Published in final edited form as:

Health Place. 2014 May ; 27: 134–141. doi:10.1016/j.healthplace.2014.01.011.

Toward a multidimensional understanding of residential neighborhood: a latent profile analysis of Los Angeles neighborhoods and longitudinal adult excess weight

Malia Jones¹ and Jimi Huh²

¹Institute for Disease Prevention and Health Promotion Research Department of Preventive Medicine Keck School of Medicine of USC 2001 N. Soto Street, Suite 312 Los Angeles, CA 90033 maliaj@usc.edu

²Institute for Disease Prevention and Health Promotion Research Department of Preventive Medicine Keck School of Medicine of USC 2001 N. Soto Street, Suite 312 Los Angeles, CA 90033 jimihuh@usc.edu

Abstract

People are embedded in a complex socio-spatial context that may affect their weight status through multiple mechanisms, including food & physical activity opportunities and chronic stress exposure. However, research to date has been unable to resolve what features of neighborhoods are causally related to weight status. We used latent profile analysis to identify three “types” of neighborhoods (based on five dimensions of neighborhood social status) in Los Angeles, CA. Our neighborhood types were both substantively interpretable and predictive of excess weight in both cross-sectional and longitudinal models. Our results are promising for a research community attempting to operationalize neighborhoods as multidimensional, complex systems.

Keywords

Neighborhood effects; latent profile analysis; obesity; longitudinal model

Introduction

Nearly two-thirds of American adults are at risk for diabetes, cardiovascular disease, respiratory disease, and other serious health problems because they are overweight or obese (Flegal et al., 2012; Kopelman, 2007). Furthermore, excess body weight disproportionately affects disadvantaged social and economic groups, particularly African Americans, Latinos and people who are living in poverty (Flegal et al., 2012). Although recent estimates suggest that the spread of obesity is leveling off in some subpopulations (Flegal et al., 2012), excess

Please address correspondence to: Malia Jones, MPH, PhD 2001 N. Soto Street, Suite 312 Los Angeles, CA 90033 310-936-6523 maliaj@usc.edu.

Publisher's Disclaimer: This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final citable form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

weight remains one of the greatest public health challenges of our time (Finkelstein et al., 2009; Mokdad et al., 2004, 2005; Visscher and Seidell, 2001; Wang et al., 2011).

The stress process model suggests that psychosocial stress can activate the body's hormonal stress response, and over the long run chronic activation can impair the body's ability to maintain homeostasis and lead to weight gain (Aneshensel, 2010). Chronic stress exposure is linked to changes in the body such as abdominal fat storage and slower metabolism (Adam and Epel, 2007; Björntorp and Rosmond, 2000; McEwen, 2008; Rosmond, 2005). Animal models show that weight increases with stress exposure (e.g., Bartolomucci et al., 2009; Bartolomucci et al., 2004; Kuo et al., 2008). Human studies have also shown associations between chronic stress exposure and weight gain (Björntorp and Rosmond, 2000; Brunner et al., 2007; Moore and Cunningham, 2012; Torres and Nowson, 2007; Wardle et al., 2011).

People are embedded in a socio-spatial context (e.g., Park et al., 1925), and are therefore exposed to elements in their environment which may be harmful (or helpful) to health (Gee and Payne-Sturges, 2004; National Research Council, 1991). A broad interpretation of this classic exposure model suggests that in addition to physical characteristics (such as pollution and park access), the social contexts of places may influence health by influencing the frequency of contact with social stressors.

Disadvantaged neighborhoods are one source of such chronic stress at the individual level. Stressors in the social environment are at times reflected in the physical environment—for example, in a socially disadvantaged neighborhood, there are often physical markers such as graffiti, litter, and poorly maintained property (Sampson and Raudenbush, 1999; Skogan, 1990). Physical disorder could therefore be a source of stress for residents, and chronic exposure to such places may lead to excess weight and other poor health outcomes (Hill et al., 2005; Ross and Mirowsky, 2001). Burdette and Hill (2008) proposed a model linking neighborhood disorder to obesity via hormonal stress response and health behaviors. They found evidence that chronic exposure to social and physical disorder is linked to central obesity, and that this association was entirely mediated by self-reported psychological distress—supporting the stress process model.

Unfortunately, direct measures of disorder in the environment have serious limitations. When collected by observational methods, they are expensive and susceptible to biases based on the race and class of both observed neighborhood and observer (Franzini et al., 2008; Sampson and Raudenbush, 2004); when collected by surveying neighborhood residents, they are also fraught with issues of same-source bias (Jones et al., 2011; Sampson and Raudenbush, 2004). However, disorder is closely related to a more readily available measure of social context, neighborhood-level socioeconomic status (Jones et al., 2011; Sampson and Raudenbush, 2004).

The presence of high neighborhood levels of social disadvantage (often operationalized as neighborhood-level poverty, minority race, or low education) or indices of concentrated disadvantage have a demonstrated relationship with individual-level chronic stress, over and above the effects of individual-level socioeconomic status (Aneshensel, 2010; Diez Roux,

2007; Diez Roux et al., 2001; Kim, 2008; Mujahid et al., 2008; Ross, 2000; Timberlake, 2007). In addition, an extensive literature has attempted to link socially disadvantaged neighborhoods with risk of excess weight. In a review, Black and Macinko (2008) conclude that neighborhood-level socioeconomic status and racial composition are generally weakly associated with obesity risk, but some conflicting evidence finds no effect of neighborhood social factors.

Neighborhood as a multidimensional construct

One possible explanation for the apparent conflicting findings for neighborhood effects on obesity is related to measurement strategy. Much of the literature linking obesity to spatio-social context has relied upon measures of social context derived from census data, and all such research struggles with the fact that space is patterned across many interrelated dimensions of social status. The economic and employment status, race, tenancy, and other measures of social standing of one's neighbors may have *separate effects* on the overall character of the place, and not always in the same direction. For example, results from the Moving to Opportunity experiment suggest that race segregation and class segregation have separate effects mental health, behavior, and self-rated health (Clampet-Lundquist and Massey, 2008). Places demonstrate complex intersections of segregation by race, class, income, and tenancy that are not easily reduced to a single measure.

Collapsing all this variation on multiple dimensions into an index using an additive process—for example, an index of concentrated disadvantage—may obscure important covariation among the dimensions of segregation. Yet, including more than one of these correlated measures *without* creating an index can introduce problems of multicollinearity into quantitative models (Allison, 2012). Sensitivity testing in our own data (not shown) shows that including more than one highly correlated neighborhood social characteristic leads to instability in effect magnitude, direction, and standard error (Jones, 2013). Nor is it possible to parse out the separate effects of correlated contextual factors using traditional modeling approaches (Leal et al., 2012).

Latent variable modeling offers an alternative approach that can be used to identify unobserved, distinct subgroups of co-located characteristics (Auerbach and Collins, 2006; Lanza et al., 2007; Magidson and Vermunt, 2002). Latent profile analysis (LPA) uses continuous indicator variables and allows for modeling the most parsimonious set of profiles while accounting for measurement error (Muthen and Muthen, 2000). Unlike the traditional, variable-centered approach, LPA yields latent (unobserved) groups of neighborhoods. While each of the identified profiles includes neighborhoods that share similar characteristics, heterogeneous neighborhoods would be captured across different profiles. LPA may be useful in discovering sets of neighborhoods that manifest meaningful between-group variation on several interrelated characteristics (Galster, 2001; Kwan, 2013).

There is a clear need for creative thinking about the multidimensional nature of neighborhood social context, which motivated our first research question: can latent profile analysis of neighborhood social characteristics help us discover “types” of neighborhoods? And secondly, based on the stress process model, are these neighborhood types meaningful

in predicting excess weight in cross-sectional and longitudinal models of adults in Los Angeles County?

Methods

Data and Sample

The Los Angeles Family and Neighborhood Survey (L.A.FANS) is a stratified probability sample of census tracts and households in Los Angeles, CA. It includes a representative sample of individuals, families and neighborhoods. Wave 1 data were collected from 2000–2001, and Wave 2 data were collected from 2006–2008. A multistage sampling strategy was used. A stratified probability sample of LA County census tracts was drawn, with an oversample of poor and very poor tracts. Within sampled tracts, households were randomly sampled; and within households, an adult respondent was randomly selected for interview and anthropometric measures. Households that were unable to complete the interviews in either English or Spanish were excluded from the survey. L.A.FANS attempted to re-interview all study participants who completed an interview at Wave 1 and were still living in Los Angeles County at Wave 2. The complete description of the study goals and sampling approach are described elsewhere (Peterson et al., 2012; Sastry et al., 2006).

Response rates were comparable to those of other in-person interview surveys. In the first wave, 85% of selected adult respondents¹ completed the survey (n=2,620) (Sastry et al., 2006). At Wave 2, 61% of all Wave 1 adults were successfully recontacted and completed an in-person interview (n=1,227) (Peterson et al., 2012). Although loss to follow up in the longitudinal study was extensive, it was not related to the outcome and key independent variables used here.

Data were collected during a lengthy in-person interview conducted by a trained field interviewer (Peterson et al., 2012; Sastry et al., 2006), and include individual-level information about education, race and ethnicity, immigration status, age, gender, and many other social and demographic variables. At wave 2, after the interview was completed, respondents also underwent an anthropometric evaluation performed by a trained interviewer. Measures included waist circumference, the specific methods for which are reported elsewhere (Peterson et al., 2012).

We also used the Los Angeles Neighborhood Services and Characteristics (L.A.NSC) database to provide neighborhood-level information, which we operationalize as the census tract (Peterson et al., 2007; U.S. Census Bureau, 2000). L.A.NSC is publically available as part of the L.A.FANS project, and provides information at the census tract level for all tracts in Los Angeles County (Peterson et al., 2007; Sastry et al., 2006).

The L.A.FANS project and this research were conducted under procedures reviewed and approved by Institutional Review Boards at RAND, UCLA and RTI International. Respondents completed standard informed consent procedures and provided written consent.

¹Our analytic sample consists of the randomly-selected adults who were interviewed at wave 1 and wave 2, or “panel RSAs” in L.A.FANS parlance. For simplicity, we refer to this group as adults.

Variables

Weight status—We primarily used body mass Index (BMI) to represent body weight. BMI is a continuous variable based on self-reported height and weight according to the formula $BMI = \text{weight (kg)} / [\text{height (m)}^2]$.

BMI is a reliable and widely accepted measure of excess fatty tissue at the population level (Deurenberg et al., 2001; Deurenberg et al., 1991) and is associated with increased risk for serious health outcomes (Centers for Disease Control and Prevention, 2011; World Health Organization, 1995). However, because a pattern of abdominal fat deposition may be more closely linked to chronic stress exposure specifically due to hormonal pathways (Wardle et al., 2010), we use waist circumference as a secondary outcome.

Stress Exposure—Social Characteristics of Neighborhoods—Our first goal was to employ latent profile analysis (LPA) to collapse several dimensions of neighborhood social disadvantage into a single, categorical variable describing the neighborhood “type.” Although we would prefer to use a rich set of variables describing the myriad elements of neighborhood social context, the limits of LPA at this time forced us to select a limited set that we thought were most influential in place-based chronic stress exposure². We included five social context variables for our LPA, each derived from the 2000 US Census:

1. The percent of the tract population who are Latino (“% Latino”)
2. The percent of the tract population who are black (“% black”)
3. The percent of the tract population who are in the civilian labor force and are unemployed (“% unemployed”)
4. The percent of the tract population who are living below the federal poverty threshold (“% poverty”)
5. The percent of housing units in the tract which are renter-occupied (“% renters”).

We selected these five characteristics based on theory and past empirical research showing links between neighborhood social characteristics and physical disorder (Franzini et al., 2008; Sampson and Raudenbush, 2004), our putative underlying chronic stressor. Socioeconomically disadvantaged neighborhoods tend to be more disordered (Jones et al., 2011) in part because the residents have less informal social control (i.e., the ability to informally enforce social norms and laws) (Cohen et al., 2003; Sampson and Raudenbush, 1999; Skogan, 1990). We included the tract proportion living in poverty, Latino and black because previous research has shown that neighborhood-level poverty and racial/ethnic minority concentration are associated with independent measures of physical disorder (Franzini et al., 2008; Sampson and Raudenbush, 2004). Spatial mismatch theory also suggests that unemployment is an important marker of neighborhood disadvantage, because changes in the manufacturing economy have left some of the poorest neighborhoods without ready access to jobs (Wilson, 1987). Finally, we include the proportion of housing that is renter-occupied. Neighborhoods with low income tend to have higher residential turnover, in

²Experimentation with LPA using additional neighborhood variables (e.g., mean number of people per household and % population over age 25 with low education) yielded models with poor convergence.

part as a result of low social capital or systems of mutual support (Volker et al., 2013). Renters also tend to move more frequently than do homeowners, and are less invested in the social fabric of their neighborhoods (Sampson et al., 1999). Places higher in renter tenancy, we speculate, are therefore more likely to be disordered neighborhoods.

Our models also control for individual-level demographic characteristics that have established links to stress or obesity, including race/ethnicity/immigration status (operationalized as a single categorical variable), age, gender, family income, education, and marital status.

Analytic Sample and Missingness

The sample of neighborhoods we used to perform LPA was all populated census tracts in Los Angeles County in 2000 (n=1,642). Complete data for tracts were available from the L.A.NSC.

For multilevel models of individual-level outcomes (BMI and waist circumference), we used the Wave 1 adult respondents who were not lost to follow up at Wave 2 as our primary sample (n=1,227). Two cases were excluded because they moved out of the sampled neighborhoods in between selection and their Wave 1 interview, making it impossible to include them in multilevel models. We also excluded 32 adults who were enrolled in the study at Wave 1, but did not complete the Wave 1 adult interview.

We imputed missing values on all remaining variables using a multiple imputation approach. Our final analytic sample included 1,193 adults who lived in Los Angeles County at both Wave 1 and Wave 2.

Analytic Approach

First, we performed LPA to discover underlying neighborhood types using the five neighborhood characteristic variables as indicators for all the census tracts in Los Angeles County in 2000, approximately contemporaneous with Wave 1 of L.A.FANS. LPA was performed using Mplus Version 6 (Muthén and Muthén, 1998–2011).

We used the resulting categorical neighborhood types to predict weight status in multilevel models including a random effect for residential census tract. The tract effect accounted for clustering in the study design. We generated a cross-sectional model of BMI, then introduced a longitudinal component by estimating the effect of Wave 1 neighborhood profiles on Wave 2 BMI, controlling for Wave 1 BMI. Including Wave 1 BMI as a control variable reduces the variation in Wave 2 BMI to the *change* which occurred between observations, providing a rigorous test of the effect of neighborhood types at time 1 on BMI approximately 6–7 years later. We expected that exposure to more socioeconomically disadvantaged neighborhood types would predict excess weight in both cross-sectional and longitudinal models, compared to advantaged neighborhood profiles. We also examined the longitudinal effects of the neighborhood profiles on waist circumference.

We used a series of multilevel models with individual characteristics at Level 1, tract level neighborhood types at Level 2, and a random effect for tract which accounts for clustering in

the sample design.³ These models were executed in Stata 11 using the -xtreg- commands (StataCorp., 2011).

Results

The health status for our adult sample at both data waves is shown in Table 1. On average, respondents were slightly overweight at Wave 1 and gained weight over time—about 1.9 BMI points, which is the equivalent of 10 pounds for an adult who is 5'5" tall. At Wave 2, over three-quarters of the sample was classified as either overweight or obese according to their BMI.

Table 2 presents distributions of the key neighborhood exposure variables we use in our study. The subset of census tracts in which our adult respondents lived is also described in terms of aggregated individual-level data. The minimum and maximum neighborhood values reveal a substantial range of average health status within the tracts. For example, although the sample as a whole was slightly overweight (BMI 26.8), the tract with the lowest mean BMI was comfortably in the healthy weight range (BMI 23.6), while the most overweight tract had a mean BMI of 29.9—a tenth of a point below the obese threshold. There is also heterogeneity by tract in how much weight people gained between survey waves. On average, respondents gained 1.9 BMI points, but in the lowest-gaining tract, they actually lost a marginal amount (BMI change = -0.3). In the highest-gaining tract, adults gained an average of 4.7 BMI points, equivalent to 28 lbs. for an adult 5'5" tall.

Results from Latent Profile Analysis

We conducted an iterative series of latent profile models to find the best-fitting set of latent neighborhood types. We encountered no model identification issues, and global maxima were achieved for all models. We evaluated several model-fit indices, including loglikelihood, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample size-adjusted BIC. We also employed the Lo-Mendell-Rubin likelihood ratio (LMRLR), which compares n vs. $n-1$ class models and informs the null hypothesis that an n -class model is better-fitted than an $n-1$ class model, with $p < .05$ suggesting that the null hypothesis can be rejected (Lo Y et al., 2001).

Although each of loglikelihood, AIC, BIC, and n -adjusted BIC incrementally decreased for the 4-class solution compared to the 3-class solution (e.g., AIC 62245.9 vs. 61162.8 and n -adjusted BIC 62294.8 vs. 61225.1), the LMRLR test clearly favored the 3-class model as better fitting than the 4-class model ($p = .116$). The 4-class model also included a very sparse class ($n = 9$), so it was not further considered as an optimal solution. Thus, comparisons of several model fit indices and relative class interpretability revealed that the best-fitted solution for LPA included three neighborhood profiles in LA County. Figure 1 shows average characteristics of the three neighborhood profiles and a map of the County displaying their spatial pattern. Type 1 neighborhoods, representing 59% of all

³Although population weights are available for this sample, weighting in multilevel models is controversial. Sensitivity testing suggests that in this data set, including the random effect for tract approximates the inclusion of weights. Therefore we used multilevel models with random effects for tracts in lieu of weights.

neighborhoods in the county, are the most advantaged. Type 1 neighborhoods are characterized by low poverty, the lowest proportions black and Latino, low unemployment, and low tenure by renters. Type 2 neighborhoods (33%) have the highest level of poverty, rentership, and Latino residents, with moderate unemployment and moderate proportion black race. Type 3 neighborhoods (9%) are the most socioeconomically disadvantaged, with the highest proportion black residents and unemployment, moderate-to-high levels of poverty, and moderate proportions of renters and Latino residents. The profile classification certainty index was good (entropy = 0.905), representing that the error in the probability of any given tract fitting to other profiles than its assigned profile was small. As the map shows, the face validity of these neighborhood types is acceptable to those who know the region.

Results from modeling excess weight

Results of cross-sectional models using BMI at Wave 1 as the outcome are presented in Table 3. Compared to those living in Type 1 neighborhoods, respondents who lived in Type 3 neighborhoods had a BMI over 2 points higher. Because the latent profile classifications seemed to be driven by racial differences in neighborhoods, we tested for cross-level interactions between individual race and profile; however none of the interaction terms were significant.

The second panel of Table 3 shows results of modeling BMI at Wave 2 based on individual characteristics and neighborhood types at Wave 1, net of BMI at Wave 1. Unsurprisingly, BMI at Wave 1 is a strong predictor of BMI at Wave 2. Women showed more weight gain than did men, and a complex pattern of race/ethnic differences emerged: compared to native-born Latinos at the same initial BMI, both documented and undocumented Latino immigrants had lower Wave 2 BMI, whereas native-born Blacks had higher Wave 2 BMI. Notably, even though the available variation in the outcome has been dramatically reduced by incorporating the control for BMI at Wave 1, those who lived in a Type 2 neighborhood had 0.6 points higher BMI at Wave 2 (marginal significance, $p=0.09$), compared to those who lived in a Type 1 neighborhood.

Finally, the third panel shows that adjusting for Wave 1 BMI⁴, adults who lived in a Type 3 neighborhood had 4.3 cm larger waist circumference at Wave 2, compared to those who lived in a Type 1 neighborhood. Residents in Type 3 neighborhoods also have significantly higher waist circumference compared to those of Type 2 neighborhoods (comparison not shown).

Discussion

Latent Profile Analysis of tracts

In our 3-profile LPA solution, Type 1 neighborhoods can be easily described as advantaged areas, with low poverty, the lowest proportions black and Latino, low unemployment, and low rates of rentership. This is the most dominant neighborhood type in the county by count

⁴Waist circumference was not collected at Wave 1. Due to a lack of precise matching control at Wave 1, results for waist circumference should not be overinterpreted.

of tracts, with almost 60% of tracts represented. Figure 1 shows a clear geospatial pattern. Type 1 neighborhoods are located in the coastal zones and peripheral parts of the County, away from the urban centers. Because census tract size is determined in part by population density, the gross area covered by this neighborhood type is somewhat misleading. The more affluent suburbs and exurbs of the County are much less densely populated, compared to the more central regions.

Interpretation of Type 2 and Type 3 neighborhoods requires guidance from the social geography of Los Angeles. The characteristics of Type 2 neighborhoods—high in proportions living in poverty, renting their homes, and Latino, along with moderate unemployment—are consistent with areas that have historically provided affordable housing options and have, in recent decades, received many immigrants from Mexico and Central America. Type 2 neighborhoods are the second most common, including 1 in 3 tracts in the County. Regionally, Figure 1 shows a concentration of type 2 neighborhoods in central, south, and East Los Angeles, hugging the urban centers. Another small concentration extends into the San Fernando valley and the Inland Empire.

Type 3 neighborhoods, with by far the highest proportion black residents and unemployment, moderate-to-high levels of poverty, and moderate proportions of renters and Latino residents, are consistent with a stable, largely homeownership class of middle- and low-income blacks in the County. The most striking difference between type 2 and type 3 neighborhoods is the racial profile, with type 3 neighborhoods having a much higher proportion of black residents. Again, this is consistent with the socio-spatial geography of the city. Only 1 in 10 Los Angelenos are African American, but these residents are tightly clustered in a small segment of the County (Wilkes and Iceland, 2004), South Los Angeles. Concomitant with the small citywide proportion black, only 9% of all tracts were classified as Type 3 neighborhoods.

Obesity Models

In the cross-sectional model of BMI, living in a Type 3 neighborhood was associated with higher BMI. This model does not allow us to sort out whether people cluster in neighborhood types based on shared characteristics that also were associated their BMI, or if something about the neighborhood type causes BMI changes. In longitudinal models, a marginally significant relationship emerges between living in a Type 2 neighborhood at Wave 1 and BMI at Wave 2, net of individual risk factors. Residing in a low-income Latino neighborhood may put individuals at higher risk of weight gain over a relatively short time span, even accounting for race/ethnicity, immigration status, income, education, age, and gender. The model for waist circumference similarly shows a deleterious effect of living in the stable, lower-income black core of South Los Angeles. These findings are consistent with other literature indicating that people with disadvantaged ethnic/economic backgrounds have, on average, been more adversely affected by the obesity epidemic (Flegal et al., 2012; Flegal et al., 2010).

Net of a robust set of individual controls, disadvantaged neighborhood types identified using LPA are marginally predictive of weight in longitudinal models. In models using more traditional approaches to characterizing social context (an index of concentrated

disadvantage or entering the 5 characteristics of neighborhoods directly (not shown)), similar contextual effects were in evidence in cross-sectional models, but disappeared in longitudinal models.

Limitations

The strength of our conclusions is tempered by several limitations of our data and methods. First, we used the census tract of residence as the operational definition of neighborhoods. Residential census tracts were the primary sampling unit selected by L.A.FANS and also have readily available data on social characteristics from the US Census. Although we are by far not the first to make this decision, it is a simplistic way of thinking about social exposures in space. Future data collection efforts in neighborhood effects research must take seriously the issue of spatial and temporal variation in exposure to places by using individual-level measures of where people spend their time, for example, by using activity spaces as a measure of context (Jones and Pebley, 2013; Kwan, 2013; Palmer et al., 2013).

A second limitation in our study is that our longitudinal change-in-health models have limited power to detect change because of the strong association between weight at Wave 1 and at Wave 2. Although the adults in our sample did gain weight in the period between survey waves, many of them were already overweight at Wave 1, suggesting that any causally relevant neighborhood exposures may have occurred prior to the first survey wave. This limitation could account for our marginal effect sizes. A longer set of longitudinal data, especially one beginning early in life before chronic diseases make their appearance, would be useful in addressing this weakness. Other research has suggested that neighborhood exposures are most influential during childhood and adolescence (Brooks-Gunn et al., 1993; Duncan et al., 1994; Jones et al., 2011; Leventhal et al., 2005; Wheaton and Clarke, 2003). Future research in neighborhood effects on excess weight should examine the notion that exposures occur across the life course, and may be most influential early in life.

Finally, as is always the case in secondary data analysis, our selection of the variables was limited by the existing measures. For example, L.A.FANS does not include a direct measure of either perceived stress or biological stress response, which would allow us to test critical mediation models. A measure of waist circumference at Wave 1 was also unavailable, which introduces an error component into models of that outcome. We have used self-reported BMI at Wave 1 as a control in the longitudinal model, which leaves the question of whether exposure to a Type 3 neighborhood has causal, adverse effects on waist circumference, or if our finding is attributable to residents of Type 3 neighborhoods having more error between self-reported BMI and waist circumference. For example, people living in moderate-to-high poverty black neighborhoods have been historically underserved by the health care system. Perhaps they are more likely to underreport their weight because they are less likely to have visited a doctor's office, leading to a larger gap between self-reported weight and measured waist circumference. An alternative explanation which supports our theory is that waist circumference is itself more closely related to stress exposure (Wardle et al., 2010); perhaps living in a Type 3 neighborhood causes selective abdominal fat deposition, leading to a larger observed gap between BMI and waist circumference. We lack the data to disentangle

these possibilities, but in light of previous research linking chronic stress exposure and waist circumference, we think our tentative conclusions are still fruitful.

We have argued that neighborhood-based exposures to social stressors such as disorder cannot be accurately represented by single variables, indices or coefficients because the experience of place is nuanced and complex. Characteristics of places covary in ways that make it difficult to attribute any putative health effect to any single characteristic of places, yet entering many related characteristics into the same model only creates statistical headaches. We have illustrated a simple, categorical typology of Los Angeles census tracts using a latent variable approach. Our neighborhood types were both substantively interpretable and predictive of excess weight in the direction predicted by theory. Indeed, the neighborhood types were predictive even in rigorous longitudinal models of weight status, whereas comparable models using neighborhood indices or multiple characteristics were not. As we expected, living in less-advantaged neighborhood types put residents at risk of greater weight gain compared to the most advantaged type of neighborhood. Although our range of neighborhood indicators was limited, our results are promising for a research community attempting to operationalize neighborhoods as multidimensional, complex, dynamic systems rather than as unidimensional, static places. We have demonstrated that residence in less-advantaged places put adults at risk for excess weight in the context of a longitudinal model. This evidence supports the popular notion—in research, policy, and lay thinking—that exposure to social disadvantage in neighborhoods is in fact related to obesity.

Acknowledgments

This study was supported by grants from the National Cancer Institute (T32 CA009492 (Pentz, PI), Eunice Kennedy Shriver National Institute of Child Health and Human Development (Grants R01HD35944 and R01HD41486), and by the Russell Sage Foundation.

Bibliography

- Adam TC, Epel ES. Stress, eating and the reward system. *Physiol Behav.* 2007; 91:449–458. [PubMed: 17543357]
- Allison, P. *Statistical Horizons.* 2012. When can you safely ignore multicollinearity?.
- Aneshensel, CS. Neighborhood as a Social Context of the Stress Process. In: Avison, WR.; Aneshensel, CS.; Schieman, S.; Wheaton, B., editors. *Advances in the Conceptualization of the Stress Process: Essays in Honor of Leonard I. Pearlin.* Springer Science+Business Media, LLC; 2010.
- Auerbach KJ, Collins LM. A multidimensional developmental model of alcohol use during emerging adulthood. *J Stud Alcohol.* 2006; 67:917–925. [PubMed: 17061010]
- Bartolomucci A, Cabassi A, Govoni P, Ceresini G, Cero C, Berra D, Dadomo H, Franceschini P, Dell'Omo G, Parmigiani S, Palanza P. Metabolic Consequences and Vulnerability to Diet-Induced Obesity in Male Mice under Chronic Social Stress. *PLoS ONE.* 2009; 4:e4331. [PubMed: 19180229]
- Bartolomucci A, Pederzani T, Sacerdote P, Panerai AE, Parmigiani S, Palanza P. Behavioral and physiological characterization of male mice under chronic psychosocial stress. *Psychoneuroendocrinology.* 2004; 29:899–910. [PubMed: 15177705]
- Björntorp P, Rosmond R. Obesity and cortisol. *Nutrition.* 2000; 16:924–936. [PubMed: 11054598]
- Black JL, Macinko J. Neighborhoods and obesity. *Nutr Rev.* 2008; 66:2–20. [PubMed: 18254880]
- Brooks-Gunn J, Duncan GJ, Klebanov PK, Sealand N. Do Neighborhoods Influence Child and Adolescent Development? *American Journal of Sociology.* 1993; 99:353–395.

- Brunner EJ, Chandola T, Marmot MG. Prospective effect of job strain on general and central obesity in the Whitehall II Study. *Am J Epidemiol*. 2007; 165:828–837. [PubMed: 17244635]
- Burdette AM, Hill TD. An examination of processes linking perceived neighborhood disorder and obesity. *Soc Sci Med*. 2008; 67:38–46. [PubMed: 18433964]
- Centers for Disease Control and Prevention. About BMI for Adults. 2011.
- Clampet-Lundquist S, Massey DS. Neighborhood effects on economic self-sufficiency: A reconsideration of the moving to opportunity experiment. *American Journal of Sociology*. 2008; 114:107–143.
- Cohen DA, Farley TA, Mason K. Why is poverty unhealthy? - Social and physical mediators. *Social Science & Medicine*. 2003; 57:1631–1641. [PubMed: 12948572]
- Deurenberg P, Andreoli A, Borg P, Kukkonen-Harjula K, de Lorenzo A, van Marken Lichtenbelt WD, Testolin G, Vigano R, Volvaard N. The validity of predicted body fat percentage from body mass index and from impedance in samples of five European populations. *Eur J Clin Nutr*. 2001; 55:973–979. [PubMed: 11641746]
- Deurenberg P, Weststrate JA, Seidell JC. Body mass index as a measure of body fatness: age- and sex-specific prediction formulas. *Br J Nutr*. 1991; 65:105–114. [PubMed: 2043597]
- Diez Roux AV. Neighborhoods and health: where are we and where do we go from here? *Rev Epidemiol Sante Publique*. 2007; 55:13–21. [PubMed: 17320330]
- Diez Roux AV, Merkin SS, Arnett D, Chambless L, Massing M, Nieto FJ, Sorlie P, Szklo M, Tyroler HA, Watson RL. Neighborhood of residence and incidence of coronary heart disease. *N Engl J Med*. 2001; 345:99–106. [PubMed: 11450679]
- Duncan GJ, Brooks-Gunn J, Klebanov PK. Economic deprivation and early childhood development. *Child Dev*. 1994; 65:296–318. [PubMed: 7516849]
- Finkelstein EA, Trogdon JG, Cohen JW, Dietz W. Annual medical spending attributable to obesity: payer- and service-specific estimates. *Health Aff (Millwood)*. 2009; 28:w822–831. [PubMed: 19635784]
- Flegal KM, Carroll MD, Kit BK, Ogden CL. Prevalence of obesity and trends in the distribution of body mass index among US adults, 1999–2010. *JAMA*. 2012; 307:491–497. [PubMed: 22253363]
- Flegal KM, Carroll MD, Ogden CL, Curtin LR. Prevalence and trends in obesity among US adults, 1999–2008. *JAMA*. 2010; 303:235–241. [PubMed: 20071471]
- Franzini L, Caughy MO, Nettles SM, O'Campo P. Perceptions of disorder: Contributions of neighborhood characteristics to subjective perceptions of disorder. *Journal of Environmental Psychology*. 2008; 28:83–93.
- Galster G. On the Nature of Neighborhoods. *Urban Studies*. 2001; 38:2111–2124.
- Gee GC, Payne-Sturges DC. Environmental health disparities: A framework integrating psychosocial and environmental concepts. *Environmental Health Perspectives*. 2004; 112:1645–1653. [PubMed: 15579407]
- Hill TD, Ross CE, Angel RJ. Neighborhood disorder, psychophysiological distress, and health. *J Health Soc Behav*. 2005; 46:170–186. [PubMed: 16028456]
- Jones, M. Under review. Spatial Demography; 2013. Neighborhood Social Context and Hypertension 7 Years Later: Sensitivity of Effects to Specification of Geospatial Scale.
- Jones, M.; Pebley, AR. Under review. Demography; 2013. Redefining neighborhoods using common destinations: social characteristics of activity spaces and home census tracts compared.
- Jones M, Sastry N, Pebley AR. Eyes on the Block: Measuring Urban Physical Disorder Through In-Person Observation. *Social Science Research*. 2011; 40:523–537. [PubMed: 21643484]
- Kim D. Blues from the neighborhood? Neighborhood characteristics and depression. *Epidemiol Rev*. 2008; 30:101–117. [PubMed: 18753674]
- Kopelman P. Health risks associated with overweight and obesity. *Obesity Reviews*. 2007; 8:13–17. [PubMed: 17316295]
- Kuo LE, Czarnecka M, Kitlinska JB, Tilan JU, Kvetnansky R, Zukowska Z. Chronic stress, combined with a high-fat/high-sugar diet, shifts sympathetic signaling toward neuropeptide Y and leads to obesity and the metabolic syndrome. *Ann N Y Acad Sci*. 2008; 1148:232–237. [PubMed: 19120115]

- Kwan, MP. *Annals of the Association of American Geographers*. 2013. Beyond Space (As We Knew It): Toward Temporally Integrated Geographies of Segregation, Health, and Accessibility.
- Lanza ST, Collins LM, Lemmon DR, Schafer JL. PROC LCA: A SAS Procedure for Latent Class Analysis. *Struct Equ Modeling*. 2007; 14:671–694. [PubMed: 19953201]
- Leal C, Bean K, Thomas F, Chaix B. Multicollinearity in associations between multiple environmental features and body weight and abdominal fat: using matching techniques to assess whether the associations are separable. *Am J Epidemiol*. 2012; 175:1152–1162. [PubMed: 22534206]
- Leventhal T, Fauth RC, Brooks-Gunn J. Neighborhood poverty and public policy: a 5-year follow-up of children's educational outcomes in the New York City moving to opportunity demonstration. *Dev Psychol*. 2005; 41:933–952. [PubMed: 16351338]
- Lo Y, Mendell NR, Rubin DB. Testing the number of components in a normal mixture. *Biometrika*. 2001; 88:767–778.
- Magidson J, Vermunt J. Latent Class Models for Clusterin: A Comparison with K-Means. *Canadian Journal of Marketing Research*. 2002; 20:37–44.
- McEwen BS. Central effects of stress hormones in health and disease: Understanding the protective and damaging effects of stress and stress mediators. *Eur J Pharmacol*. 2008; 583:174–185. [PubMed: 18282566]
- Mokdad AH, Marks JS, Stroup DF, Gerberding JL. Actual causes of death in the United States, 2000. *JAMA*. 2004; 291:1238–1245. [PubMed: 15010446]
- Mokdad AH, Marks JS, Stroup DF, Gerberding JL. Correction: actual causes of death in the United States, 2000. *JAMA*. 2005; 293:293–294. [PubMed: 15657315]
- Moore CJ, Cunningham SA. Social position, psychological stress, and obesity: a systematic review. *J Acad Nutr Diet*. 2012; 112:518–526. [PubMed: 22709702]
- Mujahid MS, Diez Roux AV, Morenoff JD, Raghunathan TE, Cooper RS, Ni H, Shea S. Neighborhood characteristics and hypertension. *Epidemiology*. 2008; 19:590–598. [PubMed: 18480733]
- Muthen B, Muthen LK. Integrating person-centered and variable-centered analyses: growth mixture modeling with latent trajectory classes. *Alcohol Clin Exp Res*. 2000; 24:882–891. [PubMed: 10888079]
- Muthén, LK.; Muthén, BO. *Mplus User's Guide*. Sixth Edition ed. Muthén & Muthén; Los Angeles, CA: 1998–2011.
- National Research Council. *Public Health and Hazardous Wastes*. Vol. Vol 1. National Academy Press; Washington, DC: 1991. Environmental Epidemiology.
- Palmer JR, Espenshade TJ, Bartumeus F, Chung CY, Ozgencil NE, Li K. New approaches to human mobility: using mobile phones for demographic research. *Demography*. 2013; 50:1105–1128. [PubMed: 23192393]
- Park, RE.; McKenzie, RD.; Burgess, E. *The City: Suggestions for the Study of Human Nature in the Urban Environment*. University of Chicago Press; Chicago, IL: 1925.
- Peterson, CE.; Pebley, AR.; Sastry, N. RAND Working Paper WR-240/12-LAFANS. 2007. The Los Angeles Neighborhood Services and Characteristics Database: Codebook.
- Peterson CE, Pebley AR, Sastry N, Yuhas K, Ghosh-Dastidar B. The Los Angeles Family and Neighborhood Survey Wave 2: User's Guide and Codebook. RAND Working Paper WR-240/20-LAFANS. 2012
- Rosmond R. Role of stress in the pathogenesis of the metabolic syndrome. *Psychoneuroendocrinology*. 2005; 30:1–10. [PubMed: 15358437]
- Ross CE. Neighborhood disadvantage and adult depression. *Journal of Health and Social Behavior*. 2000; 41:177–187.
- Ross CE, Mirowsky J. Neighborhood disadvantage, disorder, and health. *J Health Soc Behav*. 2001; 42:258–276. [PubMed: 11668773]
- Sampson RJ, Morenoff JD, Earls F. Beyond social capital: Spatial dynamics of collective efficacy for children. *American Sociological Review*. 1999; 64:633–660.
- Sampson RJ, Raudenbush S. Systematic Social Observation of Public Spaces: A new look at disorder in urban neighborhoods. *American Journal of Sociology*. 1999; 105:603–651.

- Sampson RJ, Raudenbush SW. Seeing Disorder: Neighborhood Stigma and the Social Construction of "Broken Windows". *Social Psychology Quarterly*. 2004; 67:319–342.
- Sastry N, Ghosh-Dastidar B, Adams J, Pebley AR. The design of a multilevel survey of children, families, and communities: The Los Angeles Family and Neighborhood Survey. *Social Science Research*. 2006; 35:1000–1024.
- Skogan, WG. *Disorder and Decline*. University of California Press; Berkley and Los Angeles, CA: 1990.
- StataCorp. *Stata Statistical Software: Release 11*. StataCorp LP; College Station, TX: 2011.
- Timberlake JM. Racial and Ethnic Inequality in the Duration of Children's Exposure to Neighborhood Poverty and Affluence. *Social Problems*. 2007; 54:319–342.
- Torres SJ, Nowson CA. Relationship between stress, eating behavior, and obesity. *Nutrition*. 2007; 23:887–894. [PubMed: 17869482]
- U.S. Census Bureau. *Decennial Census, SF-3 file*. 2000.
- Visscher TL, Seidell JC. The public health impact of obesity. *Annu Rev Public Health*. 2001; 22:355–375. [PubMed: 11274526]
- Volker, B.; Mollenhorst, G.; Schutjens, V. Neighborhood Social Capital and Residential Mobility. In: van Hamm, V.; Manley, D.; Bailey, N.; Simpson, L.; MacLennan, D., editors. *Understanding Neighbourhood Dynamics*. Springer; 2013. Online
- Wang YC, McPherson K, Marsh T, Gortmaker SL, Brown M. Health and economic burden of the projected obesity trends in the USA and the UK. *Lancet*. 2011; 378:815–825. [PubMed: 21872750]
- Wardle J, Chida Y, Gibson EL, Whitaker KL, Steptoe A. *Stress and Adiposity: A Meta-Analysis of Longitudinal Studies*. Obesity (Silver Spring). 2010
- Wardle J, Chida Y, Gibson EL, Whitaker KL, Steptoe A. Stress and adiposity: a meta-analysis of longitudinal studies. *Obesity (Silver Spring)*. 2011; 19:771–778. [PubMed: 20948519]
- Wheaton B, Clarke P. Space meets time: Integrating temporal and contextual influences on mental health in early adulthood. *American Sociological Review*. 2003; 68:680–706.
- Wilkes R, Iceland J. Hypersegregation in the twenty-first century. *Demography*. 2004; 41:23–36. [PubMed: 15074123]
- Wilson, WJ. *The truly disadvantaged : the inner city, the underclass, and public policy*. University of Chicago Press; Chicago: 1987.
- World Health Organization. *Physical Status: the use and interpretation of anthropometry*. Geneva, Switzerland: 1995. WHO Technical Report Series

Highlights

- Latent profile analysis was able to identify three distinct types of neighborhoods
- Neighborhood types were associated with weight in longitudinal models
- Residence in two less-advantaged neighborhood types was related to higher weight

Figure 1.
Los Angeles County census tracts, 3-profile solution

Table 1

Descriptive Characteristics of the Adult Sample (n=1,193)

	% or Mean(SD)
Age (years, W1)	40.0 (13.1)
Education (years, W1)	12.3 (4.5)
Female	62%
Family income (\$1, W1)	52,214 (76,392)
Marital Status	
Married	52%
Cohabiting	14%
Single	17%
Divorced, Separated, Widowed	17%
Race/Ethnicity/Immigration Status	
Native-born Latino	23%
Documented Latino Immigrant	19%
Undocumented Latino Immigrant	14%
Native-born white	27%
Native-born black	10%
Asian	6%
Other	2%
Latent Profile Membership Status	
Profile 1	39%
Profile 2	57%
Profile 3	4%
Wave 1 BMI	26.8 (4.2)
Wave 2 BMI	28.7 (6.4)
Wave 2 Waist Circumference (cm)	98.5 (13.3)

Table 2

Descriptive Characteristics of Los Angeles County census tracts, 2000

	LA County Tracts (n=1,642)				L.A. FANS Tracts (n=65)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Census-derived variables								
Tract population^a	5,798	3,009	0.0	29,789	7,733	4,177	900	22,000
Tract area (sq. mi.)	2.4	16.9	0.0	365.9	6.7	34.1	0	200
% Income below the federal poverty threshold^a	17.2	12.6	0.0	100.0	22.9	13.9	3	51
% black^a	9.8	16.5	0.0	91.8	8.3	10.0	0	48
% Hispanic or Latino^a	41.1	28.7	0.0	99.4	55.1	29.6	2	96
% White^a	34.0	28.6	0.0	100.0	23.8	25.6	0	89
% with 12 or less years education^b	55.1	22.8	0.0	100.0	64.6	23.8	13	94
% Unemployed^c	4.3	3.0	0.0	50.0	5.6	3.4	0	24
Renter-occupied housing^d	47.2	24.5	2.9	100.0	53.4	24.2	5	94
% vacant^d	4.2	3.8	0.0	80.0	5.2	3.6	1	18
Variables derived from L.A. FANS Data								
Disorder score	n/a	n/a	n/a	n/a	0.35	0.13	0.09	0.55
BMI at Wave 1 (within tract)	n/a	n/a	n/a	n/a	26.8	1.3	23.6	29.9
BMI at Wave 2 (within tract)	n/a	n/a	n/a	n/a	28.7	2.0	24.0	32.9
BMI change	n/a	n/a	n/a	n/a	+1.9	1.1	-0.3	+4.7
BMI change as a % of Wave 1 BMI	n/a	n/a	n/a	n/a	+6.9%	4.0%	-0.1%	+19.1%
Waist circumference at Wave 2	n/a	n/a	n/a	n/a	98.5	4.0	85.3	109.4

^a of individuals^b of individuals over age 25^c of individuals in the civilian labor force^d of housing units

Table 3

Results of Multilevel Modeling of Adult Weight Outcomes on Neighborhood Types (n=1,193)

	BMI at Wave 1	BMI at Wave 2	Waist Circumference at Wave 2 (cm)
	b	b	b
Type 1 Neighborhood (ref)	-	-	-
Type 2 Neighborhood	0.468	0.551	0.297
Type 3 Neighborhood	2.209**	0.207	4.335**
W1 Self-report BMI		1.132***	2.148***
Age at W1 (years)	0.036***	-0.059***	-0.051*
Education at W1 (years)	-0.101**	-0.068	0.007
Female	-0.267	0.943***	-0.469
W1 family income (logged)	-0.006	0.002	-0.109
Married (ref)	-	-	-
Cohabiting	-0.100	0.324	0.089
Single	-0.742*	0.688	1.628
Divorced, Separated or Widowed	-0.574	0.074	-0.093
Latino/native-born (ref)	-	-	-
Latino/foreign-born documented	-0.843*	-1.072**	-3.715***
Latino/foreign-born undocumented	-0.828	-0.367	-3.035**
White/native-born	-1.457***	0.529	1.438
Black/native-born	0.315	1.020*	0.063
Asian	-2.486***	-0.072	-3.614**
Others	-2.556**	-0.664	-1.737
_cons	27.55***	1.871***	42.761***

Note:

* = p < 0.05;

** = p-value < 0.01;

*** = p-value < 0.001