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# NEIGHBORHOOD EFFECTS ON BODY MASS: TEMPORAL AND SPATIAL DIMENSIONS

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## Abstract

Research examining the effects of neighborhood characteristics on obesity and excess body weight has generally neglected the influence of both life-course exposure and geographically-proximate communities. Using data on 9,357 respondents to the National Longitudinal Survey of Youth, 1979 Cohort, in conjunction with tract-level data from the 1980–2010 U.S. censuses, this study examines how black, Hispanic, and white individuals' cumulative exposure to varying levels of neighborhood poverty and co-ethnic density from their mid-teens through mid-adulthood, as well as the levels of poverty and co-ethnic density in nearby, or "extralocal," neighborhoods, are associated with their body mass index (BMI). Fixed-effect regression models show that, among Hispanics and whites, cumulative exposure to co-ethnic neighbors is a stronger positive predictor of BMI than the co-ethnic density of the immediate, point-in-time neighborhood. Among whites, cumulative exposure to neighborhood poverty is a stronger positive predictor of BMI than is the poverty rate of the current neighborhood of residence. And among both blacks and whites, the distance-weighted poverty rate of extralocal neighborhoods is significantly and inversely related to BMI, suggesting that relative affluence in nearby neighborhoods engenders relative deprivation among residents of the focal neighborhood, leading to increased BMI. Overall, the results suggest that greater attention to both the temporal and spatial dimensions of neighborhood effects has the potential to enhance our understanding of how neighborhoods affect obesity and related health outcomes.

### Keywords

Obesity; neighborhood effects; fixed-effect modeling; NLSY

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The increasing prevalence of obesity and excess body weight has become a major public health concern in the United States over recent decades (Flegal et al., 2016; Ogden et al., 2015; U.S. Department of Health Human Services, 2011). Excess weight gain in the population is projected to elevate the health burden of many diseases and physical disorders, including type II diabetes (American Diabetes Association, 2000; Goran et al., 2003), cardiovascular diseases (Van Gaal et al., 2006), cancers (Calle & Kaaks, 2004), infertility (Withrow & Alter, 2011), asthma (Beuther et al., 2006), and sleep apnoea (Lam et al., 2012). The health burdens stemming from increasing rates of obesity also indirectly undermine social welfare systems and labor markets. The indirect cost of excess body weight is reflected in prolonged years of life with disability, premature deaths, early retirement due to illness, disability pension, and reduced working performance (Finkelstein et al., 2010; Wang et al., 2011).

Recent research on the determinants of obesity and excess body weight has focused on characteristics of the social environment, especially neighborhoods. Indeed, some have suggested that neighborhood attributes might play as important a role as individual characteristics in determining obesity status (Wang & Beydoun, 2007; World Health Organization, 2000). But while an interest in investigating so-called "neighborhood effects" on body mass index (BMI) and obesity has grown in the past decade (Arcaya et al., 2016; Oakes et al., 2015), most studies have adopted a limited conceptualization of neighborhood effects. By ignoring the fact that BMI and obesity develop over time and are thus likely to be influenced by characteristics of neighborhoods inhabited prior to any given observation period, previous studies adopt a naïve view of time, or what has been called the "temporal dimension" of neighborhood effects (Anonymous, 2010). In addition, by treating individuals' neighborhood of residence as if it were entirely isolated from surrounding areas, most prior studies adopt a naïve view of space, or what has been called the "spatial dimension" of neighborhood effects (Anonymous, 2011).

To our knowledge, no study of neighborhood effects on BMI has explored simultaneously and systematically both the temporal and spatial dimensions of these effects. This study goes beyond the literature by exploiting long-term longitudinal data from the National Longitudinal Survey of Youth, 1979 Cohort (NLSY79), along with spatially-referenced tract-level data from the U.S. census and American Community Survey, to improve our understanding of both the temporal and spatial dimensions of neighborhood effects on increased BMI. To explore the temporal dimension of neighborhood effect on BMI, our analysis incorporates measures of the NLSY97 respondents' cumulative life-course exposure to potentially pivotal neighborhood risk factors. And, to explore the spatial dimension of neighborhood effects on BMI, our analysis incorporates characteristics of geographically proximate neighborhoods, as well as characteristics of the respondents' immediate residential neighborhood, as predictors of BMI.

## BACKGROUND AND HYPOTHESES

Two neighborhood characteristics that have been thought to affect obesity are the level of poverty and the concentration of co-ethnic residents. Both characteristics are distal, or "upstream," qualities with the potential to operate as fundamental causes of disease (Link &

Phelan, 2005; Williams & Collins, 2001). Higher neighborhood poverty might be associated with higher BMI and obesity for two reasons. First, socioeconomically disadvantaged neighborhoods are more likely to develop into an obesogenic environment via poor access to healthy food and compromised physical safety (Robert & Reither, 2004). For example, fast food restaurants are more common, and crime rates are higher, in disadvantaged neighborhoods than in affluent communities (Reidpath et al., 2002; Ross, 2000). Second, neighborhoods with high poverty rates also tend to exhibit social problems, such as high crime rates, that serve as sources of chronic stress (Steptoe & Feldman, 2001). Individuals are likely to cope with chronic stress by overeating, which is associated with obesity and high BMI (Lovejoy, 2001).

It is more difficult to anticipate how the presence of co-ethnic neighbors might influence health outcomes, especially among members of minority groups. Theoretically, living in neighborhoods that are numerically dominated by co-ethnics could be either a health advantage or a health liability. On the one hand, living in a community that contains a high concentration of one's own racial or ethnic group—that is, many co-e thnics—could provide social and institutional support that encourages healthy behaviors and positive health outcomes. An ethnically concentrated neighborhood offers co-ethnic members opportunities to easily share sociocultural norms, linguistic qualities, and religious beliefs, which in turn facilitate social integration or cohesion within the neighborhood (Pickett & Wilkinson, 2008). Strong social integration or cohesion further assists in the development of positive role models (Smaje, 1995) and provides both material and emotional support to residents of the neighborhood. For example, Hispanic Americans living in a neighborhood with more co-ethnics consume more nutrients in traditional Hispanic food, such as tomatoes and beans, than do their counterparts residing in ethnically diverse neighborhoods (Reyes-Ortiz et al., 2009). Similarly, compared to Hispanics living in ethnically diverse neighborhoods, Hispanics living near co-ethnics experience less daily stress and an improved immunity function, which helps avoid eating disorders linked to obesity (Ford & Browning, 2015).

On the other hand, it is possible that high levels of neighborhood co-ethnic density are a health liability. In particular, if the co-ethnics themselves tend to exhibit poor health behaviors, heightened exposure to them (and concomitant limited exposure to healthier racial and ethnic groups) can undermine individuals' health given the existence of neighborhood-based social ties and the transmission of health behaviors across social networks (Christakis & Fowler, 2007). Attitudes toward being overweight and obese are more relaxed among blacks than among whites (Baturka et al., 2000), and thus exposure to co-ethnic neighbors may facilitate excess body weight and BMI (Robert & Reither, 2004). Consistent with this argument, several studies find that obesity rates are higher when blacks or Hispanics are exposed to higher levels of co-ethnic density in their residential neighborhoods (Chang, 2006; Do et al., 2007). Because blacks have a very high prevalence of obesity (Flegal et al., 2012), the detrimental effect of co-ethnic density may be stronger among blacks than among Hispanics or whites.

Drawing from the discussion above, we propose three research hypotheses regarding the effects of characteristics of individuals' immediate, or concurrent, neighborhood of residence on BMI:

(H1): The level of poverty in the immediate neighborhood is positively related to individual BMI.

(H2a): Among blacks and Hispanics, higher co-ethnic density in the immediate neighborhood is inversely associated with BMI.

(H2b): Higher co-ethnic density in the immediate neighborhood is positively associated with BMI and this association is stronger among blacks than among other racial/ethnic groups.

Despite the burgeoning literature on the influence of neighborhood characteristics on BMI and obesity (Arcaya et al., 2016), our knowledge in this area remains underdeveloped in two critical ways. The typical study of neighborhood effects on obesity uses cross-sectional data and fails to recognize the possible impact of an individual's residential history on health outcomes (Arcaya et al., 2016; Oakes et al., 2015). Indeed, studies that use longitudinal data to examine the association between neighborhood characteristics and overweight often obtain different results than studies that rely solely on cross-sectional data (Anonymous, 2015; Jokela, 2014). Specifically, longitudinal analyses suggest that the relationships between neighborhood characteristics and weight-related outcomes found in cross-sectional studies are largely due to the between-person differences. When focusing on within-person differences (i.e., changes in neighborhood exposure and outcomes), many previously-observed neighborhood effects on obesity become nonsignificant, leading researchers to question the existence of neighborhood effects on body weight. Furthermore, most prior studies assume that individuals are only influenced by the neighborhood of residence and ignore the potential effects of "extralocal neighborhoods"– neighborhoods that are geographically close to one's residential neighborhood (Anonymous, 2010, 2011). We elaborate on the potential importance of these two concerns.

## The Temporal Dimension of Neighborhood Effects on BMI

There are at least three reasons why attending to " time," broadly construed, can enhance our understanding of the effects of neighborhood characteristics, including neighborhood poverty and co-ethnic density, on obesity. First, the influence of a specific neighborhood characteristic on obesity is likely to depend on how long individuals have been exposed to that characteristic (Galster, 2012). Regardless of the mechanisms through which a given neighborhood characteristic affects obesity, longer exposures are ostensibly more influential than fleeting exposures. Yet, the typical research design of neighborhood effect research largely uses single point-in-time measures of neighborhood characteristics (Oakes et al., 2015) and fails to distinguish longer from shorter exposures to salient neighborhood qualities.

Second, many problematic health statuses and behaviors develop over time, but the typical research design only measures the existence of a health problem at the time of the survey (Arcaya et al., 2016). Given both frequent migration between neighborhoods and neighborhood change around nonmovers, the neighborhood conditions to which individuals are exposed at the time of the survey may be quite different from the neighborhood conditions they were exposed to when a health problem or problematic health behavior began.

Third, exploiting longitudinal data on both individuals' residential neighborhoods and their BMI may help to generate more robust estimates than are registered in the typical study of this issue. Exposure to particular neighborhood characteristics is not a random process. Rather, individuals either choose--or are sorted into--various types of neighborhoods on the basis of often unobserved characteristics that are likely associated with obesity (James et al., 2015; Jokela, 2014). For example, minority group members who live in neighborhoods where minorities are numerically underrepresented are likely to differ from their counterparts who live in neighborhoods with high minority concentration on a variety of unobserved traits that might either enhance or jeopardize health. Selective migration could lead to the concentration of healthy (or unhealthy) minorities in areas where minorities are underrepresented, as well as the concentration of healthy (or unhealthy) minorities in areas with large minority populations. We exploit the longitudinal data in the NLSY79 on both BMI and neighborhood characteristics to estimate individual fixed-effects models that control for all time-invariant respondent characteristics that might be related both to the types of neighborhoods individuals inhabit and individuals' BMI.

Few prior studies have estimated fixed-effects models of contextual influences on health (Oakes et al., 2015) and even fewer are specific to neighborhood effects on obesity or excess body weight (Anonymous, 2015; Jokela, 2014). Anonymous (2015) recently applied fixed effects modeling to examine the influence of ethnic density at the *metropolitan level* on obesity among blacks and Hispanics and observed much different associations than in cross-sectional models. In addition to focusing on neighborhood rather than metropolitan characteristics, our analysis also uses a much longer time span--from adolescence to mid-adulthood—than most prior studies (e.g., Jokela, 2014).

The above discussion leads to the following hypotheses regarding the association between individuals' cumulative exposure to poverty and co-ethnic density in their residential neighborhoods and their BMI:

> (H3) The associations between individual's cumulative exposures to neighborhood poverty and co-ethnic density and BMI are analogous to (i.e., in the same direction as) those of concurrent neighborhood exposures.
>
> (H4) The associations between cumulative exposures to neighborhood poverty and co-ethnic density and BMI are stronger than the corresponding associations between the point-in-time measures of these neighborhood characteristics and BMI.
>
> (H5) The concurrent associations between exposures to immediate neighborhood poverty and co-ethnic density and BMI will be partially attenuated by considering the associations between the cumulative exposures to these neighborhood features and BMI.

## The Spatial Dimension of Neighborhood Effects on BMI

For two reasons, adopting a more expansive conceptualization of neighborhoods might also contribute to our understanding of neighborhood effects on BMI. First, a large body of neighborhood effects research tacitly assumes that only the characteristics of an individual's residential neighborhood matter, while the characteristics of other neighborhoods do not matter at all. This assumption ignores the fact that neighborhood effects could extend beyond the immediate residential neighborhood to nearby areas where individuals work, shop, play and more generally spend time (Morenoff, 2003). As such, characteristics of individuals' proximate neighborhoods, like the characteristics of their immediate neighborhood, could influence their risk of becoming obese. This study addresses this issue by including measures of extralocal neighborhoods to capture the potential effects of activity space on health. Given the distribution of individuals' time spent in the immediate residential neighborhood versus adjacent or otherwise nearby neighborhoods, it stands to reason that the characteristics of the immediate residential neighborhood will matter most for health, while the characteristics of extralocal neighborhoods will matter somewhat less. And, it is reasonable to posit that the influence of extralocal neighborhoods on obesity will tend to dissipate with distance from individual's neighborhood of residence given that people spend more time in closer extralocal neighborhoods than in farther extralocal neighborhoods (Kwan, 2004). Several recent studies use daily travel logs to understand how activity space is associated with health (Browning & Soller, 2014; Sharp et al., 2015) but the findings are mixed. Consequently, the role of activity space, particularly for obesity, remains unclear (Kimbro et al., 2017).

Second, it is well documented that resources (e.g., quality health care) are not evenly distributed across neighborhoods (Horev et al., 2004; Moore et al., 2008) and for many residents, the desirable resources and services are located in nearby neighborhoods rather than in their immediate residential neighborhood. Individuals' access to valued resources/services may therefore depend on the characteristics of extralocal neighborhoods. For example, being surrounded by socioeconomically disadvantaged neighborhoods might make an individual's access to required resources/services more difficult compared to living close to affluent neighborhoods, where such amenities are likely to be located. The varying distribution of health-inducing resources across neighborhoods might explain why the magnitude, statistical significance, and even direction of neighborhood effects on health are sensitive to the geographic scale used to define neighborhoods (Flowerdew et al., 2008; Spielman & Yoo, 2009).

Yet, while it is reasonable to suggest that characteristics of extralocal neighborhoods will affect individuals' body mass, whether these characteristics will operate in the same way as local neighborhood characteristics is unclear *a priori*. One possibility is that the effects of extralocal neighborhood characteristics mimic the effects of local neighborhood characteristics. For example, we might expect that high rates of poverty in extralocal neighborhoods, like high poverty rates in local neighborhoods, tend to increase obesity and body mass among residents of local neighborhoods.

Alternatively, it is possible that high poverty rates in extralocal neighborhoods serve to reduce the risk of obesity for local residents. That is, relative affluence, rather than poverty, in surrounding neighborhoods might increase the risk of obesity. People tend to compare their economic circumstances to those living nearby. When individuals live near comparatively affluent neighborhoods, they may experience or perceive relative deprivation. High relative deprivation has been linked to increased BMI (Eibner & Evans, 2005; Lakshman et al., 2010), unhealthy diet, and physical inactivity (Elgar et al., 2016). In addition, socioeconomically advantaged (e.g., low-poverty) proximate neighborhoods might siphon or divert health-inducing resources such as parks, recreational centers, and food stores from nearby, less advantaged neighborhoods. When abutting relatively well-off areas, neighborhoods are likely to lose out in the competition for community resources that might serve to reduce obesity. In contrast, when neighborhoods are enveloped by neighborhoods of similar or lower socioeconomic status, they may be as likely as not to win the competition for these resources. Studies of neighborhood effects on other social behaviors often find that affluence, rather than poverty, in extralocal neighborhoods detrimentally affects residents of a local area (Anonymous, 2011, 2016).

Two research hypotheses are proposed with respect to the effects of extralocal neighborhood characteristics on BMI:

> (H6a) The associations between extralocal neighborhood co-ethnic density and poverty and BMI are analogous to those of immediate (local) neighborhood co-ethnic density and poverty.
>
> (H6b) After controlling for co-ethnic density and poverty in the immediate neighborhood, extralocal neighborhood poverty is inversely associated with BMI.

## DATA AND METHOD

Exploring the temporal and spatial dimensions of neighborhood effects on obesity requires a dataset with the following features: (1) information on individuals' neighborhood residential histories, (2) repeated measures of BMI, and (3) data on extralocal neighborhoods. The National Longitudinal Survey of Youth—1979 Cohort (NLSY79) meets these requirements and serves as the source of our individual-level variables. The NLSY79 was first administered in 1979. The respondents were subsequently interviewed annually through 1994 and biennially since that time. More importantly, respondents' census tract of residence is available at each interview, allowing us to attach to the individual records measures of poverty and ethnic density for both the immediate residential neighborhood and extralocal neighborhoods at each wave.

The NLSY79 began with 12,686 respondents ages 14–22 (Bureau of Labor Statistics, 2010). This study uses data from the interview waves between 1979 and 2010. Over the 32-year time period, the response rate for the total sample is 81 percent and the retention rate is 76 percent (National Longitudinal Surveys, 2014). Our final samples consist of 5,784 non-Hispanic white respondents, 2,097 non-Hispanic black individuals, and 1,476 Latinos. Each NLSY79 respondent can contribute up to 19 observations to the analysis.

### Individual-level Variables

The dependent variable is the respondent's *body mass index (BMI)* calculated conventionally from self-reported heights and weights. BMI is defined as an individual's weight (in kilograms) divided by the square of height (in meters) (Centers for Disease Control and Prevention, 2015). The first available BMI measure is from the 1981 wave of the NLSY79.

The analysis considers several time-varying individual characteristics as independent variables, including *marital status*, *educational attainment*, *weekly hours worked*, *family income*, and *public assistance receipt*. Marital status is a dichotomous variable in which married individuals are coded 1 and other statuses (e.g., single or divorced) are coded 0. Educational attainment has four categories: less than high school, high school graduate (or equivalency diploma), some college, and college or above (reference group). Hours worked is measured by respondents' reports of how many hours they usually work per week in their current job. Family income is inflation-adjusted to 2010 dollars and measured in $10,000s. Public assistance receipt is coded 1 for respondents currently receiving AFDC, TANF, SSI, or other benefits. All of these variables are measured at each NLSY79 interview and treated as time-varying covariates.

### Neighborhood-level Variables

*Poverty* and *co-ethnic density* are the two neighborhood characteristics of interest. Following conventional practice, an immediate neighborhood is defined as the census tract of residence at each wave. Because census tract boundaries change frequently, we normalize the tract boundaries to 2010 census definitions using the Neighborhood Change Database (GeoLytics, 2014) to facilitate comparisons across waves. The major data sources for constructing neighborhood variables are the 1980–2010 decennial U.S. censuses and the American Community Survey. Following much research in this area (Boardman et al., 2005; Chang 2006; Kimbro et al., 2011), we measure neighborhood SES with the poverty rate. The tract poverty rate is measured conventionally by dividing the size of the tract population living in poverty by the total tract population. Our measure of neighborhood co-ethnic density is the proportion of the census tract population that is composed of non-Hispanic whites, non-Hispanic blacks, or Hispanics. We estimate the values of the tract-level characteristics for non-census years using linear interpolation (Anonymous, 2015).

To examine the temporal dimension of neighborhood effects on BMI, we calculate the average rates of neighborhood poverty and co-ethnic density for all of the census tracts that the respondents inhabited prior to (and including) each interview wave of observation. These cumulative measures of exposure to neighborhood poverty and co-ethnic density are thus sensitive to changes in the neighborhood environment incurred by moving from one type of neighborhood to another as well as to changes in the characteristics of the neighborhoods inhabited by nonmovers.

To examine the spatial dimension of neighborhood effects on BMI, we first define extralocal neighborhoods using the Euclidean distance between the geographic centroids of two tracts. Because individuals travel on average 30 miles per day (U.S. Department of Transportation, 2003), we use this distance to define extralocal neighborhoods. Specifically, if the distance between two tracts is shorter than 30 miles, these tracts are considered to be extralocal neighborhoods of each other; otherwise, they are not spatially related. We then apply a distance-decay function that gives higher weights to the extralocal neighborhoods that are closer to an individual's immediate neighborhood and lower weights to more distant extralocal neighborhoods (Kwan, 2004). Finally, we compute distance-weighted measures of the average poverty rate and co-ethnic density for each respondent's set of extralocal neighborhoods.

### Analytic Approach

To exploit the longitudinal nature of the NLSY79, we estimate individual fixed-effect models (Allison, 2005). Fixed-effect models allow us to control for all time-constant but unobserved characteristics that might influence both individual's selection of (or into) a particular type of neighborhood and their BMI status. By following each respondent over time and capturing the changes in variables of interest, each respondent serves as his/her own control and the within-person changes become the focus of the fixed-effect modeling (Allison, 2009). A fixed-effect model can be expressed as follows:

$$y_{it} = \mu_t + \boldsymbol{\beta} \boldsymbol{x}_{it} + \alpha_i + \varepsilon_{it},$$

Where $y_{it}$ is the value of BMI individual $i$ at time $t$; $\mu_t$ is an intercept that varies over time; $\boldsymbol{x}_{it}$ is a vector of time-varying independent variables; $\boldsymbol{\beta}$ is a vector of coefficients for time-varying covariates (e.g., neighborhood poverty or co-ethnic density); $\alpha_i$ is a person-specific error term and can be understood as the systematic influence of all time-invariant factors (including the unobserved covariates) on BMI; and $\varepsilon_{it}$ represents the error term for each individual at each point in time. To control for secular trends in both BMI and the covariates, all models include dummy variables for year of observation. The application of fixed-effect modeling to neighborhood effects on health has been rare but this estimation strategy provides more rigorous estimations of the causal relationships between the dependent and time-varying independent variables (Oakes et al., 2015). Time-invariant characteristics, such as nativity status, gender, and parental background, are necessarily omitted from these fixed-effect models.

Fixed-effect models are not without limitations (Angrist & Pischke, 2009; Treiman, 2014). First, as the inferences are drawn from the within-person differences, the external validity (i.e., generalizability) of the results is limited. Second, the risk of committing a type II error increases with the number of regressors. Third, the effects of the time-invariant covariates are assumed to be constant.

## RESULTS

Descriptive statistics for all variables are presented in Table 1. Several differences across the three ethnoracial groups are worth noting. First, average BMI values are higher among the non-Hispanic black and Hispanic respondents than among the non-Hispanic white participants. Second, and not surprisingly, the white respondents have higher SES than the black or Hispanic respondents. For example, the proportion of respondents having completed college is higher among whites than blacks or Hispanics and the proportion of respondents receiving public assistance is at least double among minorities than among whites.

Table 1 also reveals sharp differences by race-ethnicity in the neighborhood-level variables. On average, whether measured for the current neighborhood or cumulatively, the non-Hispanic black respondents live in neighborhoods in which almost half of their neighbors (a proportion of 0.48) are also non-Hispanic black. However, reflecting high levels of ethnoracial residential segregation, only four percent of the residents of blacks' extralocal neighborhoods are non–Hispanic black (proportion of 0.04). Coupled wi th the high level of co-ethnic density of their immediate neighborhood, this finding indicates that blacks' residential neighborhoods are likely to be isolated from more ethnically-diverse neighborhoods.

The mean poverty rate in blacks' concurrent neighborhoods is 0.21, quite similar to the cumulative rate of 0.22. However, the extralocal neighborhood poverty rate is only 0.03, indicating that black respondents' immediate neighborhoods are not only comparatively poor, but that they are segregated from more affluent neighborhoods.

Among the Hispanic respondents, roughly four out of ten residents of the current neighborhood are also Hispanic, and their cumulative exposure to co-ethnic neighbors is comparable (0.38). This pattern is generally similar to that observed for blacks. However, unlike the situation among blacks, the co-ethnic density of Hispanics' extralocal neighborhood—0.36—is fairly similar to that of their immediate neighborhood, measured either concurrently or cumulatively. The poverty rate of Hispanics' extralocal neighborhoods (0.18) is also similar to the poverty rates of their immediate neighborhood (0.18) and averaged over prior neighborhoods of residence (0.19). This pattern indicates that the Hispanic respondents are not as racially and socioeconomically segregated as the black respondents.

White respondents exhibit the highest level of co-ethnic density (over 0.80), both within the immediate neighborhood and measured as cumulative exposure over time. The low level of co-ethnic density in whites' extralocal neighborhoods (0.09) reflects whites' high level of segregation from other ethnoracial groups in the U.S.

Tables 2 through 4 present the results of the fixed-effect regression analyses (models that omit measures of cumulative exposure to immediate neighborhood characteristics are available upon request). For each ethnoracial group, time-varying individual variables and immediate neighborhood characteristics are considered in Model A; cumulative exposure to immediate neighborhood variables are added to Model B; and Model C further includes the measures of extralocal neighborhood poverty and co-ethnic density.

Table 2 presents the results for non-Hispanic black respondents. In Model A, among the time-varying individual variables, marrying, working hours, and receiving public assistance are positively and significantly related to BMI. For example, when an individual's marital status changes from other statuses to married, BMI increases by an average of 0.608 ($kg/m^2$). On average, beginning receipt of public assistance raises BMI by 0.261 ($kg/m^2$). Longer working hours are associated with a higher BMI, though the effect size is relatively small. Completing college is also associated with a higher BMI, although it is important to note that that after the mid-twenties intra-person changes in educational attainment are infrequent.

Regarding the effects of the immediate neighborhood variables in Model A, neither the proportion of neighbors who are non-Hispanic black nor the poverty rate is significantly associated with non-Hispanic blacks' BMI. This finding fails to support Hypotheses 1, 2a, or 2b.

Model B adds to Model A the measures of cumulative exposure to neighborhood co-ethnic density (proportion non-Hispanic Black) and neighborhood poverty. As with the coefficients for current (or immediate) neighborhood co-ethnic density and poverty, neither coefficient for the cumulative measures is significant. Nor does the inclusion of the cumulative measures attenuate the coefficients for the immediate neighborhood measures, which were in any event non-significant to begin with. This finding fails to support Hypotheses 3, 4, and 5.

Model C of Table 2 adds as independent variables the distance-weighted measures of co-ethnic density and poverty in extralocal neighborhoods. While the coefficient for the level of co-ethnic density in extralocal neighborhoods is not significant, the poverty rate of extralocal neighborhoods is negatively and significantly associated with BMI. When the poverty rate in extralocal neighborhoods increases by 10 percentage points (i.e., a proportion of .10), a black respondent's BMI is expected to decrease by 0.078 (0.1*(−0.78)). This finding supports Hypothesis 6b, and suggests that comparative affluence (i.e., low poverty) in nearby neighborhoods generates a sense of relative deprivation or a deficit of healthful community resources among residents of the immediate neighborhood.

Table 3 presents a parallel analysis for the Hispanic respondents. Of the individual-level predictors shown in Model A, only marital status and educational attainment are found to be significantly related to BMI. Getting married is estimated to increase BMI by 0.611 and receiving some college education but not completing college is associated with higher BMI.

Of the immediate neighborhood variables, the poverty rate is not significantly related to BMI, but the proportion of neighbors who are Hispanic is significantly and positively associated with BMI. That exposure to co-ethnic residents in the immediate neighborhood increases BMI among Hispanics ($\beta$=0.452, Model A) provides support for Hypothesis 2b.

Model B adds the measures of cumulative neighborhood co-ethnic density and the poverty rate. The positive coefficient for cumulative exposure to fellow Hispanics is four times stronger than the corresponding coefficient for co-ethnic density in the immediate, current neighborhood (1.057 vs. .250), supporting Hypotheses 3 and 4. Moreover, the inclusion of this variable attenuates the coefficient for the level of co-ethnic density in the immediate, current neighborhood and drives this coefficient to statistical non-significance, thus supporting Hypothesis 5. Perhaps surprisingly, however, the coefficient for cumulative exposure to poor neighbors is negative and statistically significant ($\beta$=−2.288).

As shown in Model C of Table 3, among Hispanics neither the level of co-ethnic density nor the poverty rate of extralocal neighborhoods is significantly associated with BMI. Moreover, including these indicators of the spatial dimension of neighborhood effects does not appreciably modify the observed effects of the other neighborhood-level independent variables.

The results for non-Hispanic whites are shown in Table 4. All of the time-varying individual-level covariates are significantly associated with BMI (Model A). BMI tends to increase when one gets married ($\beta$=0.562) or begins receiving public assistance ($\beta$=0.232), and it tends to decrease when weekly working hours are prolonged or family income improves. Completing college tends to increase BMI relative to having less than a high school education, but attending though not completing college is associated with a higher BMI relative to completing college.

Turning to the coefficients for the immediate neighborhood variables in Model A, the proportion of neighbors who are non-Hispanic white is not significantly associated with whites' BMI. However, whites' BMI tends to increase along with increases in the poverty rate of their immediate neighborhood ($\beta$=0.977), supporting Hypothesis 1. This positive association can be partially explained by the cumulative exposure to neighborhood co-ethnic density and poverty; the magnitude of the effect drops by approximately 34 percent ((0.977–0.649)/0.977) from Model A to Model B. This finding bolsters Hypothesis 5.

Among whites, the coefficients for cumulative exposures to both co-ethnic density and poverty are positive and statistically significant (Model B), even after controlling for individual and immediate neighborhood features. For example, when the cumulative exposure to white residents increases by 15 percentage points (0.15 in proportion), a white respondent's BMI is expected to increase by 0.068 (0.15*0.456). Both coefficients are larger than the analogous coefficients for co-ethnic density and poverty in the immediate, current neighborhood, supporting Hypotheses 3 and 4. That the coefficient for cumulative exposure to fellow non-Hispanic whites is statistically significant while the coefficient for co-ethnic density of the immediate neighborhood is not significant is the clearest evidence that studies that only consider the characteristics of the current residential neighborhood may underestimate the impact of neighborhood effects on BMI.

Model C adds the two measures of extralocal co-ethnic density and poverty. Although the coefficient for proportion non-Hispanic white in extralocal neighborhoods is not significant, the coefficient for the (distance-weighted) poverty rate of extralocal neighborhoods is negative and statistically significant. Holding constant the other covariates, higher levels of poverty in proximate neighborhoods tend to reduce whites' BMI ($\beta$=−0.597). This finding supports Hypothesis 6b.

## DISCUSSION AND CONCLUSIONS

Recent research on the determinants of obesity and body mass has begun to emphasize the potential importance of neighborhood characteristics. Yet, most studies of neighborhood effects on body mass index (BMI) and related physical states adopt a naïve view of neighborhood effects, typically relying on single point-in-time measures of neighborhood attributes and ignoring the possible influence of spatially-proximate, or extralocal, neighborhoods. This study uses long-term longitudinal data on both individuals and their neighborhoods of residence, along with characteristics of extralocal neighborhoods, to examine the effects of areal poverty and co-ethnic density on the body mass of black, Hispanic, and white respondents to the National Longitudinal Survey of Youth.

Our fixed-effect linear regression models of BMI are designed to test several hypotheses regarding the possible influence of individuals' current and cumulative exposure to co-ethnic and poor neighbors in their immediate neighborhood and their current exposure to co-ethnic and poor neighbors in extralocal neighborhoods. We first hypothesized that the level of poverty in the immediate neighborhood is positively related to BMI. This hypothesis finds support among non-Hispanic whites but fails to find support among non-Hispanic blacks or Hispanics, whose BMIs appear insensitive to the poverty rate of the current neighborhood of residence..,

Our second set of counter-posing hypotheses posited either an inverse (Hypothesis 2a) or a detrimentally positive (Hypothesis 2b) effect on BMI of exposure to co-ethnic neighbors in the current, immediate neighborhood. We observe partial support for the idea that high levels of co-ethnic density engender higher body weight (Hypothesis 2b). Net of the effects of established individual-level predictors of BMI, Hispanics who live in neighborhoods containing proportionately more fellow Hispanics tend to have elevated BMIs. However, we fail to observe an effect of co-ethnic density of the current neighborhood among either blacks or whites.

Among Hispanics and whites, we find partial support for the third hypothesis that the effects of cumulative exposures to neighborhood poverty and co-ethnic density mimic those of immediate neighborhood exposures. Specifically, immediate and cumulative exposures to co-ethnic neighbors are both positively related to Hispanics' BMIs, and contemporaneous and cumulative exposures to poverty both elevate whites' BMIs.

The fourth hypothesis states that cumulative exposures to immediate neighborhood poverty and co-ethnic density play more important roles than current exposures in affecting BMI. We find some support for this hypothesis among Hispanics and non-Hispanic whites. For example, among non-Hispanic whites, the associations between cumulative exposure to both local neighborhood poverty and co-ethnic density and BMI are stronger than the corresponding associations between the current neighborhood characteristics and BMI. Although the negative association between cumulative exposure to poverty and Hispanics' BMI is unexpected, it is broadly consistent with the results of a recent study reporting that cumulative exposure to family poverty is negatively related to obesity (Hernandez & Pressler, 2014).

We further hypothesized that the observed effects of neighborhood poverty and co-ethnic density of the current neighborhood are at least partially explained by cumulative exposures to these neighborhood features. This hypothesis finds some support among whites and Hispanics. Among Hispanics, the concurrent association between BMI and co-ethnic density is reduced nontrivially—and driven to statistical nonsignifica nce—after cumulative neighborhood exposure to fellow Hispanics is controlled. And among whites, only cumulative exposure to co-ethnics— and not the level of exposure to co-ethnics in the current neighborhood—is significantly associated with BMI. Overall, these findings suggest that studies employing only point-in-time measures of neighborhood characteristics may underestimate the impact of neighborhood attributes on body mass index.

Regarding co-ethnic density and poverty in extralocal neighborhoods, we expected that the effect of co-ethnic density in extralocal neighborhoods on BMI would mimic that of co-ethnic density in the immediate neighborhood (H6a) but that high poverty in extralocal neighborhoods could either increase or decrease BMI among residents of a focal neighborhoods (H6a, H6b). We find no support for H6a. For none of the three ethnoracial groups do we observe a significant association between extralocal neighborhood co-ethnic density and BMI. Nor do we observe a *positive* effect of extralocal neighborhood poverty on BMI.

However, consistent with Hypothesis 6b, among both blacks and whites we observe significant (net) associations between the poverty rate of extralocal neighborhoods and BMI. For both racial groups, higher levels of poverty in geographically proximate neighborhoods are *inversely* associated with BMI. That is, relative affluence (i.e., low poverty) in nearby neighborhoods is associated with higher BMIs among black and white residents of the focal neighborhood. These associations are consistent with a relative deprivation perspective. Presumably, relative affluence is nearby neighborhood engenders a sense of relative deprivation among residents of the focal neighborhood, thereby encouraging unhealthy behaviors conducive to excess body weight and obesity. It is also possible that affluent spatially-proximate neighborhoods divert healthful community resources from nearby neighborhoods of average or low SES. Future research might profit from exploring the social-psychological, behavioral, and institutional mechanisms that transmit the effect of extralocal neighborhood poverty on BMI.

One possible explanation for the failure to observe the expected positive effects of neighborhood poverty—measured either contemporaneously or cumulatively—among either blacks and Hispanics is that for these groups such ethnic density effects are mainly psychological in nature, yielding beneficial effects on mental health but not on the types of physical health examined in this study (Bécares et al., 2012). Itis also possible that the level of co-ethnic density is unrelated to body mass among blacks as it is among Hispanics because, among blacks, living with co-ethnics provides sources of social support and buffers of racism that counterbalance the otherwise obesogenic effects of having many co-ethnic neighbors. Several studies report that the health behaviors of Hispanics and whites are more sensitive than those of blacks to neighborhood characteristics (Burdette & Needham, 2012; Denney et al., 2018; LaVeist et al., 2007; Masi et al., 2007). Perhaps these findings can be attributed to the more limited geographic mobility among blacks. Blacks may also be especially likely to develop adaptive strategies to cope with neighborhood poverty (Rankin & Quane, 2000; Stack, 1974).

This study is subject to several limitations. First, our results may be sensitive to the operational definition of neighborhoods. While census tracts are commonly used in neighborhood effect research (Anonymous, 2013), using a different geographic level, such as census blocks or counties, may lead to different conclusions (Openshaw, 1984). Second, our results regarding the influence of extralocal neighborhood characteristics may be sensitive to how extralocal neighborhoods are defined and the relative weights assigned to nearby versus distant neighborhoods. Third, we are unable to investigate the mechanisms through which neighborhood co-ethnic density and neighborhood poverty–at either the local or extralocal neighborhood level– affect BMI. Given data limitati ons, we are also unable to consider how changes in neighborhood environments affect behavioral changes related to obesity, such as diet and physical activity. Fourth, our analysis focuses on only two potentially obesogenic neighborhood characteristics—poverty and co-ethnic density. Future research might profit from exploring other environmental attributes, such as collective efficacy and safety (Burdette et al., 2006) and features of the built environment (Feng et al., 2010), including but not limited to food availability and recreational resources (Moore et al., 2008).

Despite these limitations, our findings challenge the tacit assumption of the extant literature that neighborhood effects on excess body weight are exerted only by the characteristics of contemporaneous, local neighborhoods. Rather, our results suggest that the characteristics of both neighborhoods that individuals have inhabited in the past and the characteristics of extralocal neighborhoods also influence individuals' BMI. Future research exploring neighborhood effects on body weight and other health behaviors and outcomes might benefit from taking into account both the temporal and spatial dimensions of these effects.

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## References

Allison PD (2005). Fixed effects regression methods for longitudinal data using SAS: SAS Institute.

Allison PD (2009). Fixed effects regression models: SAGE publications.

American Diabetes Association (2000). Type 2 diabetes in children and adolescents. Pediatrics, 105, 671–680. [PubMed: 10699131]

Angrist JD, & Pischke J-S (2009). Mostly harmless econometrics: An empiricist's companion . Princeton, NJ: Princeton University Press.

Anonymous (2010). Details omitted for review

Anonymous (2011). Details omitted for review

Anonymous (2013). Details omitted for review

Anonymous (2015). Details omitted for review

Anonymous (2016). Details omitted for review

Arcaya MC, Tucker-Seeley RD, Kim R, Schnake-Mahl A, So M, & Subramanian SV (2016). Research on neighborhood effects on health in the United States: A systematic review of study characteristics. Social Science & Medicine, 168, 16–29. [PubMed: 27637089]

Baturka N, Hornsby PP, & Schorling JB (2000). Clinical implications of body image among rural African□American women. Journal of General Internal Medicine, 15, 235–241. [PubMed: 10759998]

Bécares L, Shaw R, Nazroo J, Stafford M, Albor C, Atkin K, et al. (2012). Ethnic density effects on physical morbidity, mortality, and health behaviors: a systematic review of the literature. American Journal of Public Health, 102, e33–e66.

Beuther DA, Weiss ST, & Sutherland ER (2006). Obesity and asthma. American Journal of Respiratory and Critical Care Medicine, 174, 112–119. [PubMed: 16627866]

Boardman JD, Onge JMS, Rogers RG, & Denney JT (2005). Race differentials in obesity: the impact of place. Journal of Health and Social Behavior, 46(3), 229–243. [PubMed: 16259146]

Browning CR, & Soller B (2014). Moving beyond neighborhood: Activity spaces and ecological networks as contexts for youth development. Cityscape, 16, 165. [PubMed: 25105172]

Burdette AM, & Needham BL (2012). Neighborhood environment and body mass index trajectories from adolescence to adulthood. Journal of Adolescent Health, 50, 30–37. [PubMed: 22188831]

Burdette HL, Wadden TA, & Whitaker RC (2006). Neighborhood safety, collective efficacy, and obesity in women with young children. Obesity, 14, 518–525. [PubMed: 16648624]

Bureau of Labor Statistics. (2010). National Longitudinal Survey of Youth 1979 cohort, 1979–2010 (rounds 1–24).

Calle EE, & Kaaks R (2004). Overweight, obesity and cancer: epidemiological evidence and proposed mechanisms. Nature Reviews. Cancer, 4, 579. [PubMed: 15286738]

Centers for Disease Control and Prevention. (2015). About Adult BMI

Chang VW (2006). Racial residential segregation and weight status among US adults. Social Science & Medicine, 63, 1289–1303. [PubMed: 16707199]

Christakis NA, & Fowler JH (2007). The spread of obesity in a large social network over 32 years. New England Journal of Medicine, 2007, 370–379.

Denney JT, Saint Onge JM, & Dennis JA (2018). Neighborhood Concentrated Disadvantage and Adult Mortality: Insights for Racial and Ethnic Differences. Population Research and Policy Review, 37, 301–321.

Do DP, Dubowitz T, Bird CE, Lurie N, Escarce JJ, & Finch BK (2007). Neighborhood context and ethnicity differences in body mass index: a multilevel analysis using the NHANES III survey (1988–1994). Economics & Human Biology, 5, 179–203. [PubMed: 17507298]

Eibner C, & Evans WN (2005). Relative deprivation, poor health habits, and mortality. Journal of Human Resources, 40, 591–620.

Elgar FJ, Xie A, Pförtner T-K, White J, & Pickett KE (2016). Relative deprivation and risk factors for obesity in Canadian adolescents. Social Science & Medicine, 152, 111–118. [PubMed: 26851410]

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, 175–190. [PubMed: 19880341]

Finkelstein EA, DiBonaventura M.d., Burgess SM, & Hale BC (2010). The costs of obesity in the workplace. Journal of Occupational and Environmental Medicine, 52, 971–976. [PubMed: 20881629]

Flegal KM, Carroll MD, Kit BK, & Ogden CL (2012). Prevalence of obesity and trends in the distribution of body mass index among US adults, 1999–2010. JAMA, 307, 491–497. [PubMed: 22253363]

Flegal KM, Kruszon-Moran D, Carroll MD, Fryar CD, & Ogden CL (2016). Trends in obesity among adults in the United States, 2005 to 2014. JAMA, 315, 2284–2291. [PubMed: 27272580]

Flowerdew R, Manley DJ, & Sabel CE (2008). Neighbourhood effects on health: does it matter where you draw the boundaries? Social Science & Medicine, 66, 1241–1255. [PubMed: 18177988]

Ford JL, & Browning CR (2015). Exposure to Neighborhood Immigrant Concentration from Adolescence to Young Adulthood and Immune Function among Latino Young Adults. Health Place, 32, 59–64. [PubMed: 25618565]

Galster GC (2012). The mechanism (s) of neighbourhood effects: Theory, evidence, and policy implications. Neighbourhood Effects Research: New Perspectives (pp. 23–56): Springer.

GeoLytics. (2014). Neighborhood Change Database [NCDB] Tract Data from 1970–2010 East Brunswick, NJ.

Goran MI, Ball GD, & Cruz ML (2003). Obesity and risk of type 2 diabetes and cardiovascular disease in children and adolescents. The Journal of Clinical Endocrinology & Metabolism, 88, 1417–1427. [PubMed: 12679416]

Hernandez DC, & Pressler E (2014). Accumulation of childhood poverty on young adult overweight or obese status: race/ethnicity and gender disparities. J Epidemiol Community Health, 68, 478–484. [PubMed: 24391207]

Horev T, Pesis-Katz I, & Mukamel DB (2004). Trends in geographic disparities in allocation of health care resources in the US. Health Policy, 68, 223–232. [PubMed: 15063021]

James P, Hart JE, Arcaya MC, Feskanich D, Laden F, & Subramanian S (2015). Neighborhood self-selection: the role of pre-move health factors on the built and socioeconomic environment. International journal of environmental research and public health, 12, 12489–12504. [PubMed: 26457712]

Jokela M (2014). Are neighborhood health associations causal? A 10-year prospective cohort study with repeated measurements. American Journal of Epidemiology, 180, 776–784. [PubMed: 25260937]

Kimbro RT, Sharp G, & Denney JT (2017). Home and away: Area socioeconomic disadvantage and obesity risk. Health & Place, 44, 94–102. [PubMed: 28214705]

Kwan MP (2004). GIS methods in time-geographic research: geocomputation and geovisualization of human activity patterns. Geografiska Annaler: Series B, Human Geography, 86, 267–280.

Lakshman R, McConville A, How S, Flowers J, Wareham N, & Cosford P (2010). Association between area-level socioeconomic deprivation and a cluster of behavioural risk factors: cross-sectional, population-based study. Journal of Public Health, 33, 234–245. [PubMed: 20884643]

Lam JCM, Mak JCW, & Ip MSM (2012). Obesity, obstructive sleep apnoea and metabolic syndrome. Respirology, 17, 223–236. [PubMed: 21992649]

LaVeist TA, Thorpe RJ, Mance GA, & Jackson J (2007). Overcoming confounding of race with socio-economic status and segregation to explore race disparities in smoking. Addiction, 102, 65–70. [PubMed: 17850615]

Link BG, & Phelan JC (2005). Fundamental sources of health inequalities. Policy challenges in modern health care, 71–84.

Lovejoy M (2001). Disturbances in the social body: Differences in body image and eating problems among African American and white women. Gender & Society, 15, 239–261.

Masi CM, Hawkley LC, Piotrowski ZH, & Pickett KE (2007). Neighborhood economic disadvantage, violent crime, group density, and pregnancy outcomes in a diverse, urban population. Social Science & Medicine, 65, 2440–2457. [PubMed: 17765371]

Moore LV, Roux AVD, Evenson KR, McGinn AP, & Brines SJ (2008). Availability of recreational resources in minority and low socioeconomic status areas. American Journal of Preventive Medicine, 34, 16–22. [PubMed: 18083446]

Morenoff JD (2003). Neighborhood mechanisms and the spatial dynamics of birth weight. American Journal of Sociology, 108, 976–1017.

National Longitudinal Surveys. (2014). Retention & Reasons for Noninterview

Oakes JM, Andrade KE, Biyoow IM, & Cowan LT (2015). Twenty years of neighborhood effect research: an assessment. Current Epidemiology Reports, 2, 80–87. [PubMed: 28133588]

Ogden CL, Carroll MD, Fryar CD, & Flegal KM (2015). Prevalence of obesity among adults and youth: United States, 2011–2014: US Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Health Statistics.

Openshaw S (1984). The modifiable areal unit problem Norwich, England.

Pickett KE, & Wilkinson RG (2008). People like us: ethnic group density effects on health. Ethnicity & Health, 13, 321–334. [PubMed: 18701992]

Rankin BH, & Quane JM (2000). Neighborhood poverty and the social isolation of inner-city African American families. Social Forces, 79, 139–164.

Reidpath DD, Burns C, Garrard J, Mahoney M, & Townsend M (2002). An ecological study of the relationship between social and environmental determinants of obesity. Health & Place, 8, 141–145. [PubMed: 11943585]

Reyes-Ortiz CA, Ju H, Eschbach K, Kuo Y-F, & Goodwin JS (2009). Neighbourhood ethnic composition and diet among Mexican-Americans. Public Health Nutrition, 12, 2293–2301. [PubMed: 19254428]

Robert SA, & Reither EN (2004). A multilevel analysis of race, community disadvantage, and body mass index among adults in the US. Social Science & Medicine, 59, 2421–2434. [PubMed: 15474198]

Ross CE (2000). Walking, exercising, and smoking: does neighborhood matter? Social Science Medicine, 51, 265–274. [PubMed: 10832573]

Sharp G, Denney JT, & Kimbro RT (2015). Multiple Contexts of Exposure: Activity Spaces, Residential Neighborhoods, and Self-rated Health. Social Science & Medicine, 146, 204–213. [PubMed: 26519605]

Smaje C (1995). Ethnic residential concentration and health: evidence for a positive effect? Policy & Politics, 23, 251–270.

Spielman SE, & Yoo E. h. (2009). The spatial dimensions of neighborhood effects. Social Science & Medicine, 68, 1098–1105. [PubMed: 19167802]

Stack CB (1974). All our kin: Strategies for survival in a black community: Harper and Row.

Steptoe A, & Feldman PJ (2001). Neighborhood problems as sources of chronic stress: development of a measure of neighborhood problems, and associations with socioeconomic status and health. Annals of Behavioral Medicine, 23, 177–185. [PubMed: 11495218]

Treiman DJ (2014). Quantitative data analysis: Doing social research to test ideas San Francisco, CA: John Wiley & Sons.

U.S. Department of Health Human Services (2011). Healthy people 2020: Improving the health of Americans. Healthy People. gov

U.S. Department of Transportation. (2003). NHTS 2001 Highlights Report, BTS03–05 In Bureau of Transportation Statiistics (Ed.). Washington, DC.

Van Gaal LF, Mertens IL, & De Block CE (2006). Mechanisms linking obesity with cardiovascular disease. Nature, 444, 875. [PubMed: 17167476]

Wang Y, & Beydoun MA (2007). The obesity epidemic in the United States—gender, age, socioeconomic, racial/ethnic, and geographic characteristics: a systematic review and meta-regression analysis. Epidemiologic Reviews, 29, 6–28. [PubMed: 17510091]

Wang YC, McPherson K, Marsh T, Gortmaker SL, & Brown M (2011). Health and economic burden of the projected obesity trends in the USA and the UK. The Lancet, 378, 815–825.

Williams DR, & Collins C (2001). Racial residential segregation: a fundamental cause of racial disparities in health. Public Health Reports, 116, 404–416. [PubMed: 12042604]

Withrow DR, & Alter DA (2011). The economic burden of obesity worldwide: a systematic review of the direct costs of obesity. Obesity Reviews, 12, 131–141. [PubMed: 20122135]

World Health Organization (2000). Obesity: preventing and managing the global epidemic: World Health Organization.

- Cumulative exposure to co-ethnic neighbors positively predicts Hispanics' BMI.
- Cumulative exposure to neighborhood poverty positively affects whites' BMI.
- Poverty in nearby neighborhoods is inversely related to blacks' and whites' BMI.
- Neighborhood characteristics have both temporal and spatial effects on BMI.

**Table 1.**

Descriptive Statistics for Variables Used in Analysis of Body Mass Index, by Race/Ethnicity: National Longitudinal Survey of Youth, 1981–2010

| | Black | | Hispanic | | White | |
|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** |
| ***Dependent variable*** | | | | | | |
| Body Mass Index | 27.58 | 6.15 | 27.04 | 5.60 | 25.56 | 5.30 |
| ***Independent variables*** | | | | | | |
| Marital Status (married) | 0.32 | - | 0.53 | - | 0.58 | - |
| Educational Attainment | | | | | | |
| Less than high school | 0.13 | - | 0.21 | - | 0.10 | - |
| High school graduate | 0.43 | - | 0.41 | - | 0.41 | - |
| Some college | 0.29 | - | 0.26 | - | 0.23 | - |
| College or above (= reference category) | 0.15 | - | 0.12 | - | 0.26 | - |
| Weekly hours worked | 37.09 | 20.72 | 38.93 | 19.81 | 41.43 | 17.91 |
| Adjusted family income (in $10,000s) | 6.18 | 9.24 | 7.55 | 10.87 | 9.62 | 14.56 |
| Receiving public assistance | 0.07 | - | 0.04 | - | 0.02 | - |
| **Immediate Neighborhood Variables** | | | | | | |
| Proportion non-Hispanic Black | 0.48 | 0.33 | - | - | - | - |
| Proportion Hispanic | - | - | 0.39 | 0.30 | - | - |
| Proportion White | - | - | - | - | 0.84 | 0.18 |
| Poverty Rate | 0.21 | 0.14 | 0.18 | 0.13 | 0.11 | 0.08 |
| **Cumulative Exposure to Immediate Neighborhood Variables** | | | | | | |
| Proportion non-Hispanic Black | 0.48 | 0.29 | - | - | - | - |
| Proportion Hispanic | - | - | 0.38 | 0.26 | - | - |
| Proportion White | - | - | - | - | 0.81 | 0.17 |
| Poverty Rate | 0.22 | 0.11 | 0.19 | 0.10 | 0.10 | 0.06 |
| **Extralocal Neighborhood Variables** | | | | | | |
| Proportion non-Hispanic Black | 0.04 | 0.16 | - | - | - | - |
| Proportion Hispanic | - | - | 0.36 | 0.27 | - | - |
| Proportion White | - | - | - | - | 0.09 | 0.25 |
| Poverty Rate | 0.03 | 0.08 | 0.18 | 0.10 | 0.02 | 0.05 |

| | Black | | Hispanic | | White | |
|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** |
| Number of Persons | | 2,097 | | 1,476 | | 5,784 |
| Number of Person-years | | 19,952 | | 14,926 | | 50,584 |

Note: SD is standard deviation.

**Table 2.**

Fixed-Effects Linear Regression Models Predicting Body Mass Index: Non-Hispanic Black National Longitudinal Survey of Youth Respondents, 1981–2010

| | Model A | | Model B | | Model C | |
|---|---|---|---|---|---|---|
| **Independent Variables** | **Coef.** | **S.E.** | **Coef.** | **S.E.** | **Coef.** | **S.E.** |
| Marital Status (1= married) | 0.608*** | 0.064 | 0.608*** | 0.064 | 0.608*** | 0.064 |
| Educational Attainment (ref.=college or above) | | | | | | |
| Less than high school | −0.816*** | 0.209 | −0.811*** | 0.210 | −0.819*** | 0.210 |
| High school graduate | −1.029*** | 0.171 | −1.027*** | 0.172 | −1.029*** | 0.172 |
| Some college | −0.417** | 0.133 | −0.417** | 0.133 | −0.422** | 0.133 |
| Weekly hours worked | 0.004** | 0.001 | 0.004** | 0.001 | 0.004** | 0.001 |
| Adjusted family income (in $10,000s) | −0.002 | 0.003 | −0.002 | 0.003 | −0.002 | 0.003 |
| Receiving public assistance (= 1) | 0.261* | 0.102 | 0.260* | 0.102 | 0.262* | 0.102 |
| **Immediate Neighborhood Variables** | | | | | | |
| Proportion non−Hispanic Black | 0.096 | 0.111 | 0.121 | 0.131 | 0.103 | 0.136 |
| Poverty Rate | −0.247 | 0.242 | −0.273 | 0.276 | −0.074 | 0.287 |
| **Cumulative Exposure to Immediate Neighborhood Variables** | | | | | | |
| Proportion non−Hispanic Black | | | −0.127 | 0.349 | −0.114 | 0.349 |
| Poverty Rate | | | 0.151 | 0.796 | 0.158 | 0.796 |
| **Extralocal Neighborhood Variables** | | | | | | |
| Proportion non−Hispanic Black | | | | | 0.096 | 0.164 |
| Poverty Rate | | | | | −0.780* | 0.337 |
| Constant | 23.596*** | 0.199 | 23.619*** | 0.241 | 23.638*** | 0.241 |
| $R^2$ squared (within) | 0.41 | | 0.41 | | 0.41 | |
| Number of Persons | 2,097 | | 2,097 | | 2,097 | |
| Number of Person−years | 19,952 | | 19,952 | | 19,952 | |

+ $p < 0.1$

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$.

Note: All models include dummy variables for year of observation (coefficients not shown).

**Table 3.**

Fixed-Effects Linear Regression Models Predicting Body Mass Index: Hispanic National Longitudinal Survey of Youth Respondents, 1981–2010

| | Model A | | Model B | | Model C | |
|---|---|---|---|---|---|---|
| **Independent Variables** | **Coef.** | **S.E.** | **Coef.** | **S.E.** | **Coef.** | **S.E.** |
| Marital Status (1= married) | 0.611*** | 0.062 | 0.612*** | 0.062 | 0.613*** | 0.062 |
| Educational Attainment (ref.=college or above) | | | | | | |
| Less than high school | −0.382+ | 0.213 | −0.390+ | 0.213 | −0.392+ | 0.213 |
| High school graduate | 0.059 | 0.181 | 0.056 | 0.181 | 0.054 | 0.181 |
| Some college | 0.307* | 0.151 | 0.313* | 0.151 | 0.311* | 0.151 |
| Weekly hours worked | 0.002 | 0.001 | 0.002 | 0.001 | 0.002 | 0.001 |
| Adjusted family income (in $10,000s) | −0.003 | 0.003 | −0.003 | 0.003 | −0.003 | 0.003 |
| Receiving public assistance (= 1) | −0.117 | 0.134 | −0.112 | 0.134 | −0.113 | 0.134 |
| **Immediate Neighborhood Variables** | | | | | | |
| Proportion Hispanic | 0.452** | 0.162 | 0.250 | 0.194 | 0.283 | 0.214 |
| Poverty Rate | −0.519 | 0.315 | −0.115 | 0.366 | −0.150 | 0.390 |
| **Cumulative Exposure to Immediate Neighborhood Variables** | | | | | | |
| Proportion Hispanic | | | 1.057* | 0.534 | 1.056* | 0.534 |
| Poverty Rate | | | −2.288* | 1.067 | −2.294* | 1.067 |
| **Extralocal Neighborhood Variables** | | | | | | |
| Proportion Hispanic | | | | | −0.082 | 0.214 |
| Poverty Rate | | | | | 0.084 | 0.382 |
| Constant | 22.962*** | 0.213 | 23.007*** | 0.258 | 23.009*** | 0.259 |
| $R^2$ squared (within) | 0.40 | | 0.40 | | 0.40 | |
| Number of Persons | 1,476 | | 1,476 | | 1,476 | |
| Number of Person-years | 14,926 | | 14,926 | | 14,926 | |

+ $p < 0.1$

* $p < 0.05$

** $p < 0.01$

***
$p < 0.001$.

Note: All models include dummy variables for year of observation (coefficients not shown).

**Table 4.**

Fixed-Effects Linear Regression Models Predicting Body Mass Index: Non-Hispanic White National Longitudinal Survey of Youth Respondents, 1981–2010

| | Model A | | Model B | | Model C | |
|---|---|---|---|---|---|---|
| **Independent Variables** | **Coef.** | **S.E.** | **Coef.** | **S.E.** | **Coef.** | **S.E.** |
| Marital Status (1= married) | 0.562 *** | 0.033 | 0.562 *** | 0.033 | 0.560 *** | 0.033 |
| Educational Attainment (ref.=college or above) | | | | | | |
| Less than high school | −0.459 *** | 0.109 | −0.447 *** | 0.109 | −0.448 *** | 0.109 |
| High school graduate | −0.065 | 0.087 | −0.054 | 0.087 | −0.056 | 0.087 |
| Some college | 0.129 * | 0.065 | 0.129 * | 0.065 | 0.126 + | 0.065 |
| Weekly hours worked | −0.003 *** | 0.001 | −0.004 *** | 0.001 | −0.004 *** | 0.001 |
| Adjusted family income (in $10,000s) | −0.005 *** | 0.001 | −0.005 *** | 0.001 | −0.005 *** | 0.001 |
| Receiving public assistance (= 1) | 0.232 ** | 0.087 | 0.232 ** | 0.087 | 0.232 ** | 0.087 |
| **Immediate Neighborhood Variables** | | | | | | |
| Proportion non-Hispanic White | 0.008 | 0.112 | −0.100 | 0.120 | −0.109 | 0.120 |
| Poverty Rate | 0.977 *** | 0.210 | 0.649 ** | 0.235 | 0.783 ** | 0.238 |
| **Cumulative Exposure to Immediate Neighborhood Variables** | | | | | | |
| Proportion non-Hispanic White | | | 0.456 * | 0.213 | 0.454 * | 0.213 |
| Poverty Rate | | | 1.794 ** | 0.578 | 1.789 ** | 0.578 |
| **Extralocal Neighborhood Variables** | | | | | | |
| Proportion non-Hispanic White | | | | | −0.074 | 0.043 |
| Poverty Rate | | | | | −0.597 ** | 0.182 |
| Constant | 22.491 *** | 0.142 | 22.066 *** | 0.203 | 22.133 *** | 0.203 |
| $R^2$ squared (within) | 0.33 | | 0.34 | | 0.34 | |
| Number of Persons | 5,784 | | 5,784 | | 5,784 | |
| Number of Person-years | 50,584 | | 50,584 | | 50,584 | |

+ p< 0.1

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$.

Note: All models include dummy variables for year of observation (coefficients not shown).