Applied Research in Quality of Life (2023) 18:1715–1735
https://doi.org/10.1007/s11482-023-10159-y

Residential Segregation as a Policy Priority to Address Health Disparities: a Multilevel Analysis

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Received: 12 May 2022 / Accepted: 23 February 2023 / Published online: 4 March 2023

Abstract

To address racial residential segregation, considered a reflection of structural racism, and its relative importance to social determinant of health (SDOH) pathways to health disparities, we analyze self-reported health, a known predictor of health outcomes. We use County Health Rankings, a public dataset provided by the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute. Using a panel dataset (2016 to 2019) with multilevel modelling techniques, we compare racial residential segregation at the county level to other health-outcome related county level characteristics considered pathways to disparate health outcomes. Consistent with prior research we find that higher racial residential segregation is associated with greater reporting of fair or poor health. However, the effects of education and economic stability measures of SDOH are more important for predicting fair/poor health outcomes than segregation. Our research highlights the need for more multi-level analysis and a better understanding of the complex nature of SDOH in a structural racism approach to inform where, when, how, and for whom policies are developed, funded, and implemented at the local level.

Keywords Racial residential segregation · Health disparities · Social determinants of health · Self-rated health

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Introduction

Despite decades of research, health policy focus, and social-behavioral and political interventions, health disparities continue to be a pernicious issue worldwide (Williams & Purdue-Vaughans, 2016). Public health policy priorities tend to focus on improving health as a whole (e.g. curing cancer or eliminating cardiovascular disease). Growing evidence suggest this broad approach will not reduce health disparities and there should be an emphasis on structural interventions that are not disease-specific (Brown et al., 2019). Some health disparities have been slightly reduced by interventions addressing individual risk factors such as diabetes, hypertension, obesity, and substance abuse (Bell et al., 2018; Laiteerapong et al., 2013; Zhang et al., 2014). However, public health initiatives have not so far translated to better health overall for nonwhite populations. Significant health disparities remain in a number of health indicators, most notably in disease transmission, life expectancy, and infant mortality (Singh et al., 2018).

Williams et al. (2019a) call attention to the vast literature on racial discrimination and its effect on health, especially risk factors for disease and death. A review of the relevant literature suggests that too little attention is paid to structural factors or the more multi-level and complex determinants of health disparities, including social determinants of health such as the community and social context in the places we live (Brown et al., 2019). Lorenc et al. (2013) and Fazili (2017) suggest that eliminating racial and ethnic disparities in health depends on "upstream" or structural changes such as improving living and working conditions in places where we live, as opposed to "downstream" or interventions for institutional policies or individual situations or behavioral changes.

Consistent with the growing discussion of upstream issues that may affect health disparities, Brown et al. (2019) make a strong case for focusing on structural racism issues, including the social, economic, environmental and public policy drivers of the health status of individuals and populations. Further analysis is needed to address priorities for public attention and investment to reduce health disparities, such as when and where to spend public health funds within a geopolitical jurisdiction. Health policy researchers are encouraged to advance the science of health disparities research by exploring new approaches, including well-constructed, connected, and analyzed data sets, to better measure and assess health disparities and their correlates at a structural level. Ultimately, as Brown et al. (2019) suggest, we need more analytical methods to extend the discussion beyond individual outcomes to community and system-level outcomes. Multilayered and multifaceted interventions and targeted public health resource allocation come from more robust evaluation of the relative importance of the social determinants of health in specific communities at the level of policy decision-making.

A primary target of structural racism intervention to reduce health disparities is racial residential segregation. The seminal work of Kramer and Hogue (2009) uses a systematic review to explore decades of research that relates racial residential segregation to worse health outcomes for nonwhite persons, with a focus on opportunities to improve public health interventions and investment. Kramer and

Hogue (2009) and Acevedo-Garcia et al. (2003) suggest several issues that should be addressed in future research. They suggest we should: (1) expand segregation research beyond Black-White differences; (2) develop multilevel research designs; (3) further develop the social determinants of health frameworks to better understand the relationship between segregation and health; (4) utilize longitudinal study designs; and (5) take into account more and less urbanized areas. The purpose of our paper is to continue the Kramer and Hogue (2009) and Brown et al. (2019) challenge by exploring pathways of racial residential segregation to other Social Determinants of Health (SDOH) (Artiga & Hinton, 2019) to inform public policy making to reduce disparate health outcomes.

Background and Literature Review

Despite continuing public attention to health disparities, little progress has been made to reduce inequalities in health outcomes. We are still unfortunately in the study phase as more evidence-based information is "vital for shaping policy initiatives" particularly when substantial public investment and resources are needed (Blacksher et al., 2010, p. 890). Developing sound health policy requires a better understanding of the complex nature of social and racial inequality in health to inform where, when, how, and for whom interventions are developed and implemented (Mechanic, 2002). This is the essence of the structural approach to health promotion that addresses policies and practices that affect health at a broader community level (Lapum et al., 2021), including racial residential segregation. The structural approach to health disparities recognizes that health outcomes are impacted by a variety of visible and invisible social structures such as neighborhood and physical environment and access to health care to name just two (Artiga & Hinton, 2019).

Racial residential segregation is a prime example of a multi-level and complex SDOH disparities analysis, as segregation is considered a structural and multivariate social phenomenon (LaViest, 2005; Kramer & Hogue, 2009; Yang et al., 2017). Williams and Purdie-Vaughns (2016, p. 632) note that, "…racial residential segregation creates pathogenic neighborhood and housing conditions that truncates access to social mobility by reducing education and employment opportunities". Racial residential segregation as a determinant of health disparities is complicated with multiple explanations for the reason that segregation exists and why the US remains highly segregated typically along racial and ethnic lines, and especially in urban areas (Kramer & Hogue, 2009; LaViest, 2005).

Traditional explanations of continued racial residential segregation fall into three categories of individual choice as opposed to places where we live (Crowder & Krysan, 2016). The first, or human capital approach, argues that higher socio-economic status results in access of individual to the better neighborhoods. The second or in-group/outgroup argument suggests that people use race for residential preferences, thus choosing neighborhoods dominated by like individuals. The third approach suggests that white aversion to shared residential space results in discriminatory real estate practices. This is consistent with spatial assimilation theory that posits that individual choices to live among those of similar race or ethnicity is a temporary and transitional stage to making greater socioeconomic strides to join the mainstream or the less segregated communities (Alba & Nee, 2003).

Relying on these three individually oriented explanations for health disparities, and not a structural and multivariate level explanation, has hampered policy development to address health disparities (Crowder & Krysan, 2016). Focusing on individual choices of where to live has shown to be less effective for explaining health disparities for non-whites and ethnic groups than focusing on the "place" effects on health and the role racial residential segregation plays for this aspect of the growing health disparities policy discourse (Do et al., 2008; Nelson, 2013).

Regardless of which orientation we explore (individual or structural), racial residential segregation is accepted as a fundamental contributor to racial disparities in health. Kramer and Hogue (2009) note that:

> The vast majority of black Americans live in urban settings, many but not all of which are highly segregated. It is vitally important to understand how much of their health disparities are a result of specific dimensions of segregation and whether these disparities can be reduced either by policies that reduce segregation or interventions that reduce the impact of segregation (p. 189).

Kramer and Hogue (2009) suggest there are four causal pathways through which racial residential segregation can affect health outcomes (see Fig. 1). The first pathway is through individual socioeconomic status (SES). Racial segregated areas are often associated with economic segregated communities or neighborhoods of lower income, lower educated people living in the same area. The second pathway is through neighborhood SES in that neighborhoods may be in themselves unhealthy because of concentrated poverty, crime, and poor quality housing. The third pathway is through social trust, social networks or other elements of social capital. The fourth pathway is through exposure to community behaviors such as eating healthy foods or exercising.

Other authors (Fazili, 2017; Heiman & Artiga, 2018) have identified these pathways (except individual SES) though the social determinants of health (SDOH) framework (see Fig. 2). The Social Determinants of Health (SDOH) framework,

Fig. 1 Causal pathways of segregation to health. Based on Kramer and Hogue (2009)

Community and Social Context	Economic Stability	Neighborhood and Physical Environment	Education	Healthcare System	Food
Social Integration Discrimination Segregation Community Engagement	Employment Income Income Inequality Debt	Housing Recreation Crime Transportation	Literacy Graduation rates Higher education	Provider availability Access to care Quality of care	Hunger Access to Healthy Foods

Fig. 2 Social determinants of health categories and variables considered. Note: This is original work of authors adapted from Fazili (2017) and Heiman and Artiga (2018)

including community and social context, economic stability, neighborhood and physical environment, education, healthcare system, and food categories, is the chosen model addressing health disparities. Each category of the framework is measured in a wide variety of ways, and the literature has provided many approaches for conceptualizing and using each of the contributing components (Fazili, 2017; Heiman & Artiga, 2018; Hillemeier et al., 2003). Figure 2 illustrates the categories and potential measures for each category based on the previous research of Fazili (2017) and Heiman and Artiga (2018). We use the Fazili (2017) approach that promotes the growing recognition among health policy makers that many social, economic, and environmental factors drive health outcomes and that a discussion of the connection between all categories in the framework will create new collaborations between policy makers and healthcare providers.

To address the challenges of Kramer and Hogue (2009), several authors have explored the impact of racial residential segregation on health outcomes through the individual or neighborhood SES mechanism (Brulle & Pellow, 2006; Jackson et al, 2000; Williams & Collins, 2001). For example, Okulicz-Kozaryn (2015) promotes the idea that income inequality should be a focus of health outcomes disparities. Situational and structural factors and variables, including social institutions, communities, and neighborhoods where individuals segregate by race, represent powerful determinants of the health of self and others (Rivera, 2014, p. 202). Since the degree of racial residential segregation varies across the US, studying the relationship between racial residential segregation and health disparities requires multilevel analysis taking into account competing social and economic determinants of health in terms of health policy (LaViest, 2005; Subramanian et al., 2005; O'Brien et al., 2020).

Before we can pursue this research, we need to consider measurement issues such as how we define health and better or worse health outcomes. Rivera (2014) and others (Yang et al., 2017) are proponents of studying health disparities where a person's sense of health or self-reported health status is the outcome of interest.

Self-reported health is common in health disparity research as it predicts future mortality and diseases and it is robust to response scale orientation (Garbarski et al., 2019; Jylha, 2009). Self-reported health, especially sense of fair or poor health, is relevant to our research as people, regardless of race or ethnicity, tend to change their sense of health in response to external factors such as where they live, and they change their behaviors based on their sense of health (Beck et al, 2014; Bell et al, 2018). Similarly, the relationship between self-reported health and residential segregation for a wide variety of race and ethnicity categories has shown to be "difficult to unpack" but it is possible with sophisticated analytic techniques (Nelson, 2013, p. 645). Self-rated health is a complicated measurement challenge and analytic challenge (Garbarski et al., 2019), but it is a critical analytic tool to better understand health disparities.

We use this background to pose the following research question:

> What is the relative importance of racial residential segregation compared to other social determinants of health categories and variables for policy priorities and resource allocation to reduce health disparities?

Our contribution to the literature includes continued exploration of the complicated issue of racial residential segregation as a representation of structural racism and its impact on health outcomes. We suggest an analytic that can be used for practical policy decisions to address health disparities at the local level.

Methods

Analyzing Health Disparities

As previously discussed, traditional health disparities research focuses on individuals with specific health conditions within neighborhoods or metropolitan areas (Lim & Harris, 2015). The individual-level research is informative and important, but it may not be as important as social structures or for setting public policy priorities with subsequent allocation of resources to policy-specific geographies.

We use the County Health Rankings (https://www.countyhealthrankings.org/) as a valid and reliable source of data for health disparities research at the structural or geographic level (Garbarski et al., 2019; Okulicz-Kozaryn, 2015). We include counties within states and report findings using this community-oriented policy approach. The dataset is described in the Appendix 1 to this paper.

Measuring health is complex with continuing efforts to improve measurement approaches (Bowling, 2005, Garbarski et al., 2019). Building consensus on measures of health status and outcomes is a work in progress. The traditional indices of health status are typically objective clinical outcome measures such as mortality, morbidity, complications, and physical condition. For health disparities research, more subjective quality of life and sense of health measures are highly relevant "as end points in the evaluation of public policy" (Bowling, 2005, p.7). To complicate measurement issues, including race as a variable in health disparities studies is important but not without complications and controversy. Race as a differential measure is evolving from discussions of black-white biological differences to consideration of nonwhite-white differences in health based on the context in which people live (Hogarth, 2019). As Humes and Hogan state (2009, p. 111–112) “It is well-accepted that concepts of race, ethnicity … are changing constructs that reflect the social, economic, and political climate of the times”. They further suggest that the “useful social, or at least statistical, constructs of race and ethnicity, would have three properties: 1) be recognized by society and the individual; 2) categorize individuals into the same groups over a long period of time; and 3) be predictive of social and economic opportunity”. Using this guidance and to address the controversial issues and produce as many meaningful results as possible, we use the non-white versus white construct for our analysis.

Data, Variables, Analytic Approaches

County Health Rankings includes data for a variety of health outcomes and SDOH for all counties in all states in the U.S. Our measure of health outcome is the percentage reporting fair or poor health in a county. The original data is from the Behavioral Risk Factor Surveillance System conducted by the Centers for Disease Control and Prevention (https://www.cdc.gov/brfss/) using annual telephone surveys of over 400,000 adults conducted in all 50 states. We use one question from the survey that asks “Would you say that in general your health is _ ”, answers available are Excellent, Very Good, Good, Fair, Poor. Our dependent variable is the sum of the percentage of respondents that answer either fair or poor. The County Health Rankings does not give percentages by each of the five possible answers but we do note that the county mean percentage of respondents answering fair or poor health is 17.3%, a significant percentage of the population. Using respondents that report fair or poor health is the appropriate dependent variable for this study as we want to study the relative importance of variables in the SDOH framework categories that affect health status.

Our variable of interest, racial residential segregation, represents the *Social and Community Context* category of the adapted SDOH framework (Fazili, 2017; Heiman & Artiga, 2018). Segregation refers to the degree to which two or more groups, in this case white and non-white residents, live separately from one another in a geographic area. Our measure of racial residential segregation is taken directly from the County Health Rankings and calculated as the index of dissimilarity (NWWSI). The index of dissimilarity is a demographic measure of the evenness with which two groups (non-white and white residents) are distributed across the component geographic areas (census tracts, in this case) that make up a larger area (counties, in this case). The index score is interpreted as the percentage of either non-white or white residents that would have to move to different geographic areas in order to produce a distribution that matches that of the larger area. We promote use of the NWWSI measure as it advances the work of Kramer and Hogue (2009) who advocated for other measures of segregation besides Black-White. The average county NWWSI in our dataset is 31.9, meaning almost a third of residents would have to move to a different census tract to create a distribution that was equivalent to the county. We suspected that the relationship between the NWWSI variable might be nonlinear since changes in the value of the index at the upper and lower end of the index's range may be less impactful than changes in the middle of the range. We also assessed a model integrating a cubed term of our independent variable of interest. Chi-squared test comparisons (likelihood-ratio test using latest in Stata 15.1) of the three specifications and assessments of Akaike and Bayesian Information Criterion (AIC and BIC) values resulted in the selection of the model presented here (Akaike, 1986). The model including the squared term was a statistically significant improvement in model fit over the linear model, but the model integrating the cubed (and squared) term was not a statistically significant improvement over the model including only the squared term. All models retained the underlying linear term.

Control variables are categorized according to the other five potential pathways between racial residential segregation, the community and social context variable, and disparate health outcomes (Fazili, 2017). The other dimensions include economic stability, neighborhood and physical environment, education, healthcare system, and food. We also include county demographic characteristics. Variables are chosen for their explanatory contribution to the model and lack of multicollinearity. Table 1 below describes the outcome and explanatory variables and provides their summary statistics. Table 2 provides a correlation matrix and confirms the absence of multicollinearity issues for variables used in the regression analysis.

Our methodology addresses the priorities of the seminal work of Kramer and Hogue (2009) and Acevedo-Garcia et al. (2003). Specifically, we use a panel data set to address the need for longitudinal studies over cross section. Our data contains 9,541 county level observations for years 2016 through 2019. Using county level data allows analysis of geographical areas that are not intercity or intracity data. This data was analyzed using Hierarchical Linear Modelling (HLM) regression techniques with robust standard errors, a third suggestion of Kramer and Hogue (2009). HLM is used because variance in the health outcome variable depends on predictor variables that are at varying hierarchical levels, in this case, counties and states. HLM is superior to Ordinary Least Squares that assumes that observations are independent. Our data differentiates counties in a state where certain counties are more likely to be homogeneous than a random sample of counties in the US and therefore violating the independence assumption. Analysis was conducted using Stata 15.1 with the *xtmixed* command with states as our level 2 designation. The Stata data suggest an intraclass correlation coefficient of 0.51 that easily meets standards for determining the non-independence of observations.

The estimation equation follows:

$$FairPoorHealth_{cst} = b_0 + b_1 NWWSI_{cst} + b_2 NWWSISqr_{cst} + \delta_n Economic_{cst} + \\ \theta_n Environment_{cst} + \pi_n Education_{cst} + \rho_n Healthcare_{cst} + \tau_n Food_{cst} + \\ \psi_n Demographics_{cst} + \omega_n year_t + \gamma_n State_t \upsilon_s + \varepsilon_{cst}$$

The percentage of respondents reporting fair or poor health in county c, in state s, at time t is a function of the segregation (dissimilarity) index of county c,

Table 1 Descriptive statistics for measures of health status, quality of life, and SDOH at the U.S. county level: 2016–2019

SDOH	Dependent variables	Description	N	Mean	SD
	FairPoorHealth	The percentage of adult respondents who rate their health "fair" or "poor".	9,541	17.27	4.52
	Independent Variables				
Community and social context	NWWSI	Non-white/White Segregation Index	9,541	31.86	12.06
Economic stability	Unemployment rate	The percentage of the civilian labor force, age 16 and older, that is unemployed but seeking work	9,541	5.48	1.86
	Income Ratio	The ratio of household income at the 80th percentile to that at the 20th percentile	9,541	4.55	0.70
	Child Poverty	The percentage of children under age 18 living in poverty	9,541	22.43	8.72
Neighborhood and physical environment	Access to Exercise	The percentage of individuals in a county who live reasonably close to a location for physical activity such as a park or recreational facilities	9,541	65.54	20.95
	Violent Crime Rate	The number of violent crimes reported per 100,000 population	9,541	269.66	192.86
	Severe Housing Problems	The percentage of households with at least one or more of the following housing problems: (1) housing unit lacks complete kitchen facilities; (2) housing unit lacks complete plumbing facilities; (3) household is severely overcrowded; or (4) household is severely cost burdened.	9,541	14.96	4.18
Education	HS GradRate	The percentage of the ninth-grade cohort in public schools that graduates from high school in four years	9,541	86.16	7.90
	Some College	The percentage of the population ages 25–44 with some post-secondary education, such as enrollment in vocational/technical schools, junior colleges, or four-year colleges	9,541	57.21	11.16
Health care system	PCPRate	The ratio of the population to total primary care physicians	9,541	57.72	32.43
	MHPRate	The ratio of the population to total mental health providers	9,541	142.67	141.15
Food	Healthy Food	The percentage of the population that has limited access to healthy foods	9,541	6.90	5.04
County characteristics	Asian	The percentage of the population that is Asian	9,541	1.70	2.94
	African American	The percentage of the population that is African American	9,541	9.61	14.02

Table 1 (continued)

SDOH	Dependent variables	Description	N	Mean	SD
	Hispanic	The percentage of the population that is Hispanic	9,541	9.33	13.14
	American Indian	The percentage of the population that is American Indian/Alaskan Native	9,541	1.78	5.38
	Native Hawaiian	The percentage of the population that is Native Hawaiian /Other Pacific Islander	9,541	0.13	0.47
	Female	The percentage of the population that is Female	9,541	50.16	1.88
	Logpop	Natural Log of Population	9,541	10.78	1.24
	Year	Year of Observation	9,541	2017.52	1.12

Table 2 Correlation matrix for independent variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	NWWSI	1.00																		
2	Unemployment rate	0.06	1.00																	
3	Income ratio	0.14	0.36	1.00																
4	Child poverty	0.03	0.63	0.56	1.00															
5	Access to exercise	0.17	-0.23	-0.09	-0.38	1.00														
6	Violent crime rate	0.18	0.21	0.37	0.38	0.09	1.00													
7	Severe housing problems	0.07	0.25	0.43	0.28	0.25	0.35	1.00												
8	HS grad rate	-0.08	-0.26	-0.19	-0.27	-0.11	-0.32	-0.35	1.00											
9	Some college	0.11	-0.43	-0.17	-0.66	0.55	-0.11	0.02	0.06	1.00										
10	PCPRate	0.17	-0.20	0.06	-0.27	0.46	0.08	0.17	-0.06	0.50	1.00									
11	MHPRate	0.07	-0.08	0.15	-0.10	0.35	0.14	0.26	-0.20	0.33	0.48	1.00								
12	Healthy food	0.01	0.15	0.20	0.28	-0.07	0.20	0.14	-0.20	-0.12	-0.04	0.07	1.00							
13	Asian	0.08	-0.14	0.07	-0.26	0.39	0.12	0.38	-0.07	0.37	0.34	0.26	-0.09	1.00						
14	African American	0.10	0.28	0.44	0.49	-0.14	0.49	0.28	-0.28	-0.18	-0.06	-0.05	0.15	0.02	1.00					
15	Hispanic	-0.16	0.07	0.08	0.07	0.14	0.17	0.36	-0.12	-0.12	-0.03	0.06	0.23	0.20	-0.11	1.00				
16	American Indian	0.07	0.13	0.12	0.13	-0.10	0.04	0.14	-0.20	-0.06	-0.01	0.12	0.26	-0.03	-0.11	0.05	1.00			
17	Native Hawaiian	-0.02	-0.05	-0.03	-0.06	0.09	0.05	0.21	-0.07	0.05	0.05	0.09	0.04	0.48	-0.04	0.10	0.02	1.00		
18	Female	0.15	0.06	0.13	0.07	0.16	0.15	0.11	0.00	0.22	0.19	0.09	-0.08	0.05	0.17	-0.13	-0.06	-0.04	1.00	
19	logpop	0.33	-0.09	0.05	-0.26	0.56	0.29	0.41	-0.16	0.43	0.36	0.29	-0.08	0.53	0.09	0.20	-0.09	0.13	0.25	1.00

in state *s*, at time *t*, as well as other SDOH and county characteristics. Note that *b1* and *b2* are our coefficients of interest; δ, θ, π, ρ, τ, ψ, ω, γ represent vectors of coefficients associated with our SDOH variables and year and state fixed effects; and υ_s and ϵ_{cst} represent unique errors associated with the state and county level respectively.

Results

Table 3 below presents our regression results.

The coefficient on the NWWSI variable and its squared term are both statistically significant, but present opposite signs where the coefficient on the squared term is negative. This suggests a non-linear relationship between the intensity of segregation and reporting of fair or poor health. Specifically, as levels of segregation increase, those reporting fair or poor health increases, but at a decreasing rate. The reporting of fair or

Table 3 Multilevel regression of U.S. county and state-level variables for SDOH and Quality of Life Measures, 2016–2019

		FairPoorHealth
Community and social context	NWWSI	0.0213***
	NWWSI SQR	-0.0004***
Economic stability	*Unemployment rate*	0.1915***
	Income Ratio	0.6082***
	Child Poverty	0.2004***
Neighborhood and physical environment	*Access to Exercise*	-0.0084***
	Violent Crime	0.0001
	Severe Housing Problems	0.0426***
Education	*HS Grad Rate*	0.0155***
	Some College	-0.0346***
Health care system	*PCPRate*	-0.0044***
	MHPRate	0.0007***
Food	*Healthy foods*	0.0275***
County characteristics	*Asian*	-0.0116
	African American	0.0516***
	Hispanic	0.1337***
	American Indian	0.0858***
	Native Hawaiian	0.1312
	Female	0.0069
	logpop	-0.1361***
	Constant	8.372***
	Year and State dummies	Yes
	N	9,541

*** $p<0.01$, ** $p<0.05$, $p<0.1$ based on robust standard errors poor health peaks at a NWWSI of 29, or the 5th decile, the middle of the distribution, and then declines. On average, a one standard deviation increase in NWWSI (12.06) is associated with an increase of those reporting fair or poor health by about 0.2% points.

We find compelling results for consideration of and prioritizing other SDOH for policy and resource allocation as compared to racial residential segregation. For example, all of the economic stability variables are positive and statistically significant as expected. The magnitude of the effects suggest changes in these variables have the largest effect on reporting of fair or poor health, holding constant the other variables included in our model. A one standard deviation improvement in the unemployment rate (1.86) decreases those reporting fair or poor health by 0.36% points. A one standard deviation decrease in the income ratio (0.70) reduces reporting of fair or poor health by 0.43% points. The largest effect is related to child poverty, here, a one standard deviation decrease in children in poverty (8.72) decreases those reporting fair or poor health by 1.75% points. The variable that next has the greatest impact is "some college", where a one standard deviation increase in the population with some college (11.16) reduces the reporting of fair or poor health by 0.39% points. Other variables that have modest impacts include access to exercise and healthy foods, severe housing problems, and primary care physician (PCP) rate. A one standard deviation changes in these variables is associated with a change in reporting of fair or poor health by 0.1 to 0.2% points, equal to or less than the effect of segregation.

Racial and ethnic demographics of the county are important for the analysis. A larger African American, Hispanic, and American Indian/Alaskan native population in a county is associated with an increase in the reporting of fair or poor health. The magnitude of the effect is as large as the economic stability impact. A one standard deviation increase in the percentage of the population that is African American (14.02) increases reporting of fair or poor health by 0.76% points. The equivalent magnitudes for Hispanics and American Indian are 1.76 and 0.46% points respectively. However, an increase of Asians and females in the county are not statistically significant. The Asian variable may be insignificant because the point estimate is close to zero and there is little variation in the percent Asian across counties. Moreover, Gong and Xu (2021) suggest that there is a large ethnic heterogeneity across the Asian group. Counties with larger populations report lower rates of fair or poor health which emphasizes the need to consider geospatial areas other than urban settings.

We show a practical approach to viewing these key findings on policymaking priorities by mapping the difference between racial residential segregation and PCP rate in the state of Georgia (see Figs. 2 and 3). We chose Georgia because it is at the mean and median of NWWSI (racial residential segregation) but also has a wide variation across all variables in its 159 counties. The maps were created using ArcGIS® by ESRI version 10.5 (Korte, 2001) (Fig. 4).

To provide an example of the tradeoffs and resource allocation issues for a public health policy-maker in another state or locale, we describe Georgia county differences on segregation and PCP rate. Fulton County is an urban county in metro Atlanta in Georgia with a segregation index of 63 and a PCP rate of 108, both roughly double the national average. In contrast, Screven County is a largely rural county between Savannah and Augusta and has a segregation index of 9 and a PCP rate of just 14, both well below the national average. To achieve similar

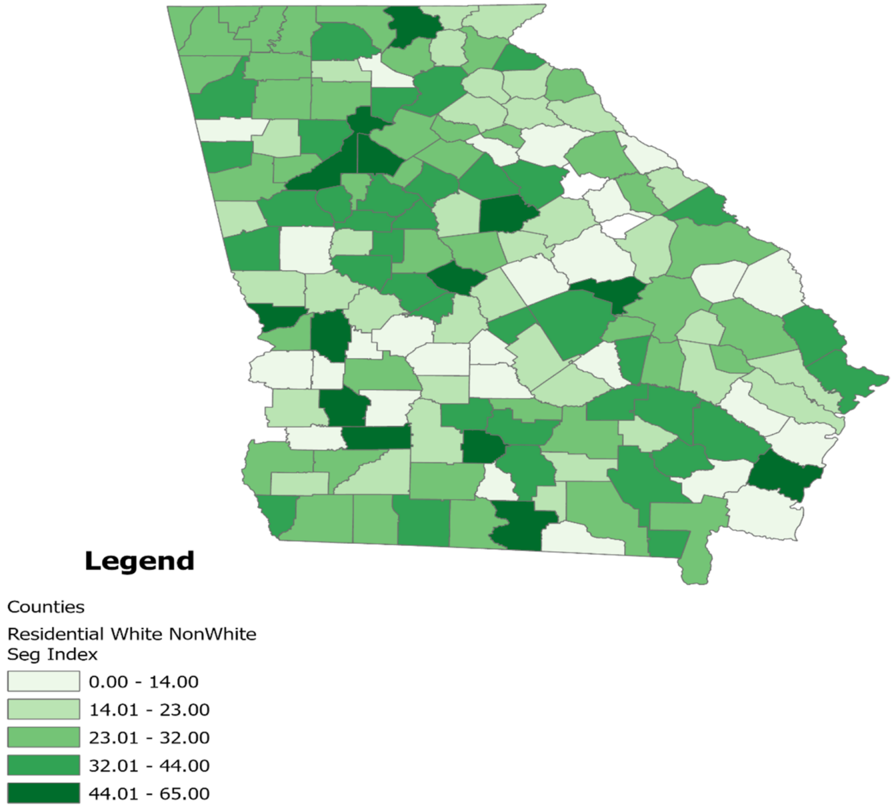

Fig. 3 Map of residential nonwhite white segregation by county in Georgia. Note: The residential nonwhite-white segregation index derives from the County Health Rankings. It is calculated as the index of dissimilarity and can be interpreted as the percentage of either nonwhite or white residents that would have to move to a different geographical area (census tract) to produce a distribution that matches the larger area (county). Map was generated using ArcGIS

improvements in lesser reporting of fair and poor health policy makers in Fulton County may dedicate resources to reducing segregation while their counterparts in Screven County may wish to attract primary care doctors to their county.

We use this mapping and visual approach to inform state and local policy makers about the trade-offs between policy options, and especially those with secondary impacts on health outcomes given scarce public resources. The maps illustrate the importance of county level analysis and policy prioritization based on place and space and where the focus is on the secondary SDOH issues of residential policy (housing) versus health policy (funding for primary care providers). Fazili (2017) advocates for a more integrated approach to health and community development issues. Specifically, in this context, "health industry professionals can leverage community developers' expertise in housing to address the upstream factors that drive population health" (p. 1). The maps of Georgia allow policy makers in that state to better understand the tradeoffs between these two SDOH criteria in their county.

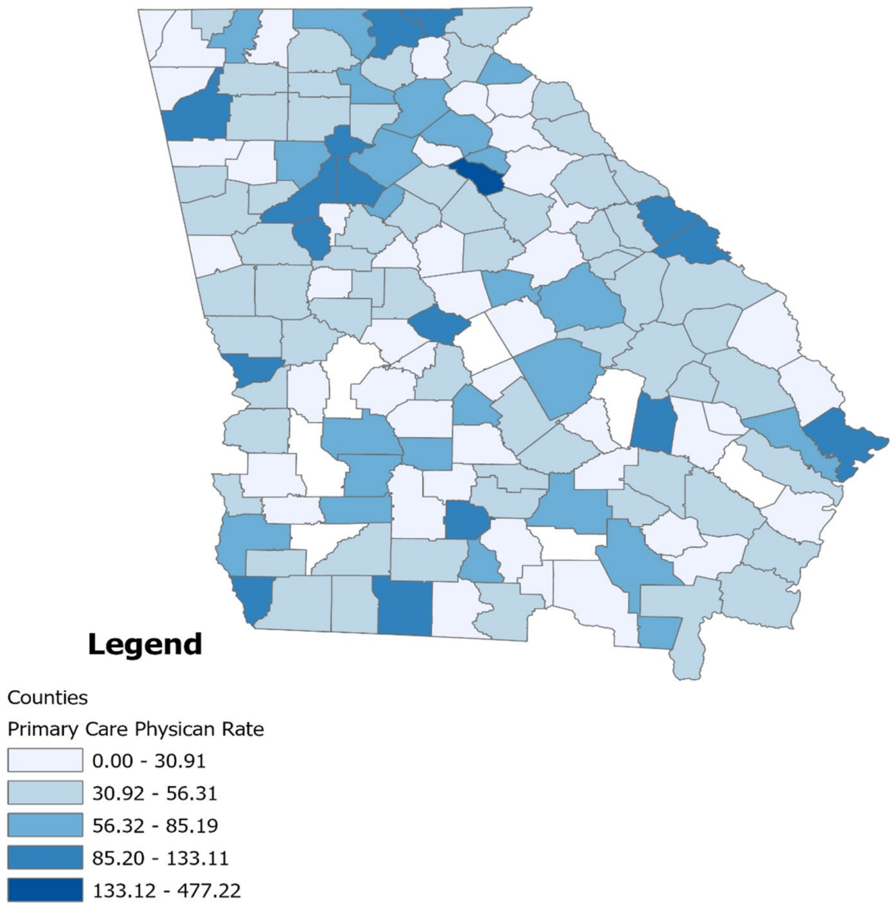

Fig. 4 Map of primary care physician rate by county in Georgia. Note: Primary Care Physician rate derives from the County Health Rankings. It is the ratio of the county population to the total primary care physicians in that county. Map was generated using ArcGIS

Similar maps can be easily created using SDOH criteria throughout the U.S. using publicly available data and basic analytic software.

Discussion and Conclusion

We find a positive relationship between racial residential segregation as measured by the dissimilarity index and reporting of fair or poor health consistent with the seminal research on this topic (Kramer & Hogue, 2009; Williams & Collins, 2001). Segregation remains a target for reducing health disparities (Kramer & Hogue, 2009). Despite measurement and analytic challenges, we do know that health pessimism or sense of fair or poor health affects healthy behaviors and health behaviors have important and relevant societal impact (Bell et al., 2018; Bailis et al., 2003). Addressing health pessimism is worthy of policy interventions. However, too little is known about the relationship between sense of health and how we address it as a health policy issue, and especially a health disparities issue.

Our research suggests that the effect of racial residential segregation on self-reported health is not as large as economic stability and education variables. Our results also support the findings of Okulicz-Kozaryn (2015) that income inequality is a highly relevant co-variate with health status. Like Okulicz-Kozaryn we find that the magnitude of the effect is similar to other economic stability variables. Moreover, inclusion of residential racial segregation as an additional independent variable indicates the effect of income inequality is twice that of racial residential segregation implying that reducing income inequality would be a policy priority over desegregation. In summary, resource constrained public policy priorities should therefore focus on economic development and education rather than racial segregation directly.

An advantage of our research design is that the unit of observation is the county not the individual. This is important for policy makers at the local level who need to allocate scarce resources to competing policies to achieve their goals. As stated earlier, our advice would be that the best way to improve health would be to allocate resources to economic development and education. However, if there are resources available after investing in economic stability and education, we documented several SDOH that have modest effects with respect to self-reported health and are of similar magnitude, including our variable of interest racial residential segregation. Here the tradeoff may be county dependent, and we provided an example in Georgia where the strength of the variable measuring availability of primary care physicians in a county was similar to segregation. However, the level of segregation and number of physicians in a specific county may vary and therefore lead to different policy responses, which is particularly relevant for rural areas (Reilly, 2021). We contend that the tradeoffs inherent in these secondary issues are worthy of more focused research and consideration for resource allocation, especially at the local policy and political level (Brown et al., 2019).

Our results support, and advance, recent research on segregation and health using a larger set of control variables than previous studies. Subramanian et al. (2005) found that an increase in the white/black dissimilarity index did not significantly increased the reporting of poor health. Consistent with our results Subramanian et al. found economic and education variables were more strongly correlated with self-reported health than segregation variables. Our study differs from Subramanian et al. in three important ways. First, the Subramanian analysis only used metropolitan statistical areas and so omitted rural areas, where there is growing interest in terms of health disparities. Second, although analysis included income and education, the Subramanian et al. research did not include other important social determinants of health. Finally, we find empirical support for a non-linear relationship between racial residential segregation and reporting of fair or poor health at the county level.

One future research area that may be fruitful is Frames of Reference (FOR) for measurement. Filus et al. (2020) and Junghaenel et al. (2018) find that when answering subjective health questionnaires people have a reference group in mind. The most popular reference group is “other people” (Junghaenel et al., 2018) and “upwards comparisons” (Filus et al., 2020). Our results suggest that people living in segregated communities may compare themselves to other people in more integrated counties and downgrade their self-reported health status. Thus, measurement and reference groups matter and future work should consider the relationship between influence of measurement approaches on respondent answers and resulting findings before specific decisions are made with respect to desegregation and racial dissimilarity policies. Previous research measurement and analytic approaches hypothesize several causal pathways from income inequality to better health (Okulicz-Kozaryn, 2015) or from racial residential segregation to better health (Kramer & Hogue, 2009). Future research may also consider if income inequality and segregation are working through the same pathway, and if so, what is the best policy intervention to mediate the effects of income inequality and segregation on health.

Public policies and public health initiatives have a foundational role in addressing SDOH priorities for health disparities (McGowan, Kramer & Teitlebaum, 2019; Grier & Schaller, 2020, p. 65). Developing effective legal and public policy health promotion strategies is dependent on sound and sophisticated research and our research suggests that not all SDOH pathways between racial residential and health disparities are equal. Priorities need to be taken into consideration for resource allocation.

However, there is very little research on local policy prioritization to reduce health disparities, suggesting the importance of our work here. Local initiatives to reduce segregation such as zoning reforms and investments in and incentives for mixed-income and intentionally affordable housing require substantial resources. We show, that in some counties, local resources spent on recruiting and supporting primary care physicians might make a better positive impact on health outcomes and reduction in health disparities (Brooks et al., 2002). According to Brown et al. (2019), researchers need to offer stakeholders such as local policy decision-makers: (1) “more robust evaluations of social and health indicators” so they can; (2) “prioritize funding for well-designed structural interventions”; and; (3) with effective evaluation mechanisms (p. S77). Our research addresses all three issues of these issues.

We make no attempt to quantify the costs of local policies to improve health outcomes. More research is needed to explore the role of racial residential segregation through SDOH pathways to health outcomes, especially those variables that require significant public financial investment at the local level.

Limitations

Our results are based on county level data and do not presume to be applicable to interventions that promote health of individual persons. However, resources for healthcare services and public health are typically funded at the county or district level and this analysis can help policy development at the local level. We note that our measure of racial residential dissimilarity has an unclear SDOH connection to the self-reported health variable (Acevedo-Garcia et al., 2003) and despite being widely used (Iceland & Nelson, 2008), it is the only measure of segregation we use. Future research may consider other measures of segregation such as isolation, clustering, centralization, and concentration (Acevedo-Garcia et al., 2003). In addition, more research is needed to relate pathways of racial residential segregation to disparate health outcomes (Williams et al., 2019b) that are both self-reported and subjective measures as well as more objective measures of health outcomes.

Appendix 1

County Health Rankings & Roadmaps is a program of the University of Wisconsin Population Health Institute. Most of the original data is publicly available from a variety of national data sources but County Health Rankings collects it all in one place. The County Health Rankings team calculates many of the measures with “raw data provided by our partners (e.g., National Center for Health Statistics) [but] many measures are also calculated by partner organizations. For example, the Behavioral Risk Factor Surveillance System estimates are calculated by staff at the Center for Disease Control and Prevention”. Many of the social and economic variables as well as the racial residential segregation variable come from the American Community Survey. For a full list of the original data sources see https://www.countyhealthrankings.org/2022-measures).

Author Contributions All authors contributed to the study conception and design. Material preparation, data collection, and data analysis were performed by: (1) Catherine P. Slade; (2) Simon K. Medcalfe; (3) C. Kevin Fortner; and (4) Kristin V. Walker. The first draft of the manuscript was written by Catherine P. Slade, corresponding author, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data Availability The data sets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

No IRB Approval Required Only publicly available data is used for this study. The data sets generated during and/or analyzed for our study are available from the corresponding author on reasonable request. If accepted for publication we will make the data generated and analyzed during our study available in a public repository.

Competing Interests The authors declare that they have no competing interests.

Conflicts of Interest We have no conflicts of interest, financial or non-financial. As corresponding author, I have submitted the required conflict of interest statement on behalf of and with the approval of my fellow authors.

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