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Neighborhoods Matter; but for Whom? Heterogeneity of Neighborhood Disadvantage on Child Obesity by Sex

Ashley W. Kranjac
Chapman University, kranjac@chapman.edu

Catherine Boyd
Rice University

Rachel T. Kimbro
Rice University

Brady S. Moffett
Baylor College of Medicine

Keila N. Lopez
Baylor College of Medicine

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Abstract

Although evidence suggests that neighborhood context, particularly socioeconomic context, influences child obesity, little is known about how these neighborhood factors may be heterogeneous rather than monolithic. Using a novel dataset comprised of the electronic medical records for over 250,000 children aged 2–17 nested within 992 neighborhoods in the greater Houston area, we assessed whether neighborhoods influenced the obesity of children differently based on sex. Results indicated that neighborhood disadvantage, assessed using a comprehensive, multidimensional, latent profile analysis-generated measure, had a strong, positive association with the odds of obesity for both boys and girls. Interactions revealed that the relationship between disadvantage and obesity was stronger for girls, relative to boys. Our findings demonstrated the complex dynamics underlying the influence of residential neighborhood context on obesity for specific subgroups of children.

Keywords: Child obesity; neighborhoods; gender

Introduction

Obesity among children and adolescents is a well-known serious public health problem, impacting almost one in five youth in the United States (Hales et al. 2017). Childhood obesity has been connected to a range of negative outcomes including poor physical health, socioemotional functioning, and academic performance (Halfon, Larson, and Slusser 2013). Moreover, children with obesity are more likely to have obesity as an adult (Gordon-Larsen, The, and Adair 2012) with an increased risk of numerous serious health conditions (Jensen et al. 2014) generating substantial economic costs (Hammond and Levine 2010) and potentially leading to premature death (Olshansky et al. 2005).

There has been a resurgence of interest in the role of place in shaping health and a call to redirect the attention of public health theorists and practitioners to explore local context (Krieger 1994; McKinlay and Marceau 1999). Out of this movement, a large body of literature emerged specifically related to "neighborhood effects" on children's healthy development (Minh et al. 2017; Oakes et al. 2015; Sharkey and Faber 2014). A substantial part of this work focused on potential causes of increases in child obesity, with considerable attention devoted to the neighborhood environment (Alvarado 2016; Grow et al. 2010; Nau et al. 2015; Singh, Siahpush, and Kogan 2010; Yang et al. 2018). Neighborhood context was thought to influence youth outcomes through collective socialization shaped by the availability of economic, social, and physical resources. Health-promoting infrastructure shared amongst neighborhood residents could influence attitudes and behaviors shaping norms and influencing weight (Jencks and Mayer 1990; Kawachi and Berkman 2003). High-quality institutional resources such as parks, schools, and community organizations were less common in disadvantaged neighborhoods, and this lack of infrastructure could undermine collective life, fostering negative social capital through adult modeling and peer approval of unhealthy behaviors (Kawachi and Berkman 2003; Leventhal, Dupéré, and Shuey 2015). Among the different features of the neighborhood environment that have been investigated, those most consistently associated with body mass index (BMI) often were multidimensional, typically constructed using measures of social, economic, safety, and physical resources (Boone-Heinonen and Gordon-Larsen 2012; Carroll-Scott et al. 2013; Wall et al. 2012)

Residential neighborhoods could provide opportunities that enhance or harm health behaviors associated with obesity incidence (Auchincloss et al. 2013). Many scholars focused on neighborhood socioeconomic measures (e.g., lower mean levels of education, median household income, and home ownership; Grow et al. 2010) as determinants of child physical activity and weight status. Children living in more socioeconomically-disadvantaged neighborhoods, for example, had lower levels of physical activity (DeWeese et al. 2018; Meyer et al. 2015; Poulsen et al. 2019), diminished walkability (Khan et al. 2009) and higher rates of obesity, after accounting for individual-level socioeconomic status. Also, researchers linked neighborhoods characterized by social disorganization to crime and delinquency (Sampson and Raudenbush 2004; Shaw and McKay 1942) which may have disrupted children's ability to safely engage in physical activity. Together, these findings indicated that something more than the composition of the neighborhood was contributing to higher levels of obesity in these neighborhoods.

Furthermore, there was evidence that boys and girls experienced neighborhoods differently, with a stronger influence of residential context on girls (Abada, Hou, and Ram 2007; Chetty et al. 2016; Clampet-Lundquist et al. 2011; Kling, Ludwig, and Katz 2005; Zuberi 2012). Some of the strongest evidence of neighborhood effect heterogeneity by gender emerged from the Moving to Opportunity Study (MTO). One of the most important and relevant findings from this investigation for our study was that adolescent girls in families that moved to lower-poverty neighborhoods showed substantial improvements in mental health and were less likely to engage in risky behavior. Additionally, girls showed improvements in physical health; whereas boys experienced no benefit (Kling et al., 2005). This suggested that neighborhood disadvantage may have had a stronger negative influence on girls than boys, such that when girls were removed from a high-poverty neighborhood, they saw improved outcomes. Although much of this work that examined differences of neighborhood context by gender focused on experiences in adolescence and outcomes later in life (Abada et al. 2007; Chetty et al. 2016; Clampet-Lundquist et al. 2011; Kling et al. 2005; Zuberi 2012), there was some evidence that gender moderated the relationship between neighborhood conditions and health and had the potential to influence the risk of obesity.

Although empirical studies support the influence of neighborhood context on children's weight, many failed to account for the differential role gender may have played in these processes (Kim, Cubbin, and Oh 2019). In a recent systematic review of neighborhood context on child obesity, only five of the thirty-nine studies identified investigated the moderating effect of gender on the relationship between neighborhood economic context and child obesity (Kim et al. 2019). Four showed a significant interaction role with gender (Kim et al. 2019). Three studies showed that neighborhood economic context (i.e. poverty, deprivation) was more strongly associated with obesity in girls than boys (Alvarado 2016; Kowaleski-Jones and Wen 2013; Lee 2009). Yet, one of these studies only studied younger children (Kowaleski-Jones and Wen 2013), while another only examined adolescents (Lee 2009) and none of these studies considered the role of the built environment or crime in their measures of neighborhood context. Furthermore, the fourth study found a significant relationship between neighborhood poverty and obesity, but only among male preschoolers, *not* female preschoolers (Lovasi et al. 2013). Indeed, more work is needed to explore the relationship between neighborhood context and obesity by gender across childhood.

Determining whether neighborhoods influence children heterogeneously by gender requires a significant number of male and female respondents nested within the same neighborhoods. To overcome these data limitations and to address these gaps in the literature, we use electronic medical records from the largest network of pediatric outpatient clinics in the nation from Houston, Texas. These data, for children ages 2–17, provide a large and diverse sample of children. In addition, in terms of racial/ethnic diversity and immigrant populations, the Houston area represents the future demographic profile of the U.S. (Emerson et al. 2012). Building upon previously validated measures of neighborhood socioeconomic disadvantage (e.g. Area Deprivation Index (ADI)) we include factors for the domains of income, education, employment, and housing quality (Kind et al. 2014). However, rather than relying entirely on socioeconomic factors to capture neighborhood context, our data also include walkability and crime measures known to independently associate with obesity (Arcaya et al. 2016; Jencks and Mayer 1990), which we combine using latent profile analysis to provide a more comprehensive and multidimensional characterization of neighborhoods. This approach allows us to more fully capture the children's neighborhood environments. With more than 200,000 children nested within 992 neighborhoods, the data provide an ideal setting to explore how the influence of neighborhood context on child obesity may differ based on sex. This study extends the existing literature by identifying how and for whom neighborhoods matter for childhood obesity.

Our first goal, therefore, is to determine whether neighborhood disadvantage, measured with a comprehensive, multidimensional measure, influences children's and adolescents' odds of obesity. Then, we establish whether neighborhood disadvantage influences obesity differently for boys and girls. This leads us to the following research questions and hypotheses.

Hypotheses

First, we explored the relationship between neighborhood disadvantage and the odds of obesity among children aged 2–17. Given past work demonstrating an association between neighborhood socioeconomic status and child obesity, we expected that neighborhood disadvantage would associate with higher odds of child obesity (Hypothesis 1). Further, we expected sex would moderate the association between neighborhood disadvantage and obesity, and that the influence of contextual factors would be higher for girls relative to boys (Hypothesis 2).

Data and Methods

Data

Our child- and family-level data were from a compilation of electronic medical and administrative records from the largest network of pediatric clinics and hospital admissions in the country in Houston, TX.

Medical records included inpatient and emergency room pediatric encounters at a large pediatric hospital as well as outpatient visits to one of 50 pediatric clinics throughout all 13 counties in the Houston area. Children who were 2–17 years old with at least one outpatient visit between 2011 and 2013 were included. We randomly selected one child per family to eliminate household-level effects. Each child record was geocoded using street addresses contemporaneous with the weight and height measurement and linked to the matching residential census tract. We followed prior work and used census tracts to represent neighborhoods (Massey, Gross, and Shibuya 1994). Social and economic indicators were extracted from the 2010 decennial Census files, 2009 – 2013 American Community Survey (ACS) data, the City of Houston police department, and Street Smart WalkScore.com. To capture the appropriate time-period for analysis, neighborhood measures were assigned to children temporally by first taking the child's address from the electronic medical record at the time of their height and weight measurement. Then, we used the five-year ACS estimates for the census tracts which 'surround' the timing of the child's records. In this way, the 5-year ACS estimates characterize the child's area within that 5-year period.

Measures

The key outcome measure derived from the focal data set of medical records was a dichotomous variable indicating whether the child has obesity. We selected each child's first visit between 2011 and 2013 and used measures from that visit. We calculated body mass index (BMI) from height and weight measures using the standard formula (weight [kg]/height [m]^2). Because providers were required to collect information on height and weight at each visit, there were no missing data for these measures. Children were coded as having obesity if they had an age- and sex-specific BMI ≥95th percentile (Wang and Chen 2012). Obesity rates in our data, both overall and for key demographic subgroups, were comparable to other local and state estimates, giving us confidence in the results reported here. For example, our obesity rate overall was 9%, compared to an estimate of 14% for the entire state of Texas in 2018 (Robert Wood Johnson Foundation 2018). Because we aimed to clarify the relationship between neighborhood disadvantage and sex on obesity, our outcome measure was child obesity. As a robustness check, we assessed whether our estimated relationships persisted with respect to children who were overweight, defined as age- and sex-specific BMI at or above the 85th percentile and below the 95th percentile, and based on BMI z-scores (i.e., the number of standard deviation units that the child's BMI deviates from the age- and sex-normed mean reference value, based on the 2000 US Centers for Disease Control and Prevention Growth Charts: United States; Wang and Chen 2012).

We included all available covariates from the medical record to represent child and familial characteristics known to associate with childhood obesity (Kracht et al. 2019; Ogden et al. 2014). Child and family characteristics included age at time of visit, sex, race/ethnicity, child's insurance type as a proxy for family socioeconomic status (SES), and whether the child had siblings. Age was a continuous measure and represented the age of the child when he/she visited the clinic. Sex was a dichotomous variable and represented whether the child was male, with female as the referent. Race/ethnicity was a categorical measure representing the parent-reported race/ethnicity of the child, categorized as non-Hispanic White (referent), non-Hispanic Black, Hispanic, and Asian/other race. Nearly 17% of children were missing on race/ethnicity, a common occurrence when working with medical records data. Typically, we would impute values for children with missing data; however, multiple imputation would not be appropriate due to the lack of comprehensive individual-level measures (Allison 2001). As such, we included an indicator for whether the child was missing on race/ethnicity. We further compared the representativeness of our electronic medical records by comparing our racial/ethnic proportions to those from the American Community Survey (ACS) in the Houston metropolitan area. For example, the ACS 5-year estimates from 2009-2013 for the population in Harris County were 33% non-Hispanic white, 19% non-Hispanic Black, 41% Hispanic, and 6% Asian, which is roughly aligned with our data presented in Table 2. Insurance type was a categorical measure indicating the type of medical insurance held by the child at the time of the visit, and was categorized as private provider (referent), public provider (e.g., Children's Health Insurance Program (CHIP) or state Medicaid), or missing/ other insurance provider. Approximately 24% of children were missing on insurance type so we combined the "missing" category with "other" insurance. Similarly, using insurance type as a proxy for SES is far from ideal; yet insurance coverage has been widely used as a marker for individual-level SES with reasonable validity (Casey et al. 2017; Goyal, Fiks, and Lorch 2011; Kristal et al. 2015). Finally, whether the child had siblings is a dichotomous variable and represented whether the child had siblings in the household at the time when he/she visited the clinic based on a unique household identifier. Specifically, if there was more than one child with the same household identifier, then we categorized that child as having at least one sibling in the household, with no siblings as the reference.

The neighborhood data included social, economic, walkability, and crime measures known to independently associate with obesity (Arcaya et al. 2016; Jencks and Mayer 1990), which we combined into a comprehensive and multidimensional measure of neighborhood context. Social and economic indicators were generated using the Census and ACS data. In addition to the more typical socioeconomic measures of income, poverty, unemployment rate, public assistance receipt, and educational attainment, we included the median year the house was built and the percent of vacant homes in a tract to capture the legacy of race-based residential disadvantage associated with property values (Taylor 2019). The percent of female-headed households captured potential disadvantage based on family structure (Snyder, McLaughlin, and Findeis 2006) and the percent of foreign-born households is included due to possible wealth gaps between U.S. and foreign-born households (Cobb-Clark and Hildebrand 2006). In addition to these factors, we included crime and walkability measures due to their established links with obesity risk (Arcaya et al. 2016; Jencks and Mayer 1990). For crime data derived from the City of Houston police department, we partitioned the time- and date-stamped geocoded offenses into violent (murder, rape, robbery, aggravated assault) and non-violent (burglary, theft, auto theft) (Tabarrok, Heaton, and Helland 2010). We then calculated the proportion of violent and non-violent crime for a given census tract. We used a validated walkability measure (Carr, Dunsiger, and Marcus 2010) extracted from Street Smart Walkscore.com to isolate whether, and the extent to which, a pedestrian could access key residential services such as grocery stores, schools, parks, and leisure spaces in a given area with minimal automobile use (Leinberger and Austin 2013). Higher scores indicated greater pedestrian accessibility for a given census tract. This research was conducted in accord with prevailing ethical principles and reviewed by the Rice University and Baylor College of Medicine Institutional Review Boards.

Statistical Analyses

We characterized neighborhoods into typologies based on a range of social, economic, and physical environment measures frequently used to define a child's neighborhood of residence (Jencks and Mayer 1990).

We used Mplus 8.3 software (Muthen and Muthen 2017) to estimate a maximum-likelihood latent profile analysis (LPA; Lazarsfeld and Henry 1968) that included median household income levels, median year the house was built, population density, mean levels of educational attainment, rates of unemployment, percent foreign born, percent receiving public assistance, percent female-headed households, percent in poverty, percent of homes that are vacant in the tract, crime, and walkability. We first estimated a 1-class model and fit successive models with an increasing number of classes to characterize neighborhoods. To select the most appropriate number of profiles, we used entropy, model fit and usefulness statistics, and theoretically driven evidence. Specifically, we identified the most parsimonious model and assessed local dependencies through Bayesian information criterion (BIC), p-value-based likelihood ratio tests, and bootstrap p-values. Model usefulness statistics further indicated that neighborhoods in the Houston metropolitan area, given our data, were most appropriately captured by a 4-class solution (see Supplementary 1). The stability of our 4-class solution was verified by the proportional class prevalence and high average posterior probabilities (0.74 to 0.77) within each neighborhood typology, which indicate that nearly all neighborhoods were likely to be in a given profile, as well as our substantive neighborhood cluster interpretations based on theoretical neighborhood stratification observed across the United States (e.g., upper class, middle class, working class, and disadvantaged communities; see Table 1 and Nylund, Asparouhov, and Muthén 2007).

To clarify the relationship between neighborhood categories and obesity across childhood, we estimated hierarchical logistic regression models (Guo and Zhao 2000; Rabe-Hesketh and Skrondal 2008) with Stata 15 software. All models used maximum likelihood estimation with adaptive quadrature (Rabe-Hesketh and Skrondal 2008). This approach controlled for the lack of independence of data within higher level groups, and adjusted for problems that otherwise downwardly bias estimated standard errors including clustering of children within neighborhoods, different sample sizes for lower and higher units, heteroscedastic error terms, and variable numbers of cases within higher level units (Raudenbush and Bryk 2002).

We first estimated models with only child/ family-level predictors (children's age at time of visit, sex, race/ethnicity, insurance type, and whether the child has siblings) included to test the influence of child- and family- factors on the odds of child obesity. Exploratory analyses indicated that childhood obesity was most appropriately captured by a quadratic function due to the non-linear relationship between BMI and age. As such, we only presented estimates with the quadratic age term included. In our next set of models, we included the LPA-created neighborhood typologies at the neighborhood-level (and a neighborhood-level error component) along with the child/ family-level predictors and an individual error term. To test hypothesis 2 we included interactions between the LPA-created neighborhood clusters at the neighborhood-level and sex at the child/family-level. All models treated the sex effect as random across neighborhoods (i.e., census tracts) and the effects of the control variables (children's age at time of visit, children's age at time of visit^2, sex, race/ethnicity, insurance type, and whether the child has siblings) as fixed. We reported odds ratios (OR) from the regression analyses for ease of interpretation.

Results

In Figure 1 we illustrated the geographic boundaries of our 4 neighborhood typologies in the Houston metropolitan area. Based on the descriptive characteristics and location of these neighborhood contexts, we assigned descriptive labels of Advantaged (i.e. high SES and low crime), Middle-Class, Working-Class, and Disadvantaged (i.e. low SES and high crime). The most advantaged neighborhoods were in the south and west parts of the city center. As shown in Table 1, Advantaged neighborhoods had the highest median household income ($124,000), highest overall levels of education (67% of residents had at least 16 years of education), lowest percentage of people living in poverty (4%), lowest proportion of violent crime (5% violent), and were the most walkable (46.72 average walk score out of 100). Middle-Class neighborhoods, in comparison, largely clustered in the north and west parts of the city and had the second highest median household income ($86,400), second highest overall levels of education (39% of residents had at least 16 years of education), next-to-lowest percentage of people living in poverty (9%), next-to-lowest proportion of violent crime (17% violent) and were the second-to-most walkable (29.49 average walk score out of 100). Working-Class communities made up the exterior perimeter of Harris county, and had the next-to-lowest median household income ($51,400), the next-to-lowest education levels (21% of adult residents lack a high school degree), the next-to-highest proportion of the population in poverty (26%), and the next-to-highest proportion of violent crime (18%). The most Disadvantaged communities made up the north, east, and southern parts of the center of the city, and scored the lowest on nearly every indicator. They had the lowest median household income ($35,100), the lowest education levels (43% of adult residents lack a high school degree), the highest proportion of the population in poverty (44%), and the highest proportion of violent crime (20%).

< Table 1 and Figure 1>

Descriptive information for the child, family, and neighborhood context overall and by sex (n=256,128 children nested in 992 neighborhoods) was displayed in Table 2. Nine percent of children in the full sample had obesity, with boys' prevalence slightly higher (10%) than girls' (9%). The mean age for the entire sample was 8.56 years, with girls somewhat older (8.59) than boys (8.54) across the sampled children. As illustrated in Figure 2, which presents the distribution of children by race/ethnicity across neighborhood typologies, although there is some clustering of children of specific race/ethnicities with neighborhood types, each race/ethnic group is represented within each neighborhood type. As shown in Table 2, boys are slightly over-represented in Middle-Class compared to those in Working-Class neighborhoods.

<Table 2 and Figure 2 >

Results from our hierarchical logistic regression models predicting child obesity were shown in Table 3. Model 1 only included the child/family-level predictors (children's age at time of visit, children's age at time of visit^2, sex, race/ethnicity, insurance type, and whether the child has siblings). Model 2 added the LPA-created neighborhoods (Advantaged, ref., Middle-Class, Working-Class, Disadvantaged) at the neighborhood-level. Fully specified Model 3 included all predictors at the child/ family-level, the LPA-generated neighborhoods, and our interactions between sex and neighborhood categories at the neighborhood-level.

The random effects estimated across all models indicated that the effect of sex on the odds of having obesity for children differed significantly across neighborhoods. First, in Model 1, we saw that boys relative to girls, non-Hispanic Blacks and Hispanics relative to whites, and publicly- and missing/other-insured children had higher odds of obesity. Asian/other children, relative to white children, and those with siblings had lower odds of obesity. The association of age with obesity was non-linear; each additional year of age increased the odds of obesity, but to a diminishing degree at older ages. In Model 2, we saw further evidence that as children aged the odds of obesity steadily increased, with each additional year associated with 40% (CI: 1.38-1.42) greater odds. Similar to Model 1, this association weakened among older children (Quadratic: 0.99; CI: 0.99-0.99). Model 2 indicated that boys had significantly higher odds of having obesity than girls once all individual, family, and neighborhood variation was considered. Specifically, boys had 5% (CI: 1.02-1.09) higher odds of obesity relative to girls. Model 2 further showed that higher levels of disadvantage associated independently with the odds of child obesity. Children living in the most disadvantaged neighborhoods, had more than two and a half times (CI: 2.68-3.07) the odds of obesity relative to children living in the most advantaged neighborhoods. Consistent with our first hypothesis, moving from left to right of the table, we saw that children living in the most disadvantaged neighborhoods had anywhere from 75% (CI: 1.64-1.68) to more than a 3-fold (OR: 3.18; CI: 2.88-3.50) increase in the odds of obesity.

<Table 3>

Next, we examined whether sex moderated the influence of neighborhood disadvantage on obesity (Table 3). Model 3 showed an interaction between neighborhood disadvantage and sex, such that as disadvantage increased, girls' obesity odds increased. While for boys, obesity also increased as disadvantage increased, but the rise was not as steep as it was for girls. This indicated that disadvantage influenced girls' obesity more than boys' obesity. The interaction between sex and neighborhood category was displayed in Figure 3 where we presented the *difference* in the predicted probabilities of obesity, relative to living in an Advantaged neighborhood. On the lower end of the age spectrum, for example, a 4-yr-old girl living in a Middle-Class neighborhood had a 0.02 higher probability of obesity compared to a girl living in an Advantaged neighborhood, and about a 0.05 increase if she was in a Working-Class or Disadvantaged neighborhood. Thus, we found further support for our second hypothesis that neighborhood disadvantage influenced obesity differently for boys and for girls, where girls were more influenced than boys.

<Figure 3>

To assess the robustness of our findings, we conducted several sensitivity analyses. First, we examined whether our results held when the outcome measure was overweight rather than obesity, and findings were substantively similar to results presented here, albeit of greater magnitude and strength (see Supplementary 2), and we still saw the sex variation reported here in the BMI z-score models (see Supplementary 3). Finally, we excluded children missing on insurance and also found substantively similar results (see Supplementary 4).

Discussion and Conclusion

We used electronic medical records from the nation's largest network of pediatric clinics to provide novel empirical insights into how and for whom neighborhoods matter for childhood obesity. To this end, we examined the relationship between LPA-constructed neighborhood typology with obesity, as well as how sex moderated these associations. Characterizing neighborhoods using latent profile analysis provided an advantage over other methods for assessing place and health effects, because it allowed us to include additional local measures of disadvantage beyond socioeconomic factors based entirely on ACS 5-year estimates (e.g. Area Deprivation Index; Kind et al. 2014). In addition to social and economic factors, our neighborhood data also included local crime and walkability measures which were not only known to be independently associated with obesity (Arcaya et al. 2016; Jencks and Mayer 1990), but also offered insight into possible explanatory mechanisms by which neighborhood disadvantage influences childhood obesity. Thus, latent profile analysis provided us with a more comprehensive and multidimensional characterization of neighborhoods. Our analyses indicated that neighborhoods in the Houston metropolitan area were most appropriately captured by a 4-class typology to which we assigned descriptive labels of Advantaged (i.e. high SES and low crime), Middle-Class, Working-Class, and Disadvantaged (i.e. low SES and high crime).

Generally speaking, and in line with previous findings (Nau et al. 2015; Poulsen et al. 2019), our results indicated that children had greater odds of obesity as neighborhood disadvantage increased. We also found evidence of heterogeneity by neighborhood context (Kolak et al. 2020; Sharkey and Faber 2014). Consistent with our first hypothesis, we saw that children living in more disadvantaged neighborhoods had greater odds of obesity. This could be due to the lack of high-quality institutional resources such as parks, schools, and community organizations, shared amongst neighborhood residents that could influence attitudes, behaviors (i.e. physical activity) and ultimately weight (Jencks and Mayer 1990; Kawachi and Berkman 2003). The absence of this health-promoting infrastructure within disadvantaged neighborhoods could undermine youth socialization through the collective adoption of unhealthy behaviors (Kawachi and Berkman 2003; Leventhal et al. 2015).

We found further support for the second hypothesis that girls were more vulnerable to neighborhood characteristics than boys. Specifically, as children's neighborhood disadvantage increased, the influence on obesity was greater for girls relative to boys. This was consistent with prior work showing that neighborhood economic context (i.e. poverty, deprivation) was more strongly associated with obesity in girls than boys (Alvarado 2016; Kowaleski-Jones and Wen 2013; Lee 2009), despite the absence of walkability or crime in previous measures of neighborhood context.

One plausible mechanism by which sex moderated neighborhood influence on childhood obesity was through parents in areas of higher disadvantage regulating the physical activity of girls more (Clampet-Lundquist et al. 2011; Zuberi 2012), which could have influenced their obesity risk. For example, girls in disadvantaged neighborhoods, or their parents, perceived unique threats to their personal safety such as harassment, domestic violence, and sexual assault (Zuberi 2012), leading them to spend more time indoors and limit their physical activity (Clampet-Lundquist et al. 2011). Previous qualitative work in this area has shown that boys were more likely to congregate outside, while girls were more likely to gather in homes or indoor public spaces such as malls (Clampet-Lundquist et al. 2011), suggesting that having safe indoor spaces for social interaction offered girls protection against the potentially harmful influence of the neighborhood. Again, this may have limited girls' physical activity. Thus, our findings demonstrated the complex dynamics underlying the influence of residential neighborhood context on childhood obesity.

While our study added to the existing literature on neighborhoods and wellbeing, we acknowledge several limitations. First, while electronic medical records provided a large and diverse number of children nested within neighborhoods with objectively measured height and weight, they were primarily intended for clinical and administrative use. Thus, the present analysis was constrained by the limited individual- and family-level variables available for analysis. For example, we did not have information on the variation in quality of health care children received though prior research indicates that quality of care differs by insurance type (Kreider et al. 2016) and quality of care has been associated with obesity in children (Cote et al. 2004; Wake et al. 2009; Walker et al. 2014). Similarly, at the neighborhood-level, despite studies that showed a connection between childhood obesity and the food environment (Elbel et al. 2020), and childhood obesity and fitness environment and park access (Wolch et al. 2011), we did not have access to data with this level of detail. In the future, researchers with more detailed individual-level data could test our findings with additional individual-, family-, and neighborhood-level covariates known to be associated with obesity (e.g., parenting behaviors, peer group influences, physical activity resources). Similarly, while our data allowed us to overcome some of the methodological challenges involved in uncovering neighborhood effect heterogeneity, our sample was still limited to the Houston metropolitan region, reducing the generalizability of our findings to a portion of children living in the area between 2011 and 2013. Moreover, the cross-sectional nature of our data limited our ability to make causal inferences. We also followed prior work and used census tracts to represent neighborhoods (Massey et al. 1994). Although census tracts were by no means a perfect operationalization of residential contexts (Tienda 1990), they remained a useful spatial entity available to us in the approximation of a neighborhood (Arcaya et al. 2016; Jargowsky 1997; White 1988).

Even with these limitations, researchers have often lacked access to data that explicitly linked social determinants of health to children's obesity prevalence among specific subgroups of children. The current study addressed this by using a large sample of medical records from a diverse group of children residing in Houston, TX, linked to demographic and multifaceted contextual data. Because these were clinical records, height and weight were objectively measured at the time of the medical visit, so this provided a distinct advantage over parent-reported survey data, which may be prone to bias (Dubois and Girad 2007). Furthermore, because our large sample has more than 200,000 children nested within over 900 neighborhoods in the Houston area, we were able to address the lack of evaluation of heterogeneity in existing research on neighborhoods and health. We showed that neighborhoods matter differently for children's obesity based on their sex. Our findings moved neighborhood research beyond simply linking neighborhood conditions to obesity and demonstrated how these associations vary for specific subgroups of children.

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Table 1. Descriptive Neighborhood-level Statistics by Neighborhood Categories Created through LPA

	Advantaged		Middle-Class		Working-Class		Disadvantaged		Sig
	Mean or %	SD	Mean or %	SD	Mean or %	SD	Mean or %	SD	
Socioeconomic Proportions									
Median Income (in $10K)	12.40	10.12	8.64	5.06	5.14	5.06	3.51	5.06	<.001
Median Year House Built	1989	50.61	1994	25.30	1984	35.43	1970	5.06	<.001
Population Density (1K people per sq. mile)	39.60	693.34	29.71	516.21	33.24	733.83	62.56	2059.79	<.001
% Adults < 12 years Education (Less than H.S)	4.00	0.00	8.00	<0.01	21.00	<0.01	43.00	91.10	<.001
% Adults = 12 years Education (High School Degree)	9.00	<0.01	20.00	<0.01	31.00	<0.01	28.00	0.00	<.001
% Adults > 12 and < 16 years Education (Some College)	20.00	<0.01	33.00	<0.01	32.00	<0.01	19.00	0.00	<.001
% Adults = 16 years Education (Bachelor's Degree)	38.00	<0.01	28.00	<0.01	12.00	<0.01	7.00	0.00	<.001
% Adults = 18 years Education (Master's Degree)	18.00	<0.01	9.00	<0.01	4.00	<0.01	2.00	0.00	<.001
% Adults > 18 and < 21 years Education (Some Graduate Work)	7.00	<0.01	2.00	<0.01	1.00	<0.01	1.00	0.00	<.001
% Adults = 21 years Education (Graduate Degree)	4.00	<0.01	1.00	<0.01	1.00	<0.01	1.00	0.00	<.001
% Unemployed	4.00	<0.01	6.00	<0.01	10.00	<0.01	12.00	0.00	<.001
% Foreign-born Residents	21.00	<0.01	16.00	<0.01	19.00	<0.01	37.00	0.00	<.001
% Receiving Public Assistance	0.00	<0.01	1.00	<0.01	2.00	<0.01	3.00	0.00	<.001
% Female-Headed Households	6.00	<0.01	11.00	<0.01	19.00	<0.01	21.00	0.00	<.001
% of Residents in Poverty	4.00	<0.01	9.00	<0.01	26.00	<0.01	44.00	10.12	<.001
% of Vacant Homes	5.00	<0.01	6.00	<0.01	10.00	<0.01	13.00	0.00	<.001
Proportion of Crimes which are Violent	5.00	<0.01	17.00	<0.01	18.00	<0.01	20.00	0.00	0.082
Walkability Score (out of 100)	46.72	34.78	29.49	24.39	30.16	19.80	42.22	11.24	<.001
Proportion of Tracts	0.21		0.39		0.27		0.13		
Average Posterior Probabilities	0.74		0.77		0.75		0.74		
Neighborhoods n =	208		387		268		129		
Children n =	54,029		100,565		68,914		36,620		

Source: Data are from the Authors' Compilation of Electronic Medical Records, the Census, American Community Survey (ACS), Houston Crime Data, and Walkscore.com

Note: Significance is evaluated using One-Way MANOVA with the neighborhood variables as the dependent variables and LPA neighborhood type as the independent variable.

Table 2: Means and Standard Deviations for Independent and Dependent Variables Overall and by Sex

	Overall		Girls		Boys	
Dependent Variable	Mean or %	SD	Mean or %	SD	Mean or %	SD
Child has Obesity	9.00		9.00		10.00***	
Independent Variables						
Sociodemographic						
Age in Years At Time of Visit	8.56	4.68	8.59	4.69	8.54**	4.66
Race						
Non-Hispanic White	41.00		41.00		42.00	
Non-Hispanic Black	14.00		14.00		14.00	
Hispanic	23.00		22.00		23.00*	
Asian/ Other Race	5.00		5.00		5.00	
Race is Missing	17.00		18.00		16.00***	
Health Insurance						
Private Provider	57.00		57.00		57.00	
Public Provider	20.00		20.00		20.00	
Other/ Missing Provider	23.00		23.00		23.00	
Siblings						
Has Siblings	34.00		34.00		34.00	
Neighborhood Context						
Advantaged	21.00		21.00		21.00	
Middle-Class	39.00		39.00		40.00*	
Working-Class	27.00		27.00		26.00**	
Disadvantaged	13.00		13.00		13.00	
N	256, 128		125, 352		130, 776	

Source: Data are from the Authors' Compilation of Electronic Medical Records, American Community Survey, the Census, and Walkscore.com
Note: Asterisks indicate significant change evaluated using two-tailed independent means t-test
****p < 0.001, ** p < 0.01,* p <0.05*

Table 3. Hierarchical logistic regression models predicting child obesity

	Model 1	Model 2	Model 3

	OR	95% CI		OR	95% CI		OR	95% CI	
Intercept	0.01***	0.01	0.01	0.01***	0.01	0.01	0.01***	0.01	0.01
Demographics									
Age in Years at Time of Visit									
Age	1.40***	1.38	1.42	1.40***	1.38	1.42	1.40***	1.38	1.42
Age2	0.99***	0.99	0.99	0.99***	0.99	0.99	0.99***	0.99	0.99
Sex (girls, ref)									
Boys	1.05*	1.00	1.10	1.05**	1.02	1.09	1.28***	1.15	1.42
Race/ ethnicity (white, ref)									
Non-Hispanic Black	1.57***	1.50	1.64	1.42***	1.36	1.49	1.42***	1.36	1.49
Hispanic	1.92***	1.85	2.00	1.74***	1.67	1.81	1.74***	1.67	1.81
Asian/ Other Race	0.73**	0.66	0.80	0.76***	0.69	0.83	0.76***	0.69	0.83
Race is Missing	1.11***	1.06	1.16	1.08**	1.03	1.12	1.08**	1.03	1.12
Insurance Type (private, ref)									
Public	1.39***	1.34	1.44	1.28***	1.23	1.33	1.28***	1.23	1.33
Other/ Missing Provider	1.00	0.97	1.04	0.97	0.93	1.00	0.97	0.93	1.00
Family Structure (no sib., ref)									
Has Siblings	0.83***	0.81	0.86	0.84***	0.81	0.86	0.84***	0.81	0.86
Neighborhood Context (adv., ref)									
Middle-Class				1.75***	1.64	1.86	1.85***	1.69	2.02
Working-Class				2.56***	2.40	2.73	3.03***	2.77	3.32
Disadvantaged				2.87***	2.68	3.07	3.18***	2.88	3.50
Interaction Effects (girls*adv., ref.)									
Boys*Middle-Class							0.90	0.80	1.02
Boys*Working-Class							0.72***	0.64	0.81
Boys*Disadvantaged							0.82**	0.72	0.94
Random Effects									
Sex	1.14***	1.12	1.15	1.04***	1.03	1.05	1.04***	1.03	1.05

**p <.05, **p <.01, ***p<.001*
Note: CI = Confidence Interval

Figure 1. Neighborhood Typologies by Census Tracts, Greater Houston Region

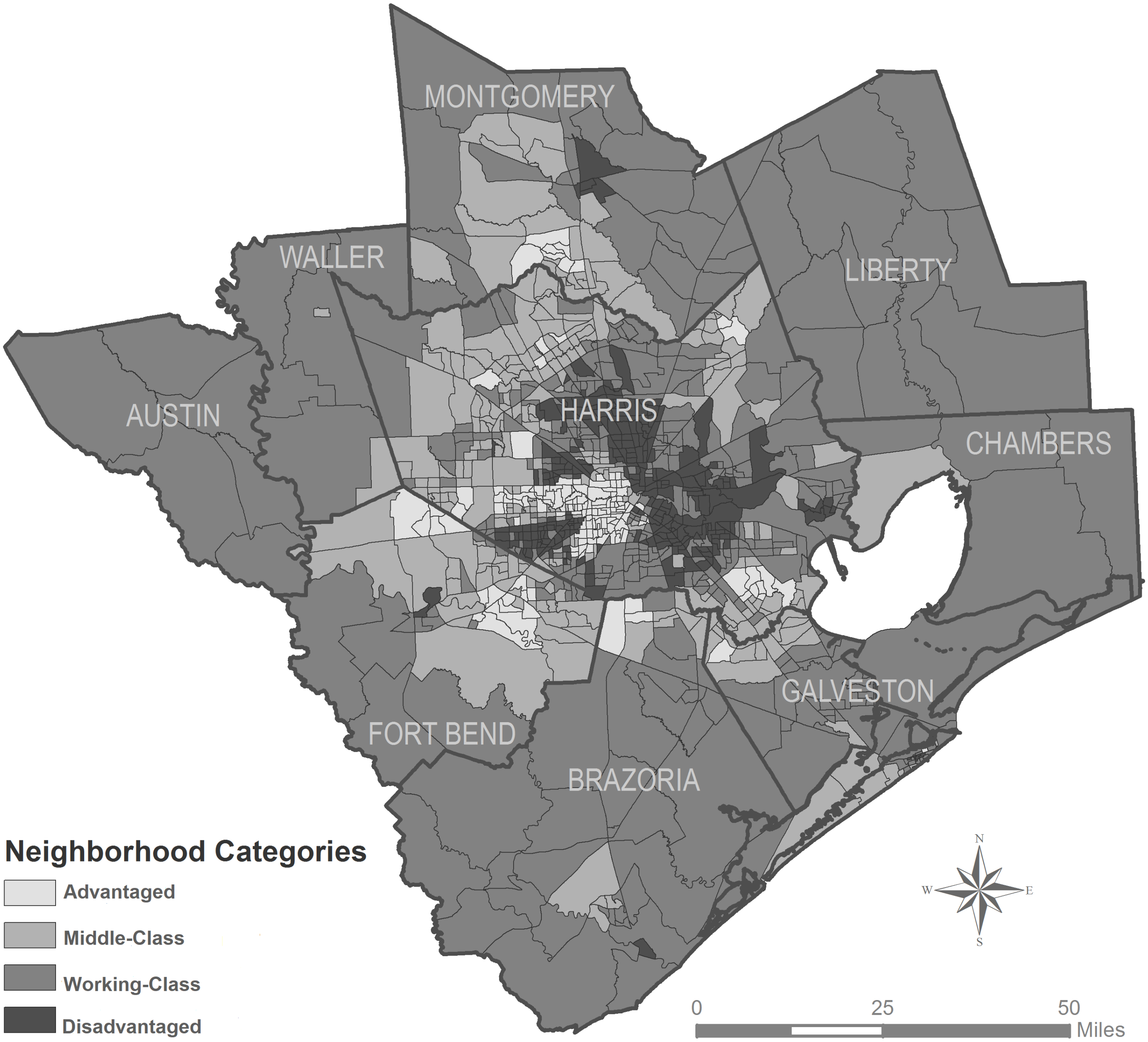

MONTGOMERY
WALLER
LIBERTY
AUSTIN
HARRIS
CHAMBERS
GALVESTON
FORT BEND
BRAZORIA
Neighborhood Categories
Advantaged
Middle-Class
Working-Class
Disadvantaged
N
W
E
S
0
25
50
Miles

Figure 2. Distribution of Children across Neighborhood Contexts by Race/ Ethnicity

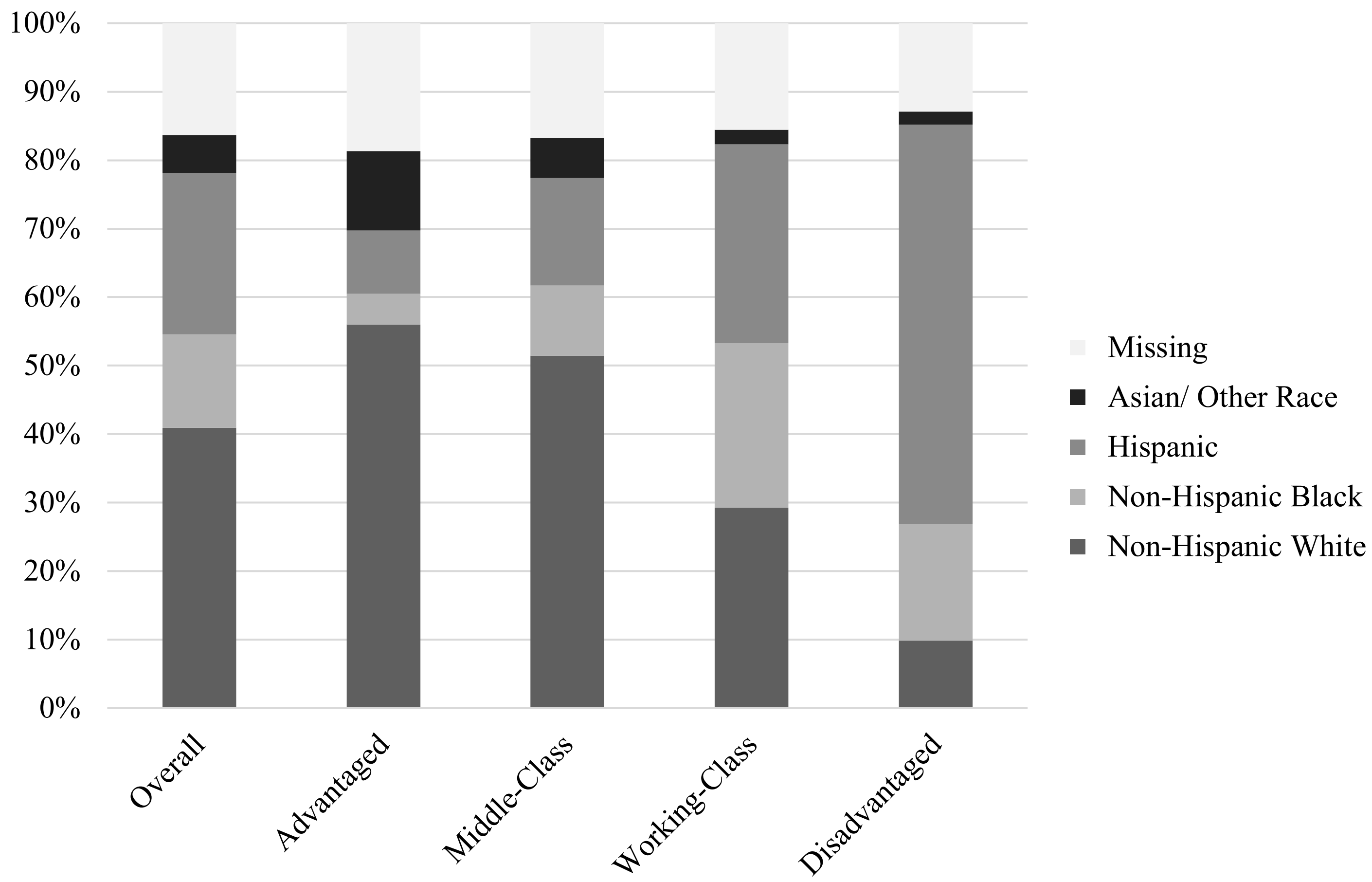
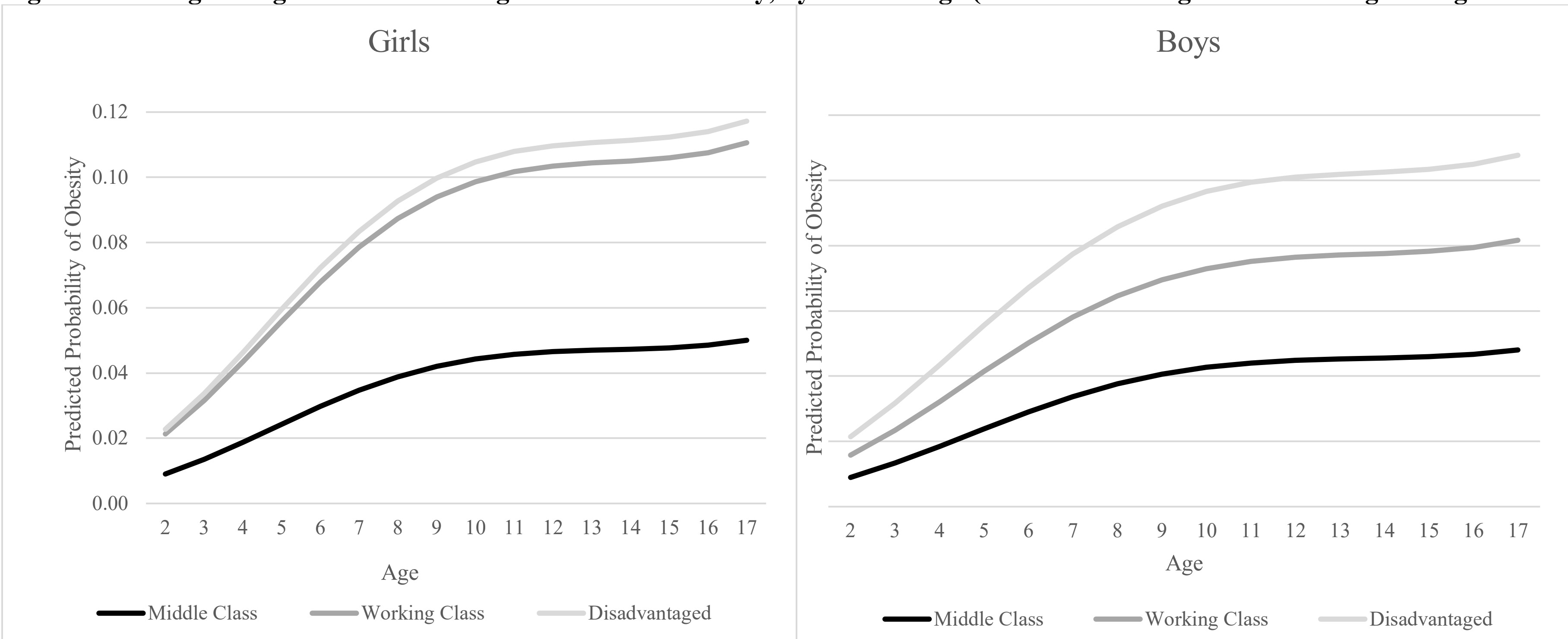


Figure 3. Average Marginal Effects of Neighborhoods on Obesity, by Sex and Age (Relative to Living in an Advantaged Neighborhood)



Source: Data are from the Authors' Compilation of Electronic Medical Records, American Community Survey, and the Census

Supplementary 1. Model Fit Information for LPAs with 1 - 5 Latent Profiles

Classes	AIC	BIC	a-BIC	LL	Entropy
1	-8868.21	-8885.13	-8834.20	5971.79	1.00
2	-8774.39	-8737.25	-8743.46	4886.07	0.24
3	-8512.48	-8641.33	-8582.12	4606.16	0.28
4	**-8349.99**	**-8457.49**	**-8407.09**	**4472.99**	**0.31**
5	-8451.24	-8513.54	-8467.2	4503.78	0.32

Source: Data are from the Authors' Compilation of Electronic Medical Records, the Census, American Community Survey (ACS), Houston Crime Data, and Walkscore.com

Supplementary 2. Hierarchical logistic regression models predicting child overweight

	Model 1			Model 2			Model 3		
	OR	95% CI		OR	95% CI		OR	95% CI	
Intercept	0.07***	0.07	0.07	0.05***	0.04	0.05	0.04***	0.04	0.04
Demographics									
Age at visit in Years									
Age	1.33***	1.32	1.34	1.33***	1.32	1.34	1.33***	1.32	1.34
Age2	0.99***	0.99	0.99	0.99***	0.99	0.99	0.99***	0.99	0.99
Sex (girls, ref)									
Boys	0.98	0.95	1.01	0.98	0.96	1.01	1.17***	1.10	1.25
Race/ ethnicity (white, ref)									
Non-Hispanic Black	1.35***	1.31	1.40	1.27***	1.23	1.31	1.27***	1.23	1.31
Hispanic	1.67***	1.63	1.72	1.57***	1.52	1.61	1.57***	1.52	1.61
Asian/ Other Race	0.81***	0.77	0.86	0.83***	0.79	0.87	0.83***	0.79	0.87
Race is Missing	1.08***	1.05	1.11	1.06***	1.04	1.09	1.06***	1.04	1.00
Insurance Type (private, ref)									
Public	1.21***	1.18	1.24	1.28***	1.11	1.17	1.14***	1.12	1.18
Other/ Missing Provider	0.98	0.96	1.00	0.97	0.93	0.98	0.96***	0.93	0.98
Family Structure (no sib., ref)									
Has Siblings	0.88***	0.86	0.90	0.84***	0.87	0.90	0.89***	0.87	0.90
Neighborhood Context (adv., ref)									
Middle-Class				1.39***	1.34	1.44	1.50***	1.42	1.58
Working-Class				1.80***	1.73	1.87	2.06***	1.95	2.18
Disadvantaged				1.97***	1.89	2.07	2.20***	2.07	2.34
Interaction Effects (girls*adv., ref.)									
Boys*Middle-Class							0.86***	0.80	0.93
Boys*Working-Class							0.77***	0.64	0.83
Boys*Disadvantaged							0.81***	0.72	0.88
Random Effects									
Sex	1.06***	1.06	1.07	1.02***	1.02	1.03	1.02***	1.02	1.02

**p* <.05, ***p* <.01, ****p*<.001*

Supplementary 3. Hierarchical Linear Regression Models Predicting Child BMI Z-scores

	Model 1			Model 2			Model 3		
	Coeff.	95% CI		Coeff.	95% CI		Coeff.	95% CI	
Intercept	-0.37***	-0.35	-0.39	-0.54***	-0.52	-0.57	-0.55***	-0.53	-0.58
Demographics									
Age at visit in Years									
Age	0.15***	0.14	0.15	0.15***	0.14	0.15	0.15***	0.14	0.15
Age^2	-0.01***	-0.01	-0.02	-0.01***	-0.01	-0.02	-0.01***	-0.01	-0.01
Sex (girls, ref)									
Boys	0.04***	0.03	0.06	0.05***	0.03	0.06	0.06***	0.04	0.09
Race/ ethnicity (white, ref)									
Non-Hispanic Black	0.16***	0.14	0.17	0.12***	0.11	0.14	0.12***	0.11	0.14
Hispanic	0.27***	0.26	0.29	0.24***	0.22	0.25	0.24***	0.22	0.25
Asian/ Other Race	-0.25***	-0.23	-0.27	-0.24***	-0.22	-0.26	-0.24***	-0.22	-0.26
Race is Missing	0.01	-0.01	0.02	0.00	0.01	-0.02	0.00	0.01	-0.02
Insurance Type (private, ref)									
Public	0.10***	0.09	0.11	0.07***	0.09	0.11	0.07***	0.06	0.08
Other/ Missing Provider	-0.08***	-0.07	-0.09	-0.09***	-0.08	-0.10	-0.09***	-0.08	-0.10
Siblings (no sib., ref)									
Has Siblings	-0.04***	-0.03	-0.05	-0.04***	-0.03	-0.05	-0.04***	-0.03	-0.05
Neighborhood Context (adv., ref)									
Middle-Class				0.13***	0.12	0.15	0.14***	0.12	0.17
Working-Class				0.27***	0.25	0.29	0.29***	0.27	0.32
Disadvantaged				0.33***	0.31	0.36	0.33***	0.30	0.36
Interaction Effects (girls*adv., ref.)									
Boys*Middle-Class							-0.02	0.01	-0.05
Boys*Working-Class							-0.04*	-0.01	-0.08
Boys*Disadvantaged							0.00	0.04	0.04
Random Effects									
Sex	0.01***	0.01	0.02	0.00***	0.00	0.01	0.00***	0.00	0.01

**p <.05, **p <.01, ***p<.001*

Supplementary 4. Hierarchical Logistic Regression Models Predicting Child Obesity with Children Missing Insurance Type Excluded

	Model 1			Model 2			Model 3		
	OR	95% CI		OR	95% CI		OR	95% CI	
Intercept	0.01***	0.01	0.01	0.00***	0.00	0.00	0.00***	0.00	0.00
Demographics									
Age at visit in Years									
Age	1.50***	1.48	1.53	1.50***	1.47	1.53	1.50***	1.47	1.53
Age^2	0.98***	0.98	0.99	0.99***	0.98	0.99	0.99***	0.98	0.99
Sex (girls, ref)									
Boys	1.04	1.00	1.10	1.05*	1.01	1.09	1.25***	1.11	1.40
Race/ ethnicity (white, ref)									
Non-Hispanic Black	1.61***	1.52	1.69	1.45***	1.38	1.52	1.45***	1.38	1.52
Hispanic	1.99***	1.90	2.08	1.79***	1.71	1.87	1.79***	1.71	1.87
Asian/ Other Race	0.73***	0.66	0.81	0.76***	0.69	0.84	0.76***	0.69	0.84
Race is Missing	1.14***	1.08	1.20	1.10***	1.05	1.16	1.11***	1.05	1.17
Insurance Type (private, ref)									
Public	1.42***	1.37	1.47	1.28***	1.23	1.33	1.28***	1.23	1.33
Other Provider	1.47***	1.29	1.67	1.45***	1.27	1.67	1.45***	1.27	1.65
Siblings (no sib., ref)									
Has Siblings	0.84***	0.81	0.87	0.85***	0.82	0.88	0.85***	0.82	0.88
Neighborhood Context (adv., ref)									
Middle-Class				1.74***	1.62	1.86	1.80***	1.63	1.98
Working-Class				2.59***	2.41	2.78	3.07***	2.78	3.39
Disadvantaged				2.85***	2.64	3.08	3.14***	2.82	3.50
Interaction Effects (girls*adv., ref.)									
Boys*Middle-Class							0.94	0.82	1.08
Boys*Working-Class							0.72***	0.63	0.82
Boys*Disadvantaged							0.83*	0.72	0.96
Random Effects									
Sex	1.13***	1.11	1.15	1.04***	1.03	1.05	1.04***	1.03	1.05

**p <.05, **p <.01, ***p<.001*