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Population-Adjusted Street Connectivity, Urbanicity and Risk of Obesity in the U.S

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Abstract

Street connectivity, defined as the number of (3-way or more) intersections per area unit, is an important index of built environments as a proxy for walkability in a neighborhood. This paper examines its geographic variations across the rural-urban continuum (urbanicity), major racial-ethnic groups and various poverty levels. The population-adjusted street connectivity index is proposed as a better measure than the regular index for a large area such as county due to likely concentration of population in limited space within the large area. Based on the data from the Behavioral Risk Factor Surveillance System (BRFSS), this paper uses multilevel modeling to analyze its association with physical activity and obesity while controlling for various individual and county-level variables. Analysis of data subsets indicates that the influences of individual and county-level variables on obesity risk vary across areas of different urbanization levels. The positive influence of street connectivity on obesity control is limited to the more but not the mostly urbanized areas. This demonstrates the value of obesogenic environment research in different geographic settings, helps us reconcile and synthesize some seemingly contradictory results reported in different studies, and also promotes that effective policies need to be highly sensitive to the diversity of demographic groups and geographically adaptable.

Keywords

built environments; population-adjusted street connectivity; physical activity; obesity; BRFSS; the U.S

1. Introduction

The prevalence of obesity in the U.S. increased during the last decades. According to the National Health and Nutrition Examination Survey (NHANES) 2009-2010, more than 35% of U.S. men and women were obese (Ogden et al., 2012). Obesity increases the risk of several health conditions such as heart disease, stroke, diabetes and some cancers (DHHS, 2012). Obesity prevalence also varies a great deal geographically, from the lowest 20.7% in Colorado to the highest 35% in Mississippi, based on the new baseline established in 2011

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for state obesity rates (CDC, 2012). Conceivably, the variations across small geographic areas such as counties and census tracts are even greater.

One possible explanation for the geographic variations of obesity is built upon the *obesogenic environment* thesis, a term first coined by Swinburn et al. (1999). The thesis argues that disparities of obesity prevalence are attributable to differentiated exposure to a healthy food environment that promotes healthier dietary choices and built environments that encourage physical activities (Hill and Peters, 1998). This paper focuses on the latter. Built environment, broadly defined as "human-formed, developed, or structured areas" (CDC, 2005), includes walkable urban form (residential density, street connectivity, and land use mix), places to be physically active (presence of sidewalks, access to parks and exercise facilities), and attractive and safe environment (Lovasi et al., 2009). There is a rich body of literature on examining the relationship between built environments and obesity (see reviews by Frank and Engelke, 2001, Papas et al., 2007, Lovasi et al., 2009, and Jackson and Sinclair, 2011), but few on a national scale until very recently (Ewing et al., 2006; Wen and Kowaleski-Jones, 2012; Wen et al., 2013). The paucity of national studies on obesogenic built environments is understandable given the challenges of data requirements and computation complexity for such research at a fine geographic resolution. A noteworthy exception is Zhang et al. (2011) where the main focus was on park accessibility at the census tract level. The present study offers another nationwide analysis, focusing on street connectivity, one of the most widely used indices of built environments, as a proxy for walkability in a neighborhood (Berrigan et al., 2010).

One paradox in the relation between built environments and obesity is that inner city neighborhoods, when compared to suburban ones, tend to have higher population density, greater street connectivity and more sidewalks but yet are also linked to higher rates of physical inactivity and obesity (Lopez and Hynes, 2006). This suggests likely different processes and complex interactions of land use, social factors and health behavior across various geographic settings. Inner cities usually have more disadvantaged populations (i.e., minorities, low socioeconomic status (SES)) and less attractive and less safe environments deterring physical activity (Wilson et al., 2004; Weir et al., 2006). Therefore, the linkage of better built environment to more physical activity in middle class and affluent suburbia may not be necessarily transferrable to inner cities (Perdue et al., 2003; Lopez and Hynes, 2006). In addition, teenagers in urban and rural areas exhibit different behaviors in physical activity (Felton et al., 2002). These previous findings suggest the need to examine possible variations of built environments' impacts on physical activity and obesity by an area's urbanicity and socio-demographic factors. Finer grained classifications and better measures of urbanicity have been reported to improve research on the urbanicity-health link than the usually used urban-rural dichotomy (Dahly and Adair, 2007; McLafferty and Wang, 2009). There is also a growing body of literature on the racial-ethnic disparities of obesity, and the majority of findings point to considerable residual effects of race and ethnicity on obesity after controlling for other variables such as individual socioeconomic status (Chang and Lauderdale, 2005; Scharoun-Lee et al., 2009; Wen and Kowaleski-Jones, 2012). To the best of our knowledge, the present paper presents the first nationwide analysis in the US of the associations between street connectivity and physical activity and obesity and the variations of these associations by urbanicity and socio-demographic factors (e.g., poverty levels).

Criticisms of the obesogenic environment thesis also warrant some brief discussion here. For example, Baillie-Hamilton (2002) emphasizes the role of environmental toxins in obesogenesis rather than the changing energy balance environments; he contends that the proliferation of synthetic chemicals called endocrine-disrupting chemicals (EDCs) since 1940, may have altered the function of hormones produced by the human body, changed developmental pathways, and led to prevalence of overweight infants (Kim et al., 2006) and adults with the latency effect (Grun and Blumberg, 2009). This perspective is useful for understanding temporal trends of obesity particularly the significant and abrupt rise since 1980 in the U.S. (Guthman, 2012), but not helpful to explain the spatial pattern, which is the focus of this paper. Moreover, this critique focuses on environmental toxins, and is not directly related to our emphasis on the role of built environment in physical activity and then obesity.

The remainder of the paper is structured as follows. Section 2 discusses data processing and definition of variables. Section 3 examines the geographic patterns of street connectivity at both the census tract and county levels and their variations by urbanicity and poverty levels. Section 4 presents the results of multilevel modeling (MLM) of the association of street connectivity with physical inactivity and obesity rates at the county level while controlling for various individual-and county-level variables. The MLM analysis is limited to using the county unit as the definition of neighborhood because the data of physical inactivity and obesity are only geocoded to the county level. The paper is concluded with a summary and discussion of outlooks for future work.

2. Data processing and definition of variables

Three major data sources are used in this study: the road network data for measuring street connectivity, the census and other data for defining neighborhood contextual variables including urbanicity and socio-demographic variables, and the Behavioral Risk Factor Surveillance System (BRFSS) data for reported health behavior and conditions of individuals.

2.1. Measuring street connectivity

Among various factors considered for measuring walkability, street connectivity is a constant component. More connected street networks are thought to be more conducive to physical activity such as walking. Better connectivity implies ease of walking between places, and often more destinations that can be reached by more and shorter routes (Moudon et al., 2006; Doyle et al., 2006). Measures of street connectivity include block length, block size, intersection density, percent four way intersections, street density, connected intersection ratio, and link node ratio. Research indicates that most of these measures are highly correlated (Berrigan et al., 2010). This research adopts *intersection density* to measure street connectivity for its wide usage in the literature and the feasibility of its implementation for the whole U.S. Specifically, street connectivity is defined as the number of intersections per square kilometer in an area (e.g., Frank et al., 2006), namely census tract or county in this study.

Spatial data of the census tracts, counties and road networks in the U.S. were constructed from the data DVDs distributed with ArcGIS 9.3 by the Environmental System Research Institute (ESRI). The 2000 census tract (county) boundary file containing the area size in square kilometer of each tract (county) is ready for use. However, computation of the number of intersections at the census tract (county) level across the U.S. has proved to be an arduous task. The road network data are based on the StreetMap USA file (a TIGER 2000-based streets data set enhanced by ESRI and Tele Atlas in 2005) from the afore-mentioned DVDs. Therefore, the street connectivity index corresponds to the 2005 road network.

The data processing is composed of three steps:

1. Only roads with the speed limit lower than 35 miles per hour are extracted. Other roads are considered highways or major roads and do not contribute to street connectivity or walkability.

2. Intersection, a key metric, is defined as a starting or ending point of a dead-end street or a 3-way, 4-way or 5-way intersection. Identification of intersections from the street centerline data from the previous step is processed in the ArcGIS network analysis module.
3. The census tract (county) layer and the intersection layer are overlaid to compute the street connectivity as the number of intersections per square mile in each tract (county).

Due to the large size of road network data, the entire U.S. was portioned to more than 40 regions: mostly by state, some neighboring small states were merged into one region, but large states such as Texas and California were split into multiple regions. The above process was implemented and repeated on each region, and the results were finally pieced together for the whole U.S.

2.2. Defining urbanicity and socio-demographic variables

As explained previously, this study uses two levels of aggregated data: census tract and county. The analysis of geographic patterns of street connectivity is conducted for both levels, but the multilevel modeling of association of street connecting with physical activity and obesity is only feasible when neighborhood is defined at the county level due to the geocoding scheme of the BRFSS data.

Two classifications of *urbanicity* are used rather than the urban-rural dichotomy. The first is based on the 2006 Urban-Rural Classification Scheme for counties by the National Center for Health Statistics (NCHS), which is developed to “study the association between urbanization level of residence and health” (NCHS, 2006). The six-level NCHS urban-rural categories include large central metro, large fringe metro, medium metro, small metro, micropolitan and noncore from most urban to most rural. Since the NCHS is based on the county unit, all census tracts within a county share the same urban-rural category regardless of its degree of urbanization. A county (particularly in large fringe, medium and small metro) is often diverse in its composition of urbanicity.

This leads us to include the second definition based on the Census 2000 Urban-Rural Classification (Census, 2002). The Census defines an urban area as an urbanized area (UA) or an urban cluster (UC) and otherwise a rural area based on a much smaller geographic unit “census block.” It uses a higher threshold of population density of at least 1,000 people per square mile for UA and a lower threshold population density of at least 500 people per square mile for UC. In this study, a census tract is considered “urban” if its centroid falls within an urban area (UA or UC). The finer geographic resolution used in the Census definition enables us to classify all census tracts into urban or rural tracts. For each county, its urbanicity can be defined as a continuous urbanization ratio, i.e., population of urban tracts over the total population in the county.

As the aforementioned literature suggests, there are wide disparities of obesity across racial/ethnic and SES groups. Two socio-demographic variables at the census tract and county levels are derived from the 2000 census data: poverty level and racial-ethnical composition. Poverty level is defined as percent residents living in poverty. Racial–ethnic composition is represented by an *racial-ethnic heterogeneity index* defined as $1 - \sum_i p_i^2$, where p_i is the fraction of the population in a given group (Sampson and Groves, 1989). The index takes into account both the relative sizes and number of population groups, and ranges from a score of zero reflecting the presence of only one group to a score near one reflecting maximum heterogeneity. Six racial-ethnic groups are used in computing the ethnic heterogeneity index: non-Hispanic Whites, Blacks, Asians/Pacific Islander, Hispanics, American Indians/Alaska Natives, and others in a census tract.

2.3. Defining individual variables from the BRFSS data

The BRFSS is an annual telephone health survey system for tracking health conditions and risk behaviors of the adult population (18 years or older) in the U.S. since 1984. This study uses the BRFSS Annual Survey Data (http://www.cdc.gov/brfss/technical_infodata/surveydata.htm) in 2005 in order to match the street connectivity index based on the 2005 road network. This data set contains a large volume of individual-level data geocoded to county. After eliminating a small portion (20.0%) of the records with missing values such as county code or any variables needed for the analysis, 251,247 observations in 50 states and Washington DC are used in this research.

Two health behavior and condition variables are derived: physical inactivity and obesity. *Physical inactivity* is measured by no leisure-time physical activity or exercise in the last 30 days. *Obesity* is indicated by a self-reported BMI (body mass index, i.e., body weight in kilograms/square of height in meters) equal to or greater than 30.

Based on the literature review (e.g., Wen and Kowaleski-Jones, 2012) and availability of data in BRFSS, the following individual risk variables are selected: *sex*, *age* (18+), *Hispanic ethnicity* (Hispanic/Latino or not), *marital status* (currently married or not), *education level* (values increasing from 1 for “no school”, 2 for “elementary”, …to 6 for “college graduate”), *employment status* (employed or not), *income level* (values increasing from 1 for “annual household income <$10,000”, 2 for “$10,000-15,000”, …to 8 for “≥$75,000”), and *smoker* (smoking or not). The 2005 BRFSS data had an overwhelming majority (94.9% or 337,967 respondents) of the samples with a missing value for the race variable (White, Black or African American, Asian, Native Hawaiian or Other Pacific Islander, American Indian or Alaska Native, Other). The remaining samples are considered too small to be reliable for defining the race variable. We had to leave out this important risk factor in the analysis.

3. Spatial patterns of street connectivity

3.1. Street connectivity by geography

Street connectivity is defined as the intersection density per square mile at the census tract, county and state levels as shown in Figures 1, 2 and 3, respectively. The index varies a great deal across census tracts (0-1,850), and its variation is smoothed significantly at the county level (0.01-241.23) and further at the state level (0.11-110.91) (Table 1). The census tract map (Figure 1) highlights that the best street connectivity areas are at the heart of major metropolitan areas and radiant toward suburbia, and the lowest values are in the massive rural areas. The county-level map (Figure 2) shows that the areas of high street connectivity are the highly-urbanized northeast coast, the corridor stretching from the North Carolina Triangle to Atlanta, Florida peninsula, and around major metropolitan areas in the inland and west coast. The state map (Figure 3) largely confirms the observation at the county level with the best connectivity in the northeast states (Rhode Island, Massachusetts, New Jersey, Connecticut, Maryland, etc.), followed by other east coastal states (Pennsylvania, Delaware, North Carolina, Florida, New York, Virginia), declining in general to the interior states and to the west with two exemptions (California with an elevated value of 7.89 above other states in the west and Mississippi with a value of 6.86 below other states east of the Mississippi River).

The following analysis of street connectivity by urbanicity and by socio-demographic factors (i.e., poverty levels and racial-ethnic groups) is based on the census tract level for its finest geographic resolution.

3.2. Street connectivity by urbanicity

As discussed above, visual examination of the street connectivity maps suggests its close association with urbanicity. The disparities of the index across various categories of urbanicity by either the NCHS six-level urban-rural categories or the Census urban-rural areas are reported in Table 2 (2^{nd}-3^{rd} columns). Among the census tracts by the NCHS six categories, the average index value declines monotonically from 127.80 in the highest urban category "large central metro" to 14.44 in the lowest "noncore" (Figure 4). Also between the urban and rural areas classified by the Census, the average index in urban tracts is 116.57, much higher than the average in rural tracts (14.34). In both cases, the differences are statistically significant across the urban-rural categories by analysis of variance (ANOVA). The urban advantage is evident in street connectivity.

3.3. Street connectivity by poverty levels

The street connectivity index by urbanicity is analyzed further by poverty level in order to examine the interaction between urbanicity and poverty levels in association with street connectivity, as reported in Table 2 (4^{th}-9^{th} columns). Census tracts are grouped into three classes according to the poverty levels: (1) *low-poverty* tracts have less than 10 percent residents living in poverty, (2) *medium-poverty* tracts have 10-20 percent residents living in poverty, and (3) *high-poverty* tracts have more than 20 percent residents living in poverty (Zhang et al., 2011). Also shown in Figure 5, the urban advantage in street connectivity is persistent across tracts of low-, medium- or high-poverty levels. Furthermore, the average value of street connectivity index increases from low-poverty to medium-poverty and to high-poverty tracts, and the pattern is consistent across the six NCHS urban-rural categories. The ANOVA indicates that the differences of street connectivity values across both urbanicity and poverty levels are statistically significant.

The ANOVA analysis based on the Census urban-rural classification confirms similar findings: the urban advantage remains, but the trend of larger index values in areas of higher-poverty level is only evident in urban areas but not in rural areas.

3.4. Street connectivity by racial-ethnic groups

The understanding of street connectivity's variation can be further enhanced by examining the differences across racial-ethnic groups. Among the racial-ethnic groups classified by the Census, the American Indian and Alaska Native group and the Native Hawaiian and Other Pacific Islander group have an overall percentage in the U.S. lower than 1%, and are not included in the analysis. The analysis by both the NCHS and the Census urban-rural classifications are conducted. The results based on the Census classification are presented here for its simplicity and a more manageable number of values. The fewer (two instead of six) classes by urbanicity also help us focus more on the variation by racial-ethnic groups.

Using population of each racial-ethnic group as weight, we compute the weighted average of street connectivity for each group across census tracts by urbanicity and by poverty level. For example, the average street connectivity for Black in all urban areas is calculated as the index's weighted average (Black population in each tract as weight) across urban tracts, and so on. The results are presented in Table 3 and also illustrated in Figures 6a and 6b. All racial-ethnic minority groups (Black, Asian, Others and Hispanic) have much higher percentages in urban areas than rural (i.e., 14.5% vs. 7.3 for Black, 4.8% vs. 1.0% for Asian, 6.8% vs. 2.5% for Others, and 15.4% vs. 6.0% for Hispanic). With the exception of Asian, minorities are disproportionally concentrated in high-poverty tracts with the lowest percentages in low-poverty tracts in both urban and rural areas. Similarly, the weighted average of street connectivity increases from low-to medium- and to high-poverty areas across all racial-ethnic groups in urban areas (Figure 6a), but inconsistent in the rural areas (Figure 6b). In urban areas, generally Asian has the highest average index, followed by Black and Others, and then Hispanic, while the white has the lowest average street connectivity, but the order varies slightly across different poverty levels. In particular, Black enjoys a higher weighted index than Hispanic in urban high-poverty areas, whereas Hispanic has a higher weighted index than Black in urban low- or medium-poverty areas. In rural areas (Figure 6b), the pattern is less clear.

In short, all racial-ethnic minority groups have greater street connectivity on average than the white, attributable to their disproportionally high concentrations in high-poverty or urban areas (particularly for Black, Hispanic and Others) that usually have better street connectivity. One interesting observation is the distinctive settlement patterns between Black and Hispanic: in high-poverty areas Black tends to be more present in areas of better street connectivity than Hispanic; and in low- or medium-poverty areas it is the opposite. The pattern is much clearer in urban than in rural areas.

4. The case for population-adjusted street connectivity measure

The above analysis on racial-ethnic disparities in street connectivity is based the average index value weighted by a specific group's population. This approach is adopted in order to account for the unevenness in geographic distribution of various racial-ethnic groups. In this section, the *population-adjusted street connectivity* measure is introduced and its value is assessed in contract to the regular street connectivity index. This is of particular importance when the index is aggregated from a small area unit to a larger area unit.

Denoting the number of intersections in a small area (e.g., tract) i as N_i, and its area size as A_i, the street connectivity index defined as intersection density such as $D_i = N_i / A_i$. For a larger area (e.g., county or state) composed of m small areas (i = 1, 2, …, m), the index is computed such as

$$D=\sum_{i=1}^{m}N_i/\sum_{i=1}^{m}A_i \quad (1)$$

which is the number of intersections per unit area (e.g., square mile) in the larger area.

Denoting the population in the small area i as P_i and others the same as in equation (1), the population-adjusted (weighted) index is defined as

$$D=\sum_{i=1}^{m}[P_i(N_i/A_i)]/\sum_{i=1}^{m}P_i \quad (2)$$

To highlight the difference between the two indices, one may consider computing a similar weighted index but using a different weight variable “area.” The area-weighted index for the larger area is

$$D=\sum_{i=1}^{m}[A_i(N_i/A_i)]/\sum_{i=1}^{m}A_i=\sum_{i=1}^{m}N_i/\sum_{i=1}^{m}A_i$$

which is identical to the index defined in equation (1). In other words, the regular street connectivity index in a larger area is the average index value of small area weighted by their corresponding areas. Due to the discrepancies between area and population across small areas, the two indices aggregated to a larger area differ significantly.

In essence, the street connectivity index is intended to capture a *local* built environment around one's residence. A simple computation based on equation (1) is reasonable for a small area such as census tract, but becomes problematic for a large area such as county and perhaps even misleading at the state level, which is well beyond a person's daily activity space. In contrast, the population-adjusted index defined by equation (2) accounts for the wide variability of built environments across the small areas and integrates them by using their relevant population as a weighting factor. A simple case is used here to highlight the concern of the regular street connectivity measure in a large area. Assume a county is composed of two tracts: an urban tract A with a high index value, occupying a small area size and containing a very large number of residents, and another rural tract B with a low index value, a large area size and a very small number of residents. The resulting regular index in the county would be very low because of the county's large area size, but its population-adjusted index is likely to be close to the value in the urban tract A. Given its population concentration in the urban tract A, the built environment for the county relevant for the health behavior of most people is better captured by the population-adjusted index.

Basic statistics for the new index at the county and state levels are reported in Table 1 (columns 5-6). For the reason explained above, the new index is not available at the census tract level. Clearly, the new index on average is much higher than the regular one (30.11 vs. 11.07 at the county level and 70.39 vs. 12.46 at the state level). The lowest values for both indices at the county level are small (in two different counties in Alaska). At the state level, the new index varies from the lowest 30.56 in Vermont to the highest 140.51 in Massachusetts, whereas the regular index ranges from 0.11 in Alaska to 110.91 in Washington DC. The map of population-adjusted street connectivity at the county level is not shown here as its difference from the regular index (Figure 2) is hard to tell on a national scale. Figure 7 is the map of the new index at the state level.

To assess the value of the new index, a simple ecological correlation analysis is briefly discussed here prior to our multilevel modeling (MLM) in the next section. Figures 8 and 9 show the variations of physical inactivity rate and obesity rate at the state level, respectively. Visual examination of the maps may detect a close correspondence between Figures 8 and 9, to a less degree between Figure 7 and 9 (i.e., a poorer population-adjusted street connectivity in brighter symbol in Figure 7 tends to be associated with a higher obesity rate in darker symbol in Figure 9). Table 4 presents the correlation coefficients between the variables and their corresponding statistical significances. The physical inactivity and obesity rates at the county and state levels are downloaded from the CDC's web site on Diabetes Data & Trends (http://apps.nccd.cdc.gov/ddtstrs/default.aspx), which was based on the same BRFSS data set discussed in section 2.

Four observations can be made from Table 4:

1. The high correlation between physical inactivity and obesity rates at both the county and state levels is no surprise.

2. The correlation between the two street connectivity indices is higher at the county level (0.7166) than the state level. That is to say, the discrepancy between the two is larger when aggregating to a larger area unit, where the regular street connectivity measure is more problematic.
3. The correlation between street connectivity and physical inactivity (or obesity) is stronger when the population-adjusted index is used than the regular index, and the regular index becomes no longer significant in association with physical inactivity or obesity at the state level.
4. The association of street connectivity with physical inactivity is weaker than its association with obesity. Considering the obesogenic theory by linking built environment to obesity through the pathway of physical exercises, this is unexpected. A plausible explanation is provided in the next section when the MLM results are discussed.

Observation (3) suggests: if street connectivity impacts health behavior and outcome as predicted by the obesogenic environment thesis, the population-adjusted index has a clear advantage over the regular index in terms of capturing a relevant built environmental attribute when a large geographic area unit is used. As discussed previously, a small area unit more in line with the range of one's daily activity space is usually a preferred choice in measuring built environment such as the street connectivity. However, due to privacy and other concerns, health data geocoded to small areas are often hard to come by (Wang et al., 2012), and neighborhood effects on health research is typically limited by available place data. In this case, the public-accessible BRFSS data are geocoded to the county level, which makes the population-adjusted street connectivity a preferred choice over the regular one.

5. Multilevel modeling of risks of physical inactivity and obesity

The above correlation analysis might suffer from the ecological fallacy when attempting to infer individual behavior from data of aggregate areal units (Robinson, 1950). A multilevel model (MLM) examines the risk of individual health behavior or outcome by including both individual- and neighborhood-level factors. Specifically, a multilevel logistic model is used for this study as the dependent variable is binary (0, 1) such as an individual being physically inactive (= 1, and 0 otherwise) or being obese (=1, and 0 otherwise). The independent variables include both the individual socio-demographic variables from the BRFSS and the county-level (neighborhood) variables such as urbanicity, street connectivity, racial-ethnic heterogeneity and poverty status, as documented in section 2. This paper focuses on the effects of county-level street connectivity and urbanicity on individual-level risks of physical inactivity and obesity.

5.1. Models using regular vs. population-adjusted street connectivity

We first examine possible impacts of the choice using the regular vs. population-adjusted street connectivity. Table 5 presents the results of six models. The first two models (PI1 and OB1) are unconditional multilevel models (MLMs) without neighborhood covariates and include only individual variables as the baseline models, and the other four MLMs include both individual and county-level variables. Among the four MLMs, the two models on physical inactivity (PI) or obesity (OB) are presented next to each other for easy comparison of possible differences of the two street connectivity measures.

While most of the variables are self-explanatory or clearly defined in section 2, a few points on the variables are made for clarifications. Among the individual variables,

1. each of five variables (i.e., female, Hispanic, married, employed and smoker) is binary with the opposite category defined as the reference category (=0);

2. the variable "age" is continuous (18+), and its squared term (age squared) is added to account for the curvilinear association between age and physical inactivity (or obesity) risks (Wen and Kowaleski-Jones, 2012); and
3. two variables, "education" and "income", have multiple discrete values such as 1-6 and 1-8, respectively.

As explained previously, the individual-level variable of race (Black, Asian, etc.) cannot be included in the models for lack of sample size. Among the county-level variables,

1. variable "racial-ethnic heterogeneity" is the heterogeneity index based on six racial-ethnic groups with values ranging continuously 0-1, and "poverty" is percent residents living in poverty;
2. either regular or population-adjusted street connectivity (not both) is included to compare their possible different effects; and
3. the six NCHS urban-rural categories are adopted here to measure urbanicity with the "core" counties as the reference category.

The next subsection will also use "urban ratio" as an alternative measure for urbanicity for comparison. Findings from Table 5 can be summarized as follows.

1. The effects of most individual variables are consistent across all models unless otherwise pointed out. Marital status is not significant in any models. Higher education, being employed, and higher income are associated with lower risks of physical inactivity (PI) and obesity (OB). Being older initially increases both the risks (given the positive and statistically significant coefficient for "age"), but the trends are reversed after passing a certain age (given the negative and statistically significant coefficient for "age squared"). Females and smokers have a higher risk of being inactive but a lower risk of obesity, and being a Hispanic is associated with a higher risk of being inactive but not with the risk of obesity. The paradox is perhaps understandable for smokers as smoking might suppress appetite and help weight control (Flegal, 2007) even it is linked to physical inactivity because unhealthy lifestyles often go hand in hand in a person; but the contradictory results for females and Hispanics beg for explanations. Lacking any scientific evidence of unique biological processes in these two demographic groups, one plausible reason for these discrepancies is the measurement gap in reliability between PI and OB. PI is based on a subjective assessment and a loose definition of leisure-time physical activity in the last 30 days by oneself, and OB is based on BMI which is based on more easily remembered and objectively assessed height and weight. The issue of inconsistency between PI and OB is observed in several scenarios, including the weaker association of street connectivity with PI than with OB in the ecological correlation analysis as reported in the previous section.
2. Among the county-level variables, poverty is positively associated with risks of PI and OB in all four MLM models. Racial-ethnic heterogeneity is positively associated with PI only in model PI3 at the significance level 0.05, contradictory to an existing finding at the census tract level (Wen and Kowaleski-Jones, 2012). The association of regular street connectivity index with PI is statistically significant but with the unexpected positive sign. The puzzling finding raises the question of validity of the regular street connectivity at the county level (as demonstrated in the previous section) or reliability of the PI measure (as discussed above). On the other side, a higher population-adjusted index is associated with a lower risk of obesity, which supports the obesogenic built environment thesis.

3. Due to the concerns raised above, our discussion on the effect of NCHS urbanicity measure focuses on model OB3. It is the two categories “large fringe metro” and “medium metro” in the middle of the urban-rural spectrum that are associated with elevated risk of obesity. This will be further elaborated in the following subsection when an alternative urbanicity measure is used.

5.2. Models using alternative urbanicity measure

Table 6 presents the MLM results of four models focusing on the impact of using “urban ratio” as an alternative measure for urbanicity. For each county, its urbanicity is defined as a continuous urbanization ratio, i.e., population of urban tracts out of the total population in the county. As the above finding (3) suggests, the impact of urbanicity may be curvilinear, and thus the term “urban ratio squared” is added.

The findings are largely consistent with those based on the NCHS urban-rural categories reported in Table 5. The signs and statistical significance levels are identical for all the individual variables as well as the county-level poverty and street connectivity in Table 5 vs. 6. Racial-ethnic heterogeneity becomes significant in model PI4 with comparison to its non-significance in its counterpart model PI2. The models once again confirm the critique of the regular street connectivity and our lack of confidence in the PI measure. Therefore, the discussion here focuses on Model OB5. The curvilinear association of urbanicity is again confirmed by the positive sign of “urban ratio” and the negative sign of its squared term (both statistically significant). In other words, after controlling for other factors, higher urbanicity is initially associated with increased risk of obesity, but then the trend is reversed toward the highest urbanicity. This complexity leads us to conduct more in-depth analysis of the role of urbanicity in its impact on obesity.

5.3. Models by distinctive urban-rural categories

In order to examine the complexity of urbanicity's impacts, the MLM analysis is conducted on the subsets of data by various urban-rural categories. While using the same variables included in the aforementioned analysis, obviously the urbanicity variables are removed. For the reason discussed above, only the models on obesity using the population-adjusted street connectivity are presented.

Table 7 shows the results by the six NCHS urban-rural county categories. Several interesting observations, particularly those different from the nationwide models, are highlighted below.

1. Among the individual variables, females are now associated with elevated obesity risk in large central metro, but reduced risk in large fringe metro, and not significant in four other categories of less urban settings. Being married is now associated with reduced risk in large central metro, but not significant in other areas. Being employed is no longer significant in the more-urbanized large central metro and large fringe metro.

2. Higher racial-ethnic heterogeneity becomes significantly associated with lower risk of obesity in large central metro. Poverty remains highly significant with the only exception in small metro.

3. Better population-adjusted street connectivity is linked to reduced obesity risk only in somehow the middle pack “large fringe metro”.

Table 8 presented the results by different urban ratio ranges in counties. After numerous experiments of various schemes by examining the correspondence between the grouping outcomes and our commonly recognized geographic areas such as “central city”, “inner suburb”, “metro fringe or edge cities”, etc., this research adopts five groups: (1) completely urban county (urban ratio > 0.99), (2) highly-urbanized county (0.90 < urban ratio ≤ 0.99), (3) mostly-urbanized county (0.50 < urban ratio ≤ 0.90), (4) marginally-urbanized county (0.01 < urban ratio ≤ 0.50), and (5) complete rural county (urban ratio ≤ 0.01). Findings are highlighted as follows.

1. Females are similarly associated with elevated obesity risk in completely urban counties, but reduced risk in highly-urbanized or mostly-urbanized counties, and not significant in four other categories of less urban settings. Being married is also similarly associated with reduced risk in completely urban or highly-urbanized counties. Being employed is not significant in the more urbanized areas (such as completely urban or highly-urbanized) as also reported in Table 7, but also not significant in the other end of urban-rural spectrum such as completely rural.

2. Similarly to Table 7, higher racial-ethnic heterogeneity is only significantly associated with reduced risk of obesity in completely urban counties. Poverty is highly significant across all areas with no exception.

3. Similarly, higher population-adjusted street connectivity is associated with lower obesity risk only in highly-urbanized counties.

The variation of association of individual variables with obesity risk across areas of different urbanization levels suggests the added value of research in different geographic settings and from a diversity of study areas. Most importantly, the positive impact of racial-ethnic heterogeneity only occurs in areas of the highest urbanicity (say central cities), and the positive influence of street connectivity is limited to the more but not the mostly urbanized areas. Both are significant findings as they help us understand the inconsistency of the impact of racial-ethnic heterogeneity in different studies, and why inner city neighborhoods are usually blessed with better street connectivity but plagued with higher rates of obesity (Lopez and Hynes, 2006). This also suggests that policy initiatives that have successfully encouraged physical activity and reduced prevalence of obesity in one geographic environment (e.g., suburb) or for one demographic group (e.g., middle class) may not be as effective in a different environment (e.g., inner city) or a different group (e.g., low-income residents) (Lopez and Hynes, 2006). There are no one-size-fit-all models in translating amenable built environment to obesity control. It is highly desirable for policy makers to design strategies “customized” to specific geographic areas and for particular population groups.

6. Concluding comments

This research uses street connectivity, defined as the number of (3-way or more) intersections per area unit, as a proxy measure for walkability in a neighborhood, and then examines its association with physical inactivity and obesity in the U.S. while controlling for various individual- and county-level socio-demographic variables. The focus of the investigation is on how the relationship varies by different urbanization levels. The analysis of spatial variation of street connectivity index at the census tract level indicates that the index value increases with the level of urbanicity and also with the poverty level; all racial-ethnic minority groups have higher street connectivity on average than the white, attributable to their disproportionally concentrations in high-poverty areas (particularly for Black, Hispanic and Others). The regular measure of street connectivity is acceptable for a small area such as census tract, but becomes problematic for a county or larger area due to likely concentration of population in limited space within the larger area. It is argued that the population-adjusted street connectivity, using the relevant population as a weighting factor, is a better measure. This proposition is also further supported by subsequent MLM risk analysis of health behavior (physical inactivity or PI) and outcome (obesity or OB) as revealed in some counterintuitive effects of street connectivity, had the regular index were used. Based on the BRFSS data, the MLM regression results indicate that individual variables such as age, marital status, education attainment level, employment status, and income are generally consistent between their impacts on PI and OB. However, the inconsistency between them for the variables such as sex and Hispanic ethnicity suggests possible gaps in data reliability of self-reported PI vs. more objective OB, which is further supported by some counterintuitive effects of certain county-level variables.

Our most important findings are generated from analysis of data subsets by various urbanicity levels, either based on the NCHS six urban-rural categories or the five urban ratio ranges. The linkage of individual variables to obesity risk varies across areas of different urbanization levels, so do the influences of racial-ethnic heterogeneity and street connectivity at the county level. Racial-ethnic heterogeneity tends to be linked to lower risk of obesity, but the association is only statistically significant in areas of the highest urbanicity. The positive influence of street connectivity on obesity control is limited to the more but not the mostly urbanized areas. This line of research demonstrates the value of obesogenic environment research in different geographic settings, helps us reconcile and synthesize some seemingly contradictory results reported in different studies, and also promotes that effective policies need to be highly sensitive to the diversity of demographic groups and geographically adaptable.

As pointed out earlier in the paper, ideally built environments need to be defined at the spatial scale that is generally in line with our daily activity space. Two obstacles make the pursuit of this goal challenging for a national study such as ours: availability of health data in small geographic areas, and data processing and measurements of multidimensional built environments. Future work along either direction or both will certainly expand and improve this research. Another limitation of our analysis is the lack of sufficient observations with clear racial identification and the lack of objectively measured physical activity variables, which would help us better untangle the pathway from built environments to physical activity and then to obesity.

Acknowledgments

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Highlights

- The BRFSS data is used to examine the geographic variations of obesity in the U.S.
- "Population-adjusted street connectivity" is a better measure than the regular one.
- Influences of individual and county variables vary across areas of urbanization levels.
- Positive influence of street connectivity is limited to the moderately urbanized areas.
- Obesogenic policies need to be geographically adaptable.

Figure 1.
Street connectivity by census tract in the U.S.

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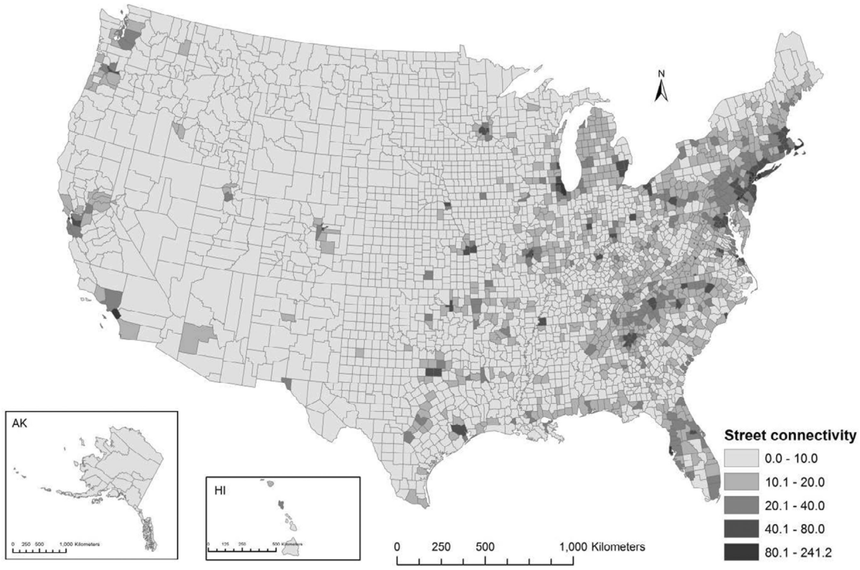

Figure 2.
Street connectivity by county in the U.S.

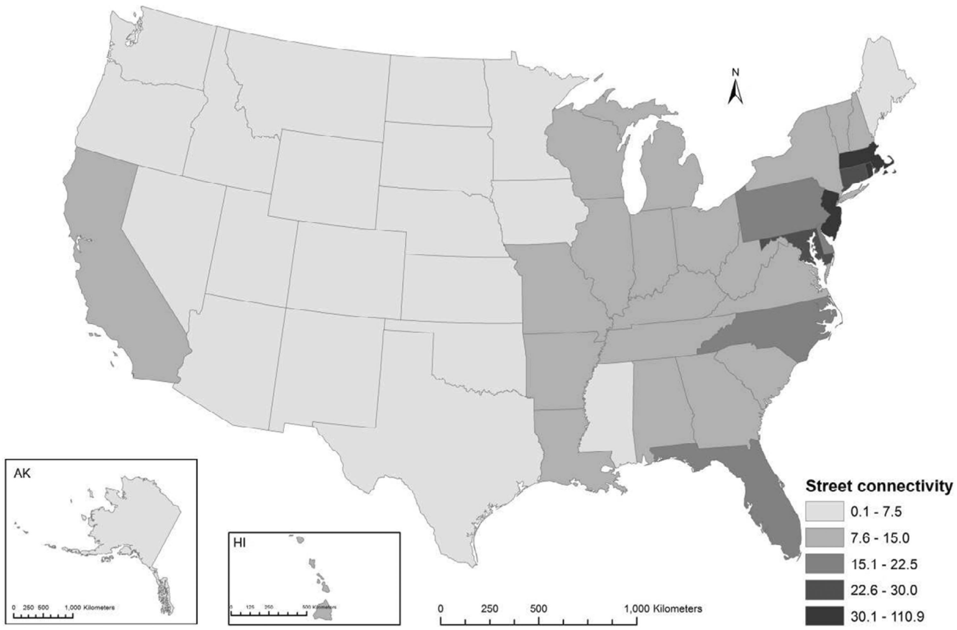

Figure 3.
Street connectivity by state in the U.S.

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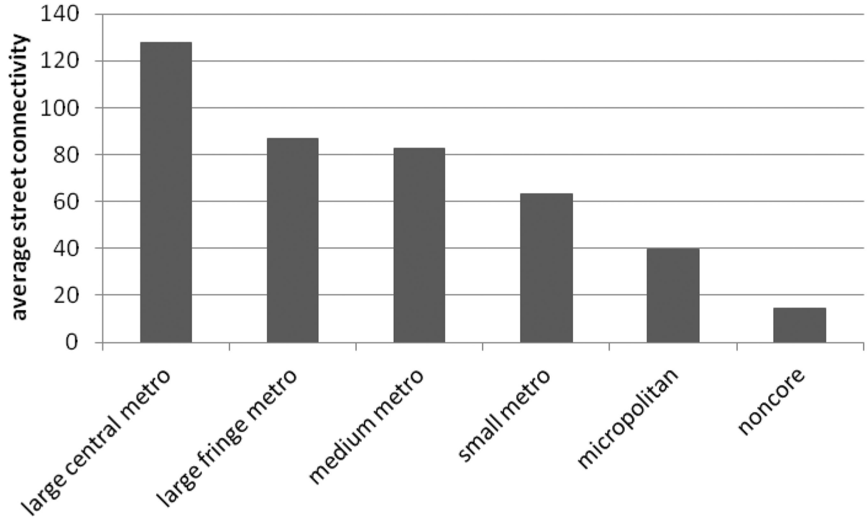


Figure 4. Street connectivity by NCHS urban-rural classification

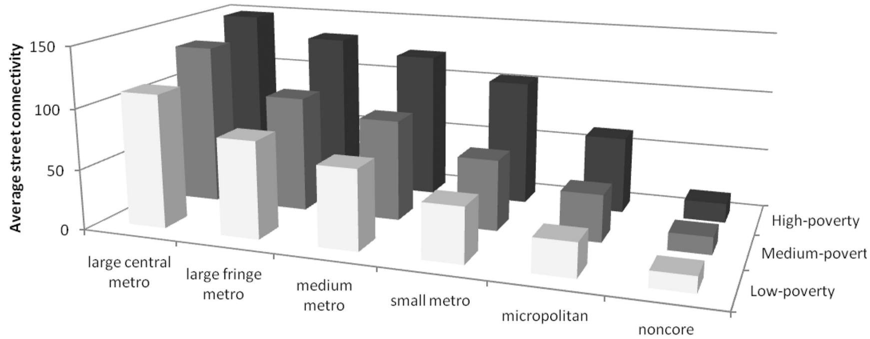
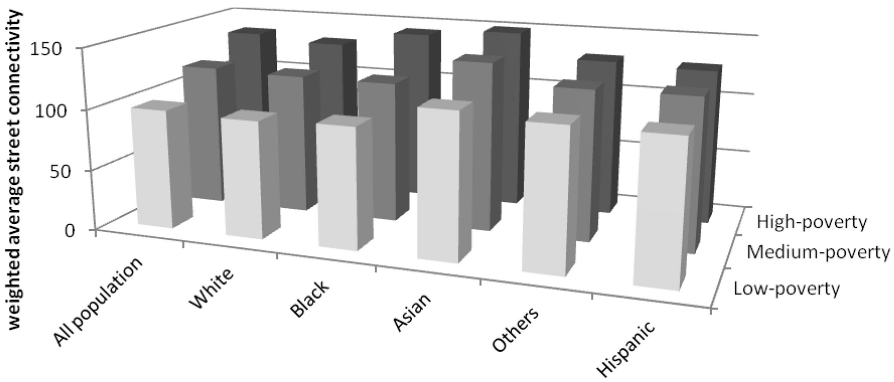


Figure 5. Street connectivity by urbanicity and by poverty level



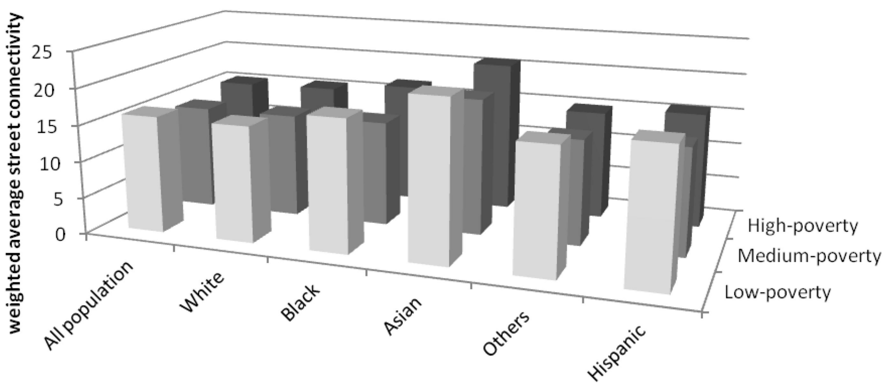


Figure 6. Figure 6a. Average street connectivity by racial-ethnic group in urban areas
Figure 6b. Average street connectivity by racial-ethnic group in rural areas

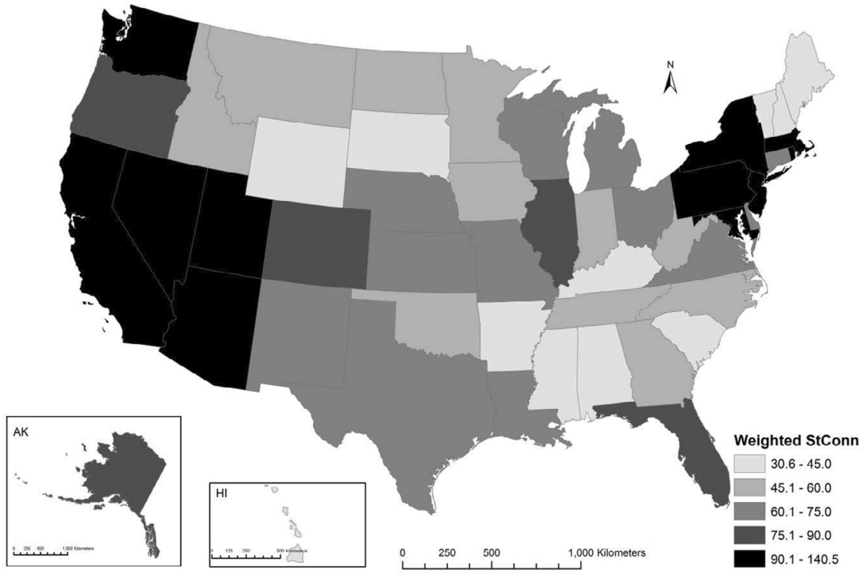


Figure 7.
Population-adjusted street connectivity by state in the U.S.

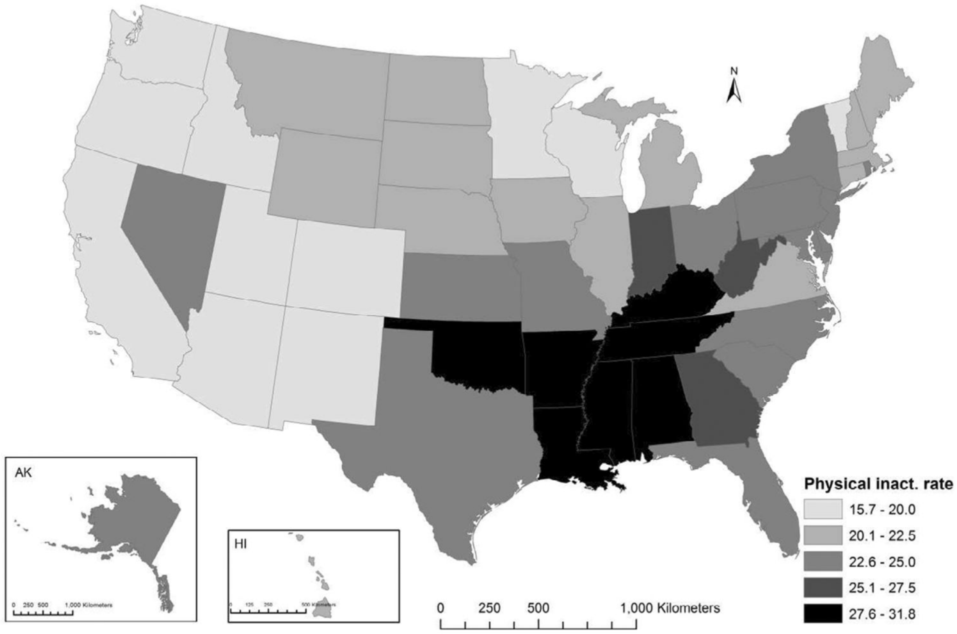


Figure 8. Physical inactivity rate by state in the U.S. (2005)

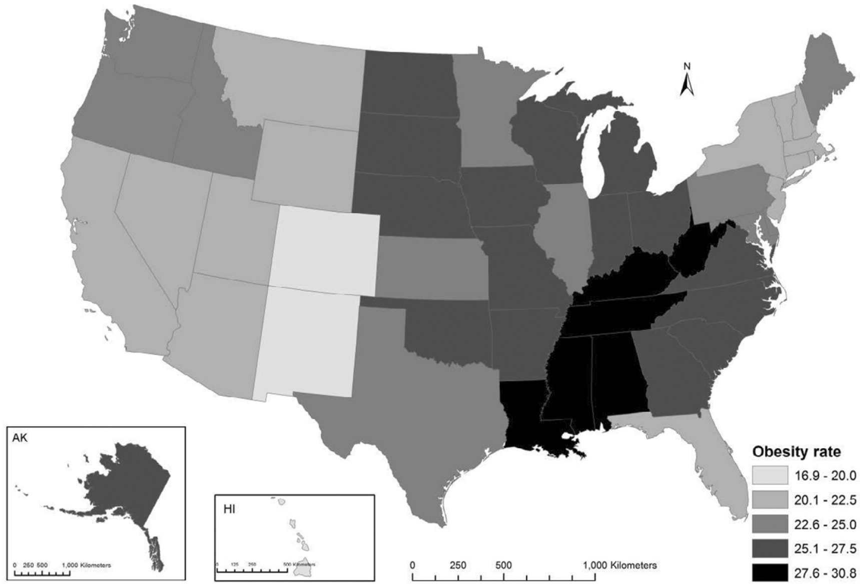


Figure 9. Obesity rate by state in the U.S. (2005)

Table 1

Basic statistics for street connectivity and population-adjusted street connectivity

	Street connectivity			Population-adjusted street connectivity[2]	
	Census tract	**County**	**State[1]**	**County**	**State[1]**
No. observations	65,345	3,141	51	3,141	51
Minimum	0	0.01	0.11	0.01	30.56
Maximum	1,850.00	241.23	110.91	325.58	140.51
Mean	85.06	11.07	12.46	30.11	70.39
Standard deviation	80.01	15.87	16.64	31.85	29.07

Note:

[1] including Washington DC;

[2] no population-adjusted index is available at the census tract level

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Table 2

Street connectivity index by urbanicity and by poverty level

Urban-rural category	all		Low-poverty		Medium-poverty		High-poverty	
	No. tracts	average index	No. tracts	average index	No. tracts	average index	No. tracts	average index
NCHS classification								
large central metro	20,095	127.80	9,057	110.68	5,046	133.69	5,992	148.72
large fringe metro	13,733	86.91	10,236	80.22	2,491	96.11	1,006	132.25
medium metro	12,610	82.41	6,665	66.06	3,280	83.73	2,665	121.66
small metro	6,196	63.09	2,732	45.43	2,075	58.67	1,389	104.41
micropolitan	6,803	39.75	2,535	27.86	2,907	38.94	1,361	63.62
noncore	5,511	14.44	1,336	13.05	2,872	14.40	1,303	15.96
Census classification								
urban	45,207	116.57	23,063	101.61	11,122	122.51	11,022	141.87
rural	20,138	14.34	9,859	14.92	7,550	13.58	2,729	14.36

Table 3

Average street connectivity index by racial-ethnic groups

	all		Low-poverty		Medium-poverty		High-poverty	
	% population	**average index**	**% population**	**average index**	**% population**	**average index**	**% population**	**average index**
Urban Areas[1]								
All population	100.0[2]	111.37	100.0[2]	98.65	100.0[2]	118.30	100.0[2]	135.87
White	70.3	105.63	82.8	96.60	65.9	116.31	43.3	130.74
Black	14.5	124.94	6.7	98.97	16.0	116.13	32.8	143.73
Asian	4.8	128.99	5.0	117.90	5.0	138.63	4.1	149.83
Others	6.8	124.42	2.7	113.79	8.7	123.06	14.8	130.40
Hispanic	15.4	122.65	7.6	113.03	19.6	123.66	30.7	127.99
Rural Areas[1]								
All population	100.0[3]	15.32	100.0[3]	16.05	100.0[3]	14.30	100.0[3]	15.36
White	86.2	15.26	92.1	15.88	85.6	14.27	63.8	15.56
Black	7.3	16.06	3.2	18.04	8.0	14.39	21.8	16.68
Asian	1.0	20.96	1.3	21.81	0.6	18.65	0.8	20.79
Others	2.5	15.29	1.4	17.00	2.8	14.38	6.1	14.95
Hispanic	6.0	16.14	3.7	18.29	6.1	14.61	14.8	15.82

Notes:

[1]The distribution of total population is 69.5% in urban areas and 30.5% in rural areas;

[2]In urban areas, the distribution of population is 54.1% in low-poverty tracts, 24.9% in medium-poverty tracts, and 21.0% in high-poverty tracts;

[3]In rural areas, the distribution of population is 50.6% in low-poverty tracts, 36.9% in medium-poverty tracts, and 12.5% in high-poverty tracts.

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Table 4

Correlations between street connectivity, population-adjusted street connectivity, physical inactivity and obesity

	County level (n=3,141)			State level (n=51)		
	population-adjusted street connectivity	**physical inactivity rate**	**Obesity rate**	**population-adjusted street connectivity**	**physical inactivity rate**	**Obesity rate**
street connectivity	0.7166***	−0.0785***	−0.1445***	0.5511***	0.0399	−0.1958
population-adjusted street connectivity		−0.2205***	−0.2366***		−0.2617	−0.5267***
physical inactivity rate			0.7110***			0.7446***

Note:

*** statistically significant at 0.001

Table 5

Multilevel logistic models for risks of physical inactivity (PI) and obesity (OB) using regular vs. population-adjusted street connectivity

	Model PI1	Model OB1	Model PI2	Model PI3	Model OB2	Model OB3
Intercept	0.48650***	0.10330***	0.45160***	0.45250***	0.07107***	0.07197***
Individual-level variables						
Female	0.01514***	−0.00569**	0.01508***	0.01509***	−0.00567**	−0.00568**
Age (18+)	0.00609***	0.01918***	0.00607***	0.00607***	0.01914***	0.01913***
Age^2	−0.00004***	−0.00019***	−0.00004***	−0.00004***	−0.00019***	−0.00019***
Hispanic	0.03282***	−0.00044	0.03058***	0.03043***	−0.00174	−0.00142
Married	0.00058	−0.00210	0.00119	0.00100	−0.00262	−0.00268
Education (1-6)	−0.05854***	−0.02618***	−0.05869***	−0.05864***	−0.02606***	−0.02601***
Employed	−0.00682***	−0.01193***	−0.00648**	−0.00649**	−0.01189***	−0.01189***
Income (1-8)	−0.03131***	−0.01764***	−0.03133***	−0.03131***	−0.01721***	−0.01720***
Smoker	0.01591***	−0.03759***	0.01590***	0.01586***	−0.03773***	−0.03773***
County-level variables						
Racial-ethnic heterogeneity			0.01664	0.02146*	−0.00753	−0.00641
Poverty			0.00176***	0.00174***	0.00253***	0.00252***
Street connectivity			0.00025**		−0.00011	
Population-adjusted street connectivity				−0.00003		−0.00012**
large central metro			−0.00560	0.01101	−0.00656	0.00018
large fringe metro			0.01921**	0.02642***	0.01119	0.01556*
medium metro			0.00757	0.01189	0.00668	0.01151*
small metro			−0.00419	−0.00186	0.00426	0.00872
micropolitan			−0.00179	−0.00068	−0.00191	0.00056
No. observations	251,247	251,247	251,247	251,247	251,247	251,247
AIC	263,174.5	288,920.8	263,110.6	263,119.2	288,845.8	288,841.2

Note: Models PI1, PI2 and PI3 for physical inactivity, and models OB1, OB2 and OB3 for obesity;

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*** statistically significant at 0.001,

** statistically significant at 0.01,

* statistically significant at 0.05

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Table 6

Multilevel logistic models for risks of physical inactivity (PI) and obesity (OB) using urban ratio as urbanicity measure

	Model PI4	Model PI5	Model OB4	Model OB5
Intercept	0.45580***	0.45920***	0.07106***	0.07172***
Individual-level variables				
Female	0.01511***	0.01510***	−0.00565**	−0.00566**
Age (18+)	0.00608***	0.00609***	0.01915***	0.01914***
Age squared	−0.00004***	−0.00004***	−0.00019***	−0.00019***
Hispanic	0.03089***	0.03065***	−0.00163	−0.00151
Married	0.00112	0.00092	−0.00267	−0.00274
Education (1-6)	−0.05867***	−0.05866***	−0.02605***	−0.02604***
Employed	−0.00661**	−0.00664**	−0.01197***	−0.01196***
Income (1-8)	−0.03126***	−0.03124***	−0.01716***	−0.01716***
Smoker	0.01590***	0.01585***	−0.03772***	−0.03773***
County-level variables				
Racial-ethnic heterogeneity	0.02169*	0.02352*	−0.00450	−0.00647
Poverty	0.00118***	0.00124***	0.00219***	0.00229***
Street connectivity	0.00033***		−0.00005	
Population-adjusted street connectivity		−0.00008		−0.00016**
Urban ratio	0.02880	0.01341	0.04220*	0.05215**
Urban ratio squared	−0.03212	0.00756	−0.04544*	−0.03987*
No. observations	251,247	251,247	251,247	251,247
AIC	263,127.8	263,140.2	288,846.1	288,839.3

Note: Models PI4 and PI5 for physical inactivity, and models OB4 and OB5 for obesity;

*** statistically significant at 0.001,

** statistically significant at 0.01,

* statistically significant at 0.05

Table 7

Multilevel logistic models for risk of obesity by urbanicity (NCHS category)

	large central metro	large fringe metro	medium metro	small metro	micropolitan	noncore
Intercept	0.13160***	0.08514***	0.07028***	0.11150***	0.07825***	0.03494***
Individual-level variables						
Female	0.01269***	−0.02052***	−0.00589	−0.00189	−0.00567	−0.01093
Age (18+)	0.01964***	0.01854***	0.01928***	0.01923***	0.01860***	0.01915***
Age squared	−0.00019***	−0.00018***	−0.00019***	−0.00020***	−0.00019***	−0.00020***
Hispanic	−0.01472	0.01099	−0.00331	−0.02153	0.01466	0.01385
Married	−0.01754***	−0.00201	−0.00419	−0.00178	0.00585	0.00684
Education (1-6)	−0.03954***	−0.03064***	−0.02348***	−0.02442***	−0.02005***	−0.01350***
Employed	−0.00332	−0.00579	−0.01267**	−0.01956***	−0.01648**	−0.01975**
Income (1-8)	−0.01604***	−0.01492***	−0.01755***	−0.01799***	−0.01742***	−0.01974***
Smoker	−0.02588***	−0.03091***	−0.03991***	−0.04086***	−0.04319***	−0.04919***
County-level variables						
Racial-ethnic heterogeneity	−0.10620**	0.01473	−0.01047	0.03866	−0.01024	0.01088
Poverty	0.00299**	0.00465***	0.00296***	−0.00054	0.00200**	0.00295***
Population-adjusted street connectivity	−0.00007	−0.00027**	−0.00010	−0.00011	−0.00004	0.00018
No. observations	41,127	50,270	55,007	35,518	46,053	23,272
AIC	5,503.7	6,264.8	3,039.3	1,623.9	4,042.1	8,148.2

Note:

*** statistically significant at 0.001,

** statistically significant at 0.01,

* statistically significant at 0.05

Table 8

Multilevel logistic models for risk of obesity by urbanicity (urban ratio range)

	Completely urban (0.99-1.00)[1]	Highly urban (0.90-0.99)	Mostly urban (0.50-0.89)	Marginally urban (0.01-0.49)	Completely rural (0-0.01)
Intercept	0.13670***	0.13880***	0.07865***	0.09523***	0.02024***
Individual-level variables					
Female	0.03315***	−0.00856*	−0.01254***	−0.00184	−0.01152
Age (18+)	0.01993***	0.01885***	0.01954***	0.01828***	0.01918***
Age squared	−0.00019***	−0.00019***	−0.00019***	−0.00019***	−0.00020***
Hispanic	−0.01487	−0.00784	−0.00334	0.00845	0.02436
Married	−0.02567***	−0.01184**	−0.00347	0.00734	0.00398
Education (1-6)	−0.04797***	−0.03150***	−0.02752***	−0.01900***	−0.01371***
Employed	0.00172	−0.00625	−0.01091**	−0.01879***	−0.01924
Income (1-8)	−0.01382***	−0.01797***	−0.01663***	−0.01761***	−0.01881***
Smoker	−0.01065	−0.03183***	−0.03556***	−0.04628***	−0.04918***
County-level variables					
Racial-ethnic heterogeneity	−0.14690*	−0.04767	0.00090	0.00828	0.00300
Poverty	0.00275*	0.00423***	0.00145**	0.00179***	0.00327***
Population-adjusted street connectivity	0.00002	−0.00039***	−0.00006	−0.00014	0.00021
No. observations	17,428	43,763	99,711	68,500	21,846
AIC	9,038.2	7,804.3	4,118.4	1,346.4	6,136.2

Note:

[1] range of urban ratio in parenthesis;

*** statistically significant at 0.001,

** statistically significant at 0.01,

* statistically significant at 0.05