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# Built environment and obesity by urbanicity in the U.S.

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ABSTRACT

Based on the data from the Behavioral Risk Factor Surveillance System 2012, this study examines the association of neighborhood built environments with individual physical inactivity and obesity in the U. S. Multilevel modeling is used to control for the effects of individual socio-demographic characteristics. Neighborhood variables include built environment, poverty level and urbanicity at the county level. Among the built environment variables, a poorer street connectivity and a more prominent presence of fast-food restaurants are associated with a higher obesity risk (especially for areas of certain urbanicity levels). Analysis of data subsets divided by areas of different urbanicity levels and by gender reveals the variability of effects of independent variables, more so for the neighborhood variables than individual variables. This implies that some obesity risk factors are geographically specific and vary between men and women. The results lend support to the role of built environment in influencing people's health behavior and outcome, and promote public policies that need to be geographically adaptable and sensitive to the diversity of demographic groups.



## 1. Introduction

Obesity is a major risk factor for heart disease, diabetes, stroke, depression, sleep apnea, osteoarthritis, and some cancers (Ahima and Lazar, 2013). Regular leisure time physical activity can help control weight and improve health. However, less than half (48.4%) of adults of 18 years of age and over met the Physical Activity Guidelines for aerobic physical activity in 2011 (National Center for Health Statistics, 2013), and more than one-third (34.9%) adults were obese in 2011–2012 (Ogden et al., 2013). Medical costs for obese people are substantially higher than those of normal weight (Finkelstein et al., 2009). In the U.S., obesity prevalence rates vary a great deal across states, ranging from 21.3% in Colorado to 35.1% in Mississippi and West Virginia in 2013 (CDC, 2015), and even more among smaller geographic areas such as counties.

The cause of obesity arises from a positive energy balance over time. Energy intake is basically from food and drink, and energy consumption is related to individual's physical activity. An individual with a high level of consumption of fast foods and sugar-sweetened beverages (Pereira et al., 2005; Schulze et al., 2004) and a low level of physical activity (Koh-Banerjee et al., 2003) has a high risk of obesity. The obesogenic environment thesis suggests that disparities of obesity prevalence are partially attributable to differentiated exposure to a healthy food environment that promotes healthier dietary choices and built environments that encourage physical activities (Swinburn et al., 1999; Powell et al., 2010). Built environment refers to human-made resources and infrastructure designed to support human activity, such as buildings, roads, parks, restaurants, grocery stores and other amenities, as compared with natural environment (Davis et al., 2005).

There is a large body of literature examining the relationship between built environment (including factors such as access to healthy food, distance to nearby amenities, walkable urban form and neighborhood safety) and obesity (Feng et al., 2010; Papas et al., 2007, O Ferdinand et al., 2012; Durand et al., 2011). However, due to challenges of data requirements and computational complexity for measuring obesogenic built environments, few studies have examined obesity in the U.S. at a national scale until recently. Among the recent national studies, Wen and Kowaleski-Jones (2012) and Wen et al. (2013) considered two major built environment factors such as distance to the nearest parks and street connectivity, and Wang et al. (2013) focused on the role of population-adjusted street connectivity. This nationwide analysis considers two built environment factors that have not been included in previous studies of such a scale, namely walk score and the ratio of fast-food to full-service restaurants.

Furthermore, recent literature suggests that the linkage between built environment and physical activity (and thus obesity) varies in different geographic settings such as urban versus rural areas (Monnat and Pickett, 2011; Ding and Gebel, 2012;

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Ewing et al., 2014). Urban neighborhoods have more sidewalks, mixed land uses, better street connectivity and more playgrounds than rural areas (Lopez and Hyness, 2006). Within urban area, children in inner city neighborhoods are engaged in less physical activity than those in suburban areas (Weir et al., 2006). More anxiety about neighborhood safety may deter physical activity and help explain a higher obesity rate in inner city areas (Felton et al., 2002, Wilson et al., 2004). A recent study shows that better street connectivity reduces obesity risk only in suburbia of large metropolitan areas, not urban areas or smaller metropolitan or rural areas (Wang et al., 2013). Some recent studies emphasize the spatial heterogeneity in the association of community environment and obesity risk (Chalkias et al., 2013; Chi et al., 2013; Slack et al., 2014). This research examines the association between built environment and obesity with an emphasis on the likely variability across different levels of urbanicity.

On the methodological front, multilevel models are common in public health research. Individual behaviors such as eating habit and physical activity are influenced by socio-environmental factors including built environment (Huang et al., 2009). This study uses the multilevel modeling approach to analyze the influence of built environment on adult physical inactivity and obesity in the U.S. while controlling for individual attributes (e.g., race, age, gender, marital status, education attainment, employment status, income, and whether an individual smokes). The focus of our work is on possible different impacts of built environment factors in areas at various urbanicity levels and between males and females.

## 2. Data sources and variable definitions

### 2.1. Individual variables from BRFSS

The Behavioral Risk Factor Surveillance System (BRFSS) is an annual health-related telephone survey system for tracking risk behaviors, health conditions, and use of preventive services in the U.S. since 1984. Since 2011, the survey data added cell-phone-only respondents to landline respondents that were covered by the survey data for 1984–2010. We used the 2012 BRFSS data####set (http://www.cdc.gov/brfss/annual_data/annual_2012.html), the most recent one available at the time this research was conducted. The data set contains a large volume of individual data geocoded to county. After eliminating the records with missing values for variables used in this study, the study area includes 328,156 observations from the BRFSS in the 48 conterminous states and Washington D.C.[1]

The BRFSS data contains two dependent variables used in this research: *physical inactivity* and *obesity*. Physical inactivity refers to no leisure-time physical activity or exercise in the last month as reported. Individuals with BMI $\geq 30$ were considered obese. They are coded as binary, i.e., 1 for no physical activity and 0 otherwise, 1 for being obese and 0 otherwise.

Individual independent variables are also from the BRFSS data set (Table 1). In addition to *age* (18+), "age squared" is added to check the curvilinear impact of age in the multilevel models. *Race-ethnicity* is categorical and includes non-Hispanic Black, Hispanic, and others with non-Hispanic White as the reference category. Binary variables include *sex* (female as the reference category), *employment status* (not employed as the reference category), *marital status* (currently not married as the reference category), and *smoker* (non-smoker as the reference category). *Education* and *income* are ordinal such as: education level = 1–4, income level = 1–5 (Table 1). For simplicity, both education and income are coded numerical in the multilevel models; and the results are consistent with those from models coding them as categorical dummy variables.

[1] The research is part of a larger project which has a component on examining spatial non-stationarity. Hawaii and Alaska are excluded for that component because of their non-contiguity with the conterminous U.S. For consistency, they are also excluded from this research.

### 2.2. Rates of physical inactivity and obesity for various socio-demographic groups

Table 1 summarizes the sample distributions across the individual socio-demographic variables reported in the 2012 BRFSS. The overall physical inactivity rate is 23.49%, and the overall obesity rate is 29.25%. Among the four major racial-ethnic groups, Non-Hispanic Whites account for the vast majority (80%), both physical inactivity rate (PIR) and obesity rate (OBR) for non-Hispanic Blacks or Hispanics are higher than the averages and more so for non-Hispanic Blacks, and the PIR for others is slightly higher than the average but the OBR for others is slightly lower than the average. The PIR increases with age, so does the OBR till the 54–65 age group but drops in the 65+ age group. The latter suggests a curvilinear association of age with obesity. The PIR for women is higher than men, but their OBRs are about the same. Married people have a lower PIR and a lower OBR than their unmarried counterparts. Both the PIR and OBR drop with increasing educational attainment. Employed people have a lower PIR than their unemployed counterparts, but their OBRs are very close. Both the PIR and OBR drop with increasing income, similar to the influence of educational attainment. Smokers have a higher PIR but a lower OBR.

For the most part, the trend for the PIR is consistent with that of OBR. However, they also differ in several cases such as the minor discrepancy in their associations with age, gaps in their associations with marital status and employment status, and the major contrast in the associations with smokers/non-smokers. The above observations do not consider the joint effects of multiple variables let alone the neighborhood effects, and thus are preliminary.

### 2.3. Neighborhood variables at the county level from Census and other sources

All neighborhood variables are defined at the county level as county is the smallest geographic unit identified in the BRFSS dataset. Guided by the literature, two social-demographic variables are included: poverty rate and race heterogeneity, both derived from the Census 2010 data. *Poverty rate* is the estimated percent of people of all ages in poverty. *Racial-ethnic heterogeneity* reflects the racial-ethnic composition defined as $1-\sum p_i^2$, where $p_i$ is the fraction of the population in a given group (Sampson and Groves, 1989). This study includes six racial-ethnic groups (Non-Hispanic Whites, Blacks, Asians/Pacific Islanders, Hispanics, American Indians/Alaska Natives, and others) for calculating the index in a county. The heterogeneity index ranges between 0 and 1. If the value equals 0, it means that there is only one racial/ethnic group in the unit; while a value approaching 1 reflects a maximum heterogeneity. A lower heterogeneity index (e.g., dominated by a disadvantaged minority group) may be tied to a lower level of social capital suggested by the social disorganization theory (Sampson and Groves, 1989) and discourages physical activity (and thus a higher obesity risk) in a community. It may also work in a reverse direction as some minorities (e.g., Blacks and Hispanics) are reported to experience higher obesity rates and thus a neighborhood with above-average representations of these minorities could have a relatively high heterogeneity index. The index is used in several studies of community environment and obesity risk (Wen and Kowaleski-Jones, 2012; Wang et al., 2013; Xu et al., Forthcoming).