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Article

Overlapping geographic clusters of food security and health: Where do social determinants and health outcomes converge in the U.S?

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ABSTRACT

We identified overlapping geographic clusters of food insecurity and health across U.S. counties to identify potential shared mechanisms for geographic disparities in health and food insecurity. By analyzing health variables compiled as part of the 2014 Robert Wood Johnson Foundation County Health Rankings, we constructed four health indices and compared their spatial patterns to spatial patterns found in food insecurity data obtained from 2014 Feeding America's County Map the Meal Gap data. Clusters of low and high food security that overlapped with clusters of good or poor health were identified using Local Moran's I statistics. Next, multinomial logistic regressions were estimated to identify sociodemographic, urban/rural, and economic correlates of counties lying within overlapping clusters. In general, poor health and high food insecurity clusters, "unfavorable cluster overlaps", were present in the Mississippi Delta, Black Belt, Appalachia, and Alaska. Overlapping good health and low food insecurity clusters, "favorable cluster overlaps", were less common and located in the Corn Belt and New England. Counties with higher black populations and higher poverty were associated with an increased likelihood of lying within overlapping clusters of poor health and high food insecurity. Generally consistent patterns in spatial overlaps between food security and health indicate potential for shared causal mechanisms. Identified regions and county-level characteristics associated with being located inside of overlapping clusters may be used in future place-based intervention and policy.

1. Introduction

Food insecurity–defined as inconsistent access to adequate food due to lack of financial and other resources–is a persistent problem in the US, particularly among low-income populations (Alisha Coleman-Jensen, Gregory, & Singh, 2014). Likewise, these same low-income populations are often more likely to have higher rates of poor health outcomes. However, little work has been done to understand the degree to which these two population health issues overlap. We fill this gap by examining the degree of spatial overlap of food insecurity and poor health in US counties.

1.1. Food Insecurity

Between 2007 and 2009, during the financial recession, the US food insecurity rate rose from 11% to 14% (Rabbitt, Coleman-Jensen, & Gregory, 2017). Since that time, overall economic conditions in the US have improved, but food insecurity rates have not returned to pre-recession levels. Roughly a quarter of the US population participates in some form of public nutrition assistance program aimed at alleviating food insecurity. These programs include the Supplemental Nutrition Assistance Program (SNAP), Women Infants and Children (WIC), or school meal programs. While food insecurity is associated with worse economic well-being, not all low-income populations and places face the same degree of food insecurity (Alaimo, 2005; Coleman-Jensen, Rabbitt, Gregory, & Singh, 2017; Rose, 1999). For example, 33% of households earning incomes below the federal poverty threshold reported no food insecurity (Wight, Kaushal, Waldfogel, & Garfinkel, 2015). Further, among SNAP participants, those living in areas with higher food prices were 5% more likely to report food insecurity than those living in average-priced food areas (Gregory & Coleman-Jensen, 2013). Food insecurity rates are similar when comparing urban and rural areas, despite the fact that poverty conditions are often worse in rural areas (Brown & Hirschl, 1995; Gundersen, Dewey, Hake, Engelhard, & Crumbaugh, 2017). One hypothesis about why food insecurity and poverty do not correlate geographically is that the spatial

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distribution of charitable food services (i.e. food banks, federal program participation, etc.) is uneven, thus resources to combat food security are more abundant in some high poverty areas than others (Gundersen et al., 2017). Thus, while higher food insecurity rates are expected in counties with higher poverty rates, the spatial pattern of food insecurity is not necessarily the same as the spatial pattern of poverty.

1.1.1. Relationship between food insecurity & health

A growing literature has established robust relationships between food insecurity and worse health. Food insecure households have difficulty meeting basic needs such as refilling medical prescriptions (Afulani, Herman, Coleman-Jensen, & Harrison, 2015) and providing adequate nutrition (Duffy, Zizza, Jacoby, & Tayie, 2009). Food insecurity is associated with poorer self-rated mental and physical health among adults (Alaimo, 2005; Stuff, Casey et al., 2004; Stuff, Horton et al., 2004) and food insecure households with children have higher risk of iron deficiency and poorer dental outcomes (Chi, Masterson, Carle, Mancl, & Coldwell, 2014; Skalicky et al., 2006).

Policy solutions for improving food insecurity and health are geographic in nature. A sophisticated network of regional food banks and component pantries associated with Feeding America exists throughout the United States. These organizations work to match available food resources (e.g. surplus retail supplies, USDA funded food items) with households in need (Prendergast, 2017), and each of these food banks has a geographically-bounded distribution region. Federal food assistance programs (i.e. SNAP and WIC) also vary by state. For example, SNAP may be administered at the county or state level, may be jointly administered with other federal programs such as Medicaid or Temporary Assistance for Needy Families (TANF), require various types of household reporting standards, and vary in eligibility standards (United States Department of Agriculture, 2018). Additionally, healthcare systems and health services providers generally serve distinct geographic regions; and healthcare policies such as those impacting Medicaid and Medicare eligibility vary at the state level.

Our work fills an immediate gap in our understanding of the relationship between food insecurity and poor health by focusing on the geographic patterns of these two inter-related aspects of well-being. We use novel spatial statistical methods to identify overlapping geographic clusters—i.e., regions with significant burdens of both poor health and high food insecurity—and assess correlates of these spatial patterns. Our results lay the foundation for future population health research efforts to understand the shared mechanisms and pathways driving observed relationships between food insecurity and poor health. Our results also have implications for intervention. For example, they may be used to prioritize place-based multi-sector collaborations between food assistance and healthcare safety-net systems in contexts in which dual burdens of poor health and food insecurity are likely to be high.

2. Materials and methods

We examined county-level health and food insecurity measures for every US County with available data (n = 3142). Data analysis took place between Jan 15 and December 29, 2017.

2.1. Variables

The percent of the population that is food insecure was obtained from Feeding America's Map the Meal Gap (MMG) 2014 data; the methodology is described in detail elsewhere (Gundersen, Engelhard, Satoh, & Waxman, 2016). These data use Current Population Survey (CPS) food security measures, which are based on the Core Food Security Module established in 1996 by the USDA as a means of measuring food insecurity status of households (Gundersen et al., 2017; Gundersen & Ziliak, 2015; Herman, Afulani, Coleman-Jensen, & Harrison, 2015). Reliability of the estimated food insecurity measures has been established in the literature (Gundersen, Engelhard, & Waxman, 2014).

Health variables were obtained from the Robert Wood Johnson Foundation County Health Rankings (CHRs) data (Roberty Wood Johnson Foundation, 2017). We identified variables reflecting the percent of each county's population –or the population of the county's Medicare enrollees-experiencing a health condition or behavior and did not include ranked data. Unless otherwise noted, variables procured from the CHRs data were provided by the Behavioral Risk Factor Surveillance System (BRFSS) (Center for Disease Control and Prevention, 2015). Variables were grouped into 4 constructs. *Food-related Population Health Indicators* include percentage of obese adults (body mass index > 30), and percent of Medicare enrollees living with diabetes as reported by the Dartmouth Institute (DI). *Preventive Health Behaviors* include the percent reporting insufficient sleep, percent of Medicare enrollees current with mammography screening reported by DI, percent of adults who smoke, and the percent of adults reporting no leisure-time physical activity. *Indicators of Poor Physical Health* include average number of reported physically unhealthy days in the past month, percent reporting fair/poor health, years of potential life lost rate per 100,000 reported by the National Center for Health Statistics (NCHS), and percent reporting frequent physical distress. Finally, *Indicators of Poor Mental Health* include the average number of reported mentally unhealthy days per month and percent reporting frequent mental distress.

County-level socio-demographic data were obtained from the US Census American Community Survey (ACS) 2011–2015 5-year estimates. Variables ascertained include race/ethnicity (percent of population that is non-Hispanic (NH) black, percent Hispanic, percent NH white, and percent Native American), percent of households below poverty, percent of adults unemployed, indicator for female headed households, percent foreign born, and population density. In addition, 2013 Rural-Urban Continuum Codes (also known as Beale Codes) were obtained from the USDA Economic Research Service (USDA, 2017).

3. Calculation

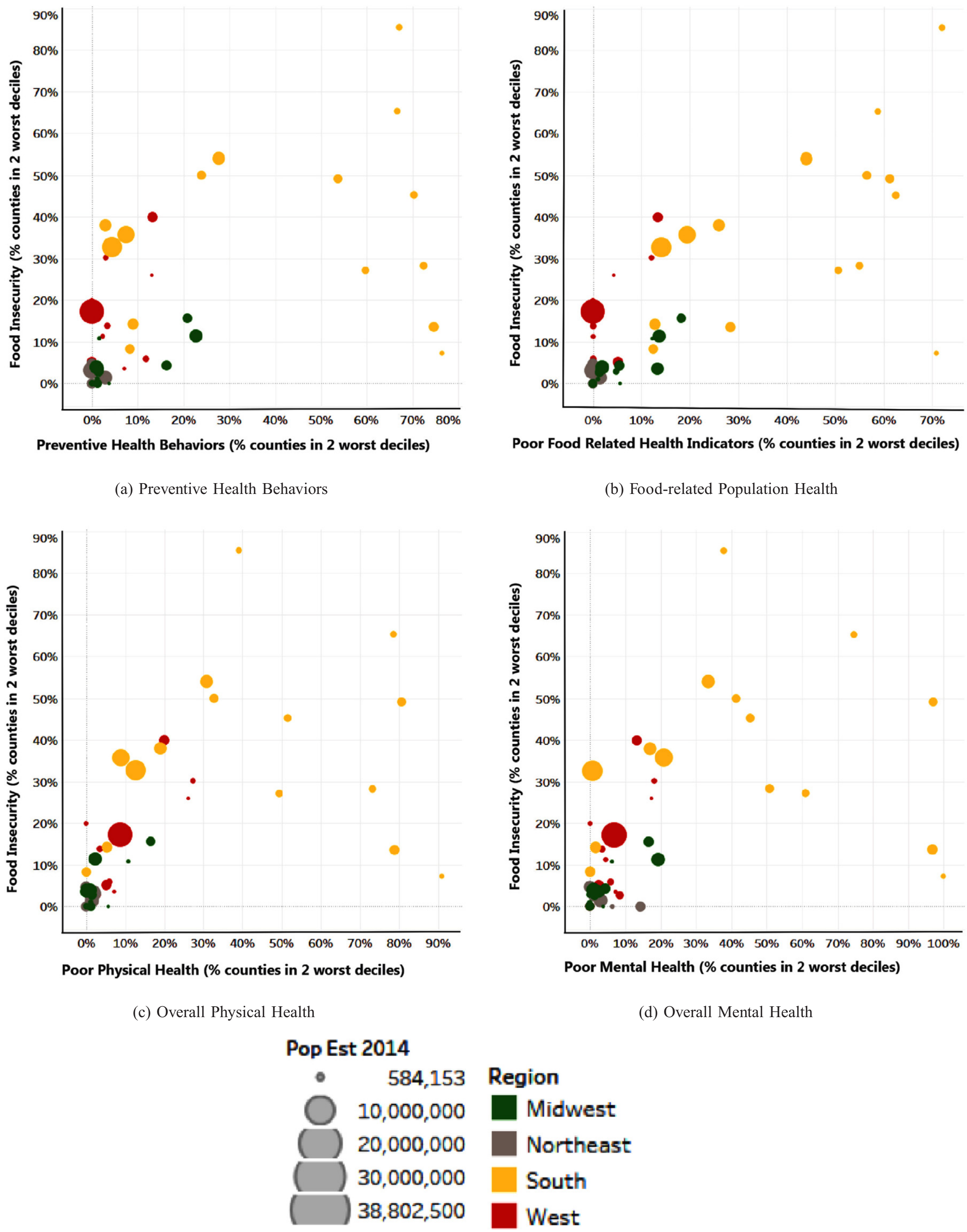
We assessed internal consistency reliability of each construct using Cronbach's alpha. To facilitate comparative analysis across US counties, each variable was standardized and reverse coded as needed so that higher values indicate more unfavorable outcomes. The standardized variables for each construct were then averaged. The construct average for each county was assigned a decile ranking with higher deciles representing more unfavorable outcomes.

To assess the relationship between food insecurity and each health construct, we created scatter plots. The plots quantify the population burden and regional distribution of residents living in counties experiencing high food insecurity and poor health and the relationship between food insecurity and poor health. The plots demonstrate how many counties are in the worst 2 deciles of both well-being indicators and show the distribution of by population size and U.S. region (Midwest, Northeast, South, West).

In order to assess the spatial distribution of clusters of counties with similar measures, we conducted univariate cluster analysis for each health construct and for food insecurity as separate variables. Univariate cluster analysis was implemented by calculating local Moran's I statistics to identify geospatial clusters of both high and low food insecurity and health. To account for multiple hypothesis testing, we implemented the Benjamini-Hochberg method for adjusting p-values. Clusters with adjusted p-values < 0.10 were selected as statistically significant.

Next we conducted bivariate analysis. We identified counties located in *overlapping clusters* of both high food insecurity and poor health constructs as having *unfavorable outcomes*, and counties located in overlapping clusters of both low food insecurity and good health as having *favorable outcomes*.

For each health construct, we created categorical variables to indicate whether counties were in overlapping favorable, unfavorable or



(a) Preventive Health Behaviors

(b) Food-related Population Health

(c) Overall Physical Health

(d) Overall Mental Health

Fig. 1. Scatter plots of health constructs and food insecurity demonstrating the percent of counties in worst 2 deciles and distribution by population size and US region.

no overlapping clusters. To identify socio-demographic and economic characteristics associated with overlapping clusters, we estimated multinomial logistic regression models. In robustness analysis, we estimated regression models using the individual health indicators to understand whether spatial patterns observed in the primary construct-level analysis were robust across each health indicators taken individually as well as to alternative definitions of poverty (i.e 185% and 200%). In additional robustness tests, we explored potential interactions between race/ethnicity and urbanity because previously documented differences in urban/rural inequality and food resources suggests that food insecurity and health outcomes for minorities may differ depending upon urbanity (Gundersen et al., 2017; Peters, 2012).

4. Results

A summary of the 4 health constructs and food security data examined are provided in the appendix (Table A1). Cronbach alphas for the health constructs ranged from .61 to .82. This indicates that the

Table 1
Frequency of spatial cluster overlap patterns among US counties (N = 3142)[a,b], by health construct.

	# of Counties in Overlapping Clusters of Health and Food Insecurity		
	Favorable Overlaps (Good health, low food insecurity)	**Unfavorable Overlaps** (Poor health, high food insecurity)	**Mixed Overlaps** (Good health, high food insecurity -OR- poor health, low food insecurity)
Preventive Health Behaviors	**37**	**127**	**0**
Sleep	49	136	0
Mammography	33	22	17
Smoking	16	83	0
Physical Activity	27	100	0
Food Related Population Health	**24**	**154**	**3**
Obesity	12	104	0
Diabetes	34	159	8
Overall Physical Health	**87**	**132**	**6**
Physically Unhealthy Days	94	115	3
Self-rated Health	35	144	7
Frequent Physical Distress	86	127	7
Overall Mental Health	**100**	**112**	**0**
Mentally Unhealthy Days	101	100	0
Frequent Mental Distress	97	125	0

This includes 2978 (Preventive Health Behaviors), 2961 (Food Related Population Health), 2917 (Overall Physical Health), and 2930 (Overall Mental Health) counties.

[a] There are 3137 US counties, but the table results include only counties with available data.

[b] Counties that did not lie within a cluster overlap were not enumerated in the table.

items comprising a single construct have a moderately high level of association. Fig. 1 shows a general positive association between food insecurity and poor health: higher food insecurity is associated with worse health. For each health construct, the greatest dispersion in these associations and the counties with the poorest outcomes were located in the South.

4.1. Spatial patterns of health constructs and food security

The distribution of counties in overlapping clusters of food insecurity and health are provided by health construct and individual health indicators in Table 1. In general, more counties were located in unfavorable overlapping clusters, compared to favorable overlaps; and even fewer counties were located in mixed overlaps (i.e. poor health and low food insecurity or vice versa).

Overlapping clusters of food insecurity and health are mapped in Fig. 2. Red indicates counties located within unfavorable clusters of both poor health and high food insecurity. Blue indicates counties within favorable clusters of both good health and low food insecurity. The patterns are consistent with those shown in Fig. 1: unfavorable clusters are more likely in the South, while favorable clusters are more likely in the Northeast and Midwest. While patterns are largely similar across all health outcomes, there are some notable differences. Favorable food-related population health clusters were concentrated fairly equally across the Eastern and Midwest regions, while all other favorable clusters were more likely in the Midwest. Additionally, overall physical and mental health had unfavorable clusters in the western US, where other outcomes did not show any cluster overlaps in these areas. Finally, Alaska does not have any overlapping clusters for food-related population health outcomes, but contains counties in unfavorable cluster overlaps for each of the other 3 constructs.

4.2. Multinomial logistic regression

Coefficient estimates for the multinomial logistic regression models are provided in Table 2. The dependent variable for the models estimated in Table 2 is a categorical variable indicating favorable cluster overlaps (dependent variable = 1) and unfavorable cluster overlaps (dependent variable = 2). The dependent variable takes on a value of 0 for the case when a county either does not lie in a cluster overlap or is in a mixed cluster overlap. High poverty counties are both more likely to lie within unfavorable clusters and less likely to lie within favorable clusters. Lower unemployment increases the likelihood of a county being located in a cluster of favorable outcomes for all constructs except Food-related Population Health. Favorable Food-related Population Health clusters are also significantly more likely in counties with larger foreign-born populations. Counties with larger American Indian populations are less likely to be in favorable clusters of Food-related Population Health, but more likely to be in favorable clusters of Mental Health. Counties with a larger black population and smaller foreign-born population are more likely to lie in unfavorable clusters for all health constructs. Additionally, fewer female-headed households are associated with lower likelihood of unfavorable clusters of Preventive Health Behaviors. Finally, with the exception of Preventive Health Behaviors, less densely populated counties are more likely to lie within unfavorable clusters, but the effect size is very small.

The county characteristics most commonly associated with overlapping clusters and having the most substantial effect size were percentage black population and poverty. Marginal effects for each of these independent variables are presented in Figs. 3 and 4 respectively. These figures demonstrate how changes in each county-level covariate (in standard deviations from the mean, denoted on the x axis) are associated with probability (denoted on the y axis) of a county being in unfavorable (in red) or favorable (in blue) overlapping clusters for each health construct when all other covariates were held constant. The higher the proportion of black population (Fig. 3), the more likely unfavorable cluster overlaps. This effect is strongest for clusters of Food-Related Population Health. Results for poverty (Fig. 4) are twofold: favorable clusters are more likely in low poverty counties, while unfavorable clusters are much more likely in high poverty counties. When approximately 20% of the county population has income less than the federal poverty income threshold, the likelihood of being in an unfavorable cluster increases until approximately 70% of the population is below this threshold, at which point it levels off.

4.3. Robustness checks

The association between county characteristics and univariate food insecurity clusters as well as overlapping clusters of food insecurity and each individual health variable were examined independently. Results

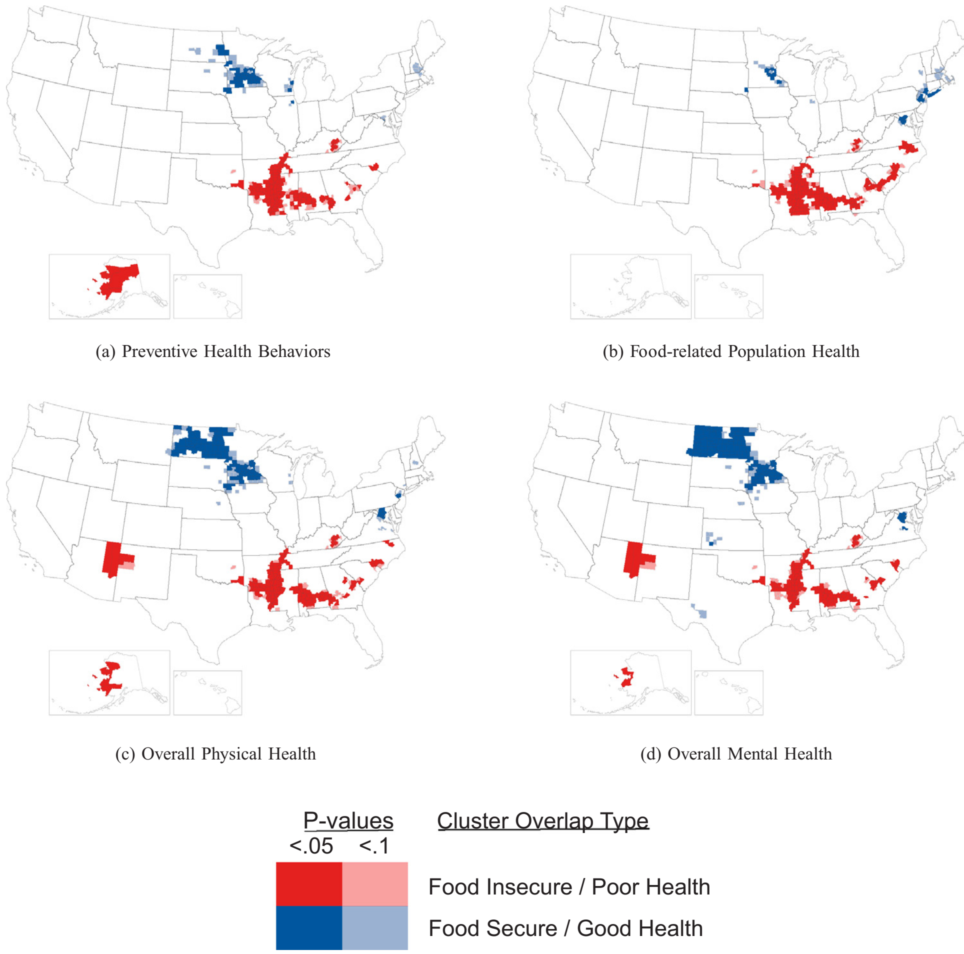


Fig. 2. Overlapping clusters of favorable/unfavorable food insecurity and health, by health construct. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

are presented in the Appendix Table A2 (Univariate Food Insecurity clusters; Overlapping Preventive Health and Food-related Population Health clusters) and Table A3 (Overall Physical and Mental Health clusters). Univariate clusters of high food insecurity are associated with counties with higher proportion black residents, higher poverty, and lower population density. In contrast, univariate clusters of low food insecurity are associated with counties with lower poverty, lower unemployment, lower proportion of Native Hawaiian residents, and higher proportion of American Indian and foreign-born residents.

Across all bivariate cluster overlap models, poverty is strongly associated with overlapping clusters: high poverty counties are more likely to be located in unfavorable clusters and less likely to located in favorable clusters. Higher proportion black residents is also associated with clusters of unfavorable outcomes in almost all models; the exceptions is mammography. Additionally, a larger foreign born population is associated with slightly decreased likelihood of unfavorable clusters across many models except for mammography and insufficient sleep. Low unemployment is also associated with an increased likelihood of favorable clusters for all health variables except smoking, physical activity, and obesity.

A striking result from our initial models was the clear poverty-related threshold around which the likelihood of a county being in overlapping clusters of unfavorable outcomes increased dramatically. In additional analysis (results available upon request), we tested the robustness of this threshold for alternative specifications of poverty (i.e. percent of the population below 185% and 200% of poverty). For these specifications, the threshold remained, and was located at around 50% of the population being below the 185% and 200% of poverty threshold.

To further explore variation in the impacts of race across urban/rural contexts, in separate models, we interacted race with indicators of rural (RUCC code 7 or 8) and urban (RUCC code 1) context. The results are consistent with our prior findings. We found that minority groups in rural areas were more likely to be in overlapping clusters of bad outcomes and/or less likely to be in overlapping clusters of good outcomes. Additionally, the increase in likelihood of being located within an unfavorable overlapping clusters of poor food related population health outcomes and high food insecurity was attenuated slightly for black communities in large urban areas, but still higher proportion black is associated with increased likelihood of being within unfavorable overlapping clusters.

5. Discussion

Our results illustrate well-defined spatial patterns in various health outcomes and food insecurity. The strongest, most robust county-level predictors of these patterns were poverty and higher proportions of black populations. While the association between poverty and food insecurity is expected; the robustness of the association between poverty and all measured health outcomes underscores the need for continued focus on the social determinants of health. Our findings suggest that these determinants should be studied and addressed using a spatial lens.

Importantly, the southern region of the US contains the largest proportion of overlapping clusters of unfavorable outcomes. This finding builds on documented high rates of food insecurity in the Mississippi Delta region (Stuff, Horton et al., 2004). However, the

Table 2
Estimated association between county characteristics and cluster overlap[a] (N = 3142), by health construct.
Relative risk ratios are reported with 95% confidence intervals in parenthesis.

	Preventive Health Behaviors	Food Related Population Health	Overall Physical Health	Overall Mental Health
Favorable Overlaps: Overlapping Clusters of Good Health and Low Food Insecurity				
% Black	0.885** (0.822, 0.952)	0.996 (0.937, 1.06)	0.992 (0.94, 1.046)	0.966 (0.902, 1.034)
% American Indian	0.872 (0.71,1.07)	0.686* (0.471, 0.999)	0.996 (0.905,1.097)	1.083** (1.03, 1.139)
% Asian	1.205* (1.045, 1.389)	1.075 (0.979, 1.179)	1.14** (1.037, 1.253)	1.083 (0.976, 1.202)
% Native Hawaiian_Pacific Islander	0.164 (0.006, 4.385)	0.077 (0.003, 1.846)	0.197 (0.025, 1.553)	0.159+ (0.021, 1.213)
% other race	0.928 (0.775, 1.112)	0.938 (0.789, 1.115)	0.891+ (0.784, 1.013)	0.897+ (0.799, 1.007)
% Below Poverty	0.751*** (0.685, 0.824)	0.535*** (0.416, 0.687)	0.764*** (0.707, 0.827)	0.811*** (0.759, 0.866)
% Unemployed	0.998** (0.997, 0.999)	1.00 (0.998, 1.002)	0.995*** (0.994, 0.996)	0.995*** (0.994, 0.996)
% Female Headed Households	1.001 (0.999, 1.003)	1.001 (0.999, 1.003)	0.999 (0.998, 1.001)	0.999+ (0.998, 1.00)
% Foreign Born	1.00 (0.998, 1.001)	1.001** (1.00, 1.002)	1.00 (0.999, 1.001)	1.00 (1.00, 1.001)
Population Density[a]	0.999 (0.998, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)
Unfavorable Overlaps: Overlapping Clusters of Poor Health and High Food Insecurity				
% Black	1.046*** (1.024, 1.069)	1.103*** (1.073, 1.134)	1.051*** (1.028, 1.075)	1.043*** (1.02, 1.067)
% American Indian	0.936* (0.886, 0.988)	0.937* (0.89, 0.987)	0.99 (0.959, 1.023)	0.973 (0.936, 1.011)
% Asian	0.774 (0.408, 1.468)	0.734 (0.375, 1.436)	1.014 (0.713, 1.442)	1.035 (0.703, 1.524)
% Native HawaiiamPacific Islander	0.389 (0.034, 4.396)	1.192 (0.25, 5.682)	0.967 (0.429, 2.179)	1.071 (0.744, 1.541)
% other race	0.962 (0.854, 1.082)	1.035 (0.955, 1.121)	0.985 (0.902, 1.075)	0.996 (0.924, 1.073)
% Below Poverty	1.206*** (1.136, 1.281)	1.236*** (1.159, 1.319)	1.22*** (1.158, 1.285)	1.246*** (1.181, 1.316)
% Unemployed	0.999+ (0.998, 1.00)	1.00 (0.999, 1.001)	1.00 (1.00, 1.001)	1.00 (1.00, 1.001)
% Female Headed Households	1.002** (1.00, 1.003)	1.001 (1.00, 1.002)	1.00 (0.999, 1.002)	1.001 (1.00, 1.002)
% Foreign Born	0.998* (0.997, 1.00)	0.997* (0.994, 1.00)	0.999* (0.998, 1.00)	0.998** (0.997, 1.00)
Population Density[a]	0.987** (0.978, 0.997)	0.993*** (0.99, 0.997)	0.993* (0.988, 0.998)	0.99* (0.981, 0.999)

** $p < 0.01$.
* $p < 0.05$.
+ $p < 0.10$.
*** $p < 0.001$.
[a] The dependent variable for the models is a categorical variable indicating favorable cluster overlaps (dependent variable =1) and unfavorable cluster overlaps (dependent variable=2). The dependent variable takes on a value of 0 for the case when a county either does not lie in a cluster overlap or is in a mixed cluster overlap. Models were estimated using multinomial logistic regression.

scatter plots also reveal that the Southern region also has the largest degree of dispersion in the association between health and food insecurity. Future work might explore if the geographic distributions of poverty and race/ethnicity in the Southern region might be related to these patterns. Further, we found that the correlation between high proportion black and unfavorable cluster overlaps was slightly less in urban areas than in rural ones. Future work will be needed to best target, adapt, and deliver food assistance and healthcare safety net services to rural, black regions of the U.S.

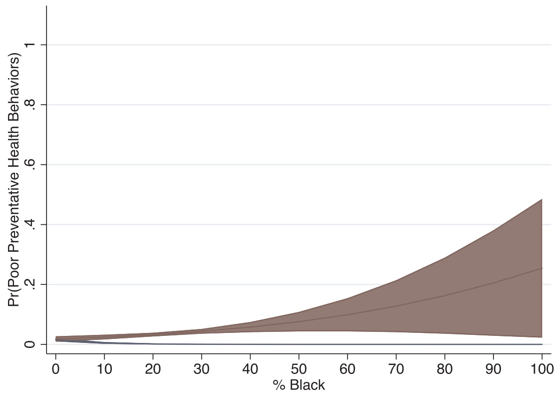
Several study limitations are a result of data estimation. First, food security data at the county level comes from Map the Meal Gap, which uses an algorithm to extrapolate food security measures for counties in which the current population survey does not have a high enough sampling rate (Gundersen et al., 2016). Likewise, county-level estimates for BRFSS data are generated using small-area estimation techniques. Thus, the food insecurity measure and some health outcomes may have some bias which we cannot quantify. In particular, the two variables that we found to be most highly related to spatial cluster overlaps (poverty and proportion black population), along with other variables not included in our study, are also used to predict food insecurity. It is possible that this produces an upward bias in the estimates of the relationship between these variables and spatial cluster overlaps. Assessment of bias may benefit from comparison of predictors of food security and cluster overlaps. Coefficients for the models used to estimate food insecurity are available in the Map the Meal Gap Technical Brief (Gundersen et al., 2016). In these models proportion black population is not a statistically significant predictor of food insecurity and the unemployment rate is the most consistent predictor of food insecurity. In contrast, our models found that unemployment was relatively weak correlate of cluster overlaps, but proportion black was a strong correlate of cluster overlaps. Poverty was a predictor of both estimated food insecurity and cluster overlaps.

Our study has a few other limitations related to the interpretation of results. In a few very sparsely populated counties, reliable small area estimates were not available and these counties are excluded from our analysis. However, in general, our results are representative of the US population. Second, because this is a cross-sectional study, results are only associative. Nevertheless, results are valuable for stimulating additional causal research questions to better explain the geospatial mechanisms driving the social determinants of health. Finally, cluster overlap results may be driven by specific spatial patterns in food security and/or other individual health variables that comprise the 4 constructs examined in our main results rather than being representative of all outcomes that comprise a given health construct. However, most results are robust across the different individual health outcomes examined.[1]

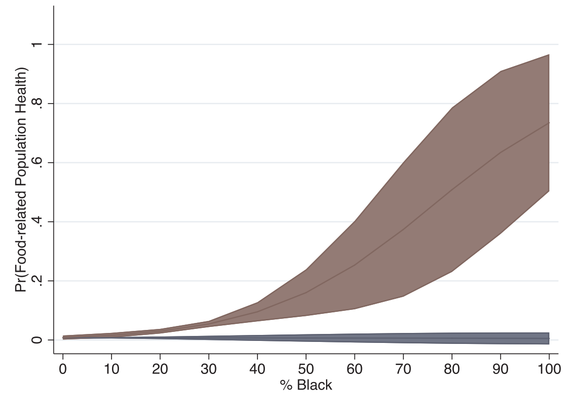
Because food insecurity data at any sub-state geographic level must be estimated, research (including the present study) is limited in its ability to analyze geospatial patterns in food security that are not influenced to some extent by the possibility of estimation error. The present study should serve as a demonstration of the types of analysis that can and likely should be undertaken at more granular geographic levels and of the need for granular, georeferenced food insecurity data to support these analyses. It is unlikely that the needed data will become available soon at a nationally representative level, but local area analysis might be undertaken by researchers working in conjunction with the food assistance sector, particularly regional food banks.

Importantly, most of the health indicators examined are not directly linked to nutrition; yet they exhibit similar spatial patterns as food insecurity. Further, the striking similarities in spatial patterns of overlapping food insecurity and health clusters suggest that mechanisms driving geographic patterns in health may also drive geographic patterns in food insecurity. Our results highlight the important role that

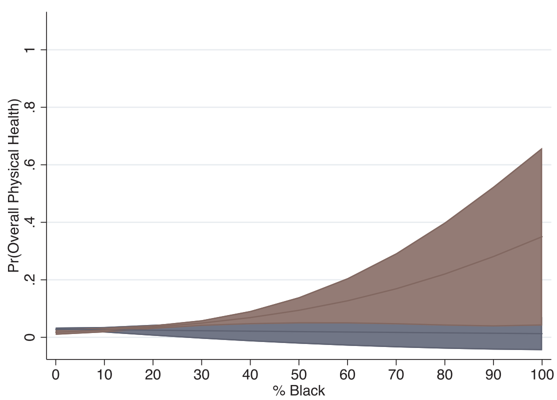
[1] Higher proportion black neighborhoods were not associated with unfavorable overlapping clusters of mammography, but were associated with all other bivariate overlapping clusters. The association between poverty and overlapping clusters was robust across all bivariate cluster overlaps.



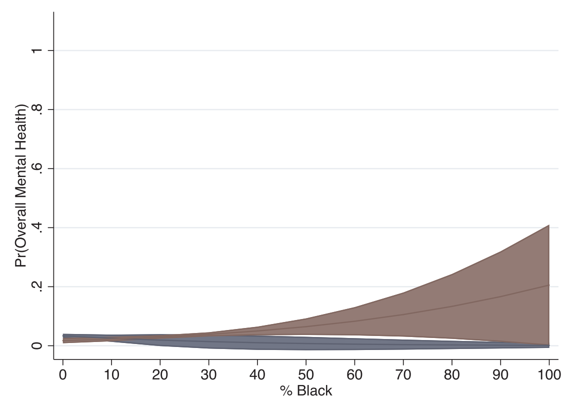
(a) Preventive Health Behaviors



(b) Food-related Population Health



(c) Overall Physical Health



(d) Overall Mental Health

Fig. 3. Marginal effects for percentage black population. Blue indicates marginal effects for favorable cluster overlaps; Red indicates marginal effects for unfavorable cluster overlaps. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the social safety net might play in solving the dual problems of food insecurity and poor health, which might ordinarily be treated in isolation. Despite a dearth of causal literature to date, hypothesized mechanisms for the association between food insecurity and health include stress, resource deprivation, and nutrition (Higashi et al., 2017; Williams, Yu, Jackson, & Anderson, 1997; Yen, 2010). Future causal studies focusing on mechanisms linking food assistance and improved health are needed.

Future work might focus on better understanding the linkages between poor health and food insecurity. While some models are emerging that allow for food insecurity to be addressed within the health context (i.e. food as medicine) (Gorn, 2017), our results suggest that the majority of health issues that spatially overlap with food insecurity are not directly related to nutrition. Thus, our results suggest a continued need for thinking broadly about the social determinants of health that might contribute to both food insecurity and poor health outcomes. One potential place to start is implementing food insecurity screening in clinic settings located in communities that have been identified as high risk for overlapping health and food insecurity problems. Screening has been effectively done at Veterans Administration clinics serving predominantly homeless populations and provided welcome information to physicians who could then better address the patients joint health and food needs (O'Toole, Roberts, & Johnson, 2017). In addition to screening for food insecurity within healthcare system settings, future work might consider patient navigation for food insecure populations who are not currently insured or connected to safety-net healthcare systems (Larsson & Kuster, 2013). Such data would then also contribute to a more refined understanding of the overlap of health and food security problems.

6. Conclusions

We examined a diverse set of health constructs and food insecurity; all exhibited statistically significant spatial clustering across US counties. Patterns were strikingly similar, although some variations emerged. Overall, counties with high levels of poverty and a higher proportion of black residents are associated with a higher likelihood of lying within overlapping clusters of food insecurity and poor health outcomes. Results imply that food insecurity and poor health may share similar social determinants; and in high poverty African American communities in particular, interventions to address both problems may be particularly impactful. These interventions might foster greater collaboration between social safety net food providers and local health service providers in areas with a high prevalence of both food insecurity and poor health.

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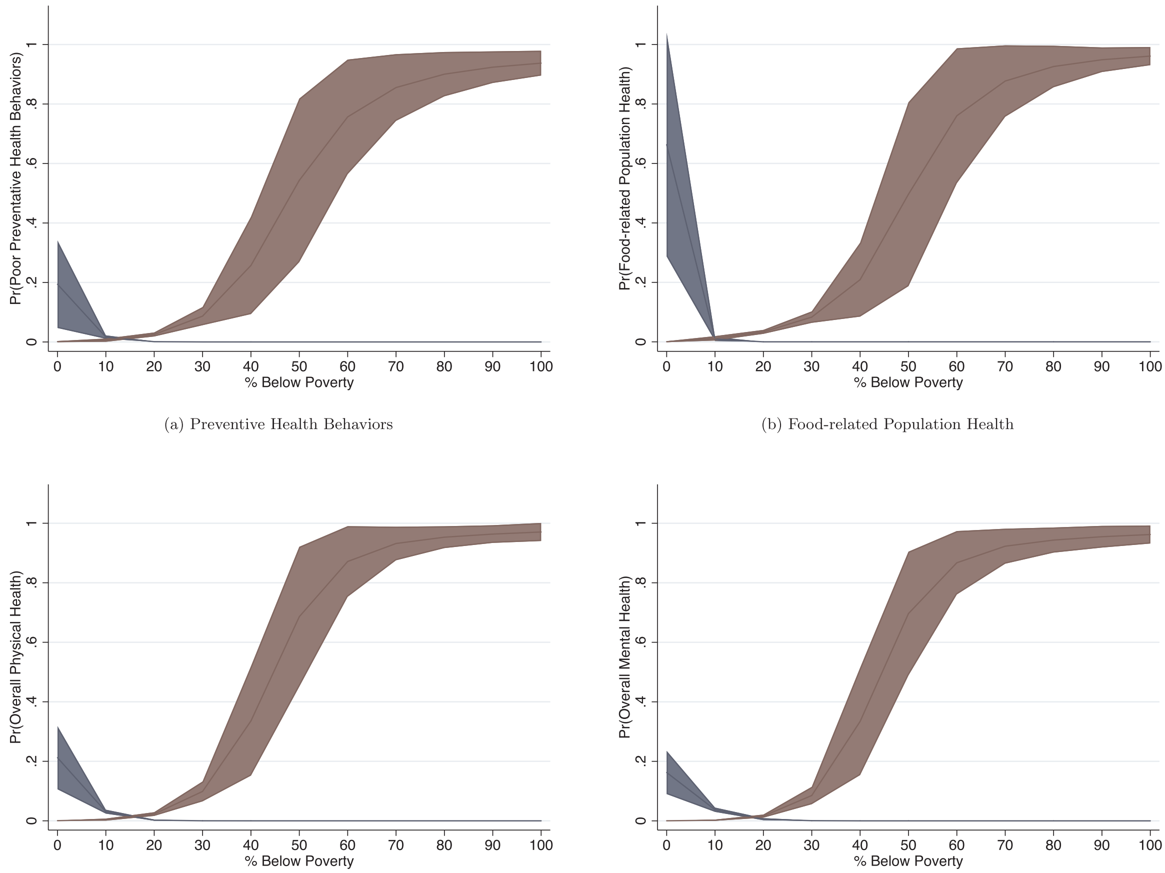

(a) Preventive Health Behaviors (b) Food-related Population Health

(c) Overall Physical Health (d) Overall Mental Health

Fig. 4. Marginal effects for percentage of population below the federal poverty threshold. Blue indicates marginal effects for favorable cluster overlaps; Red indicates marginal effects for unfavorable cluster overlaps. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Declaration of interest

The authors have no financial disclosures to report.

Appendix A

See Tables A1–A3 here.

Table A1
Summary of health measures, internal consistency reliability of health constructs, and correlation with food insecurity.

Variable	Description	Correlation with Food Insecurity (*P*)
	Preventive Health Behaviors, Cronbach's α = 0.65	
Sleep	Percent that do not receive sufficient sleep	0.5777*
Mammography	Percentage of female Medicare enrollees having at least 1 mammogram in 2 yrs (age 67–69)	−0.2485*
Smoking	Percentage of adults that reported currently smoking	0.55170*
Physical Activity	Percentage of adults that report no leisure-time physical activity	0.3888*
	Food-related Population Health, Cronbach's α = 0.61	
Obesity	Percentage of adults that report BMI > 30	0.4287*
Diabetes	Percent Diabetic	0.6497*
	Overall Physical Health, Cronbach's α = 0.82	
Physically Unhealthy Days	Average number of reported physically unhealthy days per month	0.6828*
Self-rated Health	Percent with fair/poor health	0.6748*
Frequent Physical Distress	Percent frequent physical distress	0.7045*
	Overall Mental Health, Cronbach's α=.69	
Mentally Unhealthy Days	Average number of reported mentally unhealthy days per month	0.6257*
Frequent Mental Distress	Percent frequent mental distress	0.7013*

* $p < 0.05$.

Table A2
Estimated association between county characteristics and univariate food insecurity clusters and bivariate overlapping clusters[a]: Preventive health behaviors and food-related population health (N = 3142). Relative risk ratios are reported with 95% confidence intervals in parenthesis.

	Univariate Clusters	Bivariate Overlapping Clusters					
		Preventive Health Behaviors				Food-related Population Health	
	Food Insecurity	Insufficient Sleep	Percentage Smoking	No Leisure-time Physical Activity	Percentage Mammography	Percent Diabetic	Percentage Obese
	Low Food Insecurity			**Favorable Cluster Overlaps**			
Black	0.99 (0.949, 1.032)	0.896* (0.823, 0.975)	1.021 (0.943, 1.106)	0.962 (0.889, 1.042)	0.904+ (0.816, 1.002)	0.985 (0.928, 1.045)	1.064 (0.935, 1.212)
Amer. Ind	1.058** (1.015, 1.103)	0.753* (0.595, 0.955)	0.196 (0.019, 1.995)	0.628+ (0.388, 1.019)	0.99 (0.869, 1.128)	0.922 (0.796, 1.069)	0.262 (0.012, 5.522)
Asian	1.009 (0.931, 1.094)	1.247* (1.038, 1.497)	1.141 (0.953, 1.365)	1.152* (1.033, 1.285)	1.236+ (0.997, 1.533)	1.12** (1.034, 1.213)	1.098 (0.913, 1.321)
Nat. Hawaian	0.056* (0.004, 0.745)	0.42 (0.054, 3.288)	0.053+ (0.002, 1.307)	0.021+ (0, 1.776)	0.101 (0.003, 3.03)	0.098+ (0.01, 1.003)	0.185 (0.007, 4.774)
Other race	1.042 (0.983, 1.104)	0.947 (0.835, 1.075)	1.245* (1.051, 1.474)	1.012 (0.812, 1.26)	0.858 (0.659, 1.118)	0.969 (0.871, 1.079)	0.901 (0.583, 1.392)
Poverty	0.801*** (0.749, 0.857)	0.822*** (0.754, 0.896)	0.501*** (0.375, 0.67)	0.617*** (0.526, 0.723)	0.819*** (0.735, 0.912)	0.741*** (0.653, 0.84)	0.231** (0.083, 0.643)
Unemploy	0.997*** (0.996, 0.998)	0.996*** (0.995, 0.998)	1 (0.997, 1.003)	0.999 (0.997, 1.001)	0.996*** (0.994, 0.997)	0.997*** (0.996, 0.999)	1.003 (0.995, 1.01)
Female Head	1 (0.999, 1.001)	1 (0.999, 1.001)	1 (0.997, 1.003)	1.002 (1, 1.004)	1 (0.998, 1.002)	1.001+ (1, 1.003)	0.999 (0.994, 1.005)
Foreign Born	1.001** (1, 1.001)	1 (0.998, 1.001)	1 (0.999, 1.002)	1 (1, 1.001)	1 (0.998, 1.001)	1 (1, 1.001)	1.002** (1.001, 1.004)
Pop. Density	1 (1, 1)	0.997* (0.995, 1)	1 (1, 1)	1 (1, 1)	0.999 (0.998, 1.001)	1 (1, 1)	1* (1, 1)
	High Food Insecurity	**Unfavorable Cluster Overlaps**					
Black	1.11*** (1.089, 1.132)	1.106*** (1.078, 1.135)	1.024+ (0.998, 1.05)	1.027* (1.004, 1.051)	0.979 (0.947, 1.013)	1.138*** (1.108, 1.169)	1.059*** (1.03, 1.088)
Amer. Ind	1.003 (0.975, 1.031)	0.986 (0.936, 1.038)	0.988 (0.948, 1.029)	0.924*** (0.885, 0.965)	0.96 (0.902, 1.021)	0.954* (0.911, 0.998)	0.899** (0.846, 0.955)
Asian	1.134+ (0.992, 1.295)	1.203* (1.015, 1.426)	0.825 (0.477, 1.427)	0.775 (0.294, 2.046)	1.156 (0.784, 1.704)	0.648 (0.357, 1.175)	0.663 (0.261, 1.688)
Nat. Hawaian	0.589 (0.214, 1.619)	0.815 (0.428, 1.55)	0.609 (0.124, 2.998)	0.674 (0.059, 7.625)	0.832 (0.32, 2.16)	0.716 (0.128, 3.992)	1.649 (0.863, 3.15)
Other race	0.947 (0.874, 1.026)	1.013 (0.935, 1.097)	0.99 (0.902, 1.088)	1.013 (0.918, 1.118)	0.994 (0.825, 1.197)	1.039 (0.967, 1.118)	1.06 (0.966, 1.163)
Poverty	1.205*** (1.154, 1.257)	1.281*** (1.202, 1.366)	1.194*** (1.127, 1.265)	1.06+ (0.999, 1.124)	1.212*** (1.1, 1.336)	1.369*** (1.28, 1.465)	1.062+ (0.992, 1.138)
Unemploy	1 (0.999, 1.001)	1 (0.999, 1.001)	1 (1, 1.001)	0.999 (0.999, 1)	1.001+ (1, 1.002)	1 (0.999, 1.001)	1.001 (1, 1.001)
Female Head	1 (0.999, 1.001)	1 (0.999, 1.001)	1 (0.999, 1.002)	1.002*** (1.001, 1.004)	1 (0.999, 1.002)	0.999 (0.998, 1)	1.002** (1.001, 1.004)
Foreign Born	0.999+ (0.999, 1)	0.999 (0.998, 1)	0.998* (0.997, 1)	0.996** (0.993, 0.998)	0.999 (0.996, 1.001)	0.999** (0.997, 1)	0.996** (0.992, 0.999)
Pop. Density	0.996*** (0.995, 0.998)	0.998* (0.996, 1)	0.998 (0.995, 1.001)	0.991* (0.983, 0.999)	0.984* (0.971, 0.998)	0.996*** (0.994, 0.998)	0.992* (0.985, 1)

* $p < 0.05$.
\+ $p < 0.10$.
** $p < 0.01$.
*** $p < 0.001$.
[a] The dependent variable for the models is a categorical variable indicating favorable cluster overlaps (dependent variable = 1) and unfavorable cluster overlaps (dependent variable = 2). The dependent variable takes on a value of 0 for the case when a county either does not lie in a cluster overlap or is in a mixed cluster overlap. Models were estimated using multinomial logistic regression.

Table A3
Estimated association between county characteristics and overlapping clusters[a]: Overall physical and mental health (N = 3,142).
Relative risk ratios are reported with 95% confidence intervals in parenthesis.

	Overall Physical Health			Overall Mental Health	
	Phyisical Distress	Fair/Poor Health	Physically Unhealth Days	Mental Distress	Mentally Unhealth Days
Favorable Cluster Overlaps					
Black	1.018 (0.972, 1.067)	0.93* (0.869, 0.996)	0.995 (0.949, 1.043)	0.994 (0.938, 1.054)	0.989 (0.931, 1.051)
Amer. Ind	1.072^{+} (0.992, 1.158)	0.879 (0.728, 1.062)	1.065^{+} (0.994, 1.141)	1.082** (1.03, 1.138)	1.083** (1.032, 1.136)
Asian	1.207*** (1.097, 1.327)	1.241** (1.095, 1.406)	1.156** (1.051, 1.272)	1.086 (0.976, 1.208)	1.092 (0.982, 1.215)
Nat. Hawaian	0.025** (0.003, 0.241)	0.001* (0, 0.505)	0.116* (0.014, 0.96)	0.176^{+} (0.025, 1.247)	0.154^{+} (0.022, 1.078)
Other race	0.937 (0.835, 1.051)	0.892 (0.736, 1.08)	0.928 (0.837, 1.03)	0.92 (0.824, 1.027)	1.021 (0.927, 1.125)
Poverty	0.781*** (0.723, 0.845)	0.741*** (0.658, 0.835)	0.782*** (0.725, 0.843)	0.818*** (0.764, 0.875)	0.821*** (0.768, 0.877)
Unemploy	0.995*** (0.994, 0.996)	0.997** (0.996, 0.999)	0.995*** (0.994, 0.996)	0.995*** (0.994, 0.996)	0.995*** (0.994, 0.996)
Female Head	0.999 (0.998, 1)	1.002* (1, 1.003)	1 (0.998, 1.001)	0.999^{+} (0.998, 1)	0.999^{+} (0.998, 1)
Foreign Born	1 (0.999, 1)	1 (0.999, 1.001)	1 (0.999, 1.001)	1 (1, 1.001)	1 (0.999, 1.001)
Pop. Density	1 (1, 1)	1* (0.999, 1)	1 (1, 1)	1 (1, 1)	1 (1, 1)
Unfavorable Cluster Overlaps					
Black	1.067*** (1.041, 1.093)	1.082*** (1.057, 1.107)	1.049*** (1.025, 1.074)	1.053*** (1.03, 1.076)	1.048*** (1.025, 1.072)
Amer. Ind	1.004 (0.971, 1.038)	0.986 (0.946, 1.027)	0.99 (0.955, 1.025)	0.978 (0.943, 1.015)	0.976 (0.936, 1.017)
Asian	0.918 (0.611, 1.38)	0.885 (0.509, 1.54)	1.086 (0.778, 1.515)	1.039 (0.697, 1.549)	1.051 (0.685, 1.614)
Nat. Hawaian	0.755 (0.211, 2.703)	0.487 (0.094, 2.53)	0.808 (0.281, 2.328)	0.733 (0.203, 2.649)	0.743 (0.18, 3.067)
Other race	0.997 (0.932, 1.067)	0.993 (0.9, 1.095)	0.98 (0.901, 1.067)	0.988 (0.912, 1.07)	1.014 (0.951, 1.081)
Poverty	1.263*** (1.19, 1.339)	1.282*** (1.21, 1.358)	1.227*** (1.163, 1.294)	1.25*** (1.184, 1.319)	1.245*** (1.178, 1.316)
Unemploy	1 (1, 1.001)	1 (0.999, 1.001)	1.001 (1, 1.001)	1 (0.999, 1.001)	1.001 (1, 1.001)
Female Head	1 (0.999, 1.001)	1 (0.999, 1.001)	1 (0.999, 1.001)	1.001 (0.999, 1.002)	1 (0.999, 1.001)
Foreign Born	0.999* (0.998, 1)	0.999* (0.998, 1)	0.999* (0.998, 1)	0.999** (0.998, 1)	0.999* (0.997, 1)
Pop. Density	0.991* (0.983, 0.998)	0.995* (0.991, 1)	0.99* (0.981, 0.998)	0.992** (0.986, 0.998)	0.989* (0.978, 0.999)

* $p < 0.05$.
\+ $p < 0.10$.
** $p < 0.01$.
*** $p < 0.001$.
[a] The dependent variable for the models is a categorical variable indicating favorable cluster overlaps (dependent variable = 1) and unfavorable cluster overlaps (dependent variable = 2). The dependent variable takes on a value of 0 for the case when a county either does not lie in a cluster overlap or is in a mixed cluster overlap. Models were estimated using multinomial logistic regression.

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