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Regional Disparities in Obesity Prevalence in the United States: A Spatial Regime Analysis

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Abstract

Objective—Significant clusters of high and low obesity counties have been demonstrated across the United States (U.S.). This study examined regional disparities in obesity prevalence and differences in the related structural characteristics across regions of the U.S.

Design and Methods—Drawing on model-based estimates from the Centers for Disease Control and Prevention, regional differences in county-level adult obesity prevalence (percent of the adult population [≥ 20 years] that was obese [BMI≥30kg/m^2] within a county, 2009) were assessed with a LISA (Local Indicators of Spatial Association) analysis to identify geographic concentrations of high and low obesity levels. We utilized regional regime analysis to identify factors that were differentially associated with obesity prevalence between regions of the U.S.

Results—High and low obesity county clusters and the effect of a number of county-level characteristics on obesity prevalence differed significantly by region. These included the positive effect of African American populations in the South, the negative effect of Hispanic populations in the Northeast, and the positive effect of unemployed workers in the Midwest and West.

Conclusions—Our findings suggest the need for public health policies and interventions that account for different regional characteristics underlying obesity prevalence variation across the U.S.

Keywords

obesity prevalence; regional disparities; spatial regime

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Introduction

Public health research has shown that the prevalence of obesity and related chronic diseases is not evenly distributed across the United States (U.S.), but instead tend to be geographically patterned.[1-5] Results from one recent study suggested that the South was particularly notable for clusters of high obesity counties, while other regions, such as the West and Northeast, demonstrated clusters of low obesity counties, and that local social, economic, and environmental correlates of obesity prevalence also differed across geographic space.[6] Given this evidence, further research was warranted to investigate regional differences in obesity prevalence across the U.S. and identify county-level attributes that underlie existing regional differences. Results will provide evidence of the need to geographically tailor public health policies and interventions to address issues unique to regional areas in order to achieve efficacious health improvement.

This study focused on differences in county-level adult obesity prevalence across the four Census Bureau-defined regions of the U.S.: South, Northeast, West, and Midwest.[7] We used the Centers for Disease Control and Prevention's (CDC) Diabetes Interactive Atlas, which provides model-based estimates of adult obesity prevalence for 2009 among U.S. counties.[8] These data allowed us to address the hypotheses of this study, which were that 1) spatial differences exist in county-level adult obesity prevalence across regions of the U.S., and 2) associations between county-level adult obesity prevalence and county features differ between the regions of the U.S. This objective advances purely descriptive approaches by examining significant geographic variation in obesity prevalence[4] and builds upon research demonstrating significant spatial patterns of obesity prevalence across U.S. counties.[6] Accordingly, this study holds implications for community-based obesity treatment and prevention efforts that apply a universal or one-size-fits-all approach to addressing the obesity epidemic.

Methods and Procedures

Data Sources and Variables

The present analysis used counties and county equivalents, including parishes in Louisiana and independent cities in Virginia, as the units of analysis (excluding Alaska and Hawaii). We relied upon county-level obesity estimates from the CDC as the dependent variable, specifically, the percent of the adult population (≥ 20 years) that was obese (BMI≥30kg/m^2) within a county for 2009.[8] County-level estimates of diabetes and selected risk factors (e.g., obesity, leisure-time physical inactivity) are model-based and derived from data using the CDC's Behavioral Risk Factor Surveillance System (BRFSS)[9] and the U.S. Census Bureau's Population Estimates Program.[10] While the BRFSS currently samples from nearly every county in the nation, small sample sizes prevent the direct calculation of reliable county-specific estimates for most U.S. counties. To overcome this limitation, the CDC has drawn on the aforementioned data to develop county-level obesity prevalence estimates for all U.S. counties using model-based small area estimation techniques. To increase the precision of year-specific county-level estimates, 3 years of BRFSS data are pooled for a given time point. For example, the CDC estimates for 2009 were based on data from 2008, 2009, and 2010, totaling approximately 1.3 million respondents. Validation-studies have compared estimates produced by this modeling technique against direct estimates from counties with large enough sample sizes and have shown little disagreement between the direct and model-based estimates.[11] Those involved in the production of the CDC's diabetes and associated risk factors estimates have encouraged research that explicitly incorporates spatial effects to describe and account for county-level patterns in these data.[1,5]

Drawing from Hillemeier et al., who theorized pathways through which community features impact health,[12] conceptually relevant independent variables that tapped into multiple social, economic, and environmental county-level characteristics were included in our model. Data for our independent variables were drawn from multiple sources including, the CDC, U.S. Census Bureau, U.S. Department of Agriculture (USDA), and U.S. Department of Health and Human Services.

Independent variables included: 1) the percentage of the population living at or below the federal poverty thresholds, 2) the percentage of the labor force that were unemployed, and 3) residential segregation of the poor from the non-poor to tap into the *economic context* of counties. Data for each of these variables were obtained from the U.S. Census Bureau's 2005-2009 American Community Survey (ACS) 5-year estimates. While other research has suggested that counties with greater poverty and unemployment experience greater chronic disease prevalence,[5,6] we wished to understand if these relationships maintained between regions of the U.S.

Measures of the *healthcare context* of counties included: 4) the percentage of the population without health insurance, 5) the number of physicians per 1,000 people, and 6) the number of outpatient visits per 1,000 people. Health insurance data were drawn from the U.S. Census Bureau's Small Area Health Insurance Estimates (SAHIE) for 2009. Both physicians and outpatient visits data were taken from the U.S. Department of Health and Human Services Area Health Resources Files (AHRF) for 2009. Drawing from published evidence that has shown the advantageous effect of health insurance and availability of health providers on community health,[12] we wanted to test if inter-regional differences existed in the these relationships.

The *recreational context* of counties was captured by: 7) the age-adjusted percentage of adults (≥ 20 years) who were physically inactive, 8) the number of fitness and recreation centers per 1,000 people, and 9) an index of natural amenities. The physical inactivity measure was drawn from the CDC's Diabetes Interactive Atlas, the fitness center data was from the U.S. Census Bureau's County Business Patterns (CBP), and the natural amenities measure was drawn from the USDA's Economic Research Service (ERS). Research has shown that the natural environment, aggregate levels of physical inactivity, and access to recreational facilities are each important considerations in understanding community health.[13-15] Given this evidence we sought to understand if there were regional differences in the associations between recreational resources and adult obesity prevalence.

Measures of the *food environment* included: 10) the percentage of a county's population living in food desert census tracts and 11) the number of fast food restaurants per 1,000 people. Data for fast food restaurants were drawn from the U.S. Census Bureau's CBP and the food desert measure was provided by the USDA's ERS. Access to food outlets has been shown to be related to obesity prevalence; lower obesity prevalence in the case of supermarkets and higher obesity prevalence with greater numbers of fast food restaurants.[16,17] We sought to understand if the food environment was differentially associated with adult obesity prevalence between U.S. regions.

The *population structure* of counties was captured by: 12) the percentage of families headed by single mothers, 13) the percentage of the population ≥ 65 years, 14) the percentage of the population African American, 15) the percentage of the population Hispanic, and 16) urban influence using three dummy variables: metropolitan area (reference), micropolitan area, or a non-core area. Urban influence codes were drawn from the USDA's ERS, while all other population measures were from the U.S. Census Bureau's 2005-2009 ACS 5-year estimates. Research has shown that these measures each share a significant relationship with adult obesity prevalence when examining the U.S. as a whole.[6] However, we were interested in understanding if these relationships were significantly different between regions of the U.S.

Last, *educational levels* were measured by: 17) the percentage of the population ≥25 years without a high school diploma or equivalent. This measure was taken from the U.S. Census Bureau's 2005-2009 ACS 5-year estimates. Educational attainment has been demonstrated as a critical dimension of community health.[12] More specifically, greater levels of educational attainment are related to lower obesity prevalence for all counties in the U.S.[6] We aimed to detect if this relationship was significantly different between U.S. regions.

Statistical Analysis

First, we carried out a Local Indicators of Spatial Association (LISA) analysis to provide a geographic breakdown of contiguous counties that belonged to high and low obesity clusters across the U.S. The LISA results revealed significant regional concentrations of counties characterized by both high and low obesity prevalence suggestive of structural differences across regions related to this outcome (i.e., the existence of spatial obesity regimes).[3,18,19]

Next, we conducted a spatial regime regression analysis to detect the significance of parameter differences across regions.[20-22] This modeling strategy allowed us to test for significant effects of each independent variable on county-level adult obesity prevalence within and between the four major Census Bureau-defined U.S. regions (i.e., Northeast, Midwest, South, and West). The procedure entailed specifying a fully interacted regression model between region and each independent variable (e.g., South * percent pop. poor). More specifically, we repeated regressions of the fully interacted model with regional interactions withheld sequentially for each region.

A number of steps were taken to correctly specify the model. We tested for multicollinearity among our independent variables and found no substantial issues (no variance inflation factor exceeded 4). We also grand mean centered (nation) each independent variable. In addition, because counties are situated in states and states contain varying numbers of counties, we included state fixed-effects to control for county-invariant variables within each state (e.g., state-specific health policies). Last, we included a spatial lag term to address diagnosed issues of spatial autocorrelation present in the dependent variable (Moran's I =

0.6, indicating positive spatial autocorrelation, or the significant clustering of counties with like values). Adjusting for the spatially lagged measure of adult obesity prevalence ensures that results are not biased by shared similarities in obesity levels across neighboring counties.[23,24] We utilized GeoDa 1.4.6. for the spatial diagnostics.[25] All regression analyses were carried out using IBM© SPSS© Statistics Version 20.

Results

Table 1 shows that in 2009 the mean prevalence of county-level adult obesity varied by region from 25%, in the West, to 32%, in the South. Figure 1 presents a LISA map of significant high and low obesity county clusters within each region using a pseudo p-value<0.05 based on a random permutation procedure.[26] The LISA analysis tests the probability that no spatial interdependence exists among neighboring counties in a specified measure.[5] In this case the null hypothesis of spatial randomness was rejected. Examining region specific clusters, 30% of counties in the South (n=1,423) were located in high obesity clusters, while only 2% of counties were located in low obesity clusters. For the Northeast (n=217), no counties were part of a high obesity cluster and 41% of counties belonged to a low obesity regional cluster. Fewer obesity clusters were present in the Midwest (n=1,055), with 6% and 3% of counties belonging to high and low obesity clusters, respectively. In the West (n=414), no counties were part of a high obesity cluster, while 66% of counties were members of low obesity clusters.

Motivated not only by the LISA analysis, but also by spatial Chow tests that demonstrated the unequal impact of explanatory variables between each region and across all regions [19,27,28] (supplementary analysis, shown in Table S1), we next carried out a spatial regime analysis to identify which determinants of obesity prevalence significantly differed between the regions. Table 2 provides results from the spatial regime model. The table shows unstandardized OLS regression coefficients representing the main effects for the region identified in the column heading, controlling for the full range of other region-by-covariate multiplicative interaction terms. Thus, coefficients should be interpreted as the effect of a given variable for a particular region net of the effect of that variable in other regions of the country. For example, the table cell for percent poor in the column labeled ‘South’ is an unstandardized OLS regression coefficient representing the effect of poverty in southern counties, controlling for the effects of poverty in counties in the Northeast, Midwest, and West. Asterisks demarcate the significance of each independent variable within the specified region in the column heading. Significant differences between the region in the column heading and other regions are denoted by the letter superscripts and are indicated by region-by-covariate interaction terms in each model (not shown).

Northeast

Hispanic populations were significantly related to lower obesity prevalence in the Northeast and this relationship was stronger in this region compared to each of the other three regions. Additionally, the spatial lag term was not significant in the Northeast, which was significantly different from the positive relationship with obesity prevalence witnessed in each of the other three regions.

Midwest

In the Midwest, the impact of unemployed labor force participants was significantly related to higher obesity prevalence and was different relative to the South with the effect being stronger in the Midwest. The positive association between physically inactive adults and obesity prevalence was significantly weaker in the Midwest compared to counties in each of the other three regions.

West

Unemployed workers and uninsured populations shared significant positive and negative relationships, respectively, with adult obesity prevalence in the West. These associations were significantly stronger in the West relative to counties in the South. Physically inactive adults also had a significantly stronger association with obesity prevalence in the West compared to the South.

South

In the South, residential segregation between poor and non-poor populations was significantly linked to lower obesity prevalence with this effect being stronger from that witnessed in the Northeast and Midwest. African American populations were significantly linked to higher adult obesity prevalence in the South. Importantly, this relationship was stronger in the South compared to other regions of the U.S.

Discussion

The current study aimed to identify significant regional differences in adult obesity prevalence in the U.S. Our findings demonstrated the existence of spatial regimes of obesity prevalence across U.S. regions. Specifically, the South was identified as a high obesity spatial regime, while the Northeast and West were shown to be low obesity spatial regimes. This is a unique contribution to the literature because it shows that obesity in certain regions of the country is structurally different from obesity in other regions.

One notable finding from this research is that the greatest concentration of elevated adult obesity prevalence in the country was in a large contiguous region of counties in the South that spanned Arkansas, Louisiana, Mississippi, and Alabama (Figure 1). This underscores calls for special attention to the social, economic, political, and culture factors that are linked to poor population health in the "Deep South."[29] Additionally, two secondary notable concentrations of high adult obesity prevalence counties were also shown in Kentucky/West Virginia and North Carolina/South Carolina. These two areas are also part of the U.S. South. This provides further evidence that in terms of concentrated obesity prevalence the South needs to be a focal point for research and public policy.

This study also aimed to explicitly articulate the underlying factors driving regional disparities in adult obesity prevalence. Our results identified a number of significantly different associations between county-level adult obesity prevalence and county features between U.S. regions. In the South, the positive association between African American populations and obesity prevalence is especially pronounced compared to other regions.

This stands to reason as African American population density is by far most pronounced in the South. Of the six states with an African American population in excess of 25% of the total population, all are in the South: Mississippi, Louisiana, Georgia, Maryland, South Carolina, and Alabama.[30] Again this suggests the Deep South or "Black Belt"[31] as potential focal points for obesity research and intervention. In the Midwest, as elsewhere, physical inactivity is positively associated with obesity prevalence, but this effect is significantly weaker than in other regions of the country. Why this regional distinction exists is not clear, though the uniform benefit of physical activity across regions is unmistakable. Hispanic populations in the Northeast were particularly relevant for lower obesity prevalence in this region compared to the remainder of the U.S. This finding is consistent with previous research.[6] Compared to the South, the association between unemployed workers and elevated obesity prevalence was much stronger in both the Midwest and West indicating that the deleterious consequences of unemployment on community health is particularly heightened in these two regions.

Also of importance are those factors that operated uniformly across regions. Two measures of the healthcare context held significance across regions, albeit in opposite directions. Physician density was significantly negatively correlated with obesity prevalence in all areas of the country, suggesting increasing physician supply in underserved areas is warranted. Conversely, outpatient visits were uniformly associated with higher obesity prevalence, perhaps signaling greater demands for care associated with the range of chronic health problems related to obesity. Of note are also those factors that were uniformly insignificant across all regions in the presence of other predictors. These include poverty, indicators related to the food environment, and living in small town settings (micropolitan areas) relative to metropolitan areas. Importantly, this is not to suggest that a factor like poverty does not matter, just that in the presence of a full range of other predictors it is not the influence of low income populations that stands out so much as attendant factors.

These regional differences are consonant with other public health research that has highlighted unique geographic regions of both lower and elevated levels of chronic diseases. [1-3] Given this evidence, interventions or policies aimed at addressing chronic diseases in the U.S. might be tailored to target specific contextual risks factors that are particularly vital within each region.[32] That is, that approaches that are customized for the South may be less effective if deployed in the Northeast or West, and vice versa.

Findings from this research also highlight a need for further health disparities research that adopts a regional perspective.[33,34] The national health agenda, *Healthy People 2020*, set forth four Foundation Health Measures to monitor progress in realizing the nation's primary health objectives.[35] One of these four measures includes disparities in health status. This study speaks to two types of health disparities captured by this measure, specifically disparities related to 1) race/ethnicity and 2) geography. Because African American populations were found to be uniquely important in relation to higher obesity prevalence in the South, as well as the South being identified as a high obesity spatial regime, more research is needed to address this disparity. In order to eliminate health disparities driven by geographic location and racial population composition, it is necessary to further investigate the linkages between health outcomes and residence in the South and African American populations to elucidate the pathways in these relationships. For example, this association may suggest underlying community characteristics, such as cultural norms and values related to diet, physical activity, ideal weight, and body image that are unique to particular regions or demographic groups.[36]

This study has several limitations. First, the data were cross-sectional. A more thorough analysis to elucidate the processes underlying the relationships examined in this study could be achieved with the use of longitudinal data to capture change over time. In addition, our analytical results are susceptible to both the modifiable areal unit problem (MAUP) and the uncertain geographic context problem (UGCoP), pitfalls inherent in many spatial analyses, in that the boundaries for spatial entities were created for purposes other than that under study (e.g., counties are government administrative units not health districts) and can be changed, and that ultimately the proper spatial scale is not known (e.g., obesity might be better measured at lower levels like neighborhoods or higher levels like states).[37,38] Finally, this study is limited by the fact that it must rely on model-based estimates produced by the CDC based on BRFSS data. Despite the advantages of BRFSS data because of its large sample size and wide geographic coverage, it relies on self-reported height and weight which is known to be associated with underestimates in obesity prevalence. Recent research has cautioned that geographic differences in the magnitude of this bias may be less pronounced in some regions of the country (i.e., the southeast U.S.) and more pronounced in others (i.e., the north central U.S.).[39] The region-specific approach taken in this study helps to ameliorate this concern. However, in the end, there is no question that directly measured population health census data would be invaluable for obesity research, policy, and intervention. Unfortunately, it currently does not exist in the U.S.

This study showed that regional disparities in adult obesity prevalence exist at a significant level between regions of the U.S., and that county features mattered in shaping this disparity. This study also suggests that obesity is particularly burdensome in the U.S. South, which has economic and public health implications for addressing this epidemic. Continued research focusing on space and place in relation to obesity prevalence should further elaborate distinctive areas of the U.S. in need of tailored interventions and public health policies and the unique factors linked to obesity across areas of the country.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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What is already known about this subject?

- County clusters of high adult obesity prevalence have been noted in the South United States (U.S.), while clusters of low adult obesity prevalence have been demonstrated in the West and Northeast U.S.
- Local social, economic, and environmental correlates of obesity prevalence have been identified for the U.S. as a whole.

What does this study add?

- This study extends the literature by using spatial regime analysis to demonstrate that county-level adult obesity prevalence is 1) regionally disparate across the U.S. and 2) associated with varying factors between each of the four Census Bureau-defined regions of the U.S.
- The results suggest opportunities for regional collaboration and community-level factors that might be more relevant in some regions of the U.S. and less so in others.

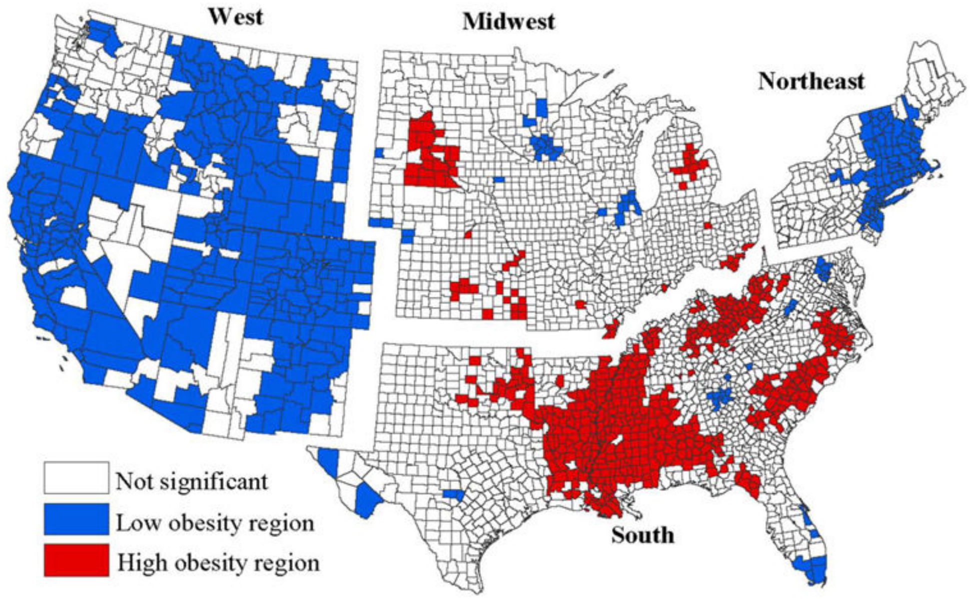

Figure 1. Local Indicators of Spatial Association (LISA) map of significant regional concentration of county-level adult obesity prevalence, 2009

Blue and red shaded counties are members of statistically significant ($p<0.05$) low and high obesity regions, respectively.

Table 1

Descriptive statistics for the nation and by region

Variables	Nation	South	Northeast	Midwest	West
Dependent Variable					
Percent adults obese	30.3 (4.2)	32.0 (3.7)	27.3 (3.8)	30.6 (2.9)	25.3 (4.4)
Independent Variables					
Economic Context					
Percent of pop. poor	15.4 (6.5)	18.2 (6.8)	11.5 (3.8)	12.9 (5.2)	14.3 (5.5)
Percent of labor force unemployed	4.1 (1.7)	4.4 (1.6)	4.2 (0.9)	3.8 (2.0)	4.0 (1.7)
Poor/non-poor segregation	18.8 (10.8)	18.4 (9.8)	27.0 (10.3)	17.9 (11.0)	18.0 (11.8)
Healthcare Context					
Percent of pop. uninsured	18.3 (5.8)	21.3 (5.2)	11.8 (2.9)	14.6 (3.6)	21.1 (4.8)
Number of physicians per 1,000 pop.	1.5 (1.8)	1.4 (1.8)	2.9 (2.9)	1.3 (1.5)	1.8 (1.4)
Number of outpatient visits per 1,000 pop.	2,431.2 (3,323.9)	1,888.7 (3,205.0)	3,692.1 (4,009.6)	2,923.4 (3,530.9)	2,380.3 (2,286.3)
Recreational Context					
Percent of adults physically inactive	26.9 (4.9)	29.3 (4.3)	24.2 (3.7)	26.5 (3.8)	21.2 (4.3)
Number of recreation facilities per 1,000 pop.	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)
Natural amenities (low of 1 to high of 7)	3.5 (1.0)	3.6 (0.7)	3.5 (0.6)	2.7 (0.7)	5.0 (1.1)
Food Environment					
Percent of pop. living in a food desert	17.3 (25.5)	16.1 (23.3)	7.7 (10.4)	19.5 (28.5)	20.6 (28.8)
Number of fast food restaurants per 1,000 pop.	0.6 (0.3)	0.6 (0.3)	0.6 (0.2)	0.5 (0.3)	0.6 (0.4)
Population Structure					
Percent of families headed by single mothers	9.6 (3.8)	11.0 (4.2)	9.5 (2.8)	8.3 (3.1)	8.3 (3.2)

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Variables	Nation	South	Northeast	Midwest	West
Percent of pop. aged 65 and older	15.4 (4.2)	14.6 (3.8)	15.0 (2.5)	16.7 (4.3)	14.7 (5.1)
Percent of pop. African American	8.9 (14.4)	16.7 (17.8)	4.7 (6.3)	2.1 (4.5)	1.2 (2.0)
Percent of pop. Hispanic	7.6 (12.8)	8.7 (14.7)	5.0 (6.9)	3.3 (4.9)	15.9 (16.6)
Metropolitan	0.4 (0.5)	0.4 (0.5)	0.6 (0.5)	0.3 (0.4)	0.3 (0.5)
Micropolitan	0.2 (0.4)	0.2 (0.4)	0.2 (0.4)	0.2 (0.4)	02 (0.4)
Noncore	0.4 (0.5)	0.4 (0.5)	0.2 (0.4)	0.5 (0.5)	0.5 (0.5)
Educational Level					
Percent of adults less than high school	17.1 (7.3)	21.6 (7.0)	12.5 (3.6)	13.3 (4.8)	13.6 (6.1)
High obesity (%)	15.8	30.3	0.0	5.8	0.0
Low obesity (%)	13.5	2.4	40.6	2.6	65.7
N	3,109	1,423	217	1,055	414

Notes: Pop. is an abbreviation for “population.” Mean (standard deviation).

Table 2

Unstandardized OLS regression coefficients from a fully interacted regional model of county-level adult obesity prevalence, 2009

Variables	South (a)	Northeast (b)	Midwest (c)	West (d)
Economic Context				
Percent of pop. poor	0.020	-0.028	-0.010	0.013
Percent of labor force unemployed	0.018*cd*	0.446	0.346***a*	0.284**a*
Poor/non-poor segregation	-0.019**bc*	0.032*a*	0.006*a*	0.009
Healthcare Context				
Percent of pop. uninsured	0.030*d*	0.054	-0.006	-0.081**a*
Number of physicians per 1,000 pop.	-0.360***	-0.250**	-0.331***	-0.468***
Number of outpatient visits per 1,000 pop.	0.093***	0.121*	0.073***	0.144**
Recreational Context				
Percent of adults physically inactive	0.302***cd*	0.426***c*	0.221***abd*	0.472***ac*
Number of recreation facilities per 1,000 pop.	-2.106*	-2.914	-0.572	-2.965*
Natural amenities (low of 1 to high of 7)	-0.081	-0.278	-0.229*	-0.228
Food Environment				
Percent of pop. living in a food desert	-0.001	0.017	-0.001	0.006
Number of fast food restaurants per 1,000 pop.	-0.042	-0.831	-0.460	-0.069
Population Structure				
Percent of families headed by single mothers	0.026	0.181	0.100**	0.089
Percent of pop. aged 65 and older	-0.035*c*	-0.062	0.034*a*	-0.018
Percent of pop. African American	0.072***bcd*	-0.060*a*	0.016*a*	-0.063*a*
Percent of pop. Hispanic	-0.016**b*	-0.191***acd*	-0.009*b*	-0.029**b*
Metropolitan (ref.)	----	----	----	----
Micropolitan	0.169	-0.346	0.009	0.081
Noncore	-0.336*	-0.611	-0.070	-0.798*
Educational Level				

Variables	South (a)	Northeast (b)	Midwest (c)	West (d)
Percent of adults less than high school	0.022	0.143	0.049*	0.083*
Spatial lag	0.154***b	-0.011acd	0.184***b	0.130**b
Intercept	30.312***			
Adjusted R^2	0.754			

Notes: 'Pop.' is an abbreviation for 'population'. Model controls for state fixed effects. Number of outpatient visits per 1,000 pop. multiplied by 1,000.

*p<0.05;

**p<0.01;

***p<0.001 indicate significant coefficients that are the main effect of the specified covariate in the region identified in the column heading.

a,b,c,d indicate significant (p<0.05) differences of each independent variable between the region denoted in the column heading and the other regions. For example, for the variable "Percent of labor force unemployed," the South, which is labeled "a" in the column heading, differed from Midwest (column c) and West (column d), but not the Northeast (column b). N=3,109.