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Health & Place

journal homepage: www.elsevier.com/locate/healthplace

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

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ARTICLE INFO

Article history:

Received 2 July 2013

Received in revised form

28 January 2014

Accepted 28 January 2014

Available online 6 March 2014

Keywords:

Neighborhood effects

Latent profile analysis

Obesity

Longitudinal model

ABSTRACT

People are embedded in a complex socio-spatial context that may affect their weight status through multiple mechanisms, including food and 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.

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1. 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 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).

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Animal models show that weight increases with stress exposure (e.g., Bartolomucci et al. (2009, 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.

1.1. 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, 2012). 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 multi-dimensional 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 second, 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?

2. Methods

2.1. 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 to 2001, and Wave 2 data were collected from 2006 to 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 ($n=2620$) (Sastry et al., 2006). At Wave 2, 61% of all Wave 1 adults were successfully recontacted and completed an in-person interview ($n=1227$) (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 publicly 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).

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

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