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Indicators of inequity: Exploring the complexities of operationalizing area-level structural racism

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1. Introduction

Structural racism has been deemed a fundamental cause of health inequities in the US. According to Bailey et al., *structural racism* is defined as "the totality of ways in which societies foster racial discrimination through mutually reinforcing systems of housing, education, employment, earnings, benefits, credit, media, health care, and criminal justice. These patterns and practices reinforce discriminatory beliefs, values, and distribution of resources" (Bailey et al., 2017). Structural racism in the US is built on interlocking systems across these domains (e.g., economic, judicial, political, educational etc.) that continuously perpetuate the dominant racial/ethnic groups' power, privilege, and control of resources. Consequently, racially and ethnically minoritized groups are excluded from resources that routinely advantages White people to secure or maintain power via historically rooted and culturally reinforced institutions, policies, and practices (Bailey et al., 2017; Krieger, 2012; Lukachko, Hatzenbuehler, & Keyes, 2014). This unequal distribution of resources manifests as racial and ethnic inequities in numerous health outcomes, with a disproportionate burden on racially and ethnically minorized groups. A nascent body of literature has sought to build evidence on the role of structural racism as a fundamental cause of racial health inequities. Accordingly, studying the effects of structural racism on health and health inequities requires consideration of how the construct is measured and operationalized.

Despite growing interest in the impacts of structural racism, there is still no "gold standard" measurement approach to empirically capture structural racism (Dean & Thorpe, 2022; Jahn, 2022). Measurement approaches have been heterogeneous with a place-based approach being the most common strategy used in empirical studies. More specifically, a place-based approach uses area-level indicators to capture place-based racial inequities across societal domains. Area-level indicators have been examined at multiple levels, including metropolitan area units, states, counties, and census tracts. Examples include state-level Black--White inequities across multiple domains (e.g., housing, income, education), county-level measures of residential segregation (e.g., dissimilarity index, isolation index, index of concentration of extremes), and measures of redlining and mortgage discrimination. Often, studies use a combination of area-level indicators to create a composite index or latent construct measure to operationalize multidimensional structural racism and then examine its relationship to a particular health outcome (Furtado et al., 2023). For example, state-level Black-White ratio measures of income inequality, poverty rate, incarceration rate, and bachelor's degree attainment have been aggregated to derive a combined index measure of structural racism (Furtado et al., 2023). Alternatively, latent construct approaches use the same indicators to derive an underlying measure of structural racism (Furtado et al., 2023). While these methods are critical for capturing the multidimensionality of structural racism, few studies have conducted a descriptive assessment of the individual area-level indicators prior to using them as inputs in a structural racism measure.

Without a descriptive assessment of the area-level indicators, we have no indication of the distribution of indicators commonly used to create multidimensional measures of structural racism. Importantly, the distribution could have implications for how a multidimensional structural racism measure might operate when assessing its relationship to health outcomes. Furthermore, the place-based nature of area-level indicators warrants an understanding of how the indicators are spatially patterned. An understanding of where the area-level indicators are patterned in the US context could give us insights into the regions where structural racism exposure may be particularly prominent. Previous

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studies have used area-level indicators as inputs in multidimensional structural racism constructs and assessed the spatial patterning of the multidimensional construct (Chantarat et al., 2021; Siegel et al., 2022). However, few studies have examined the spatial patterning of singular area-level indicators across societal domains commonly used to create structural racism measures. Arguably, equally important to describing multidimensional structural racism exposure is describing the area-level indicators used to develop a multidimensional structural racism measure.

To address this gap, the objective of this study is three-fold. First, we conduct a descriptive assessment of two types of area-level indicators commonly used in structural racism and health research – ratio measures and Index of Concentration at the Extremes (ICE) measures (Krieger et al., 2016). Second, we use choropleth maps to assess the spatial patterning of the area-level indicators. Last, we offer methodological considerations for using area-level indicators; and highlight the prospects and limits of using area-level indicators as proxies of structural racism. In the following section, we provide background on the conceptualization and operationalization of ratio and ICE measures as indicators of structural racism.

2. Background

2.1. Ratio measures: a common indicator of racial inequity

To assess the presence of place-based racial disparities, societal inequities are commonly indexed as ratios, or proportions of one race group relative to another. For example, a Black-White inequity would be calculated as Black versus White ratio for a particular societal domain ($P_b = 1/P_w = 1$, where $P_b = 1$ is the proportion of Black people in an area-unit experiencing an event and $P_w = 1$ is the proportion of White people experiencing an event) (Furtado et al., 2023). First utilized to operationalize structural racism by Lukachko et al. this approach uses area-level ratio measures across multiple societal domains in which structural racism is hypothesized to operate, including political, employment, judicial, economic, educational, and residential (Lukachko et al., 2014). In the case of Black-White measures, ratios have been used as a proxy for anti-Black structural racism in the US context. For example, Wallace et al. used population estimates to calculate state-level Black-White ratio measures in educational attainment, median household income, employment, imprisonment, and juvenile custody and then examined associations with Black and White infant mortality in the US (Wallace et al., 2017). The domains of interest reflect the United States' long history of using laws and policies to weaponize the existence and social & economic mobility of Black people, epitomizing the long-term impacts of anti-Black structural racism. Additionally, key benefits of using ratio measures are interpretability of the measures and reproducibility when using publicly available data such as US Census products. Ultimately, the purpose of using ratio measures is to capture inequities in societal domains that reflect structural racism exposure.

2.2. Index of concentration at the extremes: capturing spatial polarizations

Racial and economic Index of Concentration at the Extremes (ICE) measures are commonly used in studies of residential segregation and population health outcomes. Massey initially developed the ICE measures to capture spatial social polarization by simultaneously quantifying the extent to which an area's residents are concentrated at the extremes of socioeconomic deprivation and privilege (Massey, 2001). Krieger et al. (2016) expanded upon the original ICE measure to develop novel measures of racial segregation and racial economic segregation, individually and jointly (Krieger et al., 2016). Residential segregation, operationalized as the ICE measures, captures the physical separation of groups by race and economic status that are enforced by historical and current policies such as racially restrictive covenants and mortgage redlining (Krieger et al., 2016). Accordingly, residential segregation acts a mechanism by which structural racism operates through institutionalized practices and policies, which shape and sustain inequities in healthcare access, employment & earnings, quality education, safe and affordable housing, and other resources important for well-being (Williams & Collins, 2001). To capture conditions created by historical and ongoing segregation, we focus on two ICE measures – racialized segregation (i.e. ICE race and ICE race-income) both explicitly incorporate Black-White race into the measures, which is consistent with our ratio measures of interest. A key strength of ICE measures is that they are uniquely positioned to be adaptable at higher- and lower-level geographic scales (Feldman et al., 2015; Krieger et al., 2015). Other commonly used segregation measures (e.g. Gini coefficient and index of dissimilarity) cannot meaningfully be used at smaller geographic units (e.g., block group, census tract, city, county) due to spatial social segregation (Feldman et al., 2015; Krieger et al., 2015; Massey, 2001). Previous literature have used ICE measures at multiple levels, including census tract, ZIP code, and city. For example, previous studies have used ICE measures to examine and partially explain racial disparities in maternal morbidity, mortality, and birth outcomes (Bailey et al., 2017; Krieger, 2012; Lukachko et al., 2014). Thus, ICE measures are uniquely positioned to capture segregation as an indicator of structural racism at the intersection of racial and economic concentration in place.

3. Methods

3.1. Study overview

The data assessment of the area-level indicators was conducted in a stepwise fashion. First, we calculated the ratios and ICE measures using county-level data from the 2016–2020 American Community Survey. Next, we assessed data anomalies from the calculations that yielded undefined values, missing values or outliers. Accordingly, we identified three classes of data anomalies in our analysis: missing values, implausible values, and outliers such that the classes of data were mutually exclusive. Finally, we created choropleth maps – a spatial thematic map– to represent the values for the ratio and ICE measures across the contiguous US.

3.2. Data source

We used five-year (2016–2020) American Community Survey (ACS) county data accessed from https://www.census.gov/programs-surveys/acs/ for the contiguous US. The ACS, administered by the US Census Bureau, collects a wide range of demographic, social, economic, and housing information from households and individuals across the US. The data are collected on an ongoing basis, providing annual period estimates for multiple geographic areas. The five-year period estimates from the ACS represent the characteristics of the US population between 2016 and 2020.

3.3. Area-level indicators

We calculated the following ratio measures: White-Black educational attainment, Black-White unemployment, White-Black median household income, and Black-White poverty. The ratios were oriented such that values greater than one were indicative of a disadvantage for Black individuals relative to White individuals. The ICE measures of interest were ICE race and ICE race-income to capture residential segregation operationalized as racial and economic spatial polarization. The study population for this study includes all contiguous US counties, which were the units of analysis for all area-level indicators.

3.4. Educational attainment

The numerator for the educational attainment indicator was the proportion of non-Hispanic White (hereafter White) individuals aged 25 years and over with a Bachelor's degree or higher in each county. The denominator was the proportion of non-Hispanic Black (hereafter Black) individuals aged 25 years and over with a Bachelor's degree or higher in each county. A ratio value greater than one reflects Black individuals being underrepresented in Bachelor's degree attainment relative to White individuals. The White-Black educational attainment ratio is as follows:

$$White - Black\ Educational\ Attainment = \frac{Proportion\ of\ White\ individuals\ with\ Bachelor's\ degree\ or\ higher}{Proportion\ of\ Black\ individuals\ with\ Bachelor's\ degree\ or\ higher}$$

3.5. Unemployment rate

The Black unemployment rate is the number of unemployed Black individuals in a county divided by the number of Black individuals in the civilian labor force as the numerator. Similarly, the White unemployment rate is the number of unemployed White individuals in a county divided by the number of White individuals in the civilian labor force as the denominator. A ratio value greater than one represented Black individuals being overrepresented in the unemployment domain relative to White individuals. The Black-White unemployment ratio is as follows:

$$Black - White\ Unemployment = \frac{Black\ unemployment\ rate\ among\ civilain\ labor\ force}{White\ unemployment\ rate\ among\ civilain\ labor\ force}$$

3.6. Median household income

Median household income refers to the median household income in the past 12 months (in 2020, inflation-adjusted dollars) for each race group in a given county. The median household income is based on the distribution of the total number of households in a county. Median household income is reported as a discrete value rounded to the nearest whole dollar for each county. A ratio value greater than one reflected Black individuals were disadvantaged relative to White individuals for the median household income domain. The White-Black income ratio is as follows:

$$White - Black\ Income = \frac{White\ Median\ Household\ Income}{Black\ Median\ Household\ Income}$$

3.7. Poverty rate

The Black poverty rate is the number of Black individuals with income in the past 12 months below the poverty level divided by the number of Black individuals in a county in the numerator. The White poverty rate is the number White individuals with income in the past 12 months below the poverty level divided by the number of the White individuals in a county in the denominator. A ratio value greater than one indicated Black individuals were overrepresented relative to White individuals for the poverty domain. The Black-White poverty ratio is as follows:

$$Black - White\ Poverty = \frac{Black\ poverty\ rate}{White\ poverty\ rate}$$

3.8. Racial segregation (ICE race)

ICE race estimates the amount of space in a county occupied by Black residents (low racial privilege) relative to White residents (high racial privilege). We set the extreme groups as persons who self-identified as White vs. those who self-identified as Black, which reflects the system of inferiority of White race groups in the US context. Accordingly, ICE race was calculated as [(*N of* residents self-identified as White)−(*N* of residents self-identified as Black)]/total population with race and ethnicity data.[99] The values for ICE race range from −1 (most deprived) to 1 (most privileged). A value of 0 indicates that the county is not dominated by extreme concentrations of deprivation or privilege. The calculation for ICE race is as follows:

$$ICE_{race} = \frac{(A_i - P_i)}{T_i}$$

where for a given county j:

A_i = *N* of persons who self-identified as non-Hispanic White
P_i = *N* of persons who self-identified as non-Hispanic Black
T_i = Total population with race/ethnicity data

3.8.1. Racial and economic residential segregation (ICE race-income)

ICE race-income estimates the amount of space in a county occupied by poor Black households (low-income and low-racial privilege) compared to wealthy White households (high-racial privilege and high-income). The deprived group was Black individuals in a county who made < $25,000 annually, while the privileged group was White persons in a county who made ≥ $100,000. ICE race-income uses household income data which includes the income of the householder and all other individuals 15 years old and over in the household in the past 12 months (in 2020, inflation-adjusted dollars). Household income data was categorized into categories predefined by the US Census (e.g., less $10,000, $10,000-$14,9999, $15,000-$19,999 etc.). Accordingly, the values used in the ICE race-income calculation include the count (*N*) of individuals in each category. We defined the household income cut points as <$25,000 (low income) and households earning ≥ $100,000 (high income) based on the 20th vs. 80th US household income percentiles of household income distribution based on the 2020 US Census, respectively. The calculation for ICE race-income was [(N of Black residents who made < $25,000)−(N of White residents who made ≥ $100,000)]/ total population with race/ethnicity and household income data. Similar to ICE race, ICE race-income can range from −1 (most deprived) to 1 (most privileged). The calculation for ICE race-income is as follows:

$$ICE_{race-income} = \frac{(A_i - P_i)}{T_i}$$

where for a given county j:

A_i = *N* of persons who self-identified as "non-Hispanic White" with high income (≥$100,000)
P_i = *N* of persons who self-identified as "Black alone" with low income (<$25,000)
T_i = Total population with race/ethnicity and household income data

3.9. Data assessment

3.9.1. Missing data assessment

We conducted a thorough missing data assessment to understand the scope of missingness for the ratio measures at the national level. We identified two classes of data–*missing* values and *implausible* values—in a stepwise fashion, such that the classes of data were mutually exclusive. First, we identified *missing* values for the ratio measures, which refers to values that were missing from the ACS prior to the ratio calculation. If the numerator or the denominator of the ratio measures was missing from the ACS, the ratio value was classified as missing data for the spatial assessment (Fig. 1). Similarly, ratio values with missing values from the ACS in the numerator *and* denominator were classified as missing data in the spatial assessment.

Next, we assessed *implausible* values due to illogical or undefined values when conducting the calculations for the ratio measures. Zero

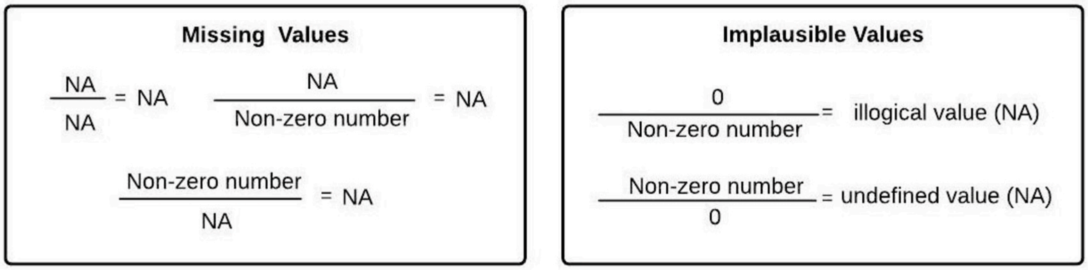

Fig. 1. Illustrative examples of missing values and implausible values for ratio measures; NA: missing value.

values can be in the numerator or the denominator of the ratio measure due to zero respondents reporting in a county for a particular domain. Values with zero in the numerator and a non-zero number in the denominator would mathematically have a ratio value of zero (Fig. 1). However, in the context of interpreting ratio values, a ratio value of zero means there is an absence of the variable of interest. Accordingly, a ratio value of zero is illogical, which is tantamount to missing. Therefore, ratio values of zero were classified as *implausible* were set to missing in the spatial assessment. Additionally, undefined values resulted from a non-zero number in the numerator of the ratio measure divided by zero, which rendered the ratio value missing. Of note, the ICE measures had no missing data because the data used to calculate the ICE measures used count data rather than proportions. The race and income data used for the ICE measures were in predefined categories, which meant there was count data available for every category of interest needed to calculate the ICE measures.

3.9.2. Outlier assessment

To ensure the integrity and robustness of ratio measures, we conducted an outlier assessment. Outliers were defined as values that appeared to be inconsistent with the rest of the observations in a dataset. We used boxplots to examine the distribution of the data and define outliers. We constructed a boxplot for each structural racism indicator, where the central box represents the interquartile range (IQR) between the first quartile (Q1) and third quartile (Q3), with the median marked within the box. Next, the IQR was calculated as Q3–Q1. According to standard outlier detection methods, we identified outliers as data points that fell below Q1 - 1.5 * IQR or above Q3 + 1.5 * IQR (Schwertman et al., 2004). These values, referred to as the lower and upper bounds, respectively, served as the thresholds for outlier detection. Any data points falling outside these bounds were considered outliers. Similar to the missing data assessment, we did not identify outliers for the ICE measures. By nature of the equations for the ICE measures, the range is bounded between −1 and 1. Therefore, we did not assess outliers at the risk of skewing the ranges of the ICE measures.

3.9.3. Spatial mapping

We created choropleth maps to represent the values for ratio and ICE measures using color shading to show patterns across US counites. First, we created maps for each of the four ratio measures that depicts the outliers. Next, we created six additional maps to describe the spatial patterning of the viable data for each measure with the missing and outlier data displayed in gray. The maps with viable data were also mutually exclusive with the data displayed being specific to each measure.

4. Results

The total sample included all 3221 US counties or equivalents from the 2016–2020 ACS. County equivalents include Alaska boroughs, municipalities, city and boroughs, and census areas; the District of Columbia; Louisiana parishes; Puerto Rico municipios; independent cities in Maryland, Missouri, Nevada, and Virginia. The counts for missing data and outlier assessments are listed in Table 1. Among the ratio measures, White-Black income had the largest proportion of missing values (40%), while White-Black education had the lowest number of *missing* values (4%). Among the *implausible values*, White-Black education had the largest number of missing values (18%). There were zero *implausible* values for White-Black income and Black-White poverty. White-Black income maintained the greatest number of total missing values (40%), which is likely due to data suppression done by the US Census for raw median household income data. In the outlier assessment, Black-White unemployment, White-Black education, and Black-White poverty both had 6% of the data detected as outliers. White-Black income had the smallest number of outliers (3%). Since the calculation for the ICE measures used count data instead of proportions, there was viable data for used in all ICE measure calculation resulting in no missing data for ICE race and ICE race-income. Additionally, we did not conduct an outlier assessment for the ICE measures because the resulting values are bounded by −1 and 1. Therefore, there are no outliers for ICE race and ICE race-income.

The counties identified as outliers for the ratio measures are displayed in Fig. 2. There are no apparent spatial patterns for the outliers for each ratio indicator. The ratio and ICE measures with viable data at the county-level are mapped in Figs. 3 and 4 with the missing and outlier data displayed in gray. Ratio measures used a sequential color scheme, where the color transitions from light to dark pink, indicating a variation in the indicator from zero to infinity. The areas in the lightest pink shade indicate indicator values less than one, which represents a disadvantage for White people relative to Black people. The pink shade darkens as the indicator values increase above one, which reflects a disadvantage for Black people relative to White people. Alternatively, the ICE measure maps use a diverging color scheme from, with contrasting colors of pink and green reflecting the ICE measure range of −1 (most deprived) to 1 (most privileged).

For White-Black education, regions with high values of disadvantage for Black people (>1.0) cluster in the South, Midwest, and along the East Coast (Fig. 3). Similarly, regions in the South, Midwest, and parts of the Mid-Atlantic indicated disadvantages for Black people relative to White people for unemployment (Fig. 3). Similar to White-Black education, we observed the highest values for disadvantage in White-Black income in the southeast and along the Atlantic coast. For Black-White poverty, we observed the largest values of disadvantage for Black people in some parts of the Midwest, South, and Northeast. The ICE race map indicated a more extreme concentration of Black residents (ICE race <0) in the South (Fig. 4). The ICE race-income map reflected a similar pattern of high concentrations of Black, low-income residents (ICE race-income <0) in the southeastern region.

5. Discussion

This study used national data from the American Community Survey to examine two types of commonly used area-level indicators of structural racism: ratio and ICE measures. We characterize the amount of

Table 1
Missing and outlier data for area-level indicators of structural racism at the county-level in the 2016–2020 American Community Survey, ACS (n = 3221).

	White-Black Education n (%)	Black-White Unemployment n (%)	White-Black Income n (%)	Black-White Poverty n (%)	ICE race n (%)	ICE race-income n (%)
Missing Values	136 (4%)	310 (10%)	1304 (40%)	176 (5%)	0 (0%)	0 (0%)
Implausible Values	592 (18%)	11 (0.3%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Total Missing[a]	728 (23%)	321 (10%)	1304 (40%)	176 (5%)	0 (0%)	0 (0%)
Outliers	206 (6%)	184 (6%)	86 (3%)	182 (6%)	0 (0%)	0 (0%)

[a] Total missing includes both missing values and implausible values.

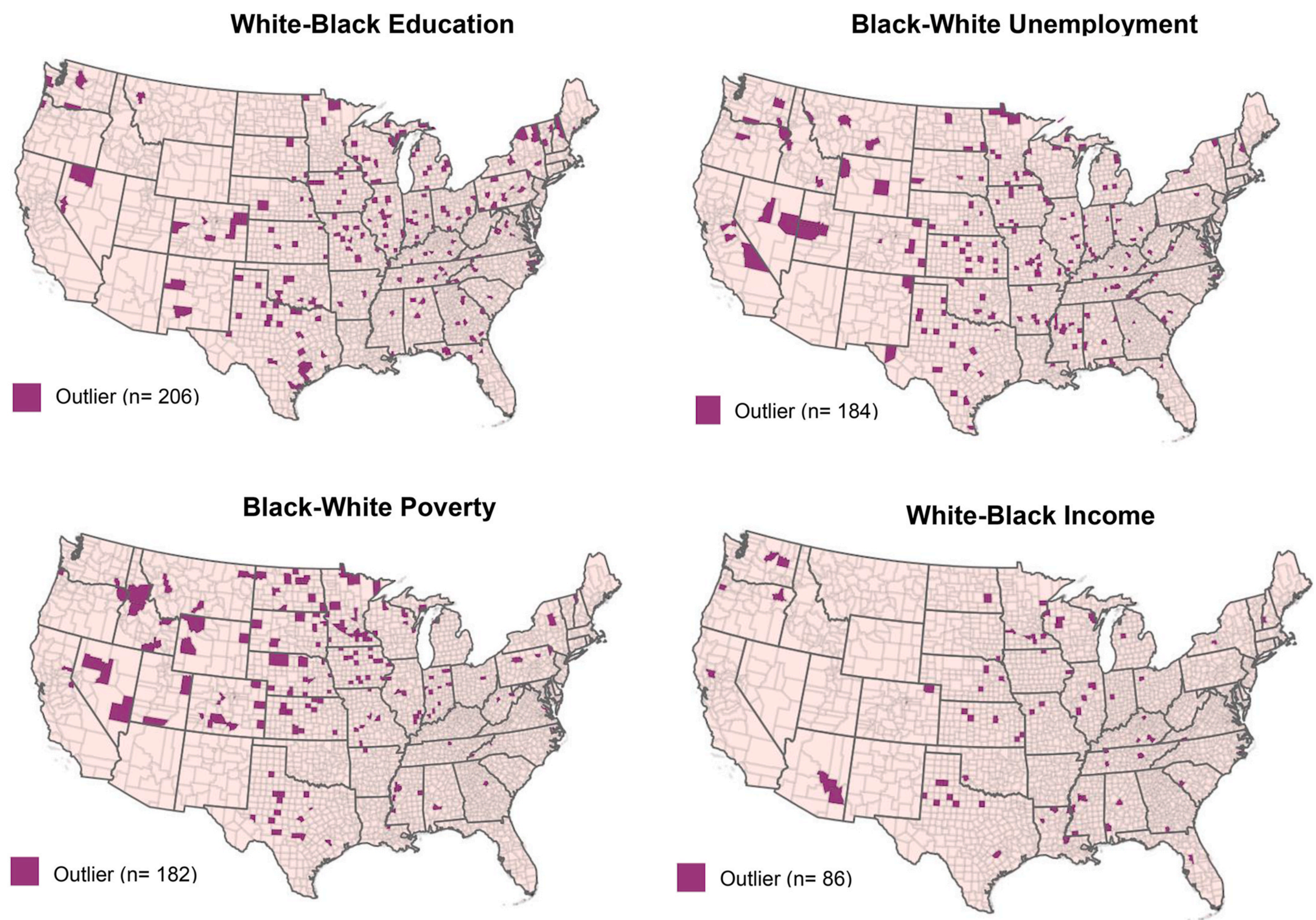

Fig. 2. Map of outliers for ratio measures at the county-level using 2016–2020 American Community Survey (ACS) (n = 3221).

missingness and outliers for the ratio measures and mapped both types of area-level indicators to determine the spatial patterning across the US. Finally, we compared the spatial patterns between the four ratio measures and the two ICE measures. Importantly, our results highlight the high levels of missing values for the ratio measures and demonstrate spatial patterns of disadvantage for Black people relative to White people in the Southeast and parts of the Midwest.

5.1. Missing data limitations

The substantial missingness observed in the context of using ratio measures as proxies of structural racism has important methodological implications. The overall counts for total missing data included *missing* values and *implausible* values. White-Black income most notably had the highest percentage of *missing* values from the ACS. Missingness for median household income for Black respondents was particularly high—likely due to data suppression of values by the US Census Bureau. High missingness for Black median household income ultimately resulted in a high percentage of missing values for the White-Black income ratio. The values could be missing for several reasons: 1) a zero count of Black households reporting income in county, 2) zero Black households interviewed in a county for this particular 5-year ACS survey, or 3) not enough Black households in a county to meet the minimum number of cases to report median household income (i.e., data suppression). Importantly, the calculation for Black-White poverty and ICE race-income use income data; however, there was far fewer missing data compared to White-Black median household income for these indicators. The difference in missingness is due to the *type* of income data used in each calculation. For example, the White-Black median household income ratio used discrete data rounded to the nearest dollar on the median household income in a given county, which is subject to missing data due to zero counts of specific race groups in a county and data suppression. Alternatively, the poverty ratio and ICE race-income measure used count data of the number of respondents in a specific

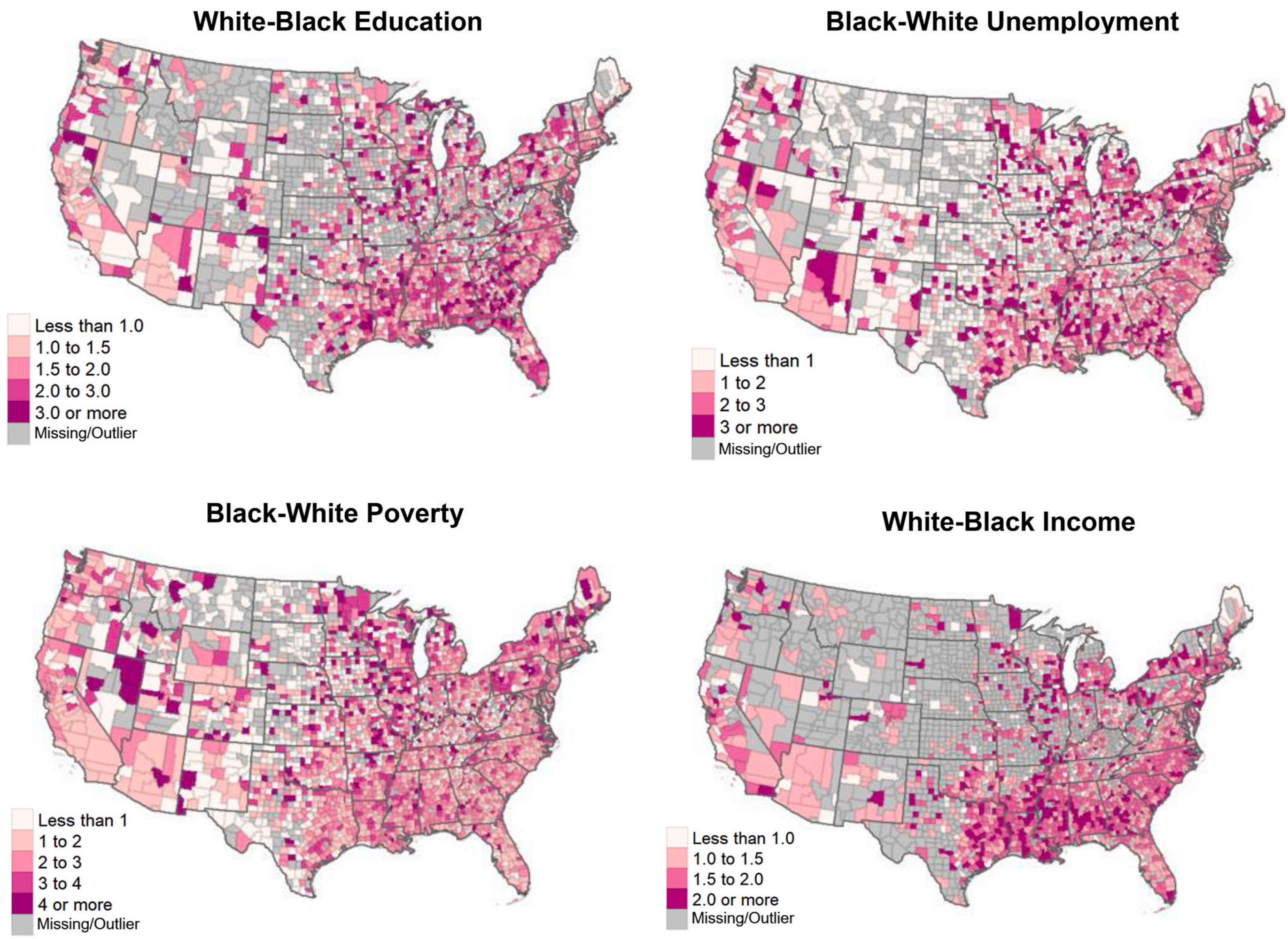

Fig. 3. Choropleth map of ratio measures at the county-level using 2016–2020 American Community Survey (ACS) (n = 3221).

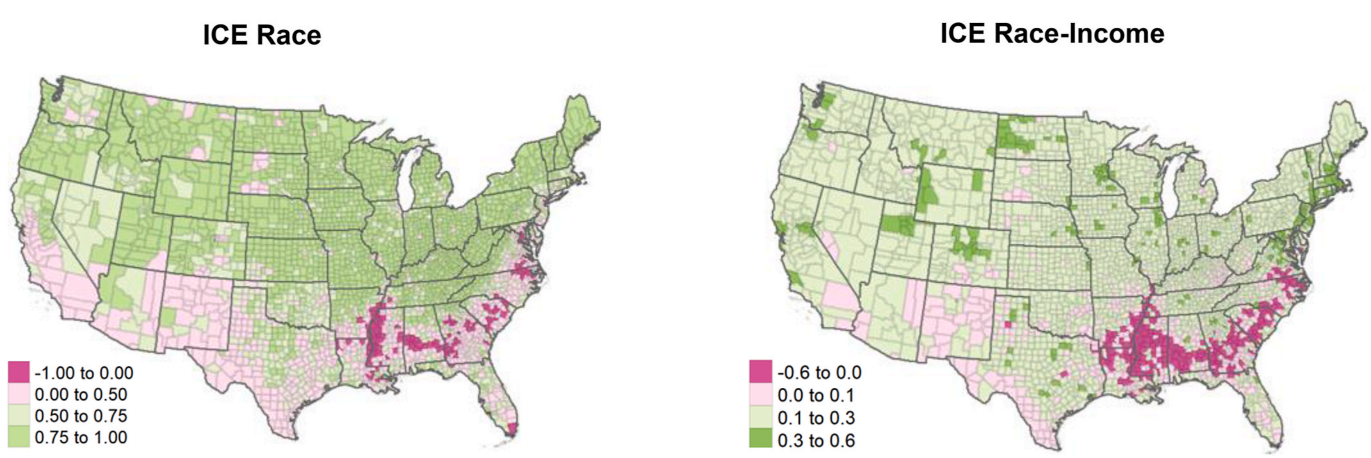

Fig. 4. Choropleth map of ICE measures at the county-level using 2016–2020 American Community Survey (ACS) (n = 3221).

category of household income (e.g., number of White respondents with household income greater than $100,000). As a result, the calculation for the median household income ratio is more sensitive to missing data compared to the ICE race-income which only required count data in each income category at the extremes (i.e., *N* of persons who self-identified as "non-Hispanic White" with high income (≥$100,000) and *N* of persons who self-identified as "Black alone" with low income (<$25,000)).

Missingness can result in underestimating or even concealing existing inequities in area-level indicators. This could compromise the accuracy of research findings observed when examining the ratio indicators in relation to population health outcomes and potentially lead to incorrect conclusions about the extent of the impact of structural racism. Previous studies have used area-level indicators, such as Black-White educational attainment, Black-White median household income, and Black-White unemployment (Lukachko et al., 2014; Wallace et al., 2017). However, few studies have mapped the geographic distribution of indicators in their study samples. Using the ACS is a key strength of our study as it provides greater detail on the limitations of using area-level structural racism indicators for the entire US. We gain insights on which indicators are more susceptible to missing data limitations, while also drawing conclusions on which US regions with viable data might have increased disadvantage for Black people relative to White people. Furthermore, the use of large and nationally representative surveys highlights the need to consider how these commonly used indicators are spatially patterned and how high levels of missingness could be biasing our estimates of area-level structural racism exposure. Accordingly, researchers should be cautious when using ratio measures to conceptualize structural racism exposure. When possible, researchers should consider examining the spatial patterning of these ratios in their study population to understand patterns of missingness prior to exploring relationships to health.

The implausible data — values missing due to undefined ratios — also present limitations when operationalizing structural racism at the area-level, particularly when using Black-White ratios. Often, the implausible values results from a zero value in the denominator of a ratio measure. Empirically, this means that there is no population of respondents of a particular race in each county, which results in an undefined value for the ratio measure. For example, we found that 18% of counties had implausible values for White-Black educational attainment. In the calculation of the education ratio, 592 of the 3221 counties in US had a zero value in the denominator for "*proportion of Black individuals with a bachelor's degree or higher*." Despite having values for the numerator, the White-Black education ratio was undefined and, in turn, rendered the ratio value missing. The absence of a Black population in a county poses a significant challenge when assessing Black-White ratio measures empirically, given there are several regions of the US that have sparse populations of Black people. This concern would be even greater when operationalizing racial inequities for other racially and ethnically minoritized groups (e.g., American Indian and Alaska Native populations) who have even smaller populations in the US. (Liebler & Ortyl, 2013; Who Counts) Improvement to data collection on minoritized groups might include oversampling in national surveys, pooled data across surveys, and targeted periodic surveys among racially and ethnically minoritized groups (Bilheimer & Klein, 2010). Furthermore, the small samples of Black people residing in specific regions (i.e., Pacific and Mountain regions of the West) brings into question the reliability and validity of the county-level ratio measures in areas with small populations of racially minoritized people. Alternative methods might be used at higher geographies such as metropolitan areas and states to increase the sample size of racially minoritized groups. Despite the small sample size, future considerations should be made on appropriate methodologies to address missing data concerns and to understand the experience of racially and ethnically minority groups who are most impacted by structural racism (Elliott et al., 2009; Fok et al., 2015; Hayward et al., 2021).

5.2. Detecting outliers

Outliers, typically defined as observations lying significantly distant from the central tendency of a dataset, can often be perceived as nuisance values to be removed to enhance the robustness of statistical analyses (Osborne & Overbay, 2019). In the case of ratio measures, outliers are values much different from the sample of viable ratio data. However, we did not observe marked spatial patterns of where the outliers were across the US for any of the ratio measures. Importantly, the distribution of outliers observed is reflective of the inclusion of all counties in the US with data to calculate the ratio and ICE measures. The prevalence of outliers can vary based on inclusion criteria (e.g., restricting analyses to counties that have at least 10 Black households and 10 White households). Additionally, outliers may not only represent data artifacts or measurement errors, but they can also embody extreme values of genuine interest. For example, there could be a county where the White-Black indicator for median household income is an extreme value that is excluded based on the outlier assessment. However, that county could represent an extreme value of interest, where income inequity, as an indicator of structural racism, is particularly pronounced. These extreme values may signify noteworthy regions that warrant further examination. Although we did not observe any spatial patterns for the outliers, further investigation of the individual counties defined as outliers may give insight into whether the outliers are truly a nuisance value or an extreme value of interest. Of note, methodology for outlier detection and management must be nuanced, aiming to strike a balance between identifying and excluding aberrant data points while preserving outliers that could offer valuable insights into the underlying patterns of the ratio measures.

5.3. Spatial distribution of area-level structural racism indicators

The geographic distribution of the ratio measures demonstrated patterns of disadvantage experienced by Black individuals relative to their White counterparts, particularly in the Southern US. These patterns in the South may be driven by the interplay of historical, social, and economic factors deeply rooted in the region's past. Historically, Southern states enforced segregation through Jim Crow laws and discriminatory practices, segregating communities along racial lines and depriving Black individuals of equal access to education, housing, and employment opportunities (Inwood, 2011). The region's historical legacy also influences poverty rates, with a higher concentration of Black residents experiencing limited access to quality education and employment opportunities. Importantly, the US South has the largest percentage of Black residents relative to other regions, which means there are more residents to contribute data when calculating the racial inequities. In 2021, the majority of US Black population lived in the South (56%), followed by the Northeast (17 %), the Midwest (17 %) and the West (10%) (Moslimani et al., 2023). Therefore, the high prevalence of Black people living in the South could be a driving force behind the patterns of racial inequity. We also observed trends of high disadvantage for Black people in parts of the Midwest for all four ratio measures. Historically, the Midwest has been perceived as a racially homogeneous region, with 73% and 10% of the Midwest population being White and Black, respectively. Therefore, the patterns in this region are a striking finding that warrants careful consideration because they highlight the complex and nuanced reality of structural racism. For example, say there were 500 residents who were Black and 100 of those Black residents were unemployed, while there are 10,000 residents who are White, and 3000 of those White residents were unemployed. An inequity metric would indicate a ratio of 0.67, making it appear as if there is a low level of Black disadvantage relative to White residents in that county. However, Black residents in counties with small populations of Black people could experience greater disadvantage just by the nature of being in the minority. Accordingly, ratio measures provide crucial insights into racial inequity but may oversimplify the reality of structural racism (Riley, 2018).

The ICE measures for race and race-income demonstrated an apparent pattern of racial and economic deprivation in the Southern states and along the Atlantic coast. Similar to the ratio measures, these findings likely reflect residential segregation and discriminatory laws and policies that have played an important role in shaping the socioeconomic landscape in the US South. As the name suggests, the ICE measures effectively capture hyper-segregated regions at the extremes with very clear patterns in the Southern regions. However, the gradient of the segregation is less apparent in the middle of the indicator, which is seen in the vast regions of the green shade in our results. Therefore, ICE measures may be considered alongside other metrics of segregation to provide a comprehensive assessment of segregation patterns across the US.

5.4. Proxy nature of area-level structural racism

Both ratio and ICE measures were calculated using publicly available data, and the accessibility of the US Census product is a key strength of area-level approaches to measuring structural racism. However, the use of US Census products has limitations that should be considered. Area-level indicators have previously been called "indirect" proxy measures of structural racism across domains such that they capture the downstream consequences of racist structures through the presence or absence of place-based inequities (Furtado et al., 2023; Needham et al., 2023; Riley, 2018). Research has argued that the use of variables from the Census serves as proxies for structural racism rather than directly measuring the actual racist policies or practices themselves (Needham et al., 2023; Riley, 2018). Consequently, the use of such area-level indicators requires proper framing of the rationale for the geographic level examined at the risk of obscuring structural processes and actors (Wien et al., 2023). Without proper framing, the utility of the indicators may be limited when it comes to identifying the root causes of racial health disparities or in devising effective interventions to dismantle the underlying structures of racism. Despite the limitations around the proxy nature of area-level indicators, they still provide a quantifiable and easily replicable means to assess the magnitude of the impact structural racism has on various domains of society. As this research area develops, area-level indicators can serve as a preliminary strategy for highlighting the existence and extent of racial disparities but should be complemented with deeper investigations into the specific policies, practices, and historical factors that perpetuate structural racism. Empirically, this could look like data linkages across multiple data sources such as the National Conference of Legislatures, US Department of Labor and Statistics, Medicaid & Medicare data, Bureau of Justice Statistics, Home Mortgage Disclosure Act data, and other publicly available data (Riley, 2018). This would enable a more comprehensive approach to understanding the impact of structural racism on population health.

5.4.1. Limitations

Our study of area-level indicators of structural racism has some limitations. First, our approach relies on the dichotomous operationalization of structural racism indicators, inherently restricted by its focus on only two racial categories through ratio calculations. This constraint may not fully capture the intricacies of structural racism experienced by diverse minoritized groups beyond the binary framework, which is a broader limitation of this research area. Relatedly the use of area-level indicators in the literature has predominantly centered on assessing the Black-White differential in structural racism experiences. While there is the potential to extend these measures to other racially and ethnically minoritized groups, the existing body of research may have limitations in terms of adequate sample size in other populations. Importantly, regional differences in the cost of living across the United States, particularly for metropolitan areas, may not accurately demonstrate the extent of disadvantage when using metrics based on income (e.g. ICE race-income, White-Black median household income). Future studies should consider analyses at a more granular level to explore alternative operationalizations of such measures in metropolitan contexts. Finally, we chose to examine area-level structural racism at the county level; however, there is likely variability in the results based on the level of geography. State-level indicators offer more complete datasets, yet they may obscure the finer granularity and variations present in smaller area units where policies are often enacted. On the other hand, county analyses provide greater granularity but are limited by a significant amount of missing data. As with other geographic studies, it is unclear what geographic level of analysis is most appropriate for the study of area-level structural racism.

6. Conclusion

This study illustrates the use of area-level structural racism indicators using a geographic approach and highlights the considerations when using these indicators. While widely used, these measures present significant analytical challenges to empirically assessing the influence of structural racism on population health. Through an examination of data from the ACS, we shed light on the missingness and spatial distribution of ratio indicators of structural racism across multiple societal domains. Additionally, our findings highlight the difficulties in discerning whether our quantitative operationalization of spatial structural racism reflects what is qualitatively occuring in these areas. Future research should explicitly justify the choice of specific area-level indicators based on both theoretical and policy considerations. Accordingly, the area-level of enactment of the structurally racist policy or practice should reflect in the area-level proxy of the exposure. Clearly articulating the rationale behind the selection of area-level measures and supplementing them with specific historical and contemporary policy measures of structural racism (e.g., redlining, Jim Crow policies, voter restriction laws, Medicaid expansion etc.) will enhance the measurement approach. Considering these complexities, future research can conduct more precise and nuanced examinations of the interplay between structural racism and population health outcomes.

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Ethical statement

Hereby, I, Joëlle Atere-Roberts, consciously assure that for the manuscript, Indicators of inequity: Exploring the complexities of operationalizing area-level structural racism, the following is fulfilled:

1) This material is the authors' own original work, which has not been previously published elsewhere.
2) The paper is not currently being considered for publication elsewhere.
3) The paper reflects the authors' own research and analysis in a truthful and complete manner.
4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
5) The results are appropriately placed in the context of prior and existing research.
6) All sources used are properly disclosed.
7) All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

CRediT authorship contribution statement

Joëlle Atere-Roberts: Writing – original draft, Visualization, Conceptualization. **Paul L. Delamater:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Whitney R. Robinson:** Writing – review & editing, Conceptualization. **Allison E. Aiello:** Writing – review & editing, Conceptualization. **Taylor W. Hargrove:** Writing – review & editing, Conceptualization. **Chantel L. Martin:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Data availability

The data used is publically available from the US Census

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