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Brief communication

The spatial distribution of gender differences in obesity prevalence differs from overall obesity prevalence among US adults

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ABSTRACT

Purpose: Although obesity disparities between racial and socioeconomic groups have been well characterized, those based on gender and geography have not been as thoroughly documented. This study describes obesity prevalence by state, gender, and race and/or ethnicity to (1) characterize obesity gender inequality, (2) determine if the geographic distribution of inequality is spatially clustered, and (3) contrast the spatial clustering patterns of obesity gender inequality with overall obesity prevalence.
Methods: Data from the Centers for Disease Control and Prevention's 2013 Behavioral Risk Factor Surveillance System were used to calculate state-specific obesity prevalence and gender inequality measures. Global and local Moran's indices were calculated to determine spatial autocorrelation.
Results: Age-adjusted, state-specific obesity prevalence difference and ratio measures show spatial autocorrelation (z-score = 4.89, *P*-value < .001). Local Moran's indices indicate the spatial distributions of obesity prevalence and obesity gender inequalities are not the same. High and low values of obesity prevalence and gender inequalities cluster in different areas of the United States.
Conclusions: Clustering of gender inequality suggests that spatial processes operating at the state level, such as occupational or physical activity policies or social norms, are involved in the etiology of the inequality and necessitate further attention to the determinates of obesity gender inequality.

Introduction

Obesity is a preventable cause of premature death among US adults [1] that does not impact social groups equally. Although obesity prevalence growth among US adults has slowed or leveled off in recent years [2], monitoring of obesity prevalence among different social groups will continue to be important in designing, targeting, and evaluating potential intervention strategies that address obesity disparities [3].

Although obesity differences among racial and/or ethnic groups, socioeconomic divides, and geographic regions have been thoroughly documented [4–7], gender inequalities have not been adequately characterized. In the work that has been done, there is little difference in obesity prevalence between men and women overall; however, once stratified by race, non-Hispanic black women have a 19.5 percentage point higher obesity prevalence than non-Hispanic black males [8]. This finding has persisted across samples, as multiple studies have shown large obesity gender inequality in non-Hispanic blacks but not in non-Hispanic whites [9–12].

It is unclear what mechanisms cause gender inequalities in obesity, although differential responses to environmental or neighborhood contexts have been proposed [13]. Recently, deprived residential environments have been found to contribute to the gender inequality [14]. Little work has been done to further explore the distribution of gender inequality using spatial units larger than neighborhoods, although geographic inequalities in overall obesity prevalence have been well documented at larger geographies [4,15]. Together this evidence indicates that spatially influenced processes (e.g., policies, societal norms, and so forth) may be operating at several geographic levels to influence obesity prevalence, and, potentially gender inequality. Spatially describing gender obesity inequalities at the state level is appropriate because health and economic policies implemented at this geography are potentially influential.

The authors have no conflicts of interest to disclose.

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This study uses obesity prevalence by state, gender, and race and/or ethnicity to (1) characterize obesity gender inequality, (2) determine whether the geographic distribution of inequality is spatially clustered throughout the contiguous US, and (3) contrast spatial clustering of gender obesity inequality versus spatial clustering of overall obesity prevalence.

Materials and methods

Data source

We used data from the 2013 Behavioral Risk Factor Surveillance System (BRFSS), a Centers for Disease Control and Prevention annual telephone survey that provides state-level prevalence estimates for the leading causes of premature mortality and morbidity among noninstitutionalized adults aged 18 years and older ($n = 491{,}773$). Data for this analysis were collected in 2013 and excluded US territories, the District of Columbia, Alaska, and Hawaii.

Statistical weights and adjustment

BRFSS data are weighted to account for (1) the probability that a respondent would be selected to participate and (2) demographic factors assigned using iterative proportional fitting [16]. Obesity prevalence measures for each state were age standardized using direct standardization, according to the US Census 2000 projected population. Prevalence and difference measures for the four nonwhite race and/or ethnicity groups (non-Hispanic (NH) Black, Hispanic, NH Multiracial, NH Other, with other including Asian, Native American, Alaskan Native, and Pacific Islander) were estimated using pooled data from 2011 to 2013.

Obesity prevalence and gender inequality measures

The outcome of interest was obesity gender inequality and the covariates were age, state of residence, and race and/or ethnicity. Obesity was defined as body mass index of 30.0 kg per m^2 or higher, calculated as self-reported weight (kilograms) divided by height (meters squared). In 2013, 25,475 participants (5.4%) were missing body mass index data and were excluded from analyses. Overall obesity prevalence, and prevalence stratified by interviewer-identified gender and self-reported race and/or ethnicity, was calculated for the 48 contiguous US states. To provide both an absolute and relative comparison of obesity prevalence, differences and ratios were calculated with males as the referent group. Prevalence, inequality measures, and standard errors were calculated using SAS software, version 9.4 (SAS Institute Inc., Cary, NC). Variance estimates accounted for the complex BRFSS survey design and weights by using Taylor series linearization through SAS PROC SURVEYREG software.

Exploratory spatial analysis and maps

Global Moran's indices (GMI), a tool of spatial exploratory data analysis, were calculated to determine spatial autocorrelation of prevalence and inequality values among the entire sample (i.e., all race/ethnicities combined) and also once stratified by race and/or ethnicity. The GMI describes, in a single measure, the overall spatial pattern of an attribute over a defined geography, in this case prevalence differences and ratios across the contiguous United States (US) [17]. The GMI statistic provides a test of the null hypothesis that there is complete randomness in the spatial distribution of the study attribute (i.e., that the attribute value at one location does not depend on the values of neighboring locations). GMI were converted to normalized z-scores with associated *P*-values $\leq$ .05 considered statistically significant (Supplemental Table 1). Statistically significant positive z-scores suggest positive spatial autocorrelation (i.e., clustering) and negative z-scores suggest negative spatial autocorrelation (i.e., dispersion). Nonsignificant values are consistent with the null hypothesis of random spatial patterning. The neighbor definition used to create the row-standardized spatial weights matrix was first-order queen contiguity (neighboring states are all those states sharing an immediate border or corner). Sensitivity analysis using both the rook neighbor definition (immediate neighboring states sharing a border but not a corner) and the eight-nearest-neighbors definition (the eight closest neighboring states, measured by distance between centroids) did not substantially alter GMI values (results not shown).

In the presence of statistically significant global spatial autocorrelation, local Moran's indices (LMI) decompose the GMI into the contributions made by each individual state. Thus, LMI statistics allow us to locate and characterize specific spatial clusters of states with similar obesity prevalence and gender inequality values [18]. Locations of spatial clustering are indicated as high-high (high-value state surrounded by high-valued states) and low-low (low-value state surrounded by low-valued states), whereas spatial outliers are indicated by high-low (high-value state surrounded by low-value states), and low-high (Fig. 1). Pseudo *P*-values for LMI were calculated (alpha $\leq$ 0.01 to account for multiple comparisons) using permutation inference (999 permutations). States with $(n_{men} + n_{women}) < 200$ after pooling were excluded from spatial analyses. Sensitivity analysis indicated that inclusion of these states did not substantively alter GMI values (results not shown). Spatial analyses were performed using GeoDa version 1.6.6 (GeoDa Center for Geospatial Analysis and Computation, Tempe, AZ), and maps were produced using QGIS version 2.4.0 (Open Source Geospatial Foundation, Beaverton, OR).

Results

Overall obesity prevalence

Nationally, measures of age-adjusted obesity prevalence did not vary by gender (28.2% vs. 28.3%) (Table 1). Global spatial autocorrelation statistics indicated spatial clustering for state-specific overall obesity prevalence with both genders combined (z-score = 5.10, *P*-value < .001) and among females (z-score = 5.82, *P*-value < .001) and males (z-score = 3.60, *P*-value < .001). In race-and/or ethnicity-stratified analyses of obesity prevalence with both genders combined, state-specific obesity prevalences were spatially clustered for all groups except among the non-Hispanic, multiracial group (data not shown). Column one of Figure 1 shows state-specific obesity prevalence and results from LMI analyses of cluster locations: states with high obesity prevalence cluster in the South and Midwest.

Gender inequality—geographic variation

State-specific prevalence ratios (Fig. 1, column 3) hover closely around the null value of one, whereas prevalence differences (Fig. 1, column 2) vacillate up to 7 percentage points in either direction of the null (i.e., −7 to +7). Gender prevalence differences were spatially autocorrelated (z-score = 4.89, *P*-value < .001) but did not show the same clustering patterns as overall obesity prevalence. LMI statistics indicated a cluster of states (Mississippi, Tennessee, North Carolina) in the Southeastern US which have higher obesity prevalence among females (Fig. 1, column 2, row 2: "high-high" indicates high difference values among states with similarly high difference values); and a cluster (Montana, North