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Poverty and childhood overweight in California Assembly districts☆

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Abstract

Objectives—The goal of the present study was to determine the association between childhood overweight and area-based socioeconomic indicators in California Assembly districts.

Design—A cross-sectional ecologic study.

Participants—California public school students.

Main exposure—Poverty and demographic data for California Assembly districts were based on the 2000 Census and obtained from the UCLA Center for Health Policy Research.

Outcome measures—Overall and race- and ethnicity-specific rates of childhood overweight for California Assembly districts ($n = 80$) were based on the 2004 statewide Fitnessgram evaluation of California public school students.

Results—Poverty was significantly associated with childhood overweight in California Assembly districts. At the Assembly district scale, childhood overweight was significantly associated with percent residents below poverty for the entire population ($r = 0.82$), and with the race/ethnicity-specific overweight prevalence for African-American ($r = 0.43$), Latino ($r = 0.61$) and White ($r = 0.54$) populations. There was also evidence that childhood overweight in California Assembly districts was spatially clustered. Linear regression models confirmed that percent of residents below poverty was an independent predictor of a higher prevalence of childhood overweight for the entire population. The results of race/ethnicity-specific models confirmed that the association between area poverty and childhood overweight was not explained by differences in the risk of overweight among specific race/ethnicity groups.

Conclusions—Area-based measures of socioeconomic status can be used to identify problem areas and can be used for optimal targeting of public health prevention and intervention efforts.

Keywords

Overweight children; Geography; Socioeconomic factors; Disparities

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Conflict of interest

None.

Introduction

Higher prevalence of childhood overweight has been associated with racial and ethnic differences and with inequalities in household education and income levels (Freedman et al., 2006; Lee et al., 2006; Wang and Zhang, 2006). The prevalence of overweight among children and adolescents is highest among African-Americans and Hispanic-Americans (Troiano and Flegal, 1998). Children and adolescents of low socioeconomic status are at increased risk of being overweight or obese. More recently, school-based physical fitness testing identified large disparities in childhood overweight in Los Angeles schools. Percent enrollment in free or reduced price meal programs at the school level was independently associated with overweight, after controlling for demographic characteristics.

School-level data of percent enrollment in subsidized meal programs are one reflection of area economic resources. Area-based socioeconomic measures (ABSMs) represent an alternative method for measuring social, economic and health disparities at the ecologic level (Krieger et al., 2003a). Numerous ABSMs have been used, including median household income, percent attaining a minimum educational level or occupational class, percent single parent households, percent unemployed, percent vacant households, crime incidence rates or tobacco use (Krieger et al., 2003b). Some measures, such as median home value, attempt to assess wealth and social cohesion (Subramanian et al., 2003). Percent of population living below the federal poverty level has been identified as a strong and reliable area-based predictor of adverse health outcomes, including all-cause mortality and low birth weight (Krieger et al., 2003a).

A geographic approach to examining health outcomes is becoming increasingly popular (Krieger, 2003), and Geographic Information Systems (GIS) (Jeffery et al., 2006) are being used in the study of the social and environmental determinants of obesity, nutrition and physical activity (Booth et al., 2005). GIS permit the overlay of diverse data to explore spatial relationships among geographic attributes, examples including census data, the density of fast food restaurants or the presence or absence of sidewalks in a neighborhood. Studies using this geographic approach have identified land neighborhood patterns that encourage sedentary behaviors or an unhealthful diet, which may influence obesity risk (Perdue et al., 2003). GIS have been used to measure, analyze and describe both exposures, area-based measures of socioeconomic status, and outcomes of interest, including the prevalence of overweight and obesity.

The number of studies utilizing a geographic approach is limited. Health data for detailed geographic scales, such as ZIP code areas, census blocks or census tracts are difficult and costly to obtain (Krieger et al., 2003a). These data are generally only available for birth and death outcomes, and have not been used extensively for obesity research (Drewnowski et al., 2007). Larger areas that span multiple neighborhoods, such as municipalities, counties or whole states, comprise a mix of heterogeneous populations, hindering meaningful epidemiologic inference. The current study uses state legislative districts as an alternative scale for disease mapping and analysis. Though larger than the ideal units of analysis, the use of political districts as units of analysis may still help focus attention on neighborhood resources, access to services, planning, zoning and the potential contribution of the built environment. In addition, assembly district data represented the finest geographic aggregation available for the present data. The hypothesis was that percent below poverty would be positively associated with increased prevalence of childhood overweight in California Assembly districts.

Data sources and methods

Data on income to poverty ratio (<100%) for people aged 65 and under are based on the 2000 US Census data and obtained from the UCLA Center for Health Policy Research (Brown et al., 2000). There are 80 Assembly districts in California with a standard population of approximately 423,400.

Prevalence of childhood overweight data by California Assembly district was obtained from the California Center for Public Health Advocacy (McCusker, 2005; Samuels and Associates and Kao, 2002). Data from the 2004 assessment were used in the present study. A previous assessment was also conducted in 2001. Prevalence estimates were based on the California Fitnessgram, the state mandated test for childhood physical fitness for grades 5, 7 and 9. Fitnessgram classifies children as either in “the healthy fitness zone” (HFZ) or “not in the healthy fitness zone” according to their BMI for age and gender (The Cooper Institute for Aerobics Research, 2007). Rather than using BMI≥85th or 95th percentile, the Fitnessgram defines overweight for students whose body composition measurement was above the upper limits of the HFZ based on age and gender-specific cut points. These thresholds, known as criterion-based standards, develop cut points based on risk of disease, rather than an arbitrary percentile (McCusker, 2005). The Fitnessgram HFZ thresholds vary slightly from the Centers for Disease Control (CDC) standards. For example, for 12-year-old girls, the CDC cut-off for childhood overweight is a BMI of 25.2, while the HFZ cut-off is 24.5. Because the current data are not based on the CDC standards, the estimates cannot be compared to data from other surveillance systems, including the Youth Risk Behavior Surveillance System or Healthy Youth Survey.

Percent of children above the HFZ (referred to as overweight) for the entire population was the dependent variable of interest. Additional analyses evaluated the race/ethnicity-specific overweight prevalence as they related to overall poverty. Percent below poverty was the independent variable of interest for all analyses. Analyses of data with a spatial component are complicated by spatial autocorrelation or dependence, where contiguous or nearby areas have correlated response or predictor values. Moran’s *I* statistic, a measure of spatial autocorrelation, was calculated to evaluate spatial autocorrelation in the prevalence of childhood overweight in California. We evaluated the univariate Moran’s *I* statistic for childhood overweight, and the multivariate Moran’s *I* statistic in models of poverty and childhood overweight. Moran’s *I* values calculated from the linear regression models were based on the model residuals. There are some concerns regarding the use of Moran’s *I* statistic to assess autocorrelation of the prevalence or proportion of disease because of population size heterogeneity. However, because the populations of California Assembly districts are comparable, this limitation does not likely bias the results. A queen weights contiguity matrix was used for spatial analyses. The queen weight defines neighbors as areas that share a boundary or a corner (Anselin, 2005).

A key assumption of ordinary least squares regression is the independence of predictors across subjects. The identification of significant spatial autocorrelation in our data necessitated the use of a spatial linear regression model, using a spatial error term, which corrects for spatial dependence (Anselin and Rey, 1991). For each race/ethnicity group, two linear regression models were evaluated: a crude model with poverty as a predictor and a spatial model including poverty and a spatial error term to correct for any residual spatial dependence.

A map of childhood overweight and poverty is also presented to explicitly identify areas with higher or lower proportions of overweight children. Assembly districts were classified as low (<10%), medium (10–19%) or high poverty (≥20%), and low (<25%) or high childhood overweight (≥25%).

Preliminary analyses were conducted using Intercooled Stata 9.2 (StataCorp., 2005), and linear regression models were conducted using GeoDa (Luc Anselin and The Regents of the University of Illinois). Mapping was done in ArcGIS 9.1 (ESRI Redlands, CA). All statistical tests were two-sided, with p values less than 0.05 considered significant.

Results

In California Assembly districts, rates of childhood overweight were strongly, consistently and significantly correlated with percent below poverty for the entire population ($r = 0.82$) and in race/ethnicity-specific analyses (African-American $r = 0.43$, Latino $r = 0.61$, White $r = 0.54$). The relationship between area-based poverty and overweight was also robust in gender-specific analyses (girls $r = 0.84$; boys $r = 0.76$). For each population group, there was also indication of spatial autocorrelation or clustering of childhood overweight. See Table 1 for the detailed results.

Results of linear regression analyses for childhood overweight as a function of area poverty are shown in Table 2. Assembly district poverty was a consistent predictor of childhood overweight for the overall population and in race/ethnicity-specific analyses. For all models, the observation of significant spatial autocorrelation necessitated the use of a spatial error model, which corrects for spatial dependence. For all models, inclusion of the spatial error term improved model fit, as evaluated by Akaike’s Information Criteria (AIC). In no model did the inclusion of the spatial error term discernibly alter the interpretation of the overweight–poverty association. For the overall population, each 10-unit change in the percent of residents below poverty would be associated with a 5.8 unit increase in the prevalence of childhood overweight. A weaker, though significant, association between area poverty and overweight was observed in the race/ethnicity-specific models. Fig. 1 shows the relationship between the overall childhood overweight prevalence and percent of residents living below poverty in California Assembly districts.

A map (Fig. 2) illustrates the clustering of high poverty and high childhood overweight in assembly districts in central Los Angeles (see map inset) and the Central Valley. No assembly district with a prevalence of childhood overweight less than 25% had a poverty rate greater than 20%, indicating the strong clustering of poverty and childhood overweight.

Discussion

A geographic analysis of poverty may permit a better understanding of the impact of environmental and social factors on health outcomes. In this ecological study, higher poverty rates at the Assembly district level were associated with higher rates of childhood overweight for the overall population and race/ethnicity groups. This relationship held when race/ethnicity-specific values were evaluated. To our knowledge, this is the first study to document area-based disparities in childhood overweight using data at the legislative district scale.

The results and differences between the race/ethnicity models are noteworthy. First, the strength of the association for the overall population was not observed in the race/ethnicity-specific models, particularly for the African-American and Latino populations. This indicates confounding by race/ethnicity for the association between area poverty and childhood overweight. Despite the observed attenuation in the race-specific models, the relationship between area poverty and childhood overweight is independent of race/ethnicity at the Assembly district scale. Furthermore, the observation of higher Moran’s I values (measure of spatial autocorrelation) in the race-specific models and the change in the strength of the association between the ordinary least squares and the spatial error model suggest greater clustering of poverty and childhood overweight among the African-American and Latino populations. Future work using both individual and area-based data should explore the mechanisms for differing extents of clustering for race/ethnicity groups.

For the overall population, childhood overweight was clustered in the Central Valley and in central Los Angeles, while more affluent areas, including portions of Orange County and the San Francisco Bay Area, had lower rates of childhood overweight and poverty. While maps have limited power for evaluating disease causation, they are valuable for identifying areas with higher rates of childhood overweight, which may allow for the better targeting of public health resources. The use of political districts as units of analysis may help focus attention on neighborhood resources, access to services, planning, zoning and the potential contribution of the built environment.

Using spatially referenced health data may play an important future role in public health surveillance (Krieger et al., 2003a; Elliott and Wartenberg, 2004). However, the arbitrariness of boundaries and the heterogeneity of populations may pose serious problems. The modifiable areal unit problem refers to the observation of an association at the one geographic scale (e.g. census tract), which may not be observed at another scale (e.g. county) (Cockings and Martin, 2005). In epidemiologic research, population heterogeneity at county or state level may be particularly problematic. Legislative districts offer an appealing alternative. First, they have comparable population sizes reducing concerns about heterogeneity of error for estimated rates and proportions. Second, legislative district boundaries are often designed to encompass homogeneous groups for political reasons (McConnell, 2004). Most importantly, findings for legislative districts may be more relevant to state policy makers than findings at other geographic scales.

The present study has numerous limitations. First, income-based threshold measures, like those used in this report, minimize the importance of social networks, social capital, overall assets and net worth (Subramanian et al., 2003). Second, our exclusive use of aggregate measures of socioeconomic status (SES) and health outcomes did not allow us to generalize to individuals (Schwartz, 1994). Multi-level approaches are needed to segregate the impact of individual versus contextual variables on health (Diez Roux, 2004). However, the evaluation of race/ethnicity-specific models partially alleviates concerns regarding the ecologic study design. The observation that area poverty was associated with overweight for separate race/ethnicity groups strengthens the plausibility of a true area poverty and overweight association. Thirdly, substantial heterogeneity of both poverty and childhood overweight within California Assembly districts is likely, raising concerns of the modifiable areal unit problem. However, these data represent finest spatial resolution available for stable estimates of childhood overweight from the Fitness-gram assessment. Additional work should focus on assessing this association at finer geographic scales. Lastly, analyses of data from public school students may not paint a complete picture of the health of all children in California. According to data from the 2006 American Community Survey, 9.2% of students in grades 5–8 are enrolled in private schools, and are therefore not captured in this data (US Census Bureau, 2006). There is some evidence that students of Catholic and non-Catholic private schools have a higher mean BMI and greater proportion above the 85th percentile (O’Malley et al., 2007). It is unclear whether private school enrollment varies between or within California Assembly districts, or how differences in enrollment in private schools might influence the relationship between childhood overweight and poverty. However, it is likely that these data underestimate the prevalence of childhood overweight in California Assembly districts.

Studies on social disparities and obesity have most often dealt with individual-level variables. The emerging emphasis on ABSMs changes the focus of research to environmental factors—including the social and physical environments (Gordon-Larsen et al., 2006; Nelson et al., 2006; Frank et al., 2004). Mapping diseases, especially at the legislative scale, may direct site- and population-specific interventions, prioritize public health policies and direct resources toward areas of greatest need.

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Abbreviations

ABSMs	area-based socioeconomic measures
GIS	Geographic Information System
HFZ	healthy fitness zone
SES	socioeconomic status

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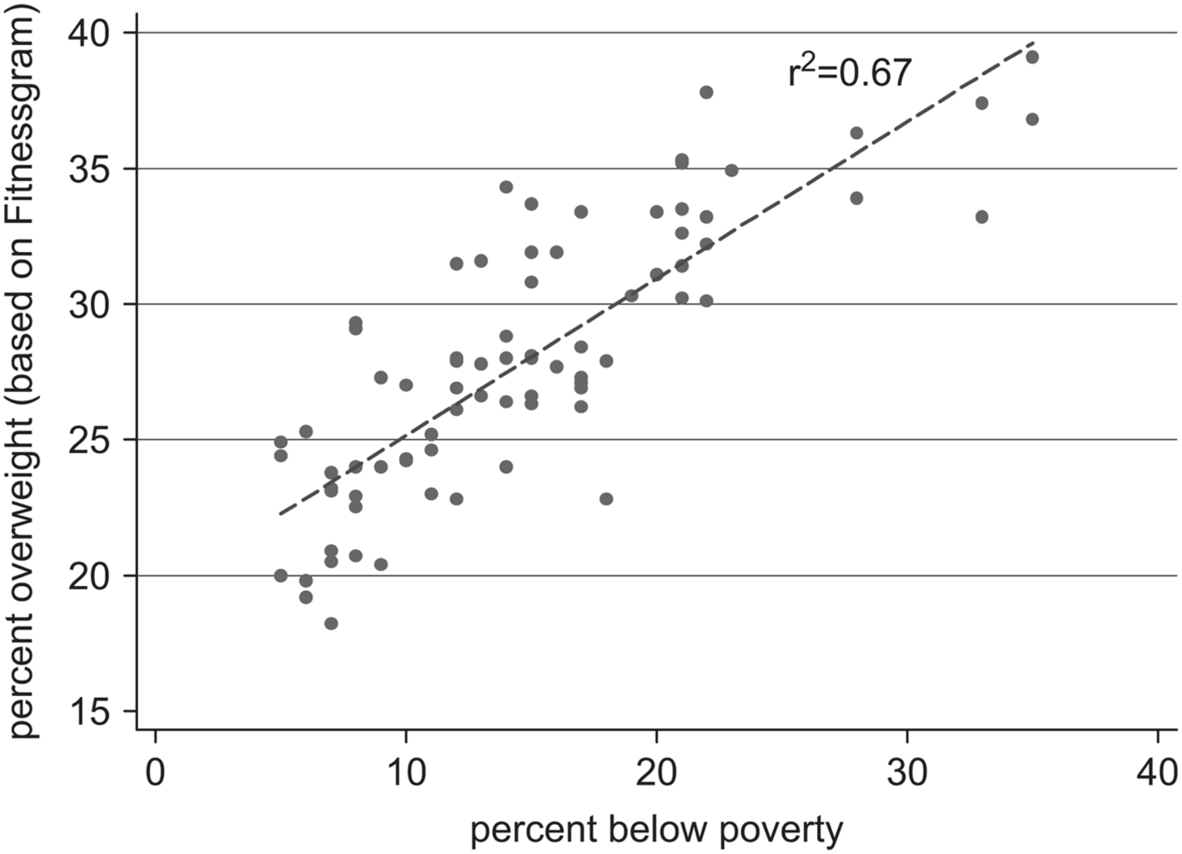

Fig. 1.
Relationship between childhood overweight and poverty by assembly district.

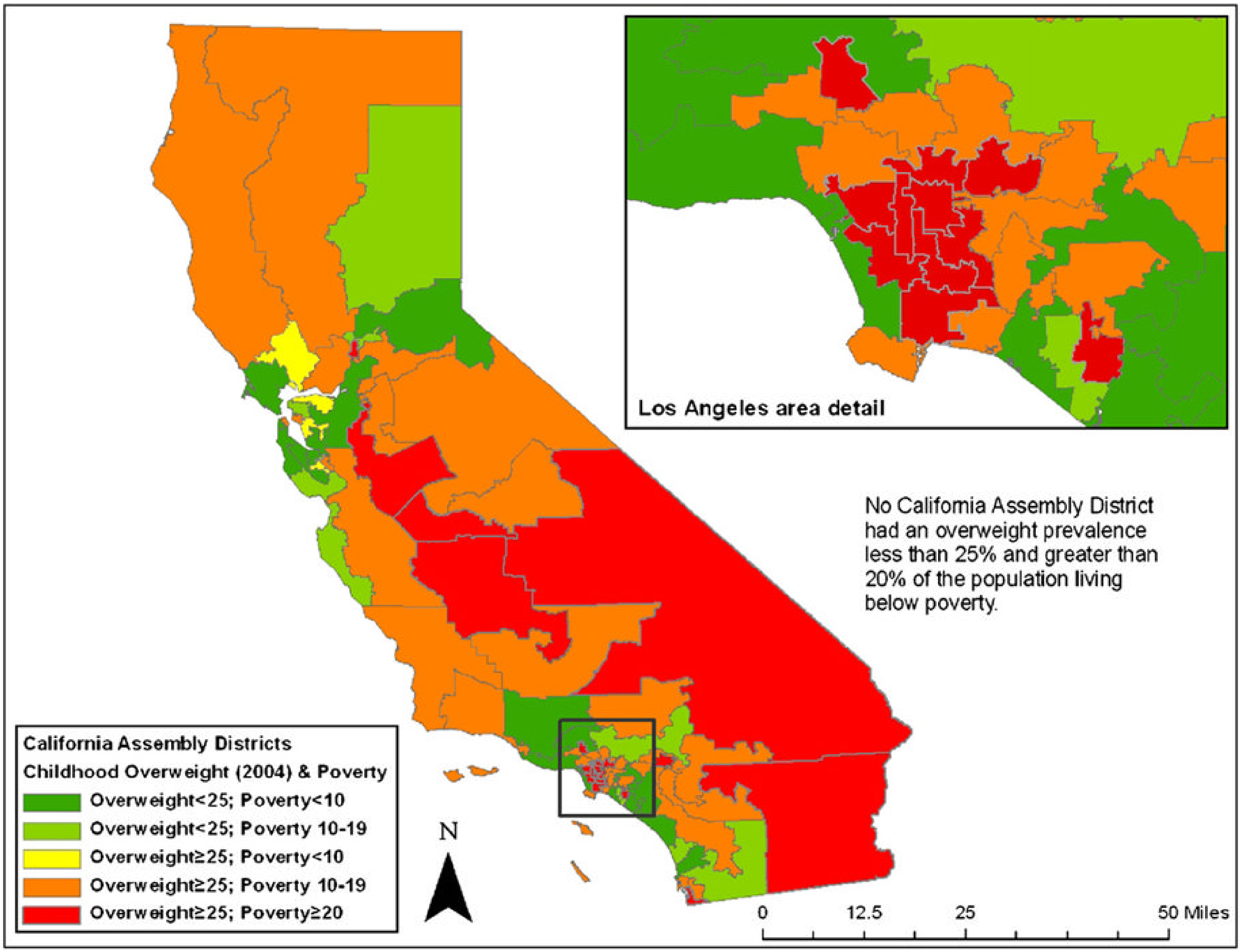

Fig. 2.
Childhood overweight prevalence (2004) and percent below poverty (2000) in California Assembly districts.

Table 1

Correlation between poverty and childhood overweight by race/ethnicity and gender and univaraite Moran's *I* statistic for childhood overweight.

	Correlation coefficient	**Univariate Moran's *I* value**[a]
Child overweight (entire population)	0.82***	0.31
Child overweight (African-American)	0.43***	0.23
Child overweight (Latino)	0.61***	0.28
Child overweight (White)	0.54***	0.24
Child overweight (girls)	0.84***	0.26
Child overweight (boys)	0.76***	0.38

*** p value <0.001.

[a] Higher Moran's *I* statistic values represent greater autocorrelation.

Table 2

Multivariate linear regression models by race/ethnicity (percent overweight as outcome).

	Overall		**African-American**		**Latino**		**White**	
	Model 1[a] Beta (95% CI[c])	**Model 2[b] Beta (95% CI)**	**Model 1[a] Beta (95% CI)**	**Model 2[b] Beta (95% CI)**	**Model 1[a] Beta (95% CI)**	**Model 2[b] Beta (95% CI)**	**Model 1[a] Beta (95% CI)**	**Model 2[b] Beta (95% CI)**
Percent below poverty	0.58 (0.49–0.67)	0.58 (0.48–0.67)	0.19 (0.10–0.27)	0.22 (0.13–0.31)	0.21 (0.15–0.27)	0.22 (0.16–0.29)	0.34 (0.22–0.46)	0.34 (0.21–0.47)
Intercept	19.4 (17.9–20.8)	19.4 (17.7–21.0)	25.4 (24–26.8)	25.0 (23.3–26.8)	31.6 (30.6–32.6)	31.5 (30.3–32.7)	17.1 (15.1–19.0)	17.1 (14.8–19.5)
Overall Model	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$
r^2	0.67	0.69	0.18	0.34	0.38	0.47	0.29	0.36
AIC[d]	397.4	394.4	393.1	380.8	336.5	326.8	443.8	437.8
Moran's *I* (*p* value)[e]	0.13 (0.03)		0.28 (<0.001)		0.25 (<0.001)		0.17 (<0.01)	

[a] Ordinary least squares regression.

[b] Spatially adjusted model–using spatial error model.

[c] Confidence interval.

[d] Akaike's Information Criteria, lower values indicating improved model fit.

[e] Moran's *I* statistic based on the residuals from the model, not calculated for models including spatial error term.