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Article

Obesity among black women in food deserts: An "omnibus" test of differential risk

Samantha Gailey[a,*], Tim A. Bruckner[b]

[a] School of Social Ecology, University of California Irvine, United States
[b] Program in Public Health, University of California Irvine, United States

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ABSTRACT

The "omnibus" hypothesis, as forwarded by Ford and Dzewaltowski (2008), asserts that poor-quality food environments differentially affect low- and high-socioeconomic status (SES) populations. Accordingly, we examine, in a large sample of non-Hispanic (NH) black women, whether low access to healthy food corresponds with increased risk of obesity among residents of low- and high-poverty neighborhoods. In addition, we analyze whether any discovered association between low-food access and obesity appears stronger in neighborhoods with a high proportion of black residents. We retrieved body mass index (BMI) data for 97,366 NH black women residing in 6258 neighborhoods from the California Department of Public Health birth files for years 2007-2010. We linked BMI data with census tract-level data on neighborhood food access from the 2010 Food Access Research Atlas and neighborhood poverty and black composition from the 2006-2010 American Community Survey 5-year estimates. We applied generalized estimating equation methods that permit analysis of clustered data within neighborhoods. Methods also controlled for individual-level characteristics which might confound the relation between food access and obesity, including health insurance status, age, education, and parity. Results indicate that low-food access does not impact risk of obesity among NH black women residing in low-poverty neighborhoods. However, low-food access varies positively with risk of obesity in high-poverty neighborhoods. Moreover, the association between low-food access and obesity appears stronger in high-poverty, high-black composition neighborhoods, relative to high-poverty, low-black composition neighborhoods. Our findings support the omnibus hypothesis and indicate a potential interaction between factors in the local food and social environments on an individual's risk of obesity.

1. Introduction

The prevalence of obesity, particularly among low-income and ethnic minority populations, rose substantially in the US in past decades (Ogden, Carroll, Kit & Flegal, 2014; Ogden, Carroll, Fryar & Flegal, 2015). Findings indicate that differences in diet across racial/ethnic and socioeconomic status (SES) groups may explain disparities in obesity (Satia, 2009; Handbury, Rahkovsky & Schnell, 2015). However, factors that influence dietary behaviors and obesity disparities remain unclear. Whereas early public health efforts focused narrowly on individual-level determinants of obesity, in recent years the focus of literature has shifted toward understanding the role of local environmental factors.

A large body of research in this area has focused on the "obesogenic" food environment (Caspi, Sorensen, Subramanian & Kawachi, 2012; Lake & Townshend, 2006; Swinburn & Egger, 2002). Accumulating evidence suggests that poor-quality food environments disproportionately affect disadvantaged populations. Compared to more affluent neighborhoods, low-income neighborhoods provide poorer access to outlets selling healthy food like supermarkets (also known as "food deserts") and greater access to outlets selling unhealthy food (Black, Moon & Baird., 2014; Cummins & Macintyre, 1999). Powell, Slater, Mirtcheva, Bao, and Chaloupka (2007), for example, find that low-income neighborhoods have only 75% of the chain supermarkets available in higher income neighborhoods. Results also indicate that predominantly white neighborhoods provide access to twice as many healthy food outlets as neighborhoods comprised of predominantly black residents (Powell et al., 2007).

Research on neighborhood disparities in food access converge with socioeconomic and racial/ethnic differences in obesity prevalence. Low-SES and minority populations have, on average, lower access to healthy food and higher risk of obesity (Black, Moon & Baird., 2014;

* Correspondence to: UCI School of Social Ecology, 5300 Social and Behavioral Sciences Gateway, Irvine, CA 92697, United States.
E-mail addresses: sgailey@uci.edu (S. Gailey), tim.bruckner@uci.edu (T.A. Bruckner).

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Ogden et al., 2014). Researchers and policy makers hold that differential access to low-quality food environments may contribute to growing obesity disparities, reflecting a "deprivation amplification" effect. Deprivation amplification refers to poor environmental conditions, such as limited supermarket availability, that "amplify," or strengthen the pathogenic influence of individual-level disadvantage. Evidence of the deprivation amplification effect of poor neighborhood food access on risk of obesity, however, remains scant.

Findings on the relation between access to healthy food and obesity do not converge. Some studies find that greater supermarket availability improves dietary quality and reduces risk of obesity among neighborhood residents (Bodor, Rice, Farley, Swalm & Rose, 2010; Dubowitz et al., 2012; Lopez, 2007; Morland et al., 2006). In the Atherosclerosis Risk in Communities Study, for example, individuals living in neighborhoods with at least one supermarket showed lower risk of obesity than residents of neighborhoods without supermarkets. However, the literature also includes reports of null associations (Drewnowski, Aggarwal, Hurvitz, Monsivais & Moudon, 2012; Hattori et al., 2013) and positive associations (Ford & Dzewaltowski, 2010; Wang, Kim, Gonzalez, MacLeod & Winkleby, 2007) between access to healthy food and obesity.

Inconsistent findings may arise from the heterogeneity of study populations and areas (Leal & Chaix, 2011; Odoms-Young, Singleton, Springfield, McNabb & Thompson, 2016). Recent evidence indicates that the relation between food access and obesity varies by individual- and neighborhood-level characteristics. For example, Morland, Wing and Roux (2002) find that, with each additional supermarket in a neighborhood, fruit and vegetable consumption increases by 32% in black residents, but only 11% in white residents. Zick, Smith, Fan, Brown, Yamada, and Kowaleski-Jones (2009) report that the presence of at least one healthy food store decreases risk of obesity among individuals living in low-income neighborhoods, but not high-income neighborhoods. Singleton, Affuso, and Sen (2016) moreover show that measures of the local food environment can explain differences in obesity prevalence between areas with low- and high-black composition. Taken together, this work indicates that individual race/ethnicity, as well as neighborhood socioeconomic characteristics, may differentially influence the extent to which the food environment determines obesity risk.

2. Omnibus Hypothesis

Ford and Dzewaltowski (2008) suggest an "omnibus hypothesis" which, consistent with evidence that food access/obesity relations vary by individual and neighborhood characteristics, forwards that low- and high-SES populations differentially respond to the food environment (Morland, Wing & Roux, 2002; Singleton, Affuso & Sen, 2016; Zick et al., 2009). Economic resources afforded to individuals of higher socioeconomic position, Ford and Dzewaltowski (2008) argue, buffer the adverse effects of poor-quality food environments on diet and obesity. Findings that support the omnibus hypothesis indicate that, in poor-food access neighborhoods, residents who do not own cars show increased risk of obesity relative to those who own cars, suggesting that non-car owners may rely to a greater extent on food outlets in the immediate residential environment (Inagami, Cohen, Brown & Asch, 2009). In low-food access neighborhoods, moreover, higher prices in small grocery stores and specialty outlets appear to deter lower, but not higher-income individuals from purchasing healthy food, which may in turn contribute to differential obesity risk (Jetter & Cassady, 2006).

In addition, Ford and Dzewaltowski (2008) contend that social and cultural resources available to higher- and lower-SES populations support different responses to the food environment. Some research, for example, indicates that prevalent social norms and beliefs about body size and diet in predominantly black neighborhoods may contribute to dietary behaviors that increase obesity risk (Boardman, Saint Onge, Rogers & Denney, 2005; Do, Dubowitz, Bird, Lurie, Escarce & Finch, 2007). However, we know of no work that examines the extent to which these social norms operate differently in low- versus high-food access neighborhoods. This research, therefore, requires additional empirical testing.

We test, among black adults living in low- and high-SES neighborhoods, whether and to what extent low access to healthy food varies with risk of obesity. Whereas the omnibus hypothesis forwarded by Ford and Dzewaltowski (2008) proposes a cross-level interaction effect in which the relation between neighborhood food access and obesity varies by individual socioeconomic position, we examine whether the food access/obesity relation differs among residents of low- versus high-poverty neighborhoods. In addition, given evidence that social factors in predominantly black neighborhoods may increase risk of obesity, we analyze whether any discovered association between low-food access and obesity appears stronger for residents of high-black composition neighborhoods (Boardman et al., 2005; Do et al., 2007). We test our hypotheses among 97,366 adult women residing in 6258 neighborhoods, which to our knowledge represents the largest study to investigate this topic. Whereas the omnibus hypothesis pertains to both men and women, we focus our analysis on women given data availability (described below).

3. Methods

3.1. Variables and data

The data used for this study, as well as the research protocol, received human-subjects approval from both the State Committee for the Protection of Human Subjects (#13-06-1251) and the UCI Institutional Review Board (HS# 2013-9716). In 2007, California adopted the revised U.S. Standard Certificate of Birth, which includes the collection of maternal weight and height data (CDC, 2003; Mendez et al., 2016). We retrieved pre-pregnancy BMI data from the California Department of Public Health birth files for years 2007-2010. The birth file contains over 99.99% of all live births in the state and includes census tract-level identifiers, demographic information, and health data from the certificate of birth (CDPH). This time frame spans the first year in which the birth file includes pre-pregnancy weight and height to the last year for which we had data available to us at the time of our tests.

We calculated pre-pregnancy BMI as pre-pregnancy weight (in kilograms) divided by height (in meters) squared. We applied conventional categories of overweight ($25.0 \leq \text{BMI} < 30.0$) and obesity ($\text{BMI} \geq 30.0$) based on the World Health Organization definitions (WHO, 2006). We excluded records with missing or implausible combinations of maternal weight and height data (N = 199,390).

Whereas weight and height data pertain only to these women, the mean and distributional characteristics of BMI recorded from this source appear comparable to BMI among a broader set of adult women in California (Krueger et al., 2014; Segal et al., 2017), including women of childbearing age (i.e., 18-40 years) in the California Health Interview Survey (CHIS), a random-dial telephone survey, representative of the non-institutionalized population [http://healthpolicy.ucla.edu/chis/data/Pages/public-use-data.aspx, accessed November 4, 2018] (see Supplemental material, Table 1-4).

We geocoded maternal address of residence using ArcGIS software version 10.4 (Redlands, California). We located maternal addresses using a 2013 street directory and assigned a corresponding census tract (a proxy of neighborhood) based on 2010 US Census geography. We removed birth records with maternal address fields that failed to reach the minimum match score of 85 percent or with unknown, missing, or non-California census tracts (N = 145,784). Excluding multiple births (N = 57,469), as well as records corresponding to mothers living in rural neighborhoods (N = 93,312) and with missing data on essential variables (N = 3143), left us with 1,670,907 birth records. The final analytic sample, restricted to mothers who self-reported their race/ethnicity as NH black, included 97,366 observations.

We linked these BMI data to census tract-level data on neighborhood food access from the U.S. Department of Agriculture (USDA) Food Access Research Atlas (ERS, 2016). The census tract provides the smallest unit of geographic resolution for this area-based measure of food access and, in urban settings, serves as a reasonably granular catchment area in terms of travel distance to food outlets. Larger geographic aggregations (e.g., zip code, county) would lose such resolution. The 2010 Food Access Research Atlas defines low-food access as living at least one mile away from a supermarket for residents of urban neighborhoods and ten miles away from a supermarket for residents of rural neighborhoods (Ver Ploeg & Wilde, 2018). The Food Access Research Atlas classifies supermarkets as stores that contain all major food departments and report at least $2 million in annual sales, based on a combined 2010 food store directory. Given the small percentage of NH black women in our sample who live in rural neighborhoods, we focused our analysis on food access in urban neighborhoods (i.e., census tracts with at least 2500 residents). Per the USDA definition, we classified neighborhoods as low-food access if at least 500 people or 33 percent of the population lived more than 1 mile from the nearest supermarket (Ver Ploeg & Wilde, 2018; ERS, 2016).

At the census tract-level we also linked BMI data with measures of neighborhood poverty and black composition using the American Community Survey 2006-2010 5-year estimates. Neighborhood poverty measures the percentage of families below the federal poverty line (FPL) and neighborhood black composition measures the percentage of non-Hispanic black residents. Based on the U.S. Census Bureau definition of "poverty areas" (1995), we dichotomized the poverty measure using a cut point of 20%; that is, we classified neighborhoods with at least 20% of families below the FPL as "high-poverty" (Duncan, Kawachi, White & Williams, 2013; Franzini, Taylor & Elliott, 2010; Krieger, Waterman, Chen, Soobader, Subramanian & Carson, 2002). We dichotomized the black composition measure using a cut-point of 25% (i.e., "high-black" neighborhoods comprise greater than 25% black residents) (Kirby, Liang, Chen & Wang, 2012; Li, Wen, & Henry, 2014).

3.2. Analysis

Obesity likely correlates positively across residents of the same neighborhood due to shared (but unmeasured) characteristics of the neighborhood and the individuals who live there. The within-neighborhood clustering of obesity violates the assumption of uncorrelated errors in linear regression (Hubbard et al., 2010). Generalized estimating equations (GEE) address this issue (Liang & Zeger, 1986) and enjoy widespread use to examine observations "clustered" within larger geographic units (e.g., Kim & Bruckner, 2016). The GEE approach provides a robust estimator of variance that accounts for the dependence (clustering) of observations within hierarchical units such as neighborhoods. The GEE approach also has the advantage of not requiring additional distributional assumptions since the model estimation applies the observed data-generating distribution, rather than the joint distribution of observed data (Cui, 2007; Hubbard et al., 2010; Zeger & Liang, 1986).

Mixed models offer an alternative approach to analyzing clustered data (Subramanian & O'Malley, 2010). Whereas GEE includes only fixed effects, mixed models comprise both fixed and random effects and thus permit greater model flexibility, as well as neighborhood-specific inference. Mixed models, however, require a much larger set of assumptions which are often unverifiable and can lead to potentially misleading estimates and biased inference. GEE, in contrast, allow robust inference even when the correlation model is misspecified (Hubbard et al., 2010; McNeish, Stapleton & Silverman, 2016). In this sense, GEE provide a more conservative but less biased estimate of the population-averaged (i.e., neighborhood) effect. Moreover, given that our study turns on population-averaged associations between food access and obesity, the population-averaged estimates returned by GEE better align with our hypothesis tests. Our general equation takes the following form:

$$\mathrm{logit}(Y_{ij}) = \beta_0 + \beta'\mathbf{X}_{ij} + \beta_1 F_j + e_{ij}$$

Where

- logit Y_{ij} is the log(odds) of obesity for woman i in neighborhood j (obesity = 1 if BMI > 30; 0 otherwise). In a separate specification, we use overweight as the outcome.
- B_0 is a constant.
- X_{ij} is a vector of individual characteristics, which could confound relations between neighborhood food access and obesity, including health insurance status (Medicaid or private insurance), age, education, and parity.
- F_j is an indicator variable for low-food access in neighborhood j, coded as 1 for low-access and 0 otherwise.
- B_1 is our coefficient of interest.
- e_{ij} is the error term. We specified the exchangeable covariance structure of i observations clustered within j neighborhoods given that it provided small QIC statistics in our model.

We proceeded through the following steps. First, we examined the relation between food access and obesity in the aggregate—that is, among residents of both high- and low-poverty neighborhoods. Based on reasoning described in the Introduction as well as previous literature, we predicted no relation between low-food access and obesity in the aggregate test. Second, to assess the "omnibus hypothesis" (Ford & Dzewaltowski, 2008), we performed separate analyses of the relation between low-food access and obesity among residents of low-poverty and high-poverty neighborhoods. Third, per the logic of the Introduction, we stratified these poverty-specific analyses by level of neighborhood black composition. Fourth, we repeated all analyses but used combined overweight/obesity instead of obesity as the dependent variable. We conducted all analyses in SAS 9.4 (Cary, North Carolina) and specified the "robust" option in all GEE analyses.

4. Results

The full analytic sample includes 97,366 NH black women. Approximately 25% of women (n = 23,972) reside in low-food access neighborhoods (Table 1). A greater proportion of NH black women with some college education, a college degree, and private health insurance have low-food access. Among NH black women with low-food access, only 16% live in high-poverty (≥20% poor) neighborhoods, and 21% live in high-black composition (≥25% black) neighborhoods. In contrast, nearly 40% of NH black women with high-food access live in high-poverty neighborhoods, and 28% live in high-black composition neighborhoods.

The prevalence of obesity is similar among NH black women in low- and high-food access neighborhoods. Unadjusted differences in obesity prevalence emerge, however, when we stratified the sample by levels of neighborhood socioeconomic characteristics. Fig. 1 shows the prevalence of obesity among NH black women residing in low-poverty neighborhoods (Fig. 1A) and high-poverty neighborhoods (Fig. 1B) as a function of neighborhood food access and black composition. In low-poverty neighborhoods, obesity prevalence among women with low- and high-food access does not differ (Fig. 1A). In high-poverty neighborhoods, however, obesity prevalence varies by level of food access and black composition (Figure 2A). In high-poverty, low-black composition neighborhoods, the prevalence of obesity among women with low- and high-food access is 29.4% and 28.8%, respectively. In contrast, in high-poverty, high-black composition neighborhoods, the prevalence of obesity among women with low- and high-food access is 31.6% and 28.6%, respectively.

Table 2 provides results of seven separate GEE analyses which control for strong individual-level correlates of obesity. In the aggregate test on the full analytic sample, we find no relation between low-food

Table 1
Characteristics of Non-Hispanic Black women of childbearing age in low- and high-food access neighborhoods in California, 2007-2010.

	Neighborhood Food Access High (N = 73,394)		Low (N = 23,972)	
	n	%	n	%
Parameter				
Pre-pregnancy weight				
Underweight (BMI < 18.5)	3027	4.1	903	3.8
Healthy (18.5 ≤ BMI < 25.0)	31,013	42.3	10,096	42.1
Overweight (25.0 ≤ BMI < 30.0)	19,260	26.2	6453	26.9
Obese (BMI ≥ 30.0)	20,094	27.4	6520	27.2
Educational attainment				
Less than HS	12,325	16.8	3569	14.9
HS degree	25,554	34.8	7767	32.4
Some college	24,843	33.9	8391	35.0
College degree	9375	12.8	3865	16.1
Other/unknown	1297	1.8	380	1.6
Payer for delivery				
Medi-Cal	39,985	54.5	11,545	48.2
Private	25,664	35.0	9856	41.1
Other	7745	10.6	2571	10.7
Age				
< 20	10,203	13.9	3451	14.4
20-24	21,908	29.9	6817	28.4
25-29	18,937	25.8	5744	24.0
30-34	13,225	18.0	4529	18.9
35-40	7032	9.6	2683	11.2
≥40 years	2089	2.9	748	3.1
Parity				
Nullipara	31,361	42.7	9799	40.9
Primipara	20,135	27.4	6541	27.3
Multipara	21,898	29.8	7632	31.8
Neighborhood characteristics				
High-black (≥25% black)	20,171	27.5	3764	15.7
High-poverty (≥20% poor)	28,816	39.3	4953	20.7

access and obesity (Model 1). We obtain similar results in analyses restricted to residents of low-poverty neighborhoods (Models 2-4). However, when we restrict the analysis to residents of high-poverty neighborhoods, low-food access corresponds with an elevated-odds of obesity (odds ratio (OR) = 1.10; 95% Confidence Interval (CI): 1.02, 1.18). When we further stratify the sample of NH black women, we find a stronger positive association between low-food access and obesity among residents of high-poverty, high-black composition neighborhoods, relative to high-poverty, low-black composition neighborhoods (Model 7, OR = 1.17, 95% CI: 1.04, 1.31).

We conducted additional sensitivity analyses to assess the robustness of our results. First, we specified as the outcome combined overweight/obesity (coded 1 if BMI ≥ 25, and 0 otherwise) and re-ran all GEE models. We, consistent with our initials tests, find positive associations between low-food access and overweight/obesity in Model 5 (restricted to women in high-poverty neighborhoods, OR= 1.09, 95% CI: 1.02-1.17) and Model 7 (restricted to women in high-poverty, high-black composition neighborhoods, OR= 1.22, 95% CI: 1.10-1.35). We also examined whether results remained robust to use of different categorical cut points for neighborhood black composition. We find consistent results using the median-split cut point for black composition of 14.23 percent (results available upon request). Finally, we repeated all analyses using generalized linear mixed models to assess robustness of results to the "mixed effects" approach; inference for the food access coefficients remains essentially the same as in the original tests (see Table 5, Supplemental material).

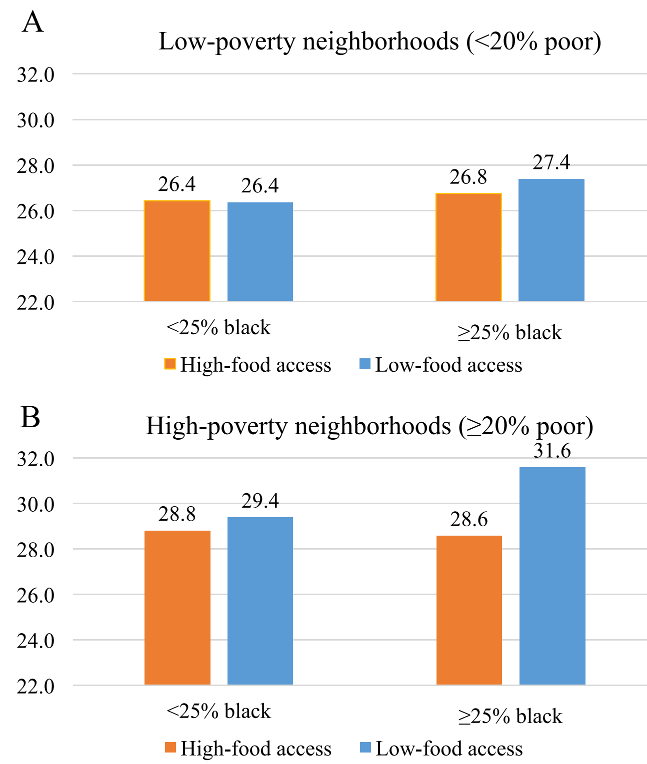

Fig. 1. A and B. Unadjusted obesity prevalence among NH black women by neighborhood food access and black composition in low- and high-poverty neighborhoods.

5. Discussion

Controversy remains as to the role of the local food environment in determining individual obesity risk. We contribute to this debate by analyzing, among a large sample of NH black women in California, whether low-food access varies positively with risk of obesity, and whether the food access/obesity relation differs according to neighborhood socioeconomic characteristics. Results on 97,366 women in 6258 neighborhoods indicate that low-food access corresponds with an elevated-odds of obesity among residents of high-poverty neighborhoods, but not among residents of low-poverty neighborhoods. Moreover, women with low-food access residing in high-poverty, high-black composition neighborhoods show increased risk of obesity relative to those in high-poverty, low-black composition neighborhoods. Although we do not interpret results as causal, risk factors for obesity, especially among NH black women living in low-income, minority neighborhoods, may include poor access to healthy food.

Our findings provide support for the "omnibus hypothesis" (Ford & Dzewaltowski, 2008) which holds that poor-quality food environments differentially impact high- and low-SES populations. In their original hypothesis, Ford and Dzewaltowski (2008) proposed a cross-level interaction effect of neighborhood food access and individual SES on obesity risk. We, however, examined obesity as a function of the interaction between neighborhood food access and neighborhood SES.

We find evidence of a relation between low-food access and obesity among residents of high-poverty, but not low-poverty neighborhoods. Economic resources may protect residents in higher income neighborhoods from the deleterious effects of poor-quality food environments (Inagami et al. 2009; Jetter & Cassady, 2006; Ford & Dzewaltowski 2008). For example, residents of low-poverty neighborhoods with limited food access might travel greater distances to supermarkets or purchase healthy food in more expensive local outlets (e.g. specialty food stores, farmer's markets). In contrast, residents of high-poverty neighborhoods may depend on low-cost food options in the immediate

Table 2
Odds ratios (95% confidence intervals in parentheses) predicting obesity among non-Hispanic black women in California as a function of neighborhood food access, neighborhood economic and racial/ethnic composition, and individual covariates.

Restrictions	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
% Poverty	**-**	**< 20%**	**< 20%**	**< 20%**	**≥ 20%**	**≥20%**	**≥20%**
% Black	**-**	**-**	**< 25%**	**≥ 25%**		**< 25%**	**≥ 25%**
Low-food access	1.00 (0.96,1.04)	1.01 (0.96,1.06)	1.01 (0.96,1.06)	1.04 (0.89,1.22)	1.10 (1.02,1.18)	1.08 (0.99,1.17)	1.17 (1.04,1.31)
Maternal Age (in years)							
< 20	0.56 (0.53,0.60)	0.53 (0.49,0.58)	0.53 (0.48,0.58)	0.54 (0.45,0.65)	0.60 (0.55,0.65)	.59 (0.53,0.65)	0.62 (0.53,0.72)
20-24 (ref)	–	–	–	–	–	–	–
25-29	1.44 (1.39,1.50)	1.43 (1.35,1.50)	1.41 (1.33,1.49)	1.51 (1.33,1.70)	1.48 (1.39,1.59)	1.146 (1.34,1.58)	1.54 (1.37,1.73)
30-34	1.63 (1.55,1.71)	1.56 (1.47,1.66)	1.51 (1.41,1.62)	1.79 (1.55,2.07)	1.80 (1.67,1.94)	1.75 (1.59,1.92)	1.93 (1.71,2.18)
35-39	1.74 (1.64,1.84)	1.67 (1.56,1.79)	1.64 (1.52,1.77)	1.79 (1.52,2.11)	1.98 (1.78,2.21)	1.96 (1.71,2.24)	2.05 (1.70,2.46)
≥ 40	1.71 (1.56,1.87)	1.62 (1.46,1.81)	1.58 (1.41,1.78)	1.78 (1.36,2.33)	2.05 (1.74,2.42)	1.74 (1.40,2.16)	2.69 (2.08,3.47)
Education							
Less than HS	1.44 (1.34,1.54)	1.53 (1.40,1.67)	1.49 (1.35,1.64)	1.68 (1.40,2.02)	1.06 (0.93,1.21)	1.06 (0.90,1.25)	1.08 (0.87,1.34)
HS degree	1.65 (1.56,1.74)	1.67 (1.57,1.78)	1.65 (1.54,1.78)	1.71 (1.49,1.96)	1.28 (1.14,1.43)	1.32 (1.14,1.53)	1.21 (1.01,1.44)
Some college	1.66 (1.57,1.74)	1.67 (1.57,1.76)	1.65 (1.54,1.75)	1.74 (1.53,1.98)	1.32 (1.18,1.48)	1.35 (1.16,1.57)	1.29 (1.08,1.53)
College degree (ref)	1.0	1.0	1.0	1.0	1.0	1.0	1.0
MediCal (vs. private insurance)	1.01 (0.97,1.05)	1.01 (0.97,1.06)	1.02 (0.98,1.08)	0.96 (0.87,1.07)	0.94 (0.88,1.00)	0.95 (0.88,1.04)	0.90 (0.81,1.00)
Parity							
1st child	1.0	1.0	1.0	1.0	1.0	1.0	1.0
2nd child	1.14 (1.10,1.19)	1.15 (1.09,1.20)	1.18 (1.12,1.25)	1.00 (0.90,1.11)	1.12 (1.05,1.20)	1.15 (1.06,1.25)	1.07 (0.97,1.18)
3rd or greater	1.25 (1.20,1.31)	1.30 (1.23,1.37)	1.36 (1.28,1.44)	1.05 (0.93,1.20)	1.13 (1.05,1.21)	1.13 (1.04,1.23)	1.13 (1.00,1.28)
Observations	*97,366*	*63,597*	*51,201*	*12,396*	*33,769*	*22,230*	*11,539*
Neighborhoods	*6,258*	*5,090*	*4,921*	*169*	*1,168*	*1,023*	*145*

residential context due to transportation and monetary restraints.

Results also indicate a potential interplay between characteristics of the social environment and the food environment in the development of obesity. Although we did not directly examine pathways between poor neighborhood conditions and obesity risk, our results suggest that the social environment of high-poverty, high-black composition neighborhoods may support unhealthy eating patterns in the absence of nearby healthy food outlets. We cannot know, however, whether these social factors operate differently in low-food and high-food access neighborhoods. Additional studies examining norms, attitudes, and beliefs about diet and obesity among residents of low-SES, minority neighborhoods may help explain how factors of the local food and social environments interact to create obesity disparities (Suglia, Shelton, Hsiao, Wang, Rundle & Link, 2016). This explanation requires further refinement and testing before being taken as anything other than informed speculation.

Strengths of our study include use of BMI data from a large, population-based cohort of women in California spanning several years. These data afforded us a much larger sample of adults to estimate food access/obesity relations than would well-known national surveys (e.g., NHANES). We also used individual-level data to control for age, health insurance status, education, and other covariates that might confound relations between food access and risk of obesity. In addition, we conducted tests of food access/obesity relations on women residing in more than 6000 neighborhoods. The large number of observations and neighborhoods allowed us to stratify analyses by neighborhood socioeconomic characteristics to conduct theory-driven tests of interactions between the local food and social environments. Moreover, given evidence that maternal pre-pregnancy overweight/obesity varies positively with risk of adverse birth outcomes, including gestational diabetes (Solomon et al., 1997), pregnancy-induced hypertension and preeclampsia (Thadhani, Stampfer, Hunter, Manson, Solomon & Curhan, 1999), postpartum anemia (Bodnar, Siega-Riz & Cogswell, 2004), and birth defects (Anderson, Waller, Canfield, Shaw, Watkins & Werler, 2005), our findings also hold relevance to efforts to document and reduce neighborhood risk factors for adverse birth outcomes.

Limitations include that our cross-sectional methods cannot account for neighborhood self-selection bias. Structural confounding due to social stratification, particularly in the context of economic and racial segregation, may bias our study of food access/obesity relations (Cobb, Appel, Franco, Jones-Smith, Nur & Anderson, 2015; Oakes, 2004). We therefore caution the reader against causal interpretation of our low-food access coefficients. As recommended by others, future studies may benefit from natural experiments or longitudinal designs to improve our understanding of whether increases in neighborhood food access precede reductions in obesity (Bodor et al., 2010; Cobb et al., 2015; Do et al., 2007; Ford & Dzewaltowski, 2008; Odoms-Young et al., 2016).

Our focus on data gathered from birth certificates may limit the external validity of findings. Given that the sample comprises NH black women who gave birth in years 2007-2010, findings may generalize only to women of childbearing age (i.e., 18-40 years). We cannot, however, know the extent to which (non-pregnant) NH black women aged 18-40 years access their local food environments differently than do pregnant women. It remains possible, moreover, that characteristics of NH black women who gave birth during the Great Recession, which overlaps with the study period, differ from those who gave birth prior to or following this period. Although we know of no work suggesting that NH black women in this study sample differentially respond to neighborhood food access, only replication of results in other populations, places and times can determine the external validity of findings. For these reasons, we caution against using results to predict individual obesity risk outside of the study base of NH black women.

The USDA measure of food access, defined as the presence or absence of a neighborhood supermarket, has several limitations. We assigned food access at the census tract-level, rather than by tracking travel distances at individual locations. Individual responses to the food environment that differ from that of the average neighborhood resident may diverge from our findings. For example, residents of low-food access neighborhoods who have access to public transportation or personal vehicles may shop at food outlets beyond the immediate residential context. In addition, the USDA measure of food access does not assess the average resident's overall exposure to healthy and unhealthy food. The full range of available food retail options may include, in addition to supermarkets, convenience stores, grocery stores, fast food and full-service restaurants.

The absence of "gold-standard" measures of food access may contribute to inconsistent findings in the literature. The complexity of the food environment makes it inherently difficult to quantify the average resident's overall exposure to healthy and unhealthy food. Research examining relations between obesity and the food environment, consequently, includes a wide variety of food access measures, with results varying according to food outlet type (e.g., supermarkets, grocery stores) and method of exposure (e.g., proximity, density) (Caspi et al. 2012). In a systematic review of the food environment literature, for example, Cobb et al. (2015) find differential associations between obesity and food access measures such as supermarket availability and index variables that assess overall levels of healthy food exposure. Moreover, uncertainty remains as to the relevant spatial context of the food environment. Studies define an individual's exposure to the food environment using buffer sizes from less than a half-mile to over two miles, as well as by varying administrative boundaries including census tracts, ZIP codes, and metropolitan statistical areas (Leal & Chaix, 2011; James et al., 2014).

Future studies may benefit from using more nuanced approximations of the neighborhood food environment. Researchers and practitioners can create multi-faceted measures of food access from USDA datafiles comprising a wide-range of food environment indicators. Users can retrieve area-level data on over 250 measures of the food environment, including food store and restaurant proximity, food prices, and nutrition assistance programs from the USDA's Food Environment Atlas. Studies that characterize the food environment by both the availability of supermarkets and corresponding food prices (e.g. Drewnowski et al., 2012), for example, may hold relevance to obesity prevention programs targeting access to affordable, healthy food for low-SES populations.

The USDA Food Access Research Atlas provides access to census tract-level data on healthy food access, measured by the presence or absence of supermarkets, in most neighborhoods in the US. Whereas this measure does not capture all aspects of the food environment, it offers a tool which research conducted in disparate areas and populations across the US can use. In addition, the USDA Food Access Research Atlas enjoys widespread use by the federal government and serves as a primary source of policy-relevant research and action related to food access in disadvantaged neighborhoods. Although other geographically-refined measures (e.g., travel distances) likely provide more precise estimates of an individual's exposure to the food environment, studies using the USDA food access measure hold implications for obesity prevention at the population level. Given that policy considerations typically turn on "net effects," rather than individual-level findings, we encourage further refinement and investigation of neighborhood food access as a cause of obesity.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ssmph.2019.100363.

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