ORIGINAL RESEARCH

Using Small-Area Estimation Method to Calculate County-Level Prevalence of Obesity in Mississippi, 2007-2009

Zhen Zhang, PhD; Lei Zhang, PhD, MBA; Alan Penman, MD, PhD; Warren May, PhD

Abstract

Introduction

Obesity is one of Mississippi's pressing public health problems. Since 2005, the state has ranked first in the nation in adult obesity prevalence. For authorities to take targeted action against the obesity epidemic, counties, regions, and subpopulations that are most affected by obesity need to be identified. The objective of this study was to assess the scope, socioeconomic and geographic characteristics, and temporal trends of the obesity epidemic in Mississippi.

Methods

Using 2007-2009 Mississippi Behavioral Risk Factor Surveillance System data and auxiliary data, we applied a small-area estimation method to estimate county-level obesity prevalence in 2007 through 2009, to assess the association between obesity and socioeconomic factors and to evaluate temporal trends. We determined geographic patterns by mapping obesity prevalence. We appraised the precision of estimates by the width of 95% confidence intervals, and we validated our small-area estimates by comparing them with direct estimates.

Results

In 2009, the county prevalence of obesity ranged from 30.5% to 44.2%. Counties with the highest prevalence of obesity were in the Delta region and along the Mississippi River. The obesity prevalence increased from 2007 through 2009. Age, sex, race, education, and employment status were associated with obesity.

Conclusion

The 2009 obesity prevalence in all Mississippi counties was substantially higher than the national average and differed by geography and race. Although urgent intervention measures are needed in the entire state, policies and programs giving higher priority to higher-risk areas and subpopulations identified by this study may be better strategies.

Introduction

In the past 25 years, the prevalence of obesity, defined as a body mass index (BMI) of at least 30 kg/m^2, has increased dramatically in the United States; more than one-third of adults are now obese (1-4). Mississippi has ranked first in the nation in obesity prevalence since 2005. Between 1995 and 2009, the prevalence of obesity in Mississippi increased substantially, from 19.5% to 35.4% (5), and there is no indication that this upward trend will level off soon. Obesity is associated with heart disease, diabetes, cancer, asthma, arthritis, stroke, and premature death (6,7). Consequently, obesity and its associated health problems have a substantial social and economic effect (6,8). According to the Mississippi State Department of Health (9), obesity is one of the state's most pressing public health problems. The high and increasing rate of diabetes in the state is highly correlated with the increasing rate of obesity (9,10). The highest obesity rates should be identified for priority intervention both because of limited resources and because obesity control programs

may be more effective when tailored according to specific community needs (11,12).

Socioeconomic characteristics, such as age, sex, race, income, and education, and community factors such as average per capita income and percentage of labor-intensive workers are associated with obesity (3,13). In an effort to establish the association of diabetes with obesity, Centers for Disease Control and Prevention (CDC) produced 2007 county-level obesity prevalence estimates for 3,141 US counties by using Bayesian multilevel modeling (10) but did not analyze geographic and socioeconomic characteristics of the obesity epidemic for the states. To our knowledge, no studies have focused on providing up-to-date small-area health statistics and related information in Mississippi for prevention and intervention purposes. In this study, we sought to produce reliable county-level estimates of obesity prevalence for all Mississippi counties, identify geographic heterogeneity and temporal trends, and evaluate associations between obesity and socioeconomic factors. This information would enable the development of appropriate obesity prevention policies and community interventions.

Methods

Data sources

Established by CDC, the Behavioral Risk Factor Surveillance System (BRFSS) is an ongoing state-based surveillance system tracking health conditions and risk behaviors among noninstitutionalized adults aged 18 years or older in the United States. The design of BRFSS aims at generating reliable prevalence estimates at the state level or for large metropolitan statistical areas. Sample size for counties are usually too small for making direct inferences with satisfactory precision. CDC suggests that a sample size of at least 300 is necessary for direct estimation (14,15). To overcome the limitation of small sample sizes, we developed a 2-step estimation method. This method belongs to a family of small-area estimation techniques that includes varied approaches for making inferences about geographic or social subdomains of the survey domain. The power of the small-area estimation method resides on its ability to borrow strength from multiple sources of data — data collected at other times, or in related areas, or both to increase the effective sample size and thus achieve adequate precision. Among current small-area estimation methods, the Hierarchical Bayes

approach and generalized linear mixed models have been primary choices (16-18). We used a generalized linear mixed model in this study. We incorporated a generalized linear mixed model and traditional synthetic methods to meet the small-area estimation needs in this study.

We acquired individual-level BRFSS data for Mississippi for 2007 through 2009. Variables included in the analytical dataset were self-reported height and weight and demographic and socioeconomic variables, including age, race, sex, education level, employment status, annual household income, and marital status. We used the Federal Information Processing Standard code as the location variable for county. We categorized BMI as binary variable, obesity (obesity = 0 if BMI <30 kg/m^2, obesity = 1 if BMI ≥30 kg/m^2). In the original Mississippi BRFSS data, age is a continuous variable. Through initial exploratory data analysis, we found a quadratic relationship between BMI and age. According to the shape of the quadratic regression line, we categorized age into 4 groups: 18 to 29, 30 to 44, 45 to 64, and 65 years or older. We categorized education as less than a bachelor's degree and bachelor's degree or higher. For employment status, we grouped employed for wages and self-employed as "employed," and grouped unemployed temporarily, those unable to work, students, retired people, and homemakers as "unemployed."

The exclusion criteria were 1) missing Federal Information Processing Standard code information (n = 39); 2) missing BMI values or biologically unlikely BMI values (BMI <12 kg/m^2 or BMI >70 kg/m^2) (n = 1,013); 3) pregnant (n = 138); 4) races other than black and white (n = 383). Taking into consideration that in Mississippi 98.5% of the population belongs to 1 of 2 categories, black alone or combined and white alone or combined (19), we excluded the small portion (1.5%) of respondents of other races to facilitate small-area estimation. Respondents who chose black alone or black and other race(s) were categorized as black alone or combined; respondents who chose white alone or white with race(s) other than black were categorized as being in the white alone or combined category. The final analytical dataset of 2007-2009 BRFSS had 25,046 observations.

The data sources for auxiliary information were the 2000 US Census (19) and the US Department of Agriculture Economic Research Service (20). We used the auxiliary information to construct predictor variables for statistical modeling. Auxiliary covariates included county-specific sociodemographic factors such as county population

composition of age, sex, race, educational achievement, county unemployment rate, rural-urban continuum characteristics, economic dependence indicators, and poverty indicator. Corresponding to the 4 age categories at the individual level, the auxiliary dataset included 4 age variables, which are the percentages of each age group 18 years or older in the county population.

Estimation method

Modified on the basis of the multilevel logistic regression model of Li and colleagues (13), our 2-step small-area estimation method is a combination of hierarchical modeling and synthetic estimation techniques. This mixed model produces a set of fixed-effect parameter estimates, which are general to all counties, and a set of random-effect parameter estimates, which are county-specific values. First, we identified the independent variables that were significantly associated with obesity by fitting a generalized linear mixed model with the relevant variables, both individual-level and county-level. We used backward elimination to prune the model. To further improve predictability, we set the selection criterion for retaining a variable or interaction term in the model at $\alpha = 0.1$ (21). In the final model, fixed effects included the following variables: age, sex, race, education level, employment status, survey year, and county-level average per capita annual household income. Random effects included individual-level variables age, sex, race, education level, and survey year. We also calculated odds ratios for associated socioeconomic factors in this step.

In the second step of the estimation, we applied a synthetic technique to link the model-generated parameter estimates to the county-specific characteristics to produce county-level estimates. This way, the strength borrowed through the model is realized for each county. Because random effects were not significant, we used only the fixed-effect values in the calculation. However, following the recommendation of Binder (22), Jiang (23), and Jia et al (24), we kept the random-effects component in the model to improve estimation for fixed effects and to enhance the proper selection of variables (Appendix). We conducted all analyses by using SAS version 9.2 (SAS Institute Inc, Cary, North Carolina) to account for the complex sampling design. We grouped the county-level obesity prevalence estimates into quartiles to examine geographic patterns. We produced the obesity map by using ArcGIS 9.2 (ESRI, Redlands, California).

We assessed the precision of our estimates by using the width of 95% confidence intervals (CIs). Following the example of another study (25), we examined correlations and mean absolute differences between model estimates and internal standards: direct estimates of the state-level obesity rate for 2007 through 2009, and direct estimates for age, sex, and race subgroups. The sample sizes for the 4 age subgroups, 2 sex subgroups, and 2 race subgroups were large enough for reliable direct estimation (range, 663-7,305). Taking into consideration the complex sampling design of BRFSS, we used SAS PROC SURVEYLOGISTIC procedure (SAS Institute, Inc, Cary, North Carolina) for direct estimations to account for the weight of each respondent.

Results

The state obesity prevalence increased significantly, from 32.5% in 2007 to 33.4% in 2008 and 35.4% in 2009. The prevalence estimates of all 82 counties were higher in 2009 than in 2007 (Tables 1 and 2). In 2009, all counties had prevalence of obesity greater than 30%. In 49 counties, the prevalence of obesity was at 35% or higher, and in 12 counties, was at least 40% or higher. Compared with the *Healthy People 2010* goal and with the 2009 national average, all of the county estimates were substantially higher (Figure 1).
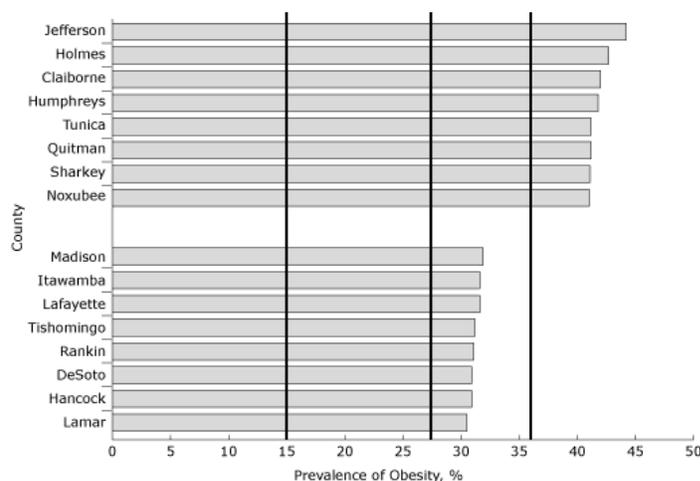

Figure 1. 2009 Mississippi County prevalence of obesity, Behavioral Risk Factor Surveillance System (BRFSS) data. Ten percent of the counties with the lowest and highest obesity rates are shown. The vertical line at 15% indicates the *Healthy People 2010* goal for obesity; vertical lines at 27.1%, and 35.4% indicate the 2009 national and state averages, respectively. Obesity is defined as a BMI ≥30.0 kg/m^2 based on 2009 BRFSS self-reported data.

There was considerable geographic variation in obesity prevalence among Mississippi counties. The difference between Jefferson County (highest) and Lamar County (lowest) was 13.7% (Figure 2). Counties with higher obesity rates were clustered in the Mississippi Delta region and along the Mississippi River (Figure 2). Counties along the coastline and in the northeast region (Appalachian foothills) had lower obesity rates, as did counties with higher socioeconomic status, such as Madison and Rankin counties.
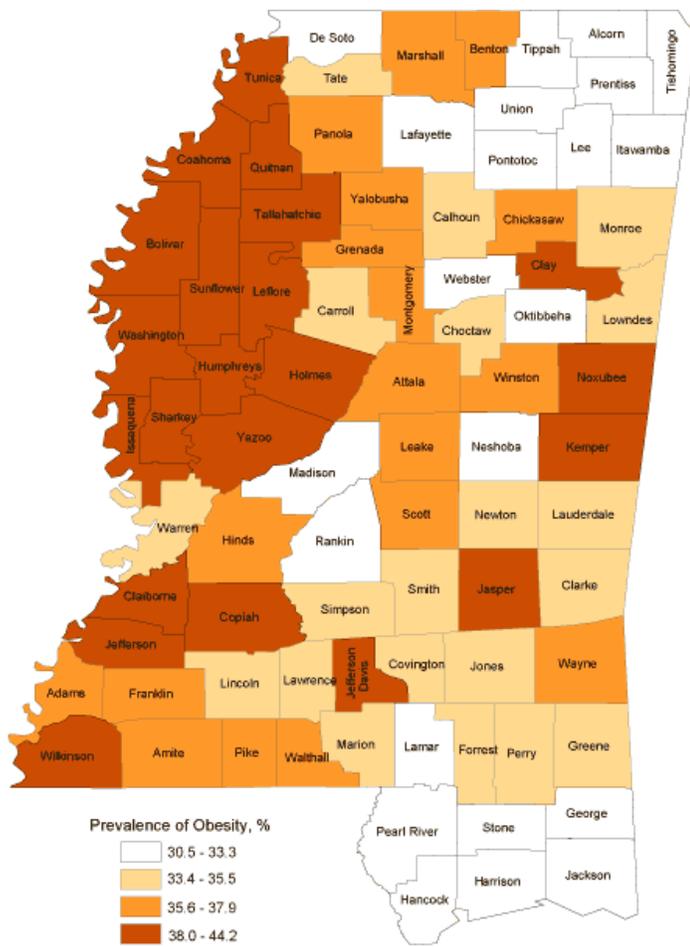

Figure 2. 2009 Mississippi county prevalence of obesity map (in quartiles), Behavioral Risk Factor Surveillance System (BRFSS) data. Lighter colors represent lower obesity rate, and darker colors represent higher obesity rate. Obesity is defined as a BMI ≥30.0 kg/m² based on 2009 BRFSS self-reported data.

Respondents aged 30 to 44 years had the highest odds of being obese (Table 3). Compared with college graduates, respondents with an education level less than a bachelor's degree were more likely to be obese. Women had slightly higher odds than men, and blacks had much higher odds than whites. The interaction between sex and race was significant (P <.001); compared with white men, the odds of obesity were 2.2 (95% CI, 2.0-2.5) for black women, 1.4 (95% CI, 1.2-1.6) for black men, and 0.8 (95% CI, 0.7-0.9) for white women.

Evaluation of county-level estimates

The width of 95% CIs for all county estimates was less than 5 percentage points (range 2.5-4.7 percentage points). This precision was comparable to that of the design-based direct estimates for the state and is considered reliable (25,26). To assess accuracy, we aggregated small-area county-level estimates to the state level for 2007 through 2009 and compared them with their respective state-level direct estimates; we also compared state-level model estimates with state-level direct estimates for 2007 through 2009. We further compared model estimates of age, sex, and race subgroups with their respective direct estimates. Pearson's correlation coefficients between the 2 sets of estimates for the comparisons were 0.95, 0.95, and 0.96, respectively, and the mean absolute differences were 0.5%, 0.5%, and 1.5%, respectively.

Discussion

Using 2007-2009 BRFSS data, we obtained stable estimates for county-level prevalence of obesity. The 2009 obesity prevalence in all Mississippi counties is high: it shows the size and scope of the problem facing the state. This finding may help raise the awareness of the obesity crisis for state policy makers, health agency officials, journalists, and the general public. The county estimates also show that obesity prevalence among Mississippi counties varies considerably, which reveals the heterogeneous nature of the obesity epidemic in the state and requires targeted prevention measures to curb the trend. Furthermore, the escalating trend observed in Mississippi necessitates aggressive action. Mississippi has taken firm steps in confronting the child obesity crisis (27); parallel measures should be taken for adults.

Similar to observations reported by Li and colleagues (13), we found that in general, socioeconomic status was inversely related to the county prevalence of obesity among adults aged 18 years or older in Mississippi, after adjusting for age, sex, and race. This information may be helpful in guiding the direction of obesity prevention campaigns.

Confirming the troubling racial and socioeconomic disparities in obesity rates observed in other studies (2,3,28), our study shows that the risk of obesity for blacks nearly doubled that of whites, and black women had the highest odds of obesity. The 2000 Census indicates that Mississippi's population consists of 33.7% blacks, the highest in the nation (19). This means that compared with the rest of the nation, a larger proportion of Mississippi's population is in a higher risk category. Therefore, racial disparity in obesity affects Mississippi more than other states. The racial disparity, along with socioeconomic disparities, may influence public health efforts to plan and implement tailored prevention policies and programs because the effectiveness of health-promoting strategies varies among racial and socioeconomic groups. For instance, walking trails may be more effective in a community where a certain ethnic group clusters, and a farmer's market may be more effective in another community of different racial combinations. Consequently, prevention polices and programs would be most effective if designed accordingly.

This study has potential biases and limitations. First, because the weight and height values in BRFSS were self-reported, bias may have occurred (29,30). Compared with other surveys that generate estimates of obesity prevalence (eg, the National Health and Nutrition Examination Survey, for which trained professionals measure the height and weight of participants), BRFSS data tend to underestimate obesity prevalence. Some similar studies, attempting to minimize self-reporting bias, developed a correction method by using auxiliary data (13). However, since self-reporting bias affects all the county-level estimates similarly, it is not expected that relative distribution of obesity would vary. When estimates are biased, concerns arise about the magnitude of the bias. In the absence of an external standard against which to compare our data, our assessment of accuracy in this study is limited. Second, because of software limitations in handling standard error estimation when using mixed models for complex sample survey data, the 95% CI produced was a reasonable approximation, not exact. Further investigation in this direction may be needed.

Acknowledgments

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Tables

Table 1. Prevalence of Obesity,[a] by County, BRFSS Mississippi, 2007

County	% (95% CI)	County	% (95% CI)
Lamar	28.7 (27.0-30.4)	Lincoln	32.8 (31.1-34.6)
Hancock	29.0 (27.5-30.6)	Monroe	33.0 (31.3-34.8)
DeSoto	29.1 (27.3-30.9)	Choctaw	33.2 (31.4-35.0)
Rankin	29.2 (27.5-31.0)	Lawrence	33.2 (31.5-34.9)
Tishomingo	29.3 (27.7-31.0)	Lowndes	33.2 (31.6-34.9)
Lafayette	29.8 (28.0-31.6)	Covington	33.3 (31.6-35.0)
Itawamba	29.8 (28.1-31.5)	Carroll	33.4 (31.8-35.1)
Madison	30.1 (27.9-32.3)	Marion	33.4 (31.5-35.3)
Alcorn	30.1 (28.5-31.8)	Warren	33.4 (31.8-35.1)
Lee	30.2 (28.4-32.0)	Clarke	33.6 (31.9-35.3)
Union	30.2 (28.6-31.9)	Simpson	33.6 (31.8-35.4)
Harrison	30.4 (28.8-32.1)	Yalobusha	33.6 (32.0-35.3)
Pearl River	30.5 (28.9-32.2)	Franklin	33.7 (31.9-35.4)
Pontotoc	30.5 (28.9-32.2)	Attala	33.9 (32.2-35.7)
George	30.6 (28.9-32.4)	Leake	33.9 (32.2-35.7)
Prentiss	30.7 (29.0-32.5)	Winston	34.0 (32.3-35.7)
Jackson	30.8 (29.2-32.4)	Benton	34.1 (32.2-36.0)
Tippah	31.2 (29.4-32.9)	Scott	34.3 (32.5-36.1)
Webster	31.3 (29.7-33.1)	Grenada	34.4 (32.6-36.2)
Neshoba	31.4 (29.7-33.1)	Wayne	34.5 (32.7-36.4)
Stone	31.4 (29.7-33.1)	Chickasaw	34.5 (32.7-36.4)
Oktibbeha	31.4 (29.6-33.3)	Montgomery	34.7 (33.0-36.5)
Forrest	31.6 (29.9-33.4)	Amite	34.9 (33.1-36.6)
Smith	31.7 (30.0-33.4)	Walthall	34.9 (33.1-36.8)
Jones	31.9 (30.2-33.6)	Hinds	35.0 (33.2-36.8)
Calhoun	32.1 (30.4-33.8)	Pike	35.0 (33.3-36.8)
Tate	32.5 (30.9-34.2)	Adams	35.2 (33.6-36.9)
Newton	32.7 (31.0-34.5)	Panola	35.4 (33.6-37.3)
Perry	32.7 (30.9-34.6)	Marshall	35.7 (33.9-37.5)
Greene	32.7 (30.8-34.7)	Clay	35.9 (34.1-37.7)
Lauderdale	32.8 (31.2-34.5)	Copiah	36.0 (34.1-37.9)

Abbreviations: BRFSS, Behavioral Risk Factor Surveillance System; CI, confidence interval.
[a] Body mass index ≥30.0 kg/m2 based on 2007 BRFSS self-reported data.

Table 1. (continued) Prevalence of Obesity,[a] by County, BRFSS Mississippi, 2007

County	% (95% CI)	County	% (95% CI)
Jasper	36.2 (34.4-38.1)	Coahoma	38.5 (36.5-40.5)
Yazoo	36.7 (34.7-38.7)	Wilkinson	38.9 (36.8-41.1)
Kemper	37.1 (35.1-39.1)	Noxubee	39.0 (37.0-41.1)
Jefferson Davis	37.2 (35.2-39.1)	Sharkey	39.0 (37.0-41.1)
Leflore	37.6 (35.7-39.6)	Quitman	39.1 (37.0-41.3)
Washington	37.6 (35.8-39.5)	Tunica	39.2 (37.1-41.2)
Bolivar	37.7 (35.7-39.7)	Humphreys	39.7 (37.6-42.0)
Tallahatchie	37.9 (35.7-40.0)	Claiborne	40.0 (37.8-42.2)
Issaquena	38.0 (35.8-40.2)	Holmes	40.7 (38.5-42.9)
Sunflower	38.2 (36.0-40.3)	Jefferson	42.2 (39.8-44.6)

Abbreviations: BRFSS, Behavioral Risk Factor Surveillance System; CI, confidence interval.
a BMI ≥30.0 kg/m2 based on 2009 BRFSS self-reported data.

Table 2. Prevalence of Obesity[a] Estimate, by County, BRFSS Mississippi, 2009

County	% (95% CI)	County	% (95% CI)
Lamar	30.5 (29.2-31.9)	Tippah	33.1 (31.7-34.5)
Hancock	30.9 (29.6-32.1)	Webster	33.2 (31.9-34.6)
DeSoto	30.9 (29.4-32.4)	Neshoba	33.3 (32.0-34.5)
Rankin	31.1 (29.6-32.6)	Stone	33.3 (32.0-34.6)
Tishomingo	31.2 (29.9-32.5)	Oktibbeha	33.3 (31.8-34.8)
Lafayette	31.6 (30.2-33.1)	Forrest	33.5 (32.2-34.9)
Itawamba	31.6 (30.3-33.0)	Smith	33.6 (32.3-34.9)
Madison	31.9 (29.9-34.0)	Jones	33.8 (32.5-35.1)
Alcorn	31.9 (30.7-33.2)	Calhoun	34.0 (32.7-35.3)
Lee	32.0 (30.6-33.4)	Tate	34.4 (33.2-35.7)
Union	32.1 (30.8-33.4)	Newton	34.6 (33.3-36.0)
Harrison	32.2 (31.0-33.6)	Perry	34.6 (33.1-36.2)
Pearl River	32.4 (31.1-33.7)	Greene	34.7 (33.0-36.3)
Pontotoc	32.4 (31.2-33.7)	Lauderdale	34.7 (33.5-36.0)
George	32.5 (31.1-33.9)	Lincoln	34.8 (33.4-36.1)
Prentiss	32.6 (31.2-34.0)	Monroe	34.9 (33.6-36.3)
Jackson	32.7 (31.4-33.9)	Choctaw	35.1 (33.7-36.5)

Abbreviations: BRFSS, Behavioral Risk Factor Surveillance System; CI, confidence interval.
a BMI ≥30.0 kg/m2 based on 2009 BRFSS self-reported data.

Table 2. (continued) Prevalence of Obesity[a] Estimate, by County, BRFSS Mississippi, 2009

County	% (95% CI)	County	% (95% CI)
Lawrence	35.1 (33.8-36.4)	Panola	37.4 (35.9-38.9)
Lowndes	35.2 (33.9-36.5)	Marshall	37.7 (36.2-39.1)
Covington	35.2 (33.9-36.5)	Clay	37.9 (36.5-39.3)
Carroll	35.3 (34.1-36.6)	Copiah	38.0 (36.4-39.6)
Marion	35.4 (33.8-36.9)	Jasper	38.2 (36.7-39.8)
Warren	35.4 (34.1-36.7)	Yazoo	38.7 (37.0-40.4)
Clarke	35.5 (34.2-36.9)	Kemper	39.1 (37.4-40.8)
Simpson	35.5 (34.1-37.0)	Jefferson Davis	39.2 (37.5-40.9)
Yalobusha	35.6 (34.3-36.9)	Leflore	39.6 (37.9-41.3)
Franklin	35.6 (34.2-37.0)	Washington	39.6 (38.1-41.2)
Attala	35.9 (34.5-37.3)	Bolivar	39.7 (38.0-41.4)
Leake	35.9 (34.5-37.3)	Tallahatchie	39.9 (38.0-41.8)
Winston	35.9 (34.6-37.3)	Issaquena	40.0 (38.0-42.0)
Benton	36.0 (34.5-37.6)	Sunflower	40.2 (38.3-42.1)
Scott	36.2 (34.8-37.6)	Coahoma	40.5 (38.8-42.2)
Grenada	36.4 (35.0-37.8)	Wilkinson	41.0 (39.0-43.0)
Wayne	36.5 (35.0-38.0)	Noxubee	41.0 (39.3-42.9)
Chickasaw	36.5 (35.1-38.0)	Sharkey	41.1 (39.2-42.9)
Montgomery	36.6 (35.3-38.0)	Quitman	41.2 (39.2-43.1)
Amite	36.8 (35.5-38.2)	Tunica	41.2 (39.4-43.0)
Walthall	36.9 (35.4-38.4)	Humphreys	41.8 (39.8-43.8)
Hinds	36.9 (35.5-38.5)	Claiborne	42.0 (39.9-44.1)
Pike	37.0 (35.6-38.4)	Holmes	42.7 (40.7-44.8)
Adams	37.2 (35.9-38.5)	Jefferson	44.2 (41.9-46.6)

Abbreviations: BRFSS, Behavioral Risk Factor Surveillance System; CI, confidence interval.
[a] Body mass index ≥30.0 kg/m^2 based on 2009 BRFSS self-reported data.

Table 3. Odds of Obesity,[a] by Socioeconomic Characteristics, Mississippi, 2007-2009

Characteristics	OR (95% CI)
Age, y	
18-29	1 [Reference]
30-44	1.77 (1.57-1.98)
45-64	1.70 (1.52-1.90)
≥65	1.03 (0.90-1.17)
Sex	
Male	1 [Reference]
Female	1.18 (1.10-1.25)
Race[b]	
White alone or combined	1 [Reference]
Black alone or combined	1.88 (1.72-2.06)
Education	
Bachelor's degree or higher	1 [Reference]
Less than bachelor's degree	1.22 (1.12-1.33)
Employment status	
Employed	1 [Reference]
Unemployed	0.96 (0.89-1.04)
Survey year	
2007	1 [Reference]
2008	1.01 (0.94-1.09)
2009	1.10 (1.02-1.17)

Abbreviation: OR, odds ratio.

[a] Body mass index ≥30.0 kg/m^2 based on 2009 BRFSS self-reported data.

[b] Respondents who chose white alone or white with race(s) other than black were categorized as being in the white alone or combined category. Respondents who chose both black and white were categorized as black alone or combined. Respondents who chose only black or who chose black and other race(s) were categorized as being in the black alone or combined category.

Appendix. Small Area Estimation Method Used to Calculate Obesity Prevalence by County, Mississippi, 2009

First step

Let y_{ij} be the observation of obesity status, with i denoting county and j denoting individual respondent. Let X denote the design matrix for fixed-effect parameters β and their interaction terms; let Z denote the design matrix for random-effect parameters γ and their interaction terms. Then we have the mixed model:

$$\text{Logit } (y_{ij} \mid \gamma) = X\beta + Z\gamma$$

$$\gamma \sim N(0, G)$$

where γ is assumed to be normally distributed with mean 0 and variance G. Let $\hat{\beta}$ and $\hat{\gamma}$ denote the model-generated matrices that contain logits of fixed-effect and random-effect parameter estimates respectively. $\hat{\beta}$ is general to every county, while $\hat{\gamma}$ contains county-specific values.

Second step

Let L represent the county-level fixed-effect coefficient matrix generated by using auxiliary data. The components in L correspond to the individual-level fixed-effect components in X. Then the logits of county-level prevalence of obesity estimates, $\hat{\theta}_i$, were calculated using formula (estimates in $\hat{\gamma}$ were too small to be included):

$$\hat{\theta}_i = L_i \hat{\beta}$$

Next, an exponential transformation was applied to $\hat{\theta}_i$ to produce prevalence of obesity estimates $\hat{\mu}_i$ for each county:

$$\hat{\mu}_i = g^{-1}(\hat{\theta}_i)) = \frac{1}{1 + \exp(-\hat{\theta}_i)}$$