year.

Mean values for intersection density, link-node ratio, and density of local roads were significantly higher with higher urbanicity, while the proportion of local relative to total roads was significantly lower with higher urbanicity (Table 2). For the Census tract-level covariates, the proportion of tract residents who walk to work and median age of housing were higher with higher urbanicity, while low urbanicity areas had a higher percentage of white residents (p-values=0.0001).

Statistical modeling results

We examined the association between street network and walking, bicycling, and jogging using two-part marginal effect models, stratified by gender, with interactions

In Part 1 of the two-part marginal effect model, we find the probability of engaging in walking, bicycling, and jogging was not associated with street network exposures (Table 3), except in high urbanicity areas where we found that women were less likely to walk, bike, or jog in neighborhoods with a higher proportion of local roads ($p<0.001$). The marginal effect model Part 2 was restricted to participants who engaged in walking, bicycling, or jogging (Table 4). We observed a complex pattern of association across urbanicity and gender, with generally positive association between street characteristics with walking, bicycling, and jogging in low urbanicity areas and diverse association in high urbanicity areas.

To interpret the joint effect of neighborhood-level street network on participation in walking, bicycling, and jogging among all participants, we examined the full two-part marginal effect (Table 5). I**n low urbanicity areas,** intersection density was positively associated with walking, bicycling, and jogging. A 1 SD increase in 3 or more-way intersection density was associated with a 1.0–1.3 unit increase in walking, bicycling, and jogging frequency. This translates to approximately 15 additional 3 or more-way intersections per 1 km^2 with an approximate 5% increase in walking, bicycling, and jogging. Density of local roads was positively associated with walking, bicycling, and jogging in men: a 1 SD increase in local road density was associated with a 1.0 unit increase in walking, bicycling, and jogging (approximately 8 km additional local roads per 1 km buffer with an approximate 5% increase in activity). **In middle urbanicity areas,** we observed no significant association between street network and walking, bicycling, and jogging. **In high urbanicity areas**, we observed inverse associations between local roads and walking, bicycling, and jogging in women: a 1 SD increase in local road density (~6 km per 1 km buffer) was associated with a 1.3 unit lower walking, bicycling, and jogging frequency (approximately 5–6% of average walking, bicycling, and jogging) and a 1 SD increase in proportion of local to total roads was associated with a 1.4 unit decrease in walking, bicycling, and jogging frequency (~6% of average walking, bicycling, and jogging).

Discussion

Using unique time-varying, GIS-derived environment data, we observed variation in the association between neighborhood-level street network and walking, bicycling, and jogging across environmental contexts and by gender. In low, but not in middle and high urban areas, we observed an association between higher density of intersections and local roads (men) and higher intersection density (women) with higher walking, bicycling, and jogging; whereas in high urbanicity areas, we observed a negative association for local road density and proportion of local roads in women. Thus overall, neighborhood street density was positively associated with walking, bicycling, and jogging in low urbanicity areas, but in middle and high urbanicity areas, these associations became null (men) or inverse (women).

Street network differs across environmental contexts. Generally higher urbanicity areas have higher intersection density and link-node ratio, which reflect greater street connectivity, largely through the provision of many possible direct routes across space. Modern suburban neighborhoods, characterized by segregated land uses and cul-de-sacs are hypothesized to constrain walking, bicycling, and jogging in less versus more urban neighborhoods, which are more compact with higher population density and traditional gridded streets(Ewing et al., 2003; Frank et al., 2005; Frumkin, 2002). While cross-sectional findings suggest that urbanization is a significant effect modifier in the association between obesity and perceived neighborhood barriers for PA(Joshu et al., 2008), there is little longitudinal research in this area.

The magnitude of the observed associations in our study is small compared to cross-sectional studies. For example, one study reported odds ratios for walking for transport ranging from 1.3 (top quartile, 95% CI: 0.95–1.7) and 1.6 (2^{nd} quartile, 95% CI: 1.2–2.0) of street connectivity (Ball et al., 2007). However, considering the contrasts across environmental settings (e.g., low urbanicity areas with rapid population growth and development), the associations we observed in our study have potential magnitude. For example, with a 1 SD increase in intersections (about 15 additional 3 or more-way intersections per km^2, a ~40% increase) in low urbanicity areas, we observed a 1.0–1.3 unit increase (~5% of the average) in walking, bicycling, and jogging frequency. As an estimate (using 4 MET for walking, as an example), the increase in 1.0–1.3 unit walking, bicycling, and jogging frequency has the equivalent energy expenditure of an additional 5–9 minutes of walking or 3–7 minutes of bicycling or jogging per week, which are significant at the population level. The fact that we observed associations in lower urbanicity areas could reflect the importance of interconnected streets and local roads in areas devoid of other environmental supports for physical activity.

Gender has also been reported to modify the relationship between environmental factors with obesity and PA. We found that gender modified the association between street network and walking, bicycling, and jogging frequency (positive association between street connectivity and walking, bicycling, and jogging in low urbanicity areas, whereas an inverse association for local roads among women living in high urbanicity areas). This inverse association was in contrast to our hypothesis. It is possible that high urbanicity areas, such as urban cores, may feature more local roads but also have greater barriers to PA, such as poorer aesthetics and higher crime rates. Crime and aesthetics may be particularly salient for women than men, while the current evidence is inconsistent(Humpel et al., 2004; Suminski et al., 2005). Though aesthetics and crime data were unavailable for this study, we observed a negative correlation between density of local roads and tract-level median household income particularly in high urbanicity areas ($r=-0.28$). It is possible that the lower income, urban neighborhoods may have less aesthetic surroundings and higher crime rates (Neckerman et al., 2009) along with more dense local roads.

The observed decrease in intersection and local road density over time parallels the shifts in CARDIA study population over time. CARDIA participants were recruited from four major metropolitan areas at baseline, but over time a considerable proportion of the sample moved to new residential locations so by the most recent follow-up the CARDIA participants have widely spread across the country with great geographic variation. Many participants moved from the four major metropolitan areas to more suburban areas as they moved from early to mid-adulthood. These residential relocations over time provide considerable environmental variation, which is an advantage of our study.

Our study also has limitations. First, it is important to recognize that while CARDIA has outstanding PA data, we only have temporal data on leisure PA, so we were unable to model walking, bicycling, and jogging for commuting purposes or to examine context-specific physical activity (Giles-Corti et al., 2005). However, there is evidence that local streets and areas proximate to residential locations are very common settings for pedestrian travel (Humpel et al., 2004; Sallis et al., 1998). Second, although Euclidean radial buffers have the advantage of capturing urban form around each residence and allowing comparability across time and space, such buffers do not take into account route-based networks to define neighborhoods. The trade off in this case is the comparability across highly urban versus less urban contexts, a main focus of our analysis. Further, research on physical activity resource counts shows little meaningful difference across Euclidean versus network buffers and in direction and strength of effects in statistical models (Boone-Heinonen et al., 2010; Boone-Heinonen et al., 2010). Third, StreetMap 2000 data were matched to CARDIA exam 0, 7, and 10 (1985–1996), whereas we used StreetMap 2003 data for year 15 (2001) data, given lack of high quality street data contemporaneous to the earlier exam years. While this is a limitation, the majority of CARDIA cities were fairly established with little change in street network over time. Whereas we are fortunate to have temporal data that span the full US, this limits the availability of detailed information on factors such as sidewalks and walking paths across the nation and over time (Chin et al., 2008; Handy et al., 2002). Whereas we observed modest associations between street network and walking, bicycling, and jogging, we were unable to fully characterize environment-level pedestrian supports, such as sidewalks, cross-walks, and pedestrian signage. This is clearly an area for future research. Given our long-term follow up, it is possible that there is some movement within the 12 month period covered by the PA assessment. Although we have information on residential mobility between exams, we cannot identify the exact time of relocation, which could introduce some mismatch. We did not restrict analysis to non-movers since it would introduce selection bias. Our sensitivity analysis indicated very similar results in models controlling for mobility. Fourth, while we measured street network from multiple approaches (basic property, index, and road classification), a recent instrument, space syntax(Penn, 2003), which incorporates urban design parameters with topological factors, may be an appropriate alternative measure, but was not feasible for our national study. Fifth, we focused on a narrow research question in order to fully investigate the association between street network and activities likely to occur in a street setting. Other built environmental attributes, such as green space, and social characteristics such as aesthetics and safety may offset the benefits of built environments (Cutts et al., 2009; Rebecca and Yan, 2009), but were not incorporated into the present analysis. Also, while it is possible that the observed inverse association between local roads and walking, bicycling, and jogging in high urbanicity areas in women is due to exercise occurring outside of the residential neighborhood, we included other forms of exercise as a control variable in our statistical models in an additional sensitivity analysis, finding a similar pattern and magnitude of associations (results not shown). Finally, the two-part marginal effect model does not have a fixed-effect option that can be a useful strategy to reduce self-selection bias by focusing on within-person variation only. To estimate the extent of residential self-selection, we performed one-step models separately with and without fixed-effect option, and observed similar results, suggesting that while we cannot completely rule out residential selection bias in the observed associations, we are confident that residential selection bias does not seem to have a major impact on the associations of interest.

There are several other strengths of this study. Our use of longitudinal data on this topic is an important first step in this body of research, with direct policy relevance in terms of street design, though additional study is warranted for other environmental attributes. In addition to rich, longitudinal individual-level data, we obtained objectively measured neighborhood environmental data for each participant with 3 follow-up measures, providing a study time frame of 15 years and a unique opportunity to research time-varying associations between environmental factors and individual-level behavioral outcomes. We used multiple measures to capture neighborhood-level street network, including street segments (links), the number of intersections (nodes), and street lengths. Further, our modeling strategy of using two-part marginal effect modeling is useful in eliminating bias by properly handling the outcome that have large proportions of zero values with remaining of the values being positive and continuous. In addition, our analysis stratification by urbanicity and gender are unique to the study of neighborhood effects. We relied upon a sophisticated measure of urbanicity, incorporating urbanized area boundaries in combination with population density.

In summary, we found positive associations between intersection density and density of local roads with overall walking, bicycling, and jogging, with variation across urban contexts and by gender. In general, we observed a positive association in low urbanicity areas, although the observed associations were modest in comparison to the established cross-sectional literature. Future research with additional information such as neighborhood safety and aesthetics, more specific categories of road types and greater detail regarding the attributes of streets that are most supportive of walking, bicycling, and jogging are needed. Our results suggest that a rather dramatic change in 3 or more-way street intersections (plus ~15 per km^2 in exurban areas) would be associated with ~5% increase in walking, bicycling, and jogging, which at the population level could translate to meaningful increases.

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References

Ball K, Timperio A, Salmon J, Giles-Corti B, Roberts R, Crawford D. Personal, social and environmental determinants of educational inequalities in walking: a multilevel study. Journal of Epidemiology and Community Health 2007;61:108–114. [PubMed: 17234868]

Berrigan D, Pickle L, Dill J. Associations between street connectivity and active transportation. International Journal of Health Geographics 2010;9:20. [PubMed: 20412597]

Berrigan D, Troiano RP. The association between urban form and physical activity in U.S. adults. American Journal of Preventive Medicine 2002;23:74–79. [PubMed: 12133740]

Boer R, Zheng Y, Overton A, Ridgeway GK, Cohen DA. Neighborhood design and walking trips in ten U.S. metropolitan areas. American Journal of Preventive Medicine 2007;32:298–304. [PubMed: 17383560]

Boone-Heinonen J, Evenson K, Song Y, Gordon-Larsen P. Built and socioeconomic environments: patterning and associations with physical activity in U.S. adolescents. International Journal of Behavioral Nutrition and Physical Activity 2010;7:45. [PubMed: 20487564]

Boone-Heinonen J, Gordon-Larsen P, Song Y, Popkin BM. What is the relevant neighborhood area for detecting built environment relationships with physical activity? Health & Place. 2010

Braza M, Shoemaker W, Seeley A. Neighborhood design and rates of walking and biking to elementary school in 34 California communities. American Journal of Health Promotion 2004;19:128–136. [PubMed: 15559713]

Brown BB, Yamada I, Smith KR, Zick CD, Kowaleski-Jones L, Fan JX. Mixed land use and walkability: Variations in land use measures and relationships with BMI, overweight, and obesity. Health & Place 2009;15:1130–1141. [PubMed: 19632875]

Carver A, Timperio A, Hesketh K, Crawford D. Are Safety-Related Features of the Road Environment Associated with Smaller Declines in Physical Activity among Youth? Journal of Urban Health. 2010

Chin GK, Van Niel KP, Giles-Corti B, Knuiman M. Accessibility and connectivity in physical activity studies: the impact of missing pedestrian data. Preventive Medicine 2008;46:41–45. [PubMed: 17920671]

Cutts BB, Darby KJ, Boone CG, Brewis A. City structure, obesity, and environmental justice: an integrated analysis of physical and social barriers to walkable streets and park access. Social Science & Medicine 2009;69:1314–1322. [PubMed: 19751959]

Duan N, Manning WG, Morris CN, Newhouse JP. A comparison of alternative models for the demand for medical care. Journal of Business and Economic Statistics 1983;1:115–126.

Duncan M, Mummery K. Psychosocial and environmental factors associated with physical activity among city dwellers in regional Queensland. Preventive Medicine 2005;40:363–372. [PubMed: 15530589]

Ewing R. Can the physical environment determine physical activity levels? Exercise and Sport Sciences Reviews 2005;33:69–75. [PubMed: 15821427]

Ewing R, Schmid T, Killingsworth R, Zlot A, Raubenbush S. Relationship between urban sprawl and physical activity, obesity, and morbidity. American Journal of Health Promotion 2003;18:47–57. [PubMed: 13677962]

Forsyth A, Hearst M, Oakes JM, Schmitz KH. Design and Destinations: Factors Influencing Walking and Total Physical Activity. Urban Studies 2008;45:1973–1996.

Frank, LD.; Engelke, PO.; Schmidt, TL. Health and community design: the impact of the physical environment on physical activity. Island Press; Washington DC: 2003.

Frank LD, Andresen MA, Schmid TL. Obesity relationships with community design, physical activity, and time spent in cars. American Journal of Preventive Medicine 2004;27:87–96. [PubMed: 15261894]

Frank LD, Kerr J, Sallis JF, Miles R, Chapman J. A hierarchy of sociodemographic and environmental correlates of walking and obesity. Preventive Medicine 2008;47:172–178. [PubMed: 18565576]

Frank LD, Schmid TL, Sallis JF, Chapman J, Saelens BE. Linking objectively measured physical activity with objectively measured urban form: findings from SMARTRAQ. American Journal of Preventive Medicine 2005;28:117–125. [PubMed: 15694519]

Friedman GD, Cutter GR, Donahue RP, Hughes GH, Hulley SB, Jacobs DR Jr, Liu K, Savage PJ. CARDIA: study design, recruitment, and some characteristics of the examined subjects. Journal of Clinical Epidemiology 1988;41:1105–1116. [PubMed: 3204420]

Frumkin H. Urban sprawl and public health. Public Health Rep 2002;117:201–217. [PubMed: 12432132]

Giles-Corti B, Timperio A, Bull F, Pikora T. Understanding physical activity environmental correlates: increased specificity for ecological models. Exercise and Sport Sciences Reviews 2005;33:175–181. [PubMed: 16239834]

Grafova IB, Freedman VA, Kumar R, Rogowski J. Neighborhoods and obesity in later life. American Journal of Public Health 2008;98:2065–2071. [PubMed: 18799770]

Haines PS, Guilkey DK, Popkin BM. Modeling Food Consumption Decisions as a Two-Step Process. American Journal of Agricultural Economics 1988;70:543–552.

Handy SL, Boarnet MG, Ewing R, Killingsworth RE. How the built environment affects physical activity: views from urban planning. American Journal of Preventive Medicine 2002;23:64–73. [PubMed: 12133739]

Hoehner CM, Brennan LK, Brownson RC, Handy SL, Killinsworth R. Opportunities for integrating public health and urban planning approaches to promote active community environments. American Journal of Health Promotion 2003;18:14–20. [PubMed: 13677959]

Hu HY, Chou YJ, Chou P, Chen LK, Huang N. Association between obesity and injury among Taiwanese adults. International Journal of Obesity 2009;33:878–884. [PubMed: 19528968]

Humpel N, Owen N, Iverson D, Leslie E, Bauman A. Perceived environment attributes, residential location, and walking for particular purposes. American Journal of Preventive Medicine 2004;26:119–125. [PubMed: 14751322]

Jacobs DR Jr, Hahn LP, Haskell WL, Pirie P, Sidney S. Validity and reliability of short physical activity history: CARDIA and the Minnesota Heart Health Program. Journal of Cardiopulmonary Rehabilitation 1989:448–459.

Jago R, Baranowski T, Zakeri I, Harris M. Observed Environmental Features and the Physical Activity of Adolescent Males. American Journal of Preventive Medicine 2005;29:98–104. [PubMed: 16005805]

Joshu CE, Boehmer TK, Brownson RC, Ewing R. Personal, neighbourhood and urban factors associated with obesity in the United States. Journal of Epidemiology and Community Health 2008;62:202–208. [PubMed: 18272734]

Lee C, Moudon AV. Physical Activity and Environment Research in the Health Field: Implications for Urban and Transportation Planning Practice and Research. Journal of Planning Literature 2004;19:147–181.

Liu L, Strawderman RL, Cowen ME, Shih Y-CT. A flexible two-part random effects model for correlated medical costs. Journal of Health Economics 2010;29:110–123. [PubMed: 20015560]

Lovasi GS, Moudon AV, Pearson AL, Hurvitz PM, Larson EB, Siscovick DS, Berke EM, Lumley T, Psaty BM. Using built environment characteristics to predict walking for exercise. International Journal of Health Geographics 2008;7:10. [PubMed: 18312660]

Madden D. Sample selection versus two-part models revisited: the case of female smoking and drinking. Journal of Health Economics 2008;27:300–307. [PubMed: 18180064]

Neckerman KM, Lovasi GS, Davies S, Purciel M, Quinn J, Feder E, Raghunath N, Wasserman B, Rundle A. Disparities in urban neighborhood conditions: evidence from GIS measures and field observation in New York City. Journal of Public Health Policy 2009;30:264–285.

Ng SW, Zhai F, Popkin BM. Impacts of China's edible oil pricing policy on nutrition. Social Science & Medicine 2008;66:414–426. [PubMed: 17996345]

Oakes JM, Forsyth A, Schmitz KH. The effects of neighborhood density and street connectivity on walking behavior: the Twin Cities walking study. Epidemiologic Perspectives & Innovations 2007;4:16. [PubMed: 18078510]

Ogilvie D, Egan M, Hamilton V, Petticrew M. Promoting walking and cycling as an alternative to using cars: systematic review. British Medical Journal 2004;329:763. [PubMed: 15385407]

Owen N, Humpel N, Leslie E, Bauman A, Sallis JF. Understanding environmental influences on walking; Review and research agenda. American Journal of Preventive Medicine 2004;27:67–76. [PubMed: 15212778]

Pendergast K, Wolf A, Sherrill B, Zhou X, Aronne LJ, Caterson I, Finer N, Hauner H, Hill J, Van Gaal L, Coste F, Despres JP. Impact of Waist Circumference Difference on Health-Care Cost among Overweight and Obese Subjects: The PROCEED Cohort. Value Health. 2010

Penn A. Space Syntax And Spatial Cognition: Or Why the Axial Line? Environment and Behavior 2003;35:30–65.

Rebecca M, Yan S. "Good" neighborhoods in Portland, Oregon: Focus on both social and physical environments. Journal of Urban Affairs 2009;31:491–509.

Riva M, Gauvin L, Apparicio P, Brodeur JM. Disentangling the relative influence of built and socioeconomic environments on walking: The contribution of areas homogenous along exposures of interest. Social Science & Medicine 2009;69:1296–1305. [PubMed: 19733426]

Rodrigue, J-P.; Comtois, C.; Slack, B. The Geography of Transport Systems. New York: 2006.

Ross NA, Tremblay S, Khan S, Crouse D, Tremblay M, Berthelot JM. Body mass index in urban Canada: neighborhood and metropolitan area effects. American Journal of Public Health 2007;97:500–508. [PubMed: 17267734]

Saelens BE, Sallis JF, Frank LD. Environmental correlates of walking and cycling: findings from the transportation, urban design, and planning literatures. Annals of Behavioral Medicine 2003;25:80–91. [PubMed: 12704009]

Sallis JF, Bauman A, Pratt M. Environmental and policy interventions to promote physical activity. American Journal of Preventive Medicine 1998;15:379–397. [PubMed: 9838979]

Smith KR, Brown BB, Yamada I, Kowaleski-Jones L, Zick CD, Fan JX. Walkability and body mass index density, design, and new diversity measures. American Journal of Preventive Medicine 2008;35:237–244. [PubMed: 18692736]

Suminski RR, Poston WSC, Petosa RL, Stevens E, Katzenmoyer LM. Features of the neighborhood environment and walking by U.S. adults. American Journal of Preventive Medicine 2005;28:149–155. [PubMed: 15710269]

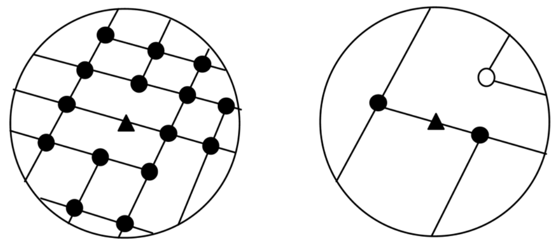
Timperio A, Ball K, Salmon J, Roberts R, Giles-Corti B, Simmons D, Baur LA, Crawford D. Personal, Family, Social, and Environmental Correlates of Active Commuting to School. American Journal of Preventive Medicine 2006;30:45–51. [PubMed: 16414423]

Trost SG, Owen N, Bauman AE, Sallis JF, Brown W. Correlates of adults' participation in physical activity: review and update. Medicine and Science in Sports and Exercise 2002;34:1996–2001. [PubMed: 12471307]

Walls TA, Fairlie AM, Wood MD. Parents do matter: a longitudinal two-part mixed model of early college alcohol participation and intensity. Journal of Studies on Alcohol and Drugs 2009;70:908–918. [PubMed: 19895767]

Willett, W. Nutritional Epidemiology. 2. Oxford Uniersity Press; New York: 1998. p. 291-301.

Panel A: Intersection Density (density of 3 or more-way intersections)



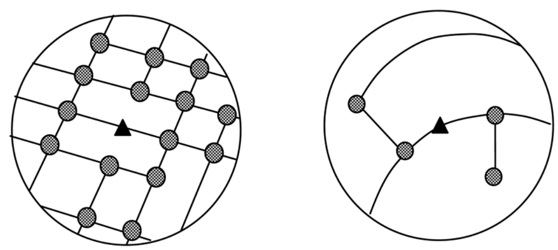
High

Number of ≥3-way intersections = 15
Intersection density = 15÷ 3.14 km^2
=4.8/km^2

Low

Number of ≥3-way intersections = 2
Intersection density = 2 ÷ 3.14 km^2
= 0.6/km^2

Panel B: Link-node Ratio [ratio of streets (links) to intersections (nodes)]



High

Number of links = 32
Number of nodes = 15
Link-node ratio = 32÷15 = 2.1

Low

Number of links = 6
Number of nodes = 4
Link-node ratio = 6÷4 =1.5

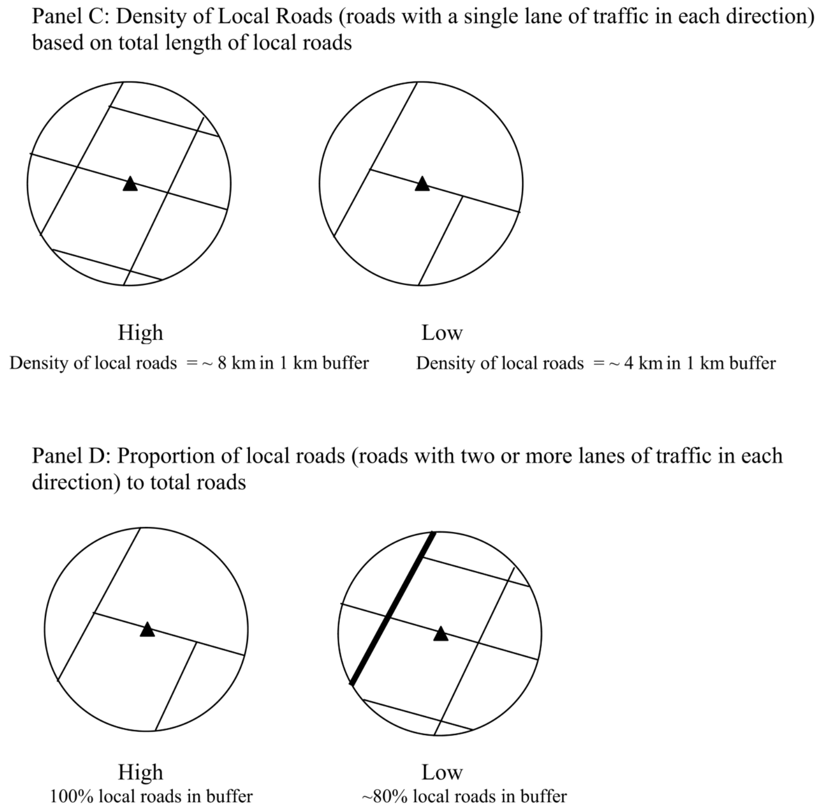


Figure 1.

Panels A–D. Illustrative examples of each of the four street network measures: (A) intersection density, (B) link-node ratio, (C) density of local roads, and (D) proportion of local relative to total roads, within 1 km Euclidean buffer from residential location. Hypothetical examples for relatively high versus relatively low values are presented for each of the four street network measures, with high values hypothesized to be positively associated with walking, bicycling, and jogging. These hypothetical illustrations do not reflect real values of street network.

▲ Residential location

● True intersection (33-way intersection)

○ Two-way intersection

● Node (any intersection, including cul-de-sac)

— Link (continuous street segment without interruption by intersection or cul-de-sac)

— Local road, generally with a single lane of traffic in each direction [(TIGER/Line™ Files, 1992, Census Feature Class Codes (A4x category 'local, neighborhood, and rural roads')]

▭ Indicates non-local roads, such as state and county highways, generally with two or more lanes of traffic in each direction [(TIGER/Line™ Files, 1992, Census Feature Class Codes (major road categories (A0x-A3x, A5x, and A6x)]

NOTE: all examples feature local roads except Panel D (low example)

Table 1

Individual- and neighborhood-level characteristics in the CARDIA study, 1985–86 to 2000–01

% or mean ± SD	Year 0 1985–86 (N=5,015)	Year 7 1992–93 (N=4,001)	Year 10 1995–96 (N=3,898)	Year 15 2000–01 (N=3,646)
Sociodemographics				
Black %	52.0%	48.1%	48.5%	47.1%
Female %	54.5%	54.8%	55.3%	55.8%
Age in years	24.8 ±3.7	32.0 ±3.6	35.0 ±3.7	40.2 ±3.6
Married %	22.1%	44.2%	49.3%	60.3%
Education %				
<=High School	40.0%	28.9%	29.4%	23.0%
>High School; <=College	50.4%	53.0%	51.2%	56.3%
>College	9.6%	18.2%	19.4%	20.7%
Walking, bicycling, and jogging				
Walking, bicycling, and jogging frequency[a]	25.9 ±21.4*	21.5±19.9	21.2±20.4	22.1±20.8
1 km radius buffer level variables				
Street Connectivity				
Intersection density/km^2	52.2±14.4	46.8 ±18.5*	41.5 ±20.0*	44.7 ±21.7*
Link-node ratio	1.8 ±0.2*	1.7 ±0.2*	1.7 ±0.3	1.6 ±0.2
Local roads				
Local road density (km in 1 km buffer)	36.5 ±7.6*	33.2 ±9.7*	30.6 ±10.9	30.2 ±10.5
Proportion of local relative to total roads (%)	78.4% ±8.7%	78.7% ±9.8%	79.9% ± 10.7%*	77.7% ±11.8%**
Census Tract-level variables*				
Population density per km^2	4,555±3,450*	4,092 ±3,814*	2,802 ±3,011	2,760 ±3,161
Proportion of residents walk to work (%)	7.7% ±9.5%*	5.4% ± 8.1%*	4.0% ±6.4%*	3.1% ±5.6%*
Median age of houses in years	43.4 ±11.3*	41.7 ±14.6	41.3 ±15.9	41.8 ±17.0
Proportion of residents of white race (%)	54.3% ±33.8%*	58.7% ±34.7%	65.8% ±33.2%*	59.6% ±32.1%
Inflation-adjusted median household income	23,467 ±10,151*	38,158 ±17,156	38,557 ±18,383	50,278 ± 23,974*

[a] Walking, bicycling, and jogging frequency = walking frequency + bicycling frequency + jogging frequency

Kruskal-Wallis rank tests with Bonferroni correction (p<0.5/6=0.0083)

* Significantly different from any other exam years

** Significantly different between year7&15

Table 2

Neighborhood-level exposures and related covariates in the CARDIA Study by neighborhood level of urbanicity, at baseline 1985–86.

	Urbanicity		
Mean ± SD	**Low**	**Middle**	**High**
Main Exposures: 1 km radius buffer level			
Street Connectivity			
Intersection density, 3+ intersections/km^2	37.6 ±14.7*	53.7 ±11.2*	57.2 ±12.3*
Link-node ratio	1.6 ±0.2*	1.8 ±0.2*	1.9 ±0.1*
Local roads			
Local road density (km in 1 km buffer)	28.6 ±8.3*	37.7 ±5.8*	38.9 ±6.3*
Proportion of local relative to total roads (%)	80.3% ±11.0%*	78.2% ±8.7%*	77.7% ±7.4%*
Covariates: Census Tract-level			
Population density (per km^2)	1,087 ±405*	2,893 ±671*	7,348 ±3,320*
Proportion of residents walk to work (%)	5.4% ±9.5%*	6.3% ±7.5%*	9.8% ±10.4%*
Median age of houses in years	32.7 ±10.4*	44.3 ±11.0*	47.2 ±8.7*
Proportion of residents of white race (%)	64.9% ±36.1%*	51.1% ±31.8%	52.6%±33.6%
Inflation-adjusted median household income	23,800 ±14,023**	23,082 ±9,870	23,641 ±8,278

Kruskal-Wallis rank tests with Bonferroni correction (p<0.5/6=0.0083)

* Significantly different from any other two columns

** Significantly different between low and high urbanicity.

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Table 3

Part 1 of the two-part marginal effect model estimating associations between neighborhood-level street network and probability of engaging in walking, bicycling, and jogging using a longitudinal probit regression model[a], the CARDIA Study 1985–86 to 2000–01.

Main Exposures (per 1 SD increase)	Urbanicity								
	Low			Middle			High		
	β	95% CI	P-value	β	95% CI	P-value	β	95% CI	P-value
	Probability of engaging in walking, bicycling, and jogging								
Men									
Street connectivity									
Model A: Intersection density, 3+ intersections/km^2	0.04	−0.04, 0.11	0.4	−0.01	−0.10,0.08	0.8	0.05	−0.04, 0.14	0.1
Model B: Link-node ratio	−0.04	−0.11,0.03	0.3	−0.02	−0.13,0.09	0.7	−0.03	−0.10,0.05	0.5
Local roads									
Model C: Local road density (km in 1 km buffer)	0.02	−0.06,0.10	0.7	−0.01	−0.10,0.08	0.8	−0.02	−0.12,0.09	0.8
Model D: Proportion of local relative to total roads (%)	−0.03	−0.10,0.04	0.3	−0.05	−0.14,0.04	0.3	−0.01	−0.11,0.08	0.8
Women									
Street connectivity									
Model A′: Intersection density, 3+ intersections/km^2	0.07	−0.01,0.14	0.07	0.03	−0.04, 0.10	0.4	−0.02	−0.10, 0.05	0.5
Model B′: Link-node ratio	0.04	−0.04,0.11	0.4	−0.01	−0.10,0.08	0.8	0.02	−0.04,0.09	0.5
Local roads									
Model C′: Local road density (km in 1 km buffer)	0.04	−0.03,0.10	0.3	−0.01	−0.09,0.07	0.8	−0.08	−0.18,0.02	0.1
Model D′: Proportion of local relative to total roads (%)	0.02	−0.04,0.09	0.5	−0.03	−0.11,0.05	0.5	**−0.17**	**−0.26, −0.08**	**<0.001**

[a]This model estimates probability of engaging in walking, bicycling, and jogging, and served as the first step of the two-part marginal effect model. Models control for individual-level age, race, education level, marital status, baseline study center, Census tract-level % white residents, inflation-adjusted median household income, % residents walk to work, and median age of houses.

Table 4

Part 2 of the two-part marginal effect model estimating associations between neighborhood-level street network and walking, bicycling, and jogging frequency using a conditional longitudinal random-effect regression model[a], the CARDIA Study 1985–86 to 2000–01.

Main Exposures (per 1 SD increase)	Urbanicity								
	Low			Middle			High		
	β	95% CI	P-value	β	95% CI	P-value	β	95% CI	P-value
	Walking, bicycling, and jogging frequency								
Men									
Street connectivity									
Model A: Intersection density, 3+ intersections/km^2	0.8	−0.03,1.7	0.06	−0.1	−0.9,0.7	0.9	−0.4	−1.2,0.3	0.3
Model B: Link-node ratio	−0.003	−0.8,0.8	0.99	0.8	−0.3,1.8	0.1	0.2	−0.6,1.0	0.6
Local roads									
Model C: Local road density (km in 1 km buffer)	**0.9**	**0.1,1.8**	**0.03**	0.1	−0.8,0.9	0.9	−0.5	−1.4,0.4	0.3
Model D: Proportion of local relative to total roads (%)	0.6	−0.2,1.3	0.1	0.1	−0.8,1.0	0.8	−0.4	−1.2,0.5	0.4
Women									
Street connectivity									
Model A′: Intersection density, 3+ intersections/km^2	**1.1**	**0.4,1.8**	**0.002**	−0.5	−1.1,0.2	0.2	−0.6	−1.3,0.1	0.09
Model B′: Link-node ratio	−0.4	−1.1,0.4	0.3	0.1	−0.8,0.9	0.9	0.2	−0.5,0.8	0.6
Local roads									
Model C′: Local road density (km in 1 km buffer)	0.6	−0.09,1.3	0.09	**−0.8**	**−1.5,0.1**	**0.02**	**−0.9**	**−1.7, −0.1**	**0.03**
Model D′: Proportion of local relative to total roads (%)	−0.2	−0.8,0.4	0.5	−0.2	−1.0,0.5	0.5	**−0.8**	**−1.5, −0.03**	**0.04**

[a]This model estimates frequency of walking, bicycling, and jogging conditioning on engaging in those activities, and served as the second step of the two-part marginal effect model. Models control for individual-level age, race, education level, marital status, baseline study center, Census tract-level % white residents, inflation-adjusted median household income, % residents walk to work, and median age of houses.

Table 5

Joint effect of the marginal effect model estimating associations between neighborhood-level street network and walking, bicycling, and jogging frequency using two-part marginal effect models[a], the CARDIA Study 1985–86 to 2000–01.

Main Exposures (per 1 SD increase)	Urbanicity: Low β	Low 95% CI	Low P-value	Middle β	Middle 95% CI	Middle P-value	High β	High 95% CI	High P-value
	Walking, bicycling, and jogging frequency								
Men									
Street connectivity									
Model A: Intersection density, 3+ intersections/km^2	**1.0**	**0.04,1.9**	**0.04**	−0.6	−1.5,0.2	0.2	−0.2	−1.1,0.6	0.6
Model B: Link-node ratio	−0.4	−1.2,0.5	0.4	0.6	−0.7,1.8	0.4	−0.1	−0.9,0.7	0.8
Local roads									
Model C: Local road density (km in 1 km buffer)	**1.0**	**0.1,2.0**	**0.03**	−0.4	−1.3,0.6	0.4	−0.7	−1.7,0.4	0.2
Model D: Proportion of local relative to total roads (%)	0.6	−0.2,1.4	0.2	−0.1	−1.0,0.7	0.7	−0.1	−1.0,0.8	0.8
Women									
Street connectivity									
Model A′: Intersection density, 3+ intersections/km^2	**1.3**	**0.6,2.0**	**0.001**	−0.3	−1.0,0.4	0.4	−0.6	−1.3,0.1	0.1
Model B′: Link-node ratio	−0.1	−0.8,0.6	0.8	0.1	−0.8,1.0	0.8	0.2	−0.5,0.9	0.6
Local roads									
Model C′: Local road density (km in 1 km buffer)	0.7	−0.06,1.4	0.07	−0.7	−1.5,0.04	0.06	**−1.3**	**−2.2, −0.3**	**0.007**
Model D′: Proportion of local relative to total roads (%)	−0.2	−0.8,0.4	0.5	−0.07	−0.9,0.7	0.9	**−1.4**	**−2.3, −0.6**	**0.001**

[a]The two-part marginal effect model includes a probit model using maximum likelihood estimation as the first step to estimate probability of engaging in walking, bicycling, and jogging. The second part is an ordinary least squares regression model conditioned on only those who engaged in walking, bicycling, and jogging. The coefficients are the marginal effect (weighted average) from the point estimates from both parts of the equation. Models control for individual-level age, race, education level, marital status, baseline study center, Census tract-level % white residents, inflation-adjusted median household income, % residents walk to work, and median age of houses.