Health & Place 46 (2017) 201–209

Contents lists available at ScienceDirect

Health & Place

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

A marginal structural modeling strategy investigating short and long-term exposure to neighborhood poverty on BMI among U.S. black and white adults

D. Phuong Do*, Cheng Zheng

Zilber School of Public Health, University of Wisconsin-Milwaukee, 1240 N 10th St, Milwaukee, WI 53205, United States

ARTICLE INFO

Keywords:
Neighborhood effects
Marginal structural model
Obesity
Longitudinal analysis

ABSTRACT

We apply a marginal structural modeling (MSM) strategy to investigate the relationship between neighborhood poverty and BMI level among U.S. black and white adults. This strategy appropriately adjusts for factors that may be simultaneously mediators and confounders (e.g., income, health behavior), strengthening causal inference and providing the total (direct and indirect) neighborhood effect estimate. Short and long-term neighborhood poverty were positively associated with being overweight for both black and white women. No link was found for either black or white men. Socioeconomic and behavioral factors do not appear to be strong mediators. Sensitivity analyses suggest that the direction of point estimates is robust to unobserved confounding, though 95% confidence intervals sometimes included the null, particularly for white women. Compared to previous cross-sectional and longitudinal analyses, MSM results provide stronger evidence for a causal link between neighborhood poverty and body weight among women.

1. Introduction

Place-based factors that generate and maintain obesogenic environments, which promote weight gain and/or deter weight loss, are hypothesized to be fundamental upstream structural determinants of the high rates of obesity in the United States (Ogden et al., 2014). Specific contextual features that have been investigated include racial/ethnic concentration, neighborhood safety, access to healthy foods, urban sprawl, and land use mix (Mackenbach et al., 2014; Giskes et al., 2011; Black and Macinko, 2008). While the overall evidence is mixed, access to supermarkets and fast-food restaurants are hypothesized to influence diet while proximity and density of parks are thought to influence level of physical activity (Bancroft et al., 2015; Gordon-Larsen, 2014). In a recent review, Mackenbach et al. (2014) concluded that the evidence between the physical environment and body weight is most consistent for land use mix and urban sprawl, within lower land use mix and higher urban sprawl linked to increased obesity. Neighborhood social environments, as well, are thought to influence body weight by shaping normative behaviors and level of exposure to chronic stressors. For example, Osypuk et al. (2009) found residence in immigrant enclaves, which is hypothesized to reinforce cultural norms regarding health-related behaviors, is associated with lower consumption of high-fat foods and lower physical activity. Further, exposures to stressors such as concentrated poverty and high rates of crime or violence may influence eating behaviors and likelihood to engage in outdoor physical activity, with subsequent consequences to body weight (Burdette et al., 2006; Chang et al., 2009; Powell-Wiley et al., 2013; Won et al., 2016).

Because many of these neighborhood attributes are associated with the socioeconomic environment, studies have also focused on the role of neighborhood poverty and its correlates, in helping to shape the patterning of the obesity epidemic across racial/ethnic and socioeconomic groups. Studies that examined neighborhood poverty and disadvantage have generally found detrimental associations, with areas characterized by higher deprivation or lower socioeconomic status (SES) predicting higher body mass index (BMI) and likelihood of being obese (Black and Macinko, 2008). However, despite the large body of evidence indicating contextual disadvantage being positively associated with body weight, the vast majority of studies have been based on cross-sectional analyses, which are characterized by numerous methodological issues such as ambiguous temporal ordering and unobserved confounding. This severely limits causal inference and policy implications. Indeed, more recent studies that have utilized longitudinal data have produced less consistent results. While neighborhood disadvantage has largely been linked to higher baseline BMI in longitudinal analyses (e.g., Mujahid et al., 2005; Ruel et al., 2010;

* Corresponding author.
E-mail address: dphuong@uwm.edu (D.P. Do).

http://dx.doi.org/10.1016/j.healthplace.2017.05.010
Received 10 November 2016; Received in revised form 6 April 2017; Accepted 9 May 2017
1353-8292/ Published by Elsevier Ltd.

Burdette and Needham, 2012), whether neighborhood SES is associated with subsequent BMI levels, gains, or trajectories remain unclear. Some studies did not find any association between contextual disadvantage and BMI or excess weight after accounting for individual characteristics (e.g., Mujahid et al., 2005; Ruel et al., 2010; Murray et al., 2010). Yet other studies have found area socioeconomic factors to be predictive of BMI and excess weight - though often only weakly so (e.g., Jones and Huh, 2014; Berry et al., 2010; Burdette and Needham, 2012). The mixed results may be due to a number of factors, including sample size, generalizability of results, methodological strategy, operationalization of neighborhood deprivation, the extent of individual-level controls, and time frame of follow-up.

While the utilization of longitudinal analyses to investigate the role of area level factors on BMI is a significant advancement over cross-sectional studies, a salient issue that has yet to be addressed in extant longitudinal as well as cross-sectional neighborhood-BMI/obesity studies is that many of the individual-level adjustments may themselves have been affected by prior neighborhood context. For example, neighborhood poverty and disadvantage have been found to be predictive of lower individual-level socioeconomic characteristics (e.g., education, employment, earnings) and adverse health behaviors (e.g., physical inactivity, smoking, drug and alcohol use) (Wodtke et al., 2011; Clampet-Lundquist and Massey 2008; Ellen et al., 2001; Algren et al., 2015). Given that these individual-level factors are associated with body weight, it follows that they may be important mediators in the pathway between neighborhood disadvantage and BMI. However, in conventional longitudinal (as well as cross-sectional) analyses of neighborhood effects, controlling for characteristics such as income and employment is the prevailing strategy to minimize confounding. Such strategies effectively sweep away the indirect effects of neighborhoods on outcomes, possibly resulting in incorrect causal effect estimates and misleading inferences about the total impact of neighborhoods on body weight, as well as other health measures.

In situations in which the treatment is time-varying and there exist time-varying factors that are simultaneously confounders and mediators, marginal structural models (MSMs) can be applied to longitudinal data to appropriately adjust for confounding while also allowing the estimated treatment effect to include the mediation effects (Robins et al., 2000). Such is the case here, in which exposure to specific neighborhood context (treatment) varies across time and time-varying factors such as income, employment, and health behaviors help determine current exposure of neighborhood context (confounder) but are also shaped by prior exposure to neighborhood context (mediator). By applying an MSM approach, estimates of neighborhood effects reflect the total (direct and indirect) effect of neighborhood context on the health outcome, thus providing a more causal interpretation of neighborhood effect estimates.

A growing number of studies are applying an MSM strategy to investigate the role of neighborhood context, particularly neighborhood disadvantage, on various health outcomes including alcohol consumption and propensity for binge drinking, self-rated poorer health, onset of disability, elevated depressive symptoms, mortality risk, cardiovascular disease, smoking initiation, and injection cessation among drug users (Glymour et al., 2010; Nandi et al., 2010; Do et al., 2013; Cerdá et al., 2010; Kravitz-Wirtz, 2016a, 2016b). With the exception of onset of disability and elevated depressive symptoms, adverse associations between neighborhood deprivation and the health outcomes being investigated were found. In many of the studies, the conventional naïve models that did not appropriately adjust for time-varying covariates generated null results, compared to the significant associations found via the MSM strategy (e.g., Cerdá et al., 2010; Nandi et al., 2010; Do et al., 2013). Hence, naïve regression strategies may not only underestimate the total effect of neighborhood disadvantage on health, but in some cases, may produce biased estimates that lead to different inferences.

To our knowledge, only one study has applied an MSM strategy to investigate the relationship between neighborhood context and body weight. Kravitz-Wirtz (2016b) examined the exposure to neighborhood disadvantage from birth through 17 years of age on incidence of obesity in early adulthood. Results indicated that exposure to neighborhood disadvantage during adolescence is associated with between 35 to 40% higher odds of being obese at least once between the ages of 18 and 30 years (Table 3: p. 555). Further, exposure to neighborhood deprivation during adolescence (ages 12–17 years) was found to be the most consequential period during childhood in predicting obesity incidence. Whether exposure to neighborhood deprivation during adulthood has similar impacts remain to be seen.

Our study builds upon the findings of Kravitz-Wirtz (2016b) by using an MSM approach to examine the relationship between exposure to neighborhood poverty during adulthood and subsequent body weight. Further, we apply sensitivity analyses to assess the extent to which MSM results are robust to unobserved confounding.

2. Materials and methods

We use the data from 1999 to 2013 years of the Panel Study of Income Dynamics (PSID) to investigate the association between neighborhood poverty and BMI. With initial data collection beginning in 1968, the PSID is a representative sample of the non-immigrant U.S. population with information on the baseline sample as well as their descendants and individuals who marry into the families. Extensive information on socioeconomic status and demographic characteristics were collected annually before 1997 and biennially thereafter. BMI and other health-related measures were consistently collected beginning in 1999. Throughout, information on the residential location of respondents at the time of each interview was collected. The resulting data provides a wealth of information at both the individual and neighborhood levels of a large sample of the U.S. population over an extensive period of time.

2.1. Outcome variable

BMI (kg/m^2) is calculated based on self-reported height (feet, inches) and weight (pounds) measurements collected from 1999 to 2013.

In all analyses, we specify BMI as three categories: normal (≥18.5 & < 25), overweight (≥25.0 & < 30), obese (≥30), reflecting the BMI category of the respondent. Respondents who were underweight (BMI < 18.5) at baseline were excluded from analyses.

2.2. Neighborhood exposure

Our area-level measure of interest is neighborhood poverty level, defined as the proportion of residents in a neighborhood that falls below the U.S. federal poverty level. We operationalize neighborhoods as census tracts, which are administrative areas designated by the U.S. Census Bureau. Though alternative proxies for neighborhoods exist, census tracts have been widely used in the U.S. neighborhood literature and is one of the few feasible strategies when using national data. In addition, census tracts boundaries respect major roads and rivers and are originally demarcated to capture a homogenous population. Census tracts have an average population size of approximately 4000 residents.

Neighborhood poverty measures are derived from the 1990 and 2000 Decennial Censuses, and the 2008–2012 American Community Survey (ACS) five-year estimates (the 2010 Decennial Census did not collect information on poverty levels). The 2008–2012 ACS neighborhood poverty measures were designated as the level for year 2010, the midpoint of the ACS data. Values for inter-census and ACS years were derived from linear interpolation and merged to the PSID via year and tract-level identifiers. Census tract boundaries were consistently defined per 2010 definitions. In 1999, the initial year for which exposure to neighborhood poverty is considered, the analytical sample consisted