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Short communication

An index of geospatial disadvantage predicts both obesity and unmeasured body weight

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ABSTRACT

Neighborhood context impacts health. Using an index of geospatial disadvantage measures to predict neighborhood socioeconomic disparities would support area-based allocation of preventative resources, as well as the use of location as a clinical risk factor in care of individual patients. This study tested the association of the Area Deprivation Index (ADI), a neighborhood-based index of socioeconomic contextual disadvantage, with elderly obesity risk. We sampled 5066 Medicare beneficiaries at the University of Missouri between September 1, 2013 and September 1, 2014. We excluded patients with unknown street addresses, excluded body mass index (BMI) lower than 18 or higher than 62 as probable errors, and excluded patients with missing BMI data. We used a plot of simple proportions to examine the association between ADI and prevalence of obesity, defined as BMI of 30 and over. We found that obesity was significantly less prevalent in the least-disadvantaged ADI decile (decile 1) than in all other deciles ($p < 0.05$) except decile 7. Obesity prevalence within the other deciles (2–6 and 8–10) was not significantly distinguishable except that decile 2 was significantly lower than decile 4. Patients with missing BMI data were more likely to reside in the most disadvantaged areas. There was a positive association between neighborhood disadvantage and obesity in this Midwestern United States Medicare population. The association of missing BMI information with neighborhood disadvantage may reflect unmeasured gaps in care delivery to the most disadvantaged patients. These preliminary results support the continued study of neighborhood socioeconomic measures to identify health disparities in populations.

1. Introduction

Obesity is a worldwide public health epidemic (World Health Organization, 2003). In the United States, more than a third of adults (Flegal et al., 2016) meet the World Health Organization criterion for obesity, a body mass index (BMI) of 30 or higher (World Health Organization, 2003). The adult obesity rate in every US state and territory is currently at least 20 percent, with nine states – Alabama, Arkansas, Iowa, Kentucky, Louisiana, Mississippi, Missouri, North Dakota, and West Virginia – having rates in excess of 35 percent (US Centers for Disease Control and Prevention, 0000). However, these nationwide rates mask critical disparities in the disease burden between persons of different socioeconomic conditions. Obesity risks are higher in socioeconomically disadvantaged neighborhoods with lower-income and less-educated populations (Wong et al., 2018; Powell-Wiley et al., 2014). The mechanisms for this effect may include inequality and other social stresses, reduced incentives, and inadequate means to reach health goals (Pampel et al., 2010). In the coming years, one population that will experience a disproportionate increase in the prevalence of obesity and the incidence of its comorbidities is the elderly (Samper-Ternent and Al Snih, 2012a). As “baby boomers” (individuals born between 1946 and 1964) age and obesity rates rise, an increase in the demands on health care is imminent. Furthermore, “baby boomers” currently have the highest obesity rates of any age group, exceeding 35 percent in 17 states (DeCaria, 2012; Fakhouri et al., 2012).

Neighborhood disadvantage is a fundamental factor in most mechanistic models of health disparities (US Department of Health & Human Services, 2018), and numerous studies have evaluated the relationship between individual socioeconomic factors and obesity in the elderly (Yen et al., 2009; Pruchno et al., 2014). However, many studies fail to acknowledge and subsequently adjust for confounding factors that have been demonstrated to influence obesity risk. To avoid this

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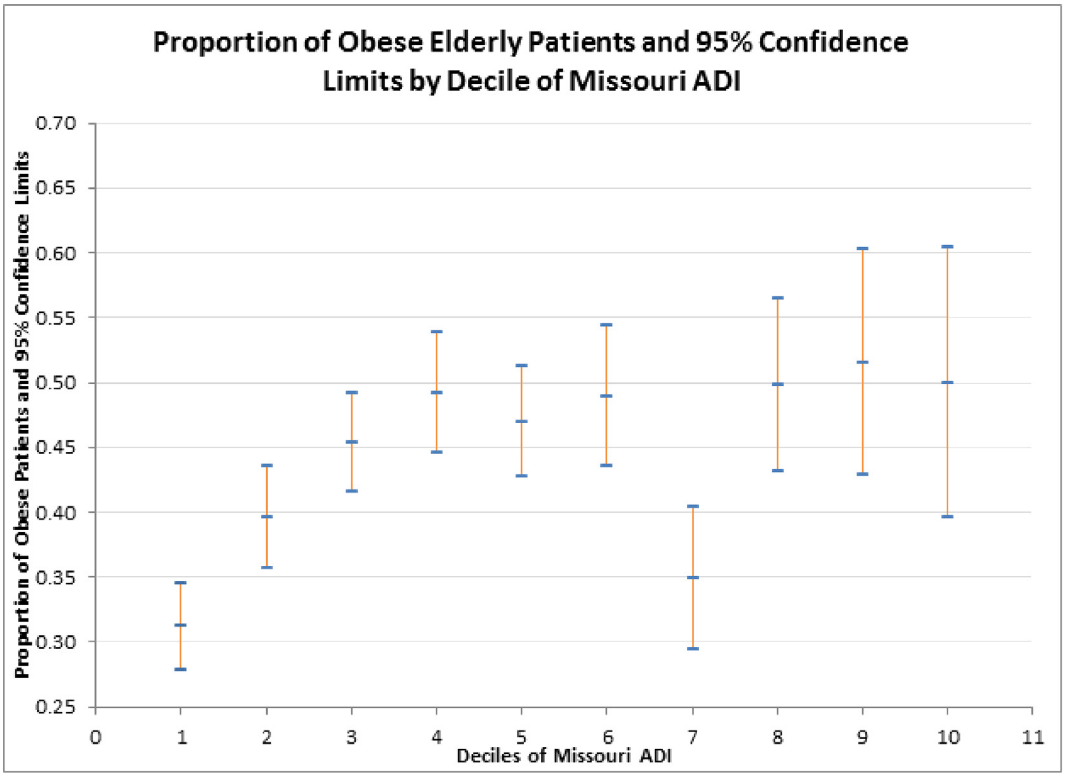

Fig. 1. Proportion of elderly patients with obesity by decile of Missouri ADI, University of Missouri, 1-Sep-2013 to 1-Sep-2014.

pitfall, this analysis considers confounding by the Area Deprivation Index (ADI), an area-based metric of socioeconomic disadvantage (Kind et al., 2014). Kind et al. (2014) updated the ADI with more current American Community Survey data and refined it to the census block group (or neighborhood) level.

The purpose of this study was to explore the association between socioeconomic status and obesity risk using the 2013 ADI in an elderly Midwestern United States (US) population. The intended purpose is to use the ADI as a geographic predictor of obesity risk, in order to assess local needs for health care intervention and inform the allocation of appropriate risk-management resources.

2. Methodology

2.1. Subjects

The study population comprised 5066 Medicare beneficiaries who were 65 years or older on September 1, 2014, and had received health care from the University of Missouri Health System in the previous 12 months. We excluded 296 patients for whom a post-office box was recorded as their mailing address, because we were unable to map their neighborhood of residence without a street address. We retrieved all patient diagnoses, demographics, and other clinical attributes from University of Missouri Health System medical records in compliance with the Institutional Review Board. We excluded another 713 patients because their BMI was not recorded, or their BMI was outside the expected range of 18–62 and thus likely recorded erroneously. These exclusions resulted in a study population of 4057 patients. All identifiers from these records were removed except mailing address, height, weight, BMI, age, sex, race, and ethnicity.

2.2. Data sources

The 2013 ADI includes 17 markers of socioeconomic status, including education level, employment, income, and level of poverty, which can be used to rank neighborhoods within a geographic region (Kind et al., 2014). Dr. Kind and her team at the University of Wisconsin School of Medicine and Public Health generated the ADI metrics used in this study from 2009 to 2013 American Community Survey data at the neighborhood level, where “neighborhoods” were defined as US Census block groups. ADI scores for all populated block groups in Missouri ranged from negative 62.6 to positive 138.3. A high score indicates higher levels of disadvantage while a low score is assigned to areas of lower disadvantage, or higher socioeconomic status. For better interpretability, we grouped the scores into deciles for use in our analysis. The 2013 ADI is freely available through the University of Wisconsin’s Neighborhood Atlas (Kind and Buckingham, 2018).

2.3. Statistical analysis

We divided raw ADI scores for Missouri into deciles and classified each patient by ADI decile based on their mailing address as of October 1, 2014. We used logistic regression to examine the association between obesity and ADI with adjustment for patient age, sex, and race/ethnicity. The dependent variable was obesity, defined as a BMI ≥ 30 based on the patient’s most recent clinical measurement of height and weight as of October 1, 2014. Prior to the regression analysis, we plotted the empirical logit against age and against ADI decile. The relationship between logit and age was linear, but the relationship was neither linear nor curvilinear for the ADI deciles; therefore, we treated the ADI decile as a nominal-scale independent variable. We treated race/ethnicity as an independent variable with three categories: Caucasian non-Hispanic, African American, and Other.

3. Results

Fig. 1 shows the prevalence of obesity in patients from neighborhoods in each of the ADI deciles, with confidence intervals of 95 percent. Obesity was significantly ($p < 0.05$) less prevalent in ADI decile 1 (least disadvantaged) than in any other ADI decile, except decile 7.

Table 1
Distribution of elderly primary-care patient characteristics, University of Missouri, 1-Sep-2013 to 1-Sep-2014.

Continuous Variables	Mean	Standard Deviation
Age (years)	75.9	7.5
BMI	30.6	7.0
Categorical Variables	Percent in Study Sample	Percent in US Population (US Census Bureau, 2014)
Female	60%	51%
Male	40%	49%
Caucasian non-Hispanic	92%	73%
African American	6%	13%
Other race/ethnicity	2%	14%
Decile of Missouri ADI	Number of Patients	Percentage with Missing BMI
Decile 1	757	11%
Decile 2	599	12%
Decile 3	665	14%
Decile 4	445	17%
Decile 5	532	17%
Decile 6	327	17%
Decile 7	295	17%
Decile 8	219	21%
Decile 9	128	20%
Decile 10	90	20%

Prevalence rose from 32 percent in the least disadvantaged to 50–52 percent in the three most-disadvantaged deciles. The positive trend plateaued at about 50 percent in deciles 4–10 except for a significant decrease in decile 7. No other inter-decile differences were significant.

To further examine the impact of decile 7, we fit the models to all data including decile 7, and to the data excluding decile 7. The minimal changes in significance levels and odds ratios were not statistically significant. The patients in decile 7 were older than the overall study population (mean age 78.0 years versus 75.9 years overall), more likely to be female (65% versus 60% overall), and less likely to be Caucasian non-Hispanic (90% versus 92% overall). The age difference between obese and non-obese persons in decile 7 was 5.0 years, almost twice the difference of 2.6 years in the other deciles combined. Refitting the logistic model with age as a simple linear term and without other covariates, the odds ratio associated with a 5-year increase in age was 0.756, which accounted for the lower obesity rate among the older population in decile 7.

Table 1 shows the distribution of demographic characteristics in the study sample, before excluding patients with missing BMI values. Missing BMI values were more prevalent in more disadvantaged areas, with an R-squared value of 0.8755. For sex and ethnicity/race, the corresponding demographic characteristics for the entire United States are shown for comparison (US Census Bureau, 2014).

4. Discussion

The mechanisms for the effect of disadvantage on obesity may include neighborhood-level "collective efficacy" (Cohen et al., 2003) in addition to individual exposure to inequality and other social stresses, reduced incentives, and inadequate means to reach health goals (US Department of Health & Human Services, 2018). A positive association between neighborhood disadvantage and obesity supports the arguments for community-based health services, improved public resources such as sidewalks and parks, and policies that support local economic development.

The higher prevalence of missing BMI values in more disadvantaged areas is concerning for the disparities in care delivery it suggests. While our study was not designed to answer questions about the reasons for this disparity in clinical data collection, it is possible that clinicians' implicit biases against disadvantaged patients and patients with obesity (Blair et al., 2011) could result in less systematic BMI measurement and obesity screening, which could reduce the quality of care for the very patients who are most vulnerable to obesity and its effects.

Under-monitoring of BMI may be more extensive in this highly rural population than in other less-rural US populations (Ford et al., 2016); but BMI may be monitored even less in communities with more African Americans and other non-Caucasians (Brown et al., 2016; Wielen et al., 2015), which were underrepresented in this sample relative to the US as a whole (see Table 1). Because rural patients were overrepresented while non-Caucasians were underrepresented in our sample, relative to the US as a whole, and because lack of access to high-quality primary care is a problem of similar magnitude for both these populations (Ford et al., 2016; Brown et al., 2016; Wielen et al., 2015), it's likely that the net effect makes these results generally representative of the problem of under-screening for obesity in US health-disparities populations.

We found a positive association between ADI and obesity in this population, except for a sharp and significant decrease in obesity among those in decile 7. Among the elderly, the odds of obesity decline with age, possibly because obese persons have shorter lifespans (Xu et al., 2018). Because the relationship between age and obesity was strong in this population, with a 24% reduction in the odds of obesity for each 5-year increase in age, the higher average age and higher age difference for non-obese persons in decile 7 had a strong effect on the linear regression when ADI was treated as a nominal-scale variable. The decile 7 results may be due to the particular sample within this study, or they could reflect a condition within the ADI dataset.

This study had some limitations, including uncertainty about its generalizability to populations outside the Medicare population, to the Missouri population with its slightly greater racial/ethnic diversity than in our study sample, and to populations outside Missouri. We used BMI as the outcome of interest because it is widely available and reproducible, but it may not be the best measure of obesity because it is an indirect measure of body fat, and because it does not reflect the changes that occur with age (Rothman, 2008). Future research should address these limitations by expanding the study population, replacing BMI with percentage of body fat where possible, and investigating whether age, sex, race/ethnicity, and rurality account for the unexpectedly low rates of obesity in decile 7 of the ADI in this sample. A more recent nationwide ADI database is now available (Kind and Buckingham, 2018), and should be used for future studies. ADI can also serve as a predictor for other important health disparities such as chronic disease prevalence (Sheets et al., 2017) and readmission rates (Kind et al., 2014), and future studies are needed to investigate these associations.

The ADI serves as an inclusive index of socioeconomic contextual disadvantage at the neighborhood level. The two major findings of this study point to the need for changes in public and institutional policies. First, the association of neighborhood socioeconomic disadvantage with obesity risk supports efforts to ameliorate the social stresses and disadvantages that may contribute to the epidemic of obesity (Samper-Ternent and Al Snih, 2012b). Second, the association of neighborhood socioeconomic disadvantage with missing BMI data may point to concerns regarding access to care for the most vulnerable in our society.

CRediT authorship contribution statement

Lincoln R. Sheets: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Laura E. Henderson Kelley:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Kristen Scheitler-Ring:** Validation, Visualization, Writing - original draft, Writing - review & editing. **Gregory F. Petroski:**

Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - review & editing. **Yan Barnett:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing - review & editing. **Chris Barnett:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Amy J.H. Kind:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - review & editing. **Jerry C. Parker:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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