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Neighborhood Environment Measurements and Anthropometric Indicators of Obesity: Results from the Women and Their Children's Health (WaTCH) Study

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Abstract

We compared geographic information system (GIS)- and Census-based approaches for measuring the physical and social neighborhood environment at the census tract-level versus and audit approach on associations with body mass index (BMI), waist circumference (WC), and waist-to-hip ratio (WHR). Data were used from the 2012–2014 Women and Their Children's Health (WaTCH) Study ($n=940$). Generalized linear models were used to obtain odds ratios (ORs) for BMI ($> 30 \text{ kg/m}^2$), WC ($> 88 \text{ cm}$), and WHR (> 0.85). Using an audit approach, more adverse neighborhood characteristics were associated with a higher odds of WC (OR: 1.10; 95% CI: 1.05, 1.15) and WHR (OR: 1.09; 95% CI: 1.05, 1.14) after adjustment for age, race/ethnicity, income, and oil spill exposure. There were no significant associations between GIS- and Census- based measures with obesity in adjusted models. Quality aspects of the neighborhood environment captured by audits at the individual-level may be more relevant to obesity than physical or social aspects at the census-tract level.

Keywords

public health; behavior change; GIS (geographic information system); mixed methods; neighborhood/community

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Conflict of interest
None declared.

Introduction

The neighborhood environment has been identified as an important risk factor for the prevention of obesity through its influence on health-related behaviors such as physical activity and diet, theoretically supported by ecological models of health behavior (Sallis & Owen, 2015). Ecological models of health behavior hypothesize that there are multiple levels of influence operating as determinants of behavior including: individual factors, inter-personal/social environment, physical environment, and policy factors. Research interest in the role of the neighborhood environment on obesity and health-related behaviors has been an expanding topic of investigation across multiple research disciplines as well as in public health.

Some empirical research has shown that characteristics of the physical or built environment, such as, parks, recreational centers, utilitarian destinations such as local shops and services, and other amenities that can provide opportunities for incidental and discretionary physical activity have been associated with adult obesity (Black, Macinko, Dixon, & Fryer, 2010; Brownson, Hoehner, Day, Forsyth, & Sallis, 2009; Eisenstein et al., 2011; Giles-Corti, Macintyre, Clarkson, Pikora, & Donovan, 2003; Michimi & Wimberly, 2012; Mujahid et al., 2008; Sallis et al., 2006). Other studies have found significant associations between aspects of the food environment (e.g., availability of and proximity to fast-food restaurants and convenience stores) and obesity (Hutchinson, Nicholas Bodor, Swalm, Rice, & Rose, 2012; Morland, Diez Roux, & Wing, 2006; Morland & Evenson, 2009; Yan, Bastian, & Griffin, 2015). Also, characteristics of the social environment, such as neighborhood safety, crime, drug problems, incivilities, social disadvantage, and psychosocial hazards, have been suggested to influence obesity by deterring healthy behaviors such as physical activity (Burdette, Wadden, & Whitaker, 2006; Christian, Giles-Corti, Knuiman, Timperio, & Foster, 2011; Yang, Spears, Zhang, Lee, & Himler, 2012).

Due to the growing interest in this sphere of research, empirical studies have included a wide range of data acquisition methods and neighborhood measures that attempt to capture environmental characteristics associated with obesity. The variety of methods and measures for capturing the neighborhood environment are evidenced in numerous reviews including Booth et al. (2005), Papas et al. (2007), Feng et al. (2010), Ding and Gebel (2012), Sugiyama et al. (2014), and Mackenbach et al (2014). These reviews substantiate the heterogeneity of measures used to investigate associations between aspects of the neighborhood environment on obesity and subsequently, the challenges that contribute to inconsistent and inconclusive inferences across studies.

Although the terminology may differ between reviews and empirical studies, data acquisition methods for measuring the neighborhood environment generally consist of 1) objective assessments including: Geographic Information Systems (GIS)- or Census- based neighborhood measures as well as in-person audits of the neighborhood environment; and 2) subjective measures that are perceived or self-reported by residents (Booth, Pinkston, & Poston, 2005). GIS- based measures capture local destinations of the physical environment (i.e., parks, recreation centers, utilitarian destinations) and aspects of the food environment (i.e., availability of and proximity to fast-food restaurants and convenience stores). Census-

based neighborhood measures often include social characteristics of the neighborhood environment such as economic and concentrated disadvantage. Another objective approach for measuring the neighborhood environment is through direct observer ratings using trained auditors, usually resulting in an individual-level measure of each participant's residential neighborhood area (e.g., immediate block area). Such observations describe an individual's specific environment, as opposed to census-level measures shared by multiple people within an administratively defined area of residence. Importantly, neighborhood audits are used less often because they impose an additional study burden with respect to training and data collection. While GIS measures are accurate in measuring the quantity aspects of the neighborhood environment, neighborhood audits are recognized as an accurate representation of quality aspects of the neighborhood environment and have been recommended for assessing current neighborhood conditions (Booth, Pinkston, & Poston, 2005; Leung, Gregorich, Laraia, Kushi, & Yen, 2010).

These three data acquisition methods not only capture different measures of the neighborhood environment, they may also differ in scales of the geographical area used to define the neighborhood environment. The type of measurement and subsequently, definition of neighborhood exposure through different data acquisition methods can affect possible associations with obesity and can determine whether or not associations are found (Diez Roux & Mair, 2010; Feng, Glass, Curriero, Stewart, & Schwartz, 2010; Sugiyama, Koohsari, Mavoa, & Owen, 2014). Yet, the problem of how to geographically define the neighborhood environment and what to measure remains unsolved. In 2003, O'Campo (2003) suggested that no single unit of the neighborhood will satisfy the needs for measuring multiple neighborhood processes, thereby promoting studies to use multiple methods and definitions of neighborhoods within the same study and to go beyond the use of administrative or census data.

Yet, of the 41 studies that examined associations between the neighborhood environment and obesity that were published since 2010 and included in the review by Sugiyama et al. (2014), none used different data acquisition methods and none reported findings at more than one scale. Of the 37 papers included in the review by Feng et al. (2010), 22 examined neighborhood associations with obesity using administrative definitions of place, and 15 evaluated relations using geographic buffers based on either objective and/or perceived measures of the neighborhood environment. Only three studies reported neighborhood factors using different methods, including both objective and perceived measures of the neighborhood environment in the same study (Boehmer, Hoehner, Deshpande, Brennan Ramirez, & Brownson, 2007; Giles-Corti, Macintyre, Clarkson, Pikora, & Donovan, 2003; Joshu, Boehmer, Brownson, & Ewing, 2008). Of the 92 studies reviewed by Mackenbach et al. (2014), nine studies included both perceived and objectively measured neighborhood factors.

Thus, there are limited studies that compare methods and geographical areas of the neighborhood environment that may help decipher how associations with obesity can be sensitive to change depending on how and what we measure as the neighborhood exposure. These comparisons may also help to define appropriate methods for defining the neighborhood environment. Further, employing multiple measures and definitions of the

neighborhood environment within the same study may provide some evidence on how different aspects of neighborhood environments may be associated with obesity and may also provide comparative insight regarding methodological concerns when using certain approaches. While the previous studies that do exist compare objective and subjective measures of the neighborhood environment, no previous studies to our knowledge have compared administrative measures at the census-tract level, including GIS- or Census- based measures versus neighborhood audit-level measures at the individual-level within the same study.

Also, importantly, different measures of adiposity such as body mass index (BMI), waist circumference (WC), and waist-to-hip ratio (WHR) may also result in different associations with the neighborhood environment and may illuminate different processes on obesity phenotypes. While the most common measure of adiposity in neighborhood studies is BMI (given its feasibility using self-reported height and weight), it is also important to examine other measures of adiposity such as WC and WHR.

Specifically, WC and WHR are measures of abdominal or central obesity that indicate the location of body fat distribution and body shape (Hu, 2008). WC and WHR are used to determine whether body fat is distributed in the upper part of the body around the abdomen (characteristic of an android or apple shape body) or lower parts of the body in the hips and thighs (characteristic of a gynecoid, or pear shape body type) (Hu, 2008). These measurements may be more predictive of cardiometabolic risk (Janssen, Katzmarzyk, & Ross, 2002, 2004; Lissner, Bjorkelund, Heitmann, Seidell, & Bengtsson, 2001; Seidell, Perusse, Despres, & Bouchard, 2001). To date, only a few studies have investigated the influence of adverse neighborhood environments on measures of obesity, other than BMI (Ellaway, Anderson, & Macintyre, 1997; Li et al., 2009).

In summary, there are several gaps in the literature: 1) there is a lack of comparative data from studies that include multiple methods to measure the neighborhood environment; 2) previous studies have not examined neighborhood associations comparing different objective measures specifically comparing neighborhood GIS/Census measures at the census-tract level and neighborhood audits at the individual-level; and 3) there is a lack of studies that have investigated whether different indices of the neighborhood environment may illuminate different processes on obesity phenotypes. Thus, the objectives of this study are to address these limitations by comparing multiple approaches and measures of the neighborhood environment on BMI, WC, and WHR. Specifically, we use GIS- measures at the census tract-level to examine the physical environment using an index score of local destinations as well as Census- measures of the social environment at the census tract-level using an index score of neighborhood disadvantage. Further, we use a neighborhood-audit level measure of neighborhood conditions that was conducted around participants' homes.

We hypothesized that relationships between neighborhood measures would differ in their magnitude of associations with obesity outcomes, with neighborhood audit-level measures having greater effect sizes than GIS- or Census- measures of the neighborhood environment at the census-tract level, perhaps showing different processes on obesity outcomes. We base this hypothesis on reviews that show modest associations between measures of

neighborhood environment at the census tract-level and obesity, and also based on previous literature that recognizes administrative units may be ill-suited to examine environmental associations (Mackenbach et al., 2014). Further, we expected that adverse neighborhood characteristics, captured by audit-level measures around a person's home would be associated with obesity. Neighborhood surroundings and conditions around a person's home may be more of a deterrent of healthy behaviors such as physical activity (a mediator in the association between neighborhood environments and obesity) regardless of whether there are local destinations within the census tract areas that are expected to promote healthy behaviors such as incidental and discretionary physical activity. We further hypothesized that these associations would be observed with measures of central adiposity (WC and WHR) compared to BMI since measures of abdominal adiposity may be especially relevant for women and may also be better estimates of adiposity compared to BMI.

Method

Study design and population

The Women and Their Children's Health (WaTCH) Study is a prospective cohort study to investigate the health effects of the Deepwater Horizon oil spill on women 18–80 years of age who resided in Orleans, St. Bernard, Jefferson, Plaquemines, Lafourche, Terrebonne, or St. Mary parishes before the oil spill (April 20, 2010). An address-based sampling frame was provided by Marketing Systems Group and household telephone numbers were called randomly to obtain a sample of the target population. Baseline data were collected between June 2012 and July 2014 ($n=2,852$) during a telephone interview using REDCap electronic data capture tools hosted at the School of Public Health (Harris et al., 2009). RedCap (Research Electronic Data Capture) is a secure, web-based application designed to support data capture for research studies, providing: 1) an intuitive interface for validated data entry; 2) audit trails for tracking data manipulation and export procedures; 3) automated export procedures for seamless data downloads to common statistical packages; and 4) procedures for importing data from external sources (Harris et al., 2009). Medical research assistants collected anthropometric measurements and neighborhood audits on a sub-sample of women who further participated in the home visit portion of the study ($n=1,233$). The WaTCH Study was approved by the University Health Sciences Center Institutional Review Board and was granted a Waiver of Documentation of Informed consent for the telephone interview for which women gave verbal consent. Women who further participated in the home visit portion of the study further provided written informed consent. More detailed information on the WaTCH study has been described elsewhere (Peters et al., 2017).

Outcome Measures

Body height, weight, waist circumference, and hip circumference were measured using standardized procedures by trained medical research assistants. Each measurement was repeated three times and the average of these measurements was used to minimize systematic measurement error. Body mass index (BMI; weight kg/height m²), waist circumference (WC; cm), and waist-to-hip ratio (WHR) were calculated and dichotomized using guidelines established by The National Institutes of Health (NIH, 1998): high BMI 30 kg/m², high WC as > 88 cm, and high WHR as >0.85.

Neighborhood Measures

GIS- and Census- Based Measures, Census-tract level—Participants' addresses at the time of their telephone interview were geocoded using latitude and longitude coordinates with ArcMap 10.2 (Environmental Systems Research Institute (ESRI), Inc., Redlands, California) and 2010 US Census TIGER/Line Shapefiles based on the North American Industry Classification (SIC). GIS- and Census- based data were merged with the WaTCH Study data at the census-tract level. In the United States, census tracts are approximately equal to nine city blocks with 4,000 to 6,000 people (Cutrona, Wallace, & Wesner, 2006). The 940 women in the WaTCH analytic dataset represented 174 census tracts across the 7 study parishes. Population estimates of the 174 census tracts ranged from 373 to 9,867 people with an average population of 3,604 people. Factor-based scores were identified, which we refer to as the physical environment and social environment, and were created using the data based on the following variables and methods.

GIS- based measures of the physical environment included the number of grocery stores, convenience stores, unhealthy outlets (i.e., fast food restaurants), fitness facilities (i.e., health clubs, recreation centers, and gyms), on-premise alcohol outlets, and liquor stores per census tract. Data on the number of grocery stores, convenience stores, unhealthy outlets, and fitness facilities within each census tract were obtained from the Environmental Systems Research Institute (ESRI) based on NAICS business classification codes provided by infoUSA. The number of alcohol outlets and liquor stores was obtained from the Louisiana Office of Alcohol and Tobacco Control (ATC). Per capita estimates (per 1,000 residents) were calculated based on the United States Census Bureau's 2012 American Community Survey (ACS) population estimates. Each variable was z-transformed so that scores at least 1 standard deviation above the mean represented a more 'adverse' characteristic of the neighborhood, and those census tracts were assigned a value of 1 and then summed. Reverse scoring procedures were calculated for supermarkets and fitness facilities so that scores that were at least 1 standard deviation below the mean represented a more 'adverse' characteristic of the neighborhood.

Census-based measures of the social neighborhood environment were used to calculate concentrated neighborhood disadvantage using six variables from the 2012 American Community Survey (5 year estimates): percent of individuals below the poverty line, percent of individuals on public assistance, percent female-headed households, percent unemployed, percent less than 18, and percent African American (RTI International; Sampson, Raudenbush, & Earls, 1997). A factor analysis was conducted with principal components and varimax rotation, which generated a sample dependent score where the z-score for each variable was multiplied by its factor loading and summed into a factor regression score (RTI International; Sampson, Raudenbush, & Earls, 1997).

Neighborhood Audit Measure, Individual-level—A neighborhood audit assessment tool (Andresen et al., 2013) of 25 items was conducted using medical research assistants who conducted a visual assessment of the surrounding participants' homes. It is important to note that the neighborhood audit is an assessment of neighborhood characteristics of the immediate block face and street of each participant's residence. Further, this results in a

neighborhood measurement at the individual-level. Using methods previously published, 16 items were scored and used for analysis (e.g., volume of traffic, condition of street, noise, smells, and presence of abandoned cars, garbage/litter/broken glass, presence of graffiti, and presence of recreational facilities) (Andresen et al., 2013). Ranked categories and all item ratings were scored using Likert-type scales or were rated as yes/no (Andresen et al., 2013; Andresen et al., 2008). A composite score was calculated by summing responses, with higher scores indicating more adverse neighborhood characteristics.

Confounders

Confounders were included based on a priori theory. Age was assessed as a categorical variable: 19–30 years of age, 31–40 years, 41–50 years, 51–60 years, 61–70 years, and 71–80 years of age. Race and ethnicity were coded as: Non-Hispanic White, Non-Hispanic African American, and Other (Hispanic, Asian/Pacific Islander, American Indian/Native American, Other, or Multi). Annual household income was: \$0–\$20,000, \$20,001–\$40,000, \$40,001–\$60,000, and \$60,001. We included self-reported oil spill exposure as a potential confounder, that was calculated using nine items related to exposure to the Deepwater Horizon Oil Spill (participation in oil spill clean-up activities; physical contact with the oil from the spill or clean-up activities; damage to commercial fishing areas; recreational hunting, fishing, or activities of household members were affected; incurred lost or damaged property; frequency and severity of smelling the oil; income loss; the influence of the oil spill on household's current financial situation; and whether participants were affected by the oil spill more than others in their community). These nine items were dichotomized and summed so that higher scores indicated greater oil spill exposure.

Statistical Analysis

Descriptive statistics were calculated for the WaTCH Study sample and neighborhood variables. To account for individuals nested within census tracts, generalized linear mixed effects models were utilized to model the relationships between the contextual neighborhood environment measures and dichotomized obesity outcomes. The intraclass correlation coefficient (ICC) values were calculated using the formula $V_A/(V_A + V_I) \times 100\%$, where V_A is the area level variance and V_I is equal to $\pi^2/3 = 3.29$, which is the individual level variance based on an underlying continuous variable (Snijders & Bosker, 2012). The median odds ratio (MOR) was calculated to translate the area level variance into the odds ratio scale where the $MOR \approx \exp(0.95\sqrt{V_A})$ (Merlo et al., 2006). The ICC and MOR values were used to estimate the proportion of the total variance of each outcome measure of obesity (BMI, WC, or WHR) between neighborhoods. Final models were calculated when using the neighborhood audit, an individual-level measure of the neighborhood environment. Adjusted models included *a priori* confounders (age, income, race/ethnicity, and oil spill exposure). Interaction terms between neighborhood environment measures and race/ethnicity as well as interaction terms between the neighborhood environment and household income were investigated but were not significant. All statistical analyses were conducted using SAS, version 9.3 (SAS Institute Inc., Cary, North Carolina).

Results

Of the 2,852 women who participated in the WaTCH Study, analyses were restricted to home visit participants ($n=1,233$). Thirty-seven women who participated in the home visit did not have neighborhood audits conducted and were removed from the dataset. Seven women resided outside the study parishes of interest and were removed from the analyses. After removing seven additional women with missing geocoded addresses, and sequentially for income ($n=51$), race/ethnicity ($n=11$), BMI ($n=98$), WC ($n=15$), and WHR ($n=4$), and with any missing values across the calculated audit scores ($n=57$), 946 women remained in the analytic dataset. Another six participants were removed due to incorrect measurement or record of height. The final sample included 940 women. Demographic characteristics of the 940 women in the analytic sample are presented in Table 1. The mean age of women was 45 years, 51% were Non-Hispanic White, and 34% reported a household income \$60,001. Fifty-three percent of women had a high BMI ($\geq 30 \text{ kg/m}^2$), 72% had high WC ($>88 \text{ cm}$), and 61% had a high WHR ($>.85$). Table 2 presents data on the neighborhood environment at the census tract level for both the physical/built environment and the social environment. Ratings, scoring, and frequencies of the neighborhood audit items are shown in Table 3. The three neighborhood scales were significantly but only slightly or moderately correlated (physical environment and social environment: $\rho = -.11$, $p\text{-value} = .0006$; physical environment and neighborhood audit: $\rho = .10$, $p\text{-value} = .0024$; social environment and neighborhood audit: $\rho = .29$, $p\text{-value} = <.0001$).

A truncated table of associations between varying neighborhood measures on BMI, WC, and WHR, are shown in Table 4. Expanded results with all covariates are presented in Tables 5, 6, 7 for BMI, WC, and WHR, respectively (see online supplemental Appendix). Models 1–5 show GIS- and Census- measures of the neighborhood physical and social environment scores using a multi-level analysis, while Models 6 and 7 investigate the associations between the neighborhood audit and obesity outcomes. For BMI, the empty model (Model 1) indicated that 2.95% of the variance in obesity may be explained at the neighborhood level. When the physical environment variable was included in Model 2 alone, there was no decline in the ICC, suggesting the physical environment did not explain any of the group level variance. The physical environment was not a significant predictor of the odds of high BMI. The social environment was significantly associated with high BMI (OR: 1.39; 95% CI: 1.21, 1.59) (Model 4) and there was no clustering of BMI between neighborhoods (ICC = 0). After adjusting for covariates in Model 5, the social environment was no longer significant (OR: 1.11; 95% CI: 0.94; 1.31). There was a significant association between the neighborhood audit score and high BMI (OR: 1.04; 95% CI: 1.00, 1.08) (Model 6); however, this association was no longer statistically significant in the covariate adjusted model (OR: 1.00; 95% CI: 0.96, 1.04) (Model 7).

The clustering of WC within neighborhoods was low, as evidenced by the ICC of 1.20% in the empty model (Model 1) and there was no change in the ICC percent when the physical environment variable was included in Model 2. The odds of high WC was not significantly associated with a measure of the physical environment in either the crude or covariate adjusted model and the ICC percent was reduced to 0. However, the social environment was associated with a higher odds of high WC (OR: 1.43; 95% CI: 1.22, 1.67) (Model 4) and the

ICC percent was 0. After adjusting for differences between individuals in Model 5, the social environment was no longer significantly associated with a higher odds of high WC (OR: 1.15; 95% CI: 0.94; 1.40). The neighborhood audit score was associated with a higher odds of high WC (OR: 1.13; 95% CI: 1.08, 1.18) in the crude model (Model 6), although was slightly attenuated (OR: 1.10; 95% CI: 1.05, 1.15) in the covariate adjusted model (Model 7).

There was no significant relationship between the physical neighborhood environment and WHR. The social environment score was associated with a higher odds of high WHR (OR: 1.25; 95% CI: 1.09, 1.43) (Model 4), however, this association was no longer significant (OR: 1.12; 95% CI: 0.94, 1.34) after adjusting for individual-level covariates in Model 5. The neighborhood audit score was associated with a higher odds of high WHR (OR: 1.11; 95% CI: 1.07, 1.16) (Model 6). This association remained significant, although slightly attenuated (OR: 1.09; 95% CI: 1.05, 1.14) after adjusting for covariates in Model 7.

Several sensitivity analyses and additional regression models were conducted to determine any changes between the neighborhood environment and obesity outcomes (data not shown). 1) Outcome measures of BMI, WC, and WHR were also calculated as continuous measures; however, few differences in results were detected regardless of how BMI, WC, or WHR were modeled. 2) Interaction terms between neighborhood environment measures and race/ethnicity as well as interaction terms between the neighborhood environment and household income were investigated but were not significant. 3) To determine the impact of small group size within the multilevel models, census tracts with only one individual were removed from the analyses; again, results did not change. 4) A composite measure (summed z-scores) of the physical environment combined with the social environment at the group-level was created to investigate whether the total neighborhood environment was related to obesity measures. After adjusting for individual-level covariates, the total neighborhood environment was not statistically associated with any obesity measures. 5) We also examined whether we may have artificially attenuated the variance in the environment through the use of composite scores of the physical and social environment by conducting bivariate and multivariate analyses of each individual variable. These results also indicated that the area level differences in obesity measures between census tracts were explained by the individual composition of those areas, even when using specific variables of the neighborhood environment (i.e., number of grocery stores, number of convenience stores) as opposed to aggregated measures.

Discussion

The present study compared GIS- and Census- based measures at the census-tract level versus a neighborhood audit approach at the individual-level for measuring neighborhood environments on BMI, WC, and WHR. The results of this study demonstrate that for GIS- (physical environment) and Census- (social environment) based measures at the census-tract level, the ICC approached zero after adjusting for individual-level covariates, indicating that the area level differences in obesity measures between census tracts were explained by the individual composition of those areas. None of the adjusted associations between these measures of the neighborhood environment and obesity reached statistical significance at an

alpha level of .05. Thus, there was not enough variation in obesity measures to attribute any variation to the random effect (neighborhoods), controlling for everything else in the model. However, when the neighborhood environment was measured using a neighborhood audit, more adverse neighborhood environments were associated with a higher odds of high WC and WHR, but not BMI. Interestingly, effect estimates for covariates (age, race/ethnicity, and household income) were similar across models for each obesity outcome measure, regardless of the neighborhood measure. In general, there was a higher odds of obesity among African American women compared to White women while there was a decrease in the odds of obesity with increasing income categories. Furthermore, the odds of obesity was higher for women in middle aged categories and decreased in older age categories.

While there appeared to be no significant association between GIS- and Census- measures at the census-tract level to describe the physical and social environment with obesity after adjusting for individual-level covariates, these findings raise important issues and challenges. First, GIS- measures of the physical environment at the census-tract level were considered unhealthy destinations (e.g., convenience stores, liquor stores, and unhealthy food outlets); however, these destinations may also provide walkable areas for neighborhood residents. Second, these neighborhood measures may represent entirely different neighborhood exposures. For example, we must not only consider how we measure the neighborhood environment, but also what we measure. In this study, the GIS- measure of the physical environment included measures of local destinations at the census-tract level, the Census- measure of the social environment included measures of economic disadvantage at the census-tract level, and the audit-level method measured adverse neighborhood conditions immediately surrounding participants' homes. Differences in associations found between GIS-and Census- measures using administrative units at the census-tract level and audit-level measures may not necessarily be due to different geographical definitions of the neighborhoods per se, but what is measured. Also, adverse neighborhood characteristics around a person's home may be more of a deterrent of healthy behaviors such as physical activity (a mediator in the association between neighborhood environments and obesity) regardless of whether there are local destinations that support healthy behaviors within the census tract areas.

Neighborhoods in the U.S. are often defined using administrative census areas since the availability of data provided by the U.S. Census and other surveys are linked to them (Kwan, 2009). The easy availability of such data makes this a convenient and attractive approach. However, the availability of GIS- and Census- data can be limited by the databases and time periods available for data acquisition. Some studies have recognized that neighborhood measures derived using neighborhood audits as a measure of an individual's neighborhood are an accurate representation of current neighborhood conditions and have been recommended for assessing the relationship between the neighborhood environment and obesity (Booth, Pinkston, & Poston, 2005; Leung, Gregorich, Laraia, Kushi, & Yen, 2010). Further, smaller area definitions of the neighborhood environment may be more consistent with how people define their neighborhood environment rather than larger areas such as census tracts, which are delineated based on administrative geographical areas (Coulton, Jennings, & Chan, 2013; O'Campo, 2003). Support for using audit measures of the neighborhood environment have also been recognized in the literature for assessing the

relationship between the neighborhood environment and measures of physical activity. For example, audit measures of the neighborhood environment identified blocks more supportive of activity living and were also consistent with participant perceptions of their home block (Werner, Brown, & Gallimore, 2010). Importantly, the neighborhood audit was able to discriminate blocks more supportive of active living within the same neighborhood area concluding that studies that use data from block groups, census tracts, or zip code areas will fail to detect smaller area-level variations in walkability (Werner, Brown, & Gallimore, 2010). Audits of pedestrian streetscapes (e.g., street design, transit stops, sidewalk qualities, and stress crossings) were also related to physical activity across four age groups, even after adjusting for GIS-based walkability at the census block group level (Cain et al., 2014). In another study, after adjusting for covariates, audit measures of the neighborhood environment were associated with young girls' energy intake and expenditure, while there was no significant associations between energy intake and expenditure with neighborhood deprivation index, measured using Census data to create individual indices for census tracts and counties within the study area (Leung, Gregorich, Laraia, Kushi, & Yen, 2010).

There are a few limitations in this study that are inherent in the study design and topic of neighborhood environment research. First, these data are cross-sectional and the temporality of living in an adverse neighborhood environment and developing obesity cannot be determined. Unmeasured confounding such as duration of residence may also lead to biased estimates. Tests of the validity and reliability for neighborhood observer rating systems have been recognized to inherently include a degree of variability between observers (Andresen et al., 2013). To minimize variability between observers in the WaTCH Study, home visit aides received extensive protocol training, visual examples were included through the use of photographs, and question-by-question guidelines were implemented in the training and for use in the field before rating any neighborhoods. Also, it is important to note that while the audit measure included a wide range of items, these were summarized into one composite measure. However, there may be multiple constructs within this scale, which may be associated differently with obesity outcomes. Further, we did not consider other aspects of the neighborhood environment such as neighborhood walkability or the presence of public transport. Also, we did not collect subjective (perceived) measures of the neighborhood environment. Previous research on the association between neighborhood environments and obesity has shown that results may differ substantially between subjective and objective (audits and GIS) approaches used for measuring the neighborhood environment (Ball et al., 2008; Boehmer, Hoehner, Deshpande, Brennan Ramirez, & Brownson, 2007; Roda et al., 2016). It is also important to note that there was a high prevalence of obesity among women in the WaTCH Study and results may not be generalizable to other population samples. Additionally, the WaTCH Study was limited to adult women who lived in Southeastern parishes in Louisiana who spoke either English or Spanish. Future research will examine the role of the neighborhood environment on mediating behaviors such as physical activity and diet.

However, there are several contributions and strengths of this study beyond providing evidence that neighborhood environments are related to obesity. No study to date has compared GIS- and Census- based measures of the physical and social environment at the census-tract level with an audit-level method for measuring the neighborhood environment

within the same study sample to compare their associations with obesity outcomes. We show that associations between the neighborhood environment and obesity are sensitive to change based on how and what we measure in the neighborhood environment. This advantage expands the current literature calling for more investigation into varying measures and definitions of neighborhoods and spatial contexts on health outcomes (Booth, Pinkston, & Poston, 2005; Diez Roux & Mair, 2010; O'Campo, 2003). Also, anthropometric measurements of height, weight, waist circumference, and hip circumference were obtained by trained medical research assistants as opposed to self-reported measurements thereby helping to limit misclassification bias of obesity outcomes. The WaTCH Study provided a unique opportunity to investigate neighborhood environmental influences on obesity. Louisiana has the highest prevalence of obesity in the nation (Centers for Disease Control and Prevention (CDC), 2012; Trust for America's Health, 2013), and the WaTCH Study provided a racially diverse sample of women.

Our results make several contributions. We show that: 1) contextual measures resulted in homogeneously defined geographical areas lacking sufficient variation to study the influence of neighborhood environments on obesity after adjusting for individual-level covariates; 2) the neighborhood environment, when directly observed using the neighborhood audit at the individual-level was associated with a higher odds of central adiposity (high WC and high WHR), but not high BMI; 3) how the neighborhood environment is measured and what is measured can affect possible associations with obesity outcomes; and 4) these data support the use of obesity measures other than BMI, such as WC and WHR, that may allow researchers to study the relationship of the neighborhood environment to body composition and body shape.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Abbreviations:

BMI	body mass index
CI	confidence interval
HPA	hypothalamic-pituitary-adrenal
OR	odds ratio
REDCap	Research Electronic Data Capture

SD	standard deviation
WC	waist circumference
WHR	Waist-to-hip Ratio
WaTCH	Women and Their Children's Health Study

References

- Andresen EM, Malmstrom TK, Schootman M, Wolinsky FD, Miller JP, & Miller DK (2013). Observer ratings of neighborhoods: Comparison of two methods. *BMC Public Health*, 13, 1024. doi: 10.1186/1471-2458-13-1024 [PubMed: 24168373]
- Andresen EM, Malmstrom TK, Wolinsky FD, Schootman M, Miller JP, & Miller DK (2008). Rating neighborhoods for older adult health: Results from the African American Health study. *BMC Public Health*, 8, 35. doi:10.1186/1471-2458-8-35 [PubMed: 18221546]
- Ball K, Jeffery RW, Crawford DA, Roberts RJ, Salmon J, & Timperio AF (2008). Mismatch between perceived and objective measures of physical activity environments. *Preventive Medicine*, 47(3), 294–298. doi:10.1016/j.ypmed.2008.05.001 [PubMed: 18544463]
- Black JL, Macinko J, Dixon LB, & Fryer GE Jr. (2010). Neighborhoods and obesity in New York City. *Health & Place*, 16(3), 489–499. doi:10.1016/j.healthplace.2009.12.007 [PubMed: 20106710]
- Boehmer TK, Hoehner CM, Deshpande AD, Brennan Ramirez LK, & Brownson RC (2007). Perceived and observed neighborhood indicators of obesity among urban adults. *International Journal of Obesity*, 31(6), 968–977. doi:10.1038/sj.ijo.0803531 [PubMed: 17224932]
- Booth KM, Pinkston MM, & Poston WS (2005). Obesity and the built environment. *Journal of the American Diet Association*, 105(5 Suppl 1), S110–117. doi:10.1016/j.jada.2005.02.045
- Brownson RC, Hoehner CM, Day K, Forsyth A, & Sallis JF (2009). Measuring the built environment for physical activity: State of the science. *American Journal of Preventive Medicine*, 36(4 Suppl), S99–123 e112. doi:10.1016/j.amepre.2009.01.005 [PubMed: 19285216]
- Burdette HL, Wadden TA, & Whitaker RC (2006). Neighborhood safety, collective efficacy, and obesity in women with young children. *Obesity (Silver Spring)*, 14(3), 518–525. doi:10.1038/oby.2006.67 [PubMed: 16648624]
- Cain KL, Millstein RA, Sallis JF, Conway TL, Gavand KA, Frank LD, ... King AC (2014). Contribution of streetscape audits to explanation of physical activity in four age groups based on the Microscale Audit of Pedestrian Streetscapes (MAPS). 116, 82–92. doi:10.1016/j.socscimed.2014.06.042
- Centers for Disease Control and Prevention (CDC). (2012). Behavioral risk factor surveillance system survey data. Retrieved from <https://www.cdc.gov/brfss/brfssprevalence/index.html>
- Christian H, Giles-Corti B, Knuiman M, Timperio A, & Foster S (2011). The influence of the built environment, social environment and health behaviors on body mass index. Results from RESIDE. *Preventive Medicine*, 53(1–2), 57–60. doi:10.1016/j.ypmed.2011.05.004 [PubMed: 21609730]
- National Institutes of Health, NHLBI Expert Panel on the Identification, Evaluation, and Treatment of Overweight in Adults. (1998). Clinical guidelines on the identification, evaluation, and treatment of overweight and obesity in adults: Executive summary. *The American Journal of Clinical Nutrition*, 68, 899–917. [PubMed: 9771869]
- Coulton CJ, Jennings MZ, & Chan T (2013). How big is my neighborhood? Individual and contextual effects on perceptions of neighborhood scale. *American Journal of Community Psychology*, 51(1–2), 140–150. doi:10.1007/s10464-012-9550-6 [PubMed: 22886284]
- Cutrona CE, Wallace G, & Wesner KA (2006). Neighborhood characteristics and depression: An examination of stress processes. *Current Directions in Psychological Science*, 15(4), 188–192. doi: 10.1111/j.1467-8721.2006.00433.x [PubMed: 18185846]
- Diez Roux AV, & Mair C (2010). Neighborhoods and health. *Annals of the New York Academy of Sciences*, 1186, 125–145. doi:10.1111/j.1749-6632.2009.05333.x [PubMed: 20201871]

- Ding D, & Gebel K (2012). Built environment, physical activity, and obesity: What have we learned from reviewing the literature? *Health & Place*, 18(1), 100–105. doi:10.1016/j.healthplace.2011.08.021 [PubMed: 21983062]
- Eisenstein AR, Prohaska TR, Kruger J, Satariano WA, Hooker S, Buchner D, ... Hunter RH (2011). Environmental correlates of overweight and obesity in community residing older adults. *Journal of Aging and Health*, 23(6), 994–1009. doi:10.1177/0898264311404557 [PubMed: 21508306]
- Ellaway A, Anderson A, & Macintyre S (1997). Does area of residence affect body size and shape? *International Journal of Obesity and Related Metabolic Disorders* 21(4), 304–308. [PubMed: 9130028]
- Feng J, Glass TA, Curriero FC, Stewart WF, & Schwartz BS (2010). The built environment and obesity: A systematic review of the epidemiologic evidence. *Health & Place*, 16(2), 175–190. doi: 10.1016/j.healthplace.2009.09.008 [PubMed: 19880341]
- Giles-Corti B, Macintyre S, Clarkson JP, Pikora T, & Donovan RJ (2003). Environmental and lifestyle factors associated with overweight and obesity in Perth, Australia. *American Journal of Health Promotion*, 18(1), 93–102. [PubMed: 13677967]
- Harris PA, Taylor R, Thielke R, Payne J, Gonzalez N, & Conde JG (2009). Research electronic data capture (REDCap)--a metadata-driven methodology and workflow process for providing translational research informatics support. *Journal of Biomedical Informatics*, 42(2), 377–381. doi: 10.1016/j.jbi.2008.08.010 [PubMed: 18929686]
- Hu F (2008). *Obesity Epidemiology*. New York, New York: Oxford University Press.
- Hutchinson PL, Nicholas Bodor J, Swalm CM, Rice JC, & Rose D (2012). Neighbourhood food environments and obesity in southeast Louisiana. *Health & Place*, 18(4), 854–860. doi:10.1016/j.healthplace.2012.03.006 [PubMed: 22480887]
- Janssen I, Katzmarzyk PT, & Ross R (2002). Body mass index, waist circumference, and health risk: Evidence in support of current National Institutes of Health guidelines. *Archives of Internal Medicine*, 162(18), 2074–2079. [PubMed: 12374515]
- Janssen I, Katzmarzyk PT, & Ross R (2004). Waist circumference and not body mass index explains obesity-related health risk. *The American Journal of Clinical Nutrition*, 79(3), 379–384. [PubMed: 14985210]
- Joshu CE, Boehmer TK, Brownson RC, & Ewing R (2008). Personal, neighbourhood and urban factors associated with obesity in the United States. *Journal of Epidemiology and Community Health*, 62(3), 202–208. doi:10.1136/jech.2006.058321 [PubMed: 18272734]
- Kwan MP (2009). From place-based to people-based exposure measures. *Social Science & Medicine*, 69(9), 1311–1313. doi:10.1016/j.socscimed.2009.07.013 [PubMed: 19665828]
- Leung CW, Gregorich SE, Laraia BA, Kushi LH, & Yen IH (2010). Measuring the neighborhood environment: Associations with young girls' energy intake and expenditure in a cross-sectional study. *The International Journal of Behavioral Nutrition and Physical Activity*, 7, 52. doi: 10.1186/1479-5868-7-52 [PubMed: 20515487]
- Li F, Harmer P, Cardinal BJ, Bosworth M, Johnson-Shelton D, Moore JM, ... Vongjaturapat N (2009). Built environment and 1-year change in weight and waist circumference in middle-aged and older adults: Portland Neighborhood Environment and Health Study. *American Journal of Epidemiology*, 169(4), 401–408. doi:10.1093/aje/kwn398 [PubMed: 19153214]
- Lissner L, Bjorkelund C, Heitmann BL, Seidell JC, & Bengtsson C (2001). Larger hip circumference independently predicts health and longevity in a Swedish female cohort. *Obesity Research*, 9(10), 644–646. doi:10.1038/oby.2001.85 [PubMed: 11595782]
- Mackenbach JD, Rutter H, Compernelle S, Glonti K, Oppert JM, Charreire H, ... Lakerveld J (2014). Obesogenic environments: A systematic review of the association between the physical environment and adult weight status, the SPOTLIGHT project. *BMC Public Health*, 14, 233. doi: 10.1186/1471-2458-14-233 [PubMed: 24602291]
- Merlo J, Chaix B, Ohlsson H, Beckman A, Johnell K, Hjerpe P, ... Larsen K (2006). A brief conceptual tutorial of multilevel analysis in social epidemiology: Using measures of clustering in multilevel logistic regression to investigate contextual phenomena. *Journal of Epidemiology and Community Health*, 60(4), 290–297. doi:10.1136/jech.2004.029454 [PubMed: 16537344]

- Michimi A, & Wimberly MC (2012). Natural environments, obesity, and physical activity in nonmetropolitan areas of the United States. *The Journal of Rural Health* 28(4), 398–407. doi: 10.1111/j.1748-0361.2012.00413.x [PubMed: 23083086]
- Morland K, Diez Roux AV, & Wing S (2006). Supermarkets, other food stores, and obesity: The atherosclerosis risk in communities study. *American Journal of Preventive Medicine*, 30(4), 333–339. doi:10.1016/j.amepre.2005.11.003 [PubMed: 16530621]
- Morland KB, & Evenson KR (2009). Obesity prevalence and the local food environment. *Health & Place*, 15(2), 491–495. doi:10.1016/j.healthplace.2008.09.004 [PubMed: 19022700]
- Mujahid MS, Diez Roux AV, Shen M, Gowda D, Sanchez B, Shea S, ... Jackson SA (2008). Relation between neighborhood environments and obesity in the Multi-Ethnic Study of Atherosclerosis. *American Journal of Epidemiology*, 167(11), 1349–1357. doi:10.1093/aje/kwn047 [PubMed: 18367469]
- O'Campo P (2003). Invited commentary: Advancing theory and methods for multilevel models of residential neighborhoods and health. *American Journal of Epidemiology*, 157(1), 9–13. [PubMed: 12505885]
- Papas MA, Alberg AJ, Ewing R, Helzlouer KJ, Gary TL, & Klassen AC (2007). The built environment and obesity. *Epidemiology Reviews*, 29, 129–143. doi:10.1093/epirev/mxm009
- Peters ES, Rung AL, Bronson MH, Brashear MM, Peres LC, Gaston S, ... Trapido EJ (2017). The Women and Their Children's Health (WaTCH) study: Methods and design of a prospective cohort study in Louisiana to examine the health effects from the BP oil spill. 7(7), e014887. doi:10.1136/bmjopen-2016-014887
- Roda C, Charreire H, Feuillet T, Mackenbach JD, Compernelle S, Glonti K, ... Oppert JM, (2016). Mismatch between perceived and objectively measured environmental obesogenic features in European neighbourhoods. *Obesity Reviews* 17 Suppl 1, 31–41. doi:10.1111/obr.12376 [PubMed: 26879111]
- RTI International. PhenX Toolkit. Neighborhood Social Disadvantage. Retrieved from <http://www.phenxtoolkit.org>
- Sallis JF, Cervero RB, Ascher W, Henderson KA, Kraft MK, & Kerr J (2006). An ecological approach to creating active living communities. *Annual Reviews of Public Health*, 27, 297–322. doi: 10.1146/annurev.publhealth.27.021405.102100
- Sallis JF, & Owen N (2015). Ecological models of health behavior In Glanz K, Rimer BK, & Lewis FM (Eds.), *Health Behavior and Health Education. Theory, Research, and Practice*. (4th ed., pp. 43–64). San Francisco: Jossey-Bass.
- Sampson RJ, Raudenbush SW, & Earls F (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science*, 277(5328), 918–924. [PubMed: 9252316]
- Seidell JC, Perusse L, Despres JP, & Bouchard C (2001). Waist and hip circumferences have independent and opposite effects on cardiovascular disease risk factors: the Quebec Family Study. *The American Journal of Clinical Nutrition*, 74(3), 315–321. [PubMed: 11522554]
- Snijders TAB, & Bosker RJ (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling* (2nd ed.). Los Angeles: Sage.
- Sugiyama T, Koohsari MJ, Mavoa S, & Owen N (2014). Activity-friendly built environment attributes and adult adiposity. *Current Obesity Reports*, 3(2), 183–198. doi:10.1007/s13679-014-0096-9 [PubMed: 26626602]
- The Louisiana Office of Alcohol and Tobacco Control (ATC). Retrieved from <http://www.atc.rev.state.la.us/>
- Trust for America's Health. (2013). *F as in Fat: How Obesity Threatens America's Future 2013*. Retrieved from <http://healthyamericans.org/assets/files/TFAH2013FasInFatReportFinal%209.9.pdf>
- Werner CM, Brown BB, & Gallimore J (2010). Light rail use is more likely on “walkable” blocks: Further support for using micro-level environmental audit measures. 30(2), 206–214. doi:10.1016/j.jenvp.2009.11.003
- Yan R, Bastian ND, & Griffin PM (2015). Association of food environment and food retailers with obesity in US adults. *Health & Place*, 33, 19–24. doi:10.1016/j.healthplace.2015.02.004 [PubMed: 25725484]

Yang W, Spears K, Zhang F, Lee W, & Himler HL (2012). Evaluation of personal and built environment attributes to physical activity: A multilevel analysis on multiple population-based data sources. *Journal of Obesity*, 2012, 548910. doi:10.1155/2012/548910 [PubMed: 22655174]

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Table 1.Demographic Characteristics, WaTCH Study ($N=940$), 2012–2014.

	<i>N</i> (%)
Total	940
Oil Spill Exposure (mean $\pm$ <i>SD</i>)	1.7 $\pm$ 1.6
Age, years (mean $\pm$ <i>SD</i>)	45.4 $\pm$ 11.9
Age Categories	
19–30	93 (10)
31–40	229 (24)
41–50	385 (41)
51–60	122 (13)
61–70	75 (8)
71–80	36 (4)
Race/Ethnicity	
White	482 (51)
African American	380 (40)
Other	78 (8)
Household Income	
\$0–\$20,000	266 (28)
\$20,001–\$40,000	191 (20)
\$40,001–\$60,000	166 (18)
\$60,001	317 (34)
BMI, kg/m ² (mean $\pm$ <i>SD</i>)	32.0 $\pm$ 8.0
BMI Categories	
<30 kg/m ² (Non-Obese)	443 (47)
30 kg/m ² (Obese)	497 (53)
Waist Circumference (mean $\pm$ <i>SD</i>)	98.7 $\pm$ 17.4
Waist Circumference Categories	
88 cm	266 (28)
>88 cm	674 (72)
Waist to Hip Ratio (mean $\pm$ <i>SD</i>)	0.88 $\pm$ 0.1
Waist to Hip Ratio Categories	
.85	370 (39)
>.85	570 (61)

Abbreviations: *SD*, standard deviation; WaTCH, Women and Their Children's Health Study.

Table 2.

Physical and Social Neighborhood Characteristics by Data Sources and Census Tracts (174), WaTCH (N=940).

Variable	Data Source	Mean	SD	Min	Max
Variables of the Physical/Built Environment (per 1,000 Residents)					
Number of grocery stores	ESRI	0.33	0.66	0	16.09
Number of convenience stores	ESRI	0.58	0.78	0	18.77
Number of unhealthy outlets ^a	ESRI	0.99	1.10	0	18.77
Number of fitness facilities	ESRI	0.16	0.24	0	1.58
Number of on-premise alcohol outlets ^b	ATC	1.01	1.03	0	8.04
Number of liquor stores	ATC	1.47	1.42	0	18.77
Variables of the Social Environment (Mean Percent)					
Living below federal poverty level	ACS	19.49	10.54	0.7	55.90
Living on public assistance	ACS	1.94	1.98	0	10.20
Female headed households	ACS	19.31	9.33	0	52.90
Unemployed	ACS	5.48	2.99	1	17.90
Less than 18 years of age	ACS	25.72	4.48	10.1	41.80
African American	ACS	37.71	31.95	0	100.00
Physical environment score		2.82	1.36	0	6.00
Social environment score		0.00	1.00	-1.66	3.41

^aConvenience stores and fast food restaurants.

^bBars/pubs, clubs, and restaurants that allow the consumption of alcohol on-site.

Abbreviations: ACS, American Community Survey (2012); ATC, The Louisiana Office of Alcohol and Tobacco Control (2014); ESRI, Environmental Systems Research Institute (2010); SD, Standard Deviation; WaTCH, Women and Their Children's Health Study.

Table 3.

Neighborhood Characteristics Obtained from Neighborhood Audit: Items, Ratings, and Frequencies, WaTCH (N=940).

Variable	Items Rating	N (%)
Volume of Traffic		
None	0	255 (27)
Light	1	431 (46)
Moderate	2	157 (17)
Heavy	3	97 (10)
Condition of Street		
Very good	0	370 (39)
Moderate	1	278 (30)
Fair	2	217 (23)
Poor	3	75 (8)
Amount of noise		
Very quiet	0	497 (53)
Fairly quiet	1	311 (33)
Somewhat noisy	2	125 (13)
Very noisy	3	7 (1)
Smells		
None	0	914 (97)
Any	1	26 (3)
Dirt or dust		
None	0	929 (99)
Any	1	11 (1)
Abandoned car		
None	0	779 (83)
Any	1	161 (17)
Beer, liquor bottles		
None	0	849 (90)
Any	1	91 (10)
Cigarette, tobacco litter		
None	0	716 (76)
Any	1	224 (24)
Garbage, litter, broken glass		
None	0	494 (53)
Light	1	363 (39)
Moderate	2	54 (6)
Heavy	3	29 (3)
Condition of residential homes		
Very well kept	0	427 (45)
Moderately kept	1	318 (34)

Variable	Items Rating	N (%)
Fair	2	161 (17)
Poor/badly deteriorated	3	34 (4)
Bars/gates on doors or windows		
None	0	665 (71)
Any	1	275 (29)
Condition of recreational facilities (if present)?		
Very well kept/good condition	0	33 (55)
Moderately well-kept condition	1	21 (35)
Fair condition	2	5 (8)
Poor/badly deteriorated condition	3	1 (2)
Graffiti		
None	0	912 (97)
Any	1	28 (3)
Tobacco Advertisements		
None	0	924 (98)
Any	1	16 (2)
Alcohol Advertisements		
Non	0	920 (98)
Any	1	20 (2)
Home “for sale” signs		
None	0	691 (74)
Any	1	249 (27)
Mean		5.3
<i>SD</i>		3.8
Min		0
Max		19

Abbreviations: *SD*, standard deviation; WaTCH, Women and Their Children’s Health Study.

Table 4.
Generalized Linear/Generalized Linear Mixed Models for High BMI, WC, and WHR, WaTCH (N=940), 2012–2014

	BMI				WC				WHR			
	Random Effects		Fixed Effects		Random Effects		Fixed Effects		Random Effects		Fixed Effects	
	ICC	MOR	OR	(95% CI)	ICC	MOR	OR	(95% CI)	ICC	MOR	OR	(95% CI)
Model 1 Empty	2.95	1.35			1.20	1.20			0	1.00		
Model 2 Physical, Unadjusted	2.95	2.95	0.98	(0.88, 1.09)	1.20	1.20	0.96	(0.86, 1.07)	0	1.00	0.98	(0.89, 1.07)
Model 3 Physical, Adjusted	0	1.00	1.01	(0.91, 1.11)	0	1.00	0.98	(0.88, 1.09)	0	1.00	0.97	(0.88, 1.08)
Model 4 Social, Unadjusted	0	1.00	1.39	(1.21, 1.59)**	0	1.00	1.43	(1.22, 1.67)**	0	1.00	1.25	(1.09, 1.43)*
Model 5 Social, Adjusted	0	1.00	1.11	(0.94, 1.31)	0	1.00	1.15	(0.94, 1.40)	0	1.00	1.12	(0.94, 1.34)
Model 6 Audit, Unadjusted	NA	NA	1.04	(1.01, 1.08)*	NA	NA	1.13	(1.08, 1.18)**	NA	NA	1.11	(1.07, 1.16)**
Model 7 Audit, Adjusted	NA	NA	1.00	(0.96, 1.04)	NA	NA	1.10	(1.05, 1.15)**	NA	NA	1.09	(1.05, 1.14)**

Abbreviations: CI, confidence interval; ICC, Intraclass correlation coefficient; MOR, Median odds ratio; OR, odds ratio; WaTCH, Women and Their Children's Health Study.

* $p < .05$;

** $p < .0001$