Piloting an Index of Segregation at the Census Tract Level:

Associations with Place and Racial/Ethnic Disparities in Life Expectancy

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Abstract

This study considers residential segregation as a critical driver of racial/ethnic health disparities and introduces an index of segregation, the Representation Index, that measures segregation degree at the neighborhood level with a metric capturing the overrepresentation of a racialized/ethnic group in a census tract in relation to that group's representation at the city level. Using Dallas, Texas as a pilot city, the index is used to investigate the association between Latinx, non-Hispanic white, non-Hispanic Black, and Asian-American groups' over-representation at the neighborhood level with neighborhood rates of life expectancy at birth. This study aimed to expose the possibility of neighborhood mechanisms beyond socioeconomic characteristics as a critical determinant of health and draw attention to the importance of critically engaging the experience of place in examinations of racial and ethnic health disparities.

Multivariable linear regression modeling resulted in significant findings for non-Hispanic Black, non-Hispanic white, and Asian groups, indicating increased life expectancy at the census tract level for Black and white census tract residents compared to state means and decreased life expectancy for Asian census tract residents. Unadjusted models demonstrated structural inequities between first and fourth quartile census tracts and point to the importance of mixed methods in health disparities research and the importance of including the voice of racialized group members to critically engage places and people's relationships with them.

Keywords: place, segregation, health disparities

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Piloting an Index of Segregation at the Census Tract Level: Associations with Place and Racial/Ethnic Disparities in Life Expectancy

Decades of discriminatory housing practices established enduring patterns of racialized/ethnic residential segregation which are linked to structural inequities with multigenerational consequences (Woods, 2018; Williams et al., 2019; White et al., 2021). Spatial patterns in metropolitan areas continue to follow historic lending boundaries established by the discriminatory *redline* maps sanctioned by the Federal Housing Administration in the 1930s (Rothstein, 2019; National Community Reinvestment Coalition [NCRC], 2020a). Recent studies demonstrate a statistically significant relationship between formerly redlined areas and neighborhood characteristics, including increased minority presence, poverty rates, social vulnerability, poor mental health, and risk of morbidity in COVID-19 patients (Macon, 2017; NCRC, 2020a). As such, the historical practice of redlining demonstrates the place-bound nature of racialized divisions (Lipsitz, 2011) and the lasting impact of structural racism on the health and wellbeing of minoritized groups.

Due to its part in shaping multiple factors important for health promotion and disease prevention, segregation has been established as a root cause of racial/ethnic health disparities (Williams & Collins, 2001; White & Borrell, 2011; Popescu et al., 2018). While the adverse relationship between segregation and health continues to be implicated as a key driver of Black-white health disparities (Kershaw et al., 2011; Jones, 2013; Bravo et al., 2018), few have examined variations in segregation's relationship with health outcomes among different minoritized groups (Yang et al., 2020). Further, extant studies tend to rely on indices measuring segregation across large geographical areas, leaving a critical gap in the examination of segregation at the neighborhood level (Kramer & Hogue, 2009; Yang et al., 2020). Reliance on these large-scale measures mask the impacts of segregation as a daily lived experience.

This study introduces an index of segregation, the Representation Index, that measures segregation degree at the neighborhood level with a metric capturing the overrepresentation of a racialized/ethnic group in a census tract in relation to that group's representation at the city level. Using Dallas, Texas as a pilot city, the index is used to investigate the association between Latinx, non-Hispanic white, non-Hispanic Black, and Asian-American groups' over-representation at the neighborhood level with neighborhood rates of life expectancy at birth. This study aimed to expose the possibility of neighborhood mechanisms beyond socioeconomic characteristics as a key determinant of health and draw attention to the importance of critically engaging the experience of place in examinations of racial and ethnic health disparities.

Background

The practice of redlining began with the creation of the Home Owners' Loan Corporation (HOLC) in 1933. This New Deal-era government sponsored corporation was initially created to prevent the foreclosure of homes by refinancing defaulted mortgages. However, the HOLC operated under the belief that the presence of Black homeowners, regardless of economic class, devalued white-owned properties (Rothstein, 2019). As such, the HOLC drafted color-coded maps of every major metropolitan area in the United States, denying federally insured home mortgages to buyers in red-coded areas (i.e., Black neighborhoods) while backing buyers' mortgages in green-coded areas (i.e., white neighborhoods). This federal policy aimed to disinvest in communities determined to be *hazardous* or predicted to be *deteriorating* based on racial composition, while subsidizing suburban growth through federally insured home mortgages. This history of *de jure* segregation in the United States serves as an example of institutionalized injustice that maintains place-based divisions among racialized groups through the inheritance of policies that “racialize space and spatialize race” (Lipsitz, 2011, p. 6).

The extrication of lending sources in urban areas inevitably led to neighborhood decay (Squires et al., 1979). It established enduring patterns of segregation which has been identified as a critical driver of racial inequities operating through multiple pathways related to public and private disinvestment. Segregation impacts communities of color as a determinant of 1) socioeconomic status and the likelihood of living in areas of concentrated poverty, 2) lack of access to quality health care, education, employment opportunities, and housing stock, 3) exposure to high levels of neighborhood violence and crime, and 4) exposure to psychosocial stressors and environmental hazards (Williams et al., 2019). As such, segregation implicates racism and oppression as spatial acts, demonstrating how places are socially and differentially constructed and geographies of subjugation and displacement are maintained (Gilmore, 2002). These *power geometries* (Massey, 1991) outline inequities associated with place, exposing how the inequitable distribution of power and resources are woven as lines of color into the fabric of American life (McKittrick, 2006; Ratliff, 2019).

Health Disparities Research

Although the disproportionate impact of the SARS-CoV-2 pandemic on communities of color has generated considerable interest in the study of health disparities, their root cause has been a probing question for public health and social work researchers for decades. However, the literature primarily emphasizes individual-level factors (e.g., socioeconomic status, genetics, health behaviors) as fundamental causes of health disparities (White & Borrell, 2011). For example, a 2019 study by Alvidrez and colleagues found that place-based factors related to the built environment and neighborhood, or community-level factors are underrepresented in health disparities research funded by National Institute on Minority Health and Health Disparities (NIMHD) R01 grants. The predominant focus on individual-level factors neglects to consider that deep-seated structural disparities—such as those exposed by the pandemic—are place-based and have place-based impacts, effecting people of color within a unique lived environment.

Over the past 15 years, the shift in focus to segregation as a key determinant of health has been an important area of interest in health disparities research. These studies have increased the understanding of the impact of distal and intermediate influences on the health of minoritized groups. However, because the predominant measures used in segregation-focused research are indices measuring segregation across large geographical areas (Massey & Denton, 1988), few have examined the association of segregation at the neighborhood level and the lived experience of place (Kramer & Hogue, 2009; Yang et al., 2020). The structural inequities of the lived environment implicated as the mediating factor in segregation's adverse relationship with health—the concentrated poverty, lack of access to critical resources, and exposure to psychosocial stressors and environmental hazards (Williams et al., 2019)—are masked by such large-scale measures. Coupled with a lack of research exploring health disparities outside the Black-white paradigm (Yang et al., 2020), current methods obscure the examination of the lived experience of place and segregation's differential association with the health of diverse groups.

Residential Segregation and Health

Health disparities are the metric by which progress toward health equity is measured among minoritized communities (Braveman, 2014). They are 1) systematic and avoidable, 2) arise from discrimination and marginalization, and 3) reinforce social disadvantage and vulnerability (Braveman et al., 2011). According to the U.S. Department of Health and Human Services Office of Minority Health (OMH, 2020), national estimates of life expectancy at birth for non-Hispanic Blacks is 77.0 years, compared to 80.6 years for non-Hispanic whites, 80.7 years for Asians, and 82.1 years for Latinx. Considering that the OMH (2020) estimates that 21.2% of people who identify as Black and 17.2% of Hispanics live at the federal poverty level (compared to 9.0% of whites and 9.6% of Asians), economic disparities do not explain the difference in life expectancy between members of the Black and Latinx communities.

Although structural inequities related to social stratification are commonly identified as the mechanisms through which segregation impacts health, studies indicate that some minoritized groups have better health despite neighborhood context and socioeconomic status. According to the Hispanic Epidemiological Paradox, Latinx Americans tend to have better health and live longer than white Americans, notwithstanding lower socioeconomic status and barriers to quality education and health care (Markides & Correll, 1986; Markides & Eschbach, 2005). According to a 2015 report issued by the U.S. Centers for Disease Control and Prevention (CDC), the Latinx population in the U.S. has a 24% lower all-cause mortality risk than whites, despite 40% of respondents reporting that they lack access to health insurance. In contrast, when considering Black-white disparities in hypertension rates (40.3% and 27.8%, respectively), it is interesting to note that Black populations in Caribbean countries and Africa have lower hypertension rates than people who identify as white in the United States (Adler & Rehkopf, 2008). Such findings motivate pivoting the study of health disparities away from individual-level characteristics, shifting the focus to social systems and structures, including place and people's relationship to place as determinants of health.

While it is critical to keep in mind that segregation is a determinant of the likelihood of living in concentrated poverty and lacking access to resources and opportunities (William & Collins, 2001; White & Borrell, 2011; Popescu et la., 2018), the variability in health outcomes between groups necessitates an approach to segregation as an experience of discrimination. The expression of power and racialization through segregation, and place-related identity development and stress that occurs as a result, call for the development of methods that make a distinction between experiences of segregation within and between groups. For example, some theorize that the ethnic enclave may provide health-protective benefits in the form of social capital, such as strong community ties and social cohesion (Eschbach et al., 2004; White & Borrell, 2011; Yang et al., 2020). While intragroup differences among Latinx have been identified, studies indicate that health-protective factors for Mexican Americans living in densely populated Mexican American neighborhoods offset elevated levels of poverty and other structural inequities (Eschbach et al., 2004). Thus, the primary focus on the Black-white binary, which largely neglects comparisons with Latinx and Asian groups (Yang et al., 2020), overlooks the importance of examining the experience of place as a site of power and identity-making and how that lived experience impacts the health of different groups.

Measuring Segregation

The body of empirical knowledge tying segregation to health disparities relies on long-established standardized segregation measures. According to a seminal article by Massey and Denton (1988), there are five axes of measurement describing the dimensions of segregation: 1) *evenness* measures the degree to which groups are unevenly distributed over areal units, 2) *exposure* measures the degree of potential contact between members of different groups, 3) *concentration* measures the relative amount of geographical space that a group occupies in an urban area, 4) *centralization* measures the degree to which a group is spatially located near the central business district of a city, and 5) *clustering* measures the extent to which clusters of minority groups adjoin one another in space.

Considering the field of segregation research to be in a state of theoretical and methodological disorder, Massey and Denton (1988) evaluated twenty indices of segregation based on the five axes described above. They used factor analysis to determine a single best indicator for each dimension of segregation. These five indices have served as the standard segregation measures for over thirty years (Iceland et al., 2002; U.S. Census Bureau, 2021a). Among them are the Index of Dissimilarity measuring evenness, the P^* Indices (i.e., Interaction or Isolation) measuring exposure, the Relative Concentration Index measuring concentration, the Absolute Centralization Index measuring centralization, and the Index of Spatial Proximity measuring clustering.

According to Yang and colleagues (2020), measures of evenness and exposure dominate segregation-focused health disparities research. As the foundation of segregation research, the Index of Dissimilarity, a measure of evenness, represents the proportion of minority group members who would have to move to a different census tract to achieve an even distribution of groups in a large geographical area (e.g., county, metropolitan statistical area (MSA)). In contrast, exposure indices measure the experience of segregation, indicating the possibility of contact between group members. One of the most common exposure indices, the Interaction Index, directly measures the potential for majority and minority group contact. Another standard exposure index is the Isolation Index, with values indicating the percentage of same-group population in a census tract where the average group member lives.

While the Index of Dissimilarity, the Interaction Index, and the Isolation Index are reliable and widely used measures of segregation over large geographical areas, there remains a critical lack of understanding segregation’s impact on the physical environment at the neighborhood level. This gap persists because most of the published literature calculates segregation by describing the distribution of groups across micro-units (i.e., census tracts) within a larger macro-area (e.g., county, MSA) (White & Borrell, 2011). Investigating health outcomes with such broad measures statistically masks subunit conditions (Kettner et al., 2017) and neglects neighborhood characteristics related to the determinants of health implicated as the structural mechanisms responsible for the relationship between segregation and health disparities. In other words, measuring segregation across a county or MSA dilutes the meaning or effect of information about neighborhood characteristics associated with segregation that impact health—concentrated poverty, lack of access to critical resources, and exposure to psychosocial stressors and environmental hazards (Williams et al., 2019). For example, according to the most recent ACS 5-year estimates (2021), Asians make up 3.75% of the total population of Dallas. Using the overall high school completion rate for Asians of 85.56% as an indicator of educational equity masks place-based disparities such as those found in a densely populated census tract in which the Asian population makes up 21.55% of the total population and the Asian high school completion rate is 4.7% (U.S. Census Bureau, 2021b).

Measuring segregation at the census tract level allows for analysis to capture and account for structural and neighborhood characteristics that cascade from segregation and other forms of structural discrimination. However, according to Kramer and Hogue (2009), the limited studies that used the census tract as a proxy for neighborhood considered the racial/ethnic composition of a tract as if it were an isolated geometry; it offers no understanding of how groups distribute in relation to the larger city or town, nor does it offer a reference point against which to measure the census tract's racial composition.

Therefore, this study took into consideration Kramer and Hogue's critique in its development of a segregation index using the residential tract as the primary unit of analysis. It recognized that a small-scale index is critical in examining the impact of neighborhood context; however, to be an effective measure, it recognized, too, that the index must also consider a group's distribution within the total population. Bringing into focus the mechanisms identified as the link between segregation and individual health—and examining these structural mechanisms at a more granular level—the current study observed for differential relationships between groups and the places where they live.

Method

This study's primary objective was to construct and pilot an index, the Representation Index, that estimates degrees of segregation at the census tract level. The index was then tested by assessing the association between mean life expectancy at birth and census tracts' degree of segregation, as measured by the Representation Index, while adjusting for structural inequities between tracts where groups are relatively under- and overrepresented. The research questions to be answered by this study were three-fold: 1) Are there observable inequities in poverty levels, rates of uninsurance, food insecurity, and education levels between tracts where groups are relatively under- and overrepresented? 2) Is there a statistically significant difference between the mean life expectancy at birth of census tracts where a group is relatively overrepresented and that group's mean life expectancy at the state level? 3) Do these differences vary across racial and ethnic groups?

Census tract estimates were compared with state estimates rather than national estimates to account for political, social, and economic structures unique to the state of Texas that may also impact health and wellbeing of all Texans. It was hypothesized that inequities in poverty levels, rates of uninsurance, food insecurity, and levels of education would be observed between tracts where groups are relatively under- and overrepresented. Further, increases in the relative overrepresentation of a given racialized/ethnic group of residents in a census tract would be associated with significant differences in the tract's mean life expectancy when compared to that group's life expectancy at the state level—and the nature and size of this difference would vary across minoritized groups.

Study Setting

In its broadest conceptualization, this study intended to examine the association of urban residential segregation and mean life expectancy at birth in the United States. However, the extensive geographical range of such an undertaking is outside the study's scope. For this reason, it was necessary to delimit the study by piloting the Representation Index in a single U.S. city. The study setting consists of all individuals reported to reside in census tracts located in Dallas, Texas (N = 303).

Dallas was selected for several reasons, listed here in no specific order. The research team has familiarity with Dallas, including knowledge of its history and an understanding of the nuances of neighborhood composition throughout the city. Additionally, Dallas County is ranked 26 of the 52 most segregated urban counties in the United States (Federal Reserve Bank of St. Louis, 2020). Moreover, according to the CDC's Social Vulnerability Index scores, the most vulnerable Dallas census tract boundaries align with the historic lending patterns established by the 1930s redline maps (NCRC, 2020b).

Key Variables

Independent Variable: The Representation Index

This study's primary predictor, the Representation Index, is a measure of segregation at the census tract level. Because disparities are not uniformly distributed in a large geographical area, this study aimed to construct and pilot an index that measures degrees of segregation at a more granular level to assess associations with life expectancy, adjusting for structural inequities among tracts. The Representation Index parts ways with standard indices of segregation by considering the census tract as the macro unit of analysis, establishing a group's segregation degree through a metric comparing a group's relative representation in a census tract when compared to its overall representation in the city where it is nested. According to the U.S. Census (2021c), a census tract is a small, relatively stable statistical county subdivision, ideally populated by 4,000 people. For this study's purposes, the census tract was used as a proxy for neighborhood. The maintenance of census tract boundaries over time allows for statistical comparisons from one census to the next. This continuity enables the index's use for future longitudinal studies.

As presented in Table 1, population estimates from the 2015-2019 American Community Survey (ACS) were used to identify the percent of a group residing in a census tract and city. These population estimates were collected by the U.S. Census Bureau between January 1, 2015, and December 31, 2019, and include data for all populations, disaggregated by racialized/ethnic group, regardless of geographic size. The decision to use the ACS five-year estimates was based on the guidance of the U.S. Census Bureau (2021d). This dataset was selected for three reasons: 1) The collected data represent the most reliable estimates compared to the ACS one-year supplemental and three-year estimates. 2) The five-year estimates are the most appropriate choice when precision is critical in analyzing relatively small populations, such as census tracts. 3) The 2015-2019 population estimates overlap with the collection dates of the life expectancy data used in this study.

The resulting metric subtracts the percentage of a group in the city's total population from its percentage of a census tract's total population. The difference indicates the estimated degree of segregation (i.e., relative representation) of that group at the census tract level, capturing segregation degree in the context of the neighborhood or lived environment. Positive values indicate the overrepresentation of a group in a tract, while negative values indicate underrepresentation. Values close to zero indicate that a group's representation in the tract is relatively proportional to its representation in the city's population. See Table 1 for data sources used to calculate segregation degree.

The metric is scalable as it addresses an issue with standard indices measuring segregation; it is sensitive to the heterogeneity of U.S. cities and the distribution of group members among areal units by considering their proportions above or below the city's population (Massey & Denton, 1988). As such, the metric can be precisely adapted to any urban area in the United States, as census tract data on racial/ethnic demographics is publicly available through the ACS five-year estimates.

Dependent Variable

The dependent variable in this study was mean life expectancy at birth for each of the four groups at the state level and was established using life expectancy data for Texas counties (N = 254) from County Health Rankings and Roadmaps (CHRR, 2022). CHRR's county life expectancy data was collected from the CDC's National Center for Health Statistics (NCHS) U.S. Small-area Life Expectancy Estimates Project (USALEEP) (CHRR, 2021). It is important to note the issue of random missingness when using life expectancy data. This study's approach to missing data was listwise deletion in Stata 17, which, when handling data that is missing completely at random, will produce unbiased and conservative estimates (Kang, 2013).

Control Variables

Three covariates were used in statistical models to control for structural inequities at the census tract level. They were chosen based on the Healthy People 2030 social determinants of health framework (U.S. Department of Health and Human Services, 2021). Covariates were used to adjust for the extent to which the association of mean life expectancy and degree of segregation may be confounded by secondary factors related to the social determinants of health. These factors include rates of 1) poverty, 2) uninsurance, and 3) high school completion. These variables, for each census tract and for each county in Texas, were drawn from the 2015-2019 ACS. A binary variable for food insecurity was also included for each census tract but was not available at the county level. This variable was determined by the USDA's Low Income Low Access (LILA) tract designation at one and ten miles. Table 1 presents information on data sources used to establish all variables.

Data Analysis

The Representation Index was tested for its ability to predict the mean life expectancy at birth of Dallas census tracts. However, due to limitations of the data, it is important to note that though life expectancy estimates are disaggregated by racialized/ethnic group at the county level, it is an aggregate estimate at the census tract level. For this reason, it is impossible to understand the association between the Representation Index and life expectancy for each racialized/ethnic group. Instead, this analysis assessed the difference between the mean life expectancy at birth for census tracts with the highest degree of over-representation (4^{th} quartile) of a given group and the life expectancy at birth for that group at the state level (averaged across all Texas counties). The underlying assumption of this approach was that this difference would indicate the association between segregation degree and life expectancy: if census tracts with the highest level of overrepresentation of a given racialized/ethnic group had lower life expectancy than those for that group at the state level, then segregation may play an important role in that difference.

The Representation Index was used to determine the degree of segregation for groups (Latinx, non-Hispanic white, non-Hispanic Black, and Asian) in Dallas census tracts (N = 303). Tracts with the highest degrees of relative segregation were identified by examining each group by quartiles. The first quartile consisted of census tracts where a group is relatively underrepresented, while the fourth quartile consisted of tracts where a group is relatively overrepresented. Because this study focused on measuring and understanding the effects of structurally influenced concentration of racialized/ethnic groups at the neighborhood level, analysis focused on the fourth quartile census tracts.

Descriptive analysis estimated the mean degree of segregation, life expectancy, and control variables for each group's fourth quartile census tracts and for Texas counties and assessed the difference in values between each group's first quartiles and fourth quartiles (Tables 2 and 3). The difference between fourth quartile census tracts' life expectancy for each group and the state mean life expectancy for that group was assessed for significance, controlling for rates of poverty, uninsurance, and high school completion, multivariable linear regression (Table 4). A separate model was used to assess the relationship between the independent and dependent variables for each racialized/ethnic group, constructing a total of four models. All models controlled for rates of poverty, uninsurance, and high school completion. Many Texas counties did not report life expectancy for each racialized/ethnic group, so counties were dropped listwise from regression analysis if missing outcome data. All analysis was conducted in Stata 17.

Results

Unadjusted means of segregation degree and life expectancy at birth for fourth quartile census tracts and Texas counties, are presented in Table 2, stratified by racialized/ethnic group. The difference in means for each variable between first quartile census tracts and the state of Texas and fourth quartile census tracts are also presented for each group. Each quartile of census tracts included 75 census tracts. The means for segregation degree of fourth quartile tracts for each group were 32.87 for Latinx (*SE* = 1.33), 47.84 for whites (*SE* = 1.09), 33.79 for Blacks (*SE* = 1.82), and 8.77 for Asians (*SE* = 1.11). Unadjusted means for each group at the state level were 80.82 years (*SE* = 0.16) for Latinx, 76.25 years (*SE* = 0.22) for whites, 73.62 years (*SE* = 0.37) for Blacks, and 87.99 years (*SE* = 0.77) for Asians.

As relative overrepresentation of the Latinx community increased from first to fourth quartiles, unadjusted mean life expectancy decreased by 3.25 years, from 79.92 years (*SE* = 0.54) in the first quartile to 76.67 years in the fourth quartile (*SE* = 0.27). The unadjusted life expectancy decrease was more dramatic (7.02 years) with increased Black segregation degree, from 80.40 years (*SE* = 0.31) in the first quartile to 73.38 years (*SE* = 0.48) in fourth quartile tracts. Unadjusted means for life expectancy increased with increased white segregation degree by 6.89 years, from 74.26 years (*SE* = 0.44) in the first quartile to 81.15 years (*SE* = 0.25) in the fourth quartile, and for Asian segregation degree by 5.74 years, from 74.25 years (*SE* = 0.45) in the first quartile to 79.99 years (*SE* = 0.34) in the fourth quartile.

Table 3 presents the unadjusted means of neighborhood characteristics for Texas and fourth quartile census tracts, stratified by racialized/ethnic group. It also reports differences in unadjusted means of covariates between first and fourth quartiles and between fourth quartile and state level means. Also reported is the percentage of food insecure census tracts among quartiles, and changes in this variable between fourth quartile and first quartile census tracts.

Comparing unadjusted means between first and fourth quartile tracts demonstrated increases in poverty, uninsurance, and food insecurity as Latinx segregation degree increased. Poverty rose by 13.6 *pp*, while uninsurance rose by 25.0 *pp* and food insecurity by 20.0 *pp*. Uninsurance rates were highest in fourth quartile tracts overrepresented by the Latinx community (M = 33.1, SE = 0.97), and high school diploma rates were lowest (M = 56.7, SE = 1.16). Poverty rates for fourth quartile tracts were 7.2 *pp* higher than the rate in Texas. Similarly, fourth quartile tracts were 11.3 *pp* higher than the state uninsurance mean. Conversely, high school diploma rates were 25.1 *pp* lower than the state mean.

Differences in unadjusted means were pronounced between first and fourth quartiles for the white population. Poverty decreased by 23.0 *pp* and was found to be 9.8 *pp* lower than the state mean. A similar pattern was observed for uninsurance rates, which decreased by 21.9 *pp* between first and fourth quartiles and were lower than the state rate by 15.2 *pp*. Food insecurity decreased by 55.3 *pp* as relative white representation increased in a tract. Conversely, the high school diploma rate increased by 31.8 *pp* as the white population increased between quartiles, which was the highest among the four groups (M = 96.49, SE = 0.54) and were 14.7 *pp* higher than the state rate. Further, there were no fourth quartile tracts with relative white overrepresentation with a LILA designation, indicating no food insecurity in those tracts.

Poverty, uninsurance, and food insecurity rates increased with relative Black overrepresentation. Poverty rose by 18.4 *pp* between the first and fourth quartiles and was 12.7 *pp* above the state poverty rate. Fourth quartile tracts had the highest poverty rate among groups (M = 28.0%, SE = 1.12), and were as high as 50.8%. Uninsurance also increased with Black representation in the census tract (8.2 *pp*) and was 3.1 *pp* higher than the state rate. Food insecurity was highest among groups (M = 53.3%) and increased sharply between first and fourth quartile tracts (48.07 *pp*). Conversely, high school diploma rates decreased by 4.6 *pp* as relative black representation increased and were 5.4 *pp* below the state mean.

Increased Asian representation in tracts followed patterns of decreased poverty, uninsurance, and food insecurity, and increased high school diploma rates. Poverty decreased by 14.2 *pp* as Asian representation increased in census tracts and was 3.0 *pp* above the state rate. Uninsurance decreased by 13.7 *pp*, with rates 7.0 *pp* below the Texas mean. Food insecurity decreased by 46.7 *pp* as Asian representation increased, while high school diploma rates increased by 24.8 *pp* between first and fourth quartile tracts and was 8.7 *pp* higher than the state rate.

Results for linear models are presented in Table 4. When controlled for rates of poverty, uninsurance, and high school diploma, white life expectancy at the state level was negatively associated with mean life expectancy in tracts where the white population is relatively overrepresented (β = -3.73; 95% CI [-3.60, -0.44], p = .00). Adjusted models for Black life expectancy also demonstrated a negative association between the group's life expectancy in Texas and mean life expectancy in fourth quartile tracts where the Black community is overrepresented (β = -2.02; 95% CI [-3.60, -0.44]; p = .01). However, life expectancy for Asians in Texas was positively associated with increases in mean life expectancy for tracts where the Asian population is relatively overrepresented (β = 8.92, 95% CI [6.96, 10.07], p = .00). Findings were not significant for the Latinx population.

Discussion

This study aimed to construct and pilot an index of segregation at the census tract level and test the association between life expectancy in tracts in which racialized/ethnic groups are relatively overrepresented and life expectancy for the same group at the state level. Using values from the Representation Index to isolate census tracts with the greatest degrees of relative overrepresentation, the study also focused on observing for intergroup differences in social determinants of health to identify structural inequities in tracts with the highest segregation degree. It was hypothesized that inequities in poverty levels, rates of uninsurance, food insecurity, and levels of education would be observed between tracts where groups are relatively under- and overrepresented. Further, it was hypothesized that increases in the relative overrepresentation of a given racialized/ethnic group of residents in a census tract would be associated with significant differences in the tract's mean life expectancy when compared to that group's life expectancy at the state level—and the nature and size of this difference would vary across minoritized groups.

While linear models were not significant for the Latinx population—suggesting that census tract membership is not the driver in the 4.2-year decrease in life expectancy between fourth quartile residents in Dallas and the Latinx population in Texas—both hypotheses were confirmed by study findings for Black, white, and Asian groups. While unadjusted means indicated decreases in life expectancy in tracts as the relative representation of the Black community increased, linear models demonstrated that, despite sharp increases in structural inequities, the adjusted mean Black life expectancy in Texas was lower than that of census tracts where the Black community is relatively overrepresented. Conversely, while structural equity increased as the relative representation of the Asian community increased, linear models gave evidence of a significant decrease in life expectancy when comparing fourth quartile adjusted means to the that of Asians statewide. Considering decreases in poverty, uninsurance, and food insecurity in fourth quartile tracts where the Asian community is relatively overrepresented, this finding challenges the assumption that the socioeconomic gradient is a primary driver of health disparities among minoritized groups.

It is important to consider people's relationship to place when interpreting the differential association of census tract membership with the life expectancy of Black and Asian groups. For example, considering that Texas has the highest percentage of rural populations in the nation, with 22.8% of Texas' 254 counties being solely rural (Texas Almanac, 2021), the place-based disparity in life expectancy between Dallas census tracts where the Black community is relatively overrepresented and the life expectancy for people who identify as Black in Texas raises the question of rurality and its association with decreased life expectancy for Black Texans. Race-discrimination health pathway models recognize the mental health impact of social disadvantage as a concentrated source of acute and chronic stress (Massey, 2005). This study's findings suggest that increases in life expectancy are correlated with census tract membership, despite pronounced socioeconomic stratification observed in those tracts. These findings, which controlled for the influence of structural inequities on life expectancy, underscore the need to take seriously the findings of recent studies that demonstrate statistically significant associations between racial discrimination and accelerated health decline in longitudinal studies of Black Americans (Chae et al., 2020). According to the USDA ERS (2019), Texans who identify as Black make up eight percent of the rural population and 13 percent of the urban population. Considering that this study's findings indicated a relationship between census tract membership and increases in life expectancy, it is imperative to expand health disparities research to include studies on the experience of people of color living in rural populations.

Findings also indicated a relationship between white overrepresentation and increased life expectancy and demonstrated structural inequities between first and fourth quartile white census tracts benefiting those tracts where white representation is greatest. Considering that the placement of fourth quartile groups largely follows historic lending boundaries established by the practice of redlining (NCRC, 2020b), this finding underscores the critical question of place as a site of power (i.e., racialized privilege), demonstrating that place is not a neutral setting. Rather, in these tracts, "whiteness operates as spatialized and structured advantage" (Tuck & McKenzie, 2015, p. 37), co-creating place and race in an urban area (Lipsitz, 2011). Further, these findings demonstrate the "place-bound nature of white identity in the United States" (Tuck & McKenzie, 2015, p. 12) and how historic racialized divisions preserve color lines that determine multiple domains of urban life, privileging some and disadvantaging others.

Implications

Recognizing the complex pathways connecting marginalization, health risks, and disparities in health outcomes, this study argued the importance of culturally and structurally competent research methods sensitive to the embeddedness of social life in places and the role of power in where people are placed (Tuck & McKenzie, 2015). This study's findings point to the importance of mixed methods in health disparities research and the importance of including the voice of racialized group members to critically engage places and people's relationships with them. Methodological frameworks must be informed, and findings must be interpreted through, the lived experience of the group's being study. The strength of combined methods can inform policymakers on place-based factors related to health.

Observing for structural inequities related to segregation degree and its association with life expectancy, this study exposed the possibility of mechanisms beyond the socioeconomic factors and draws attention to the importance of critically engaging the experience of place as a key determinant of health. Its theoretical framework leveraged the understanding that ZIP code, rather than genetic code, is a stronger indicator of health (Goodman, 2014). Findings suggest that people's relationship with place plays a critical role in understanding the differential associations of segregation on health and further research is warranted that studies health disparities through the critical lens of place.

This study's findings indicate a need to examine variables beyond individual-level actions, predispositions, and socioeconomic characteristics to determine alternative pathways that influence the health of diverse groups. Particularly, there may be psychosocial influences related to the experiences of place as a site power and identity that influence health and well-being. Further, findings underscore the need to approach the study of health disparities through the lens of critical place inquiry, considering place and power as co-produced determinants of health, implicating place, structure, and power as the organizing thread of future research (Tuck & McKenzie, 2015).

As the primary deliverable of this study, the Representation Index addresses the shortcomings of the most common indices of segregation which measure segregation across large geographic areas, masking the observation of place-based mechanisms implicated as a key driver of health. Implications for future research involve testing the index's ability to isolate place-based disparities and health outcomes by scaling its application. Larger sample sizes consisting of an aggregate of census tracts with the highest degrees of relative segregation across urban areas would allow for regression analysis by decile, supporting the examination of health outcomes and structural inequities at a more granular level. Health outcome variables might be constructed through use of other types of datasets, including health care claims or hospitalization data, that identify race and ethnicity and locate individuals served within ZIP codes or service areas that could be associated with specific census tracts.

The Representation Index was constructed from the unique perspective of social work practice which prioritizes an understanding of the person within the context of the social environment. However, findings demonstrate a need for a more nuanced understanding of the person-in-environment framework that incorporates a serious consideration of the physical spaces that human persons, as embodied beings, occupy. Health disparities research must take seriously the understanding that where you live is a stronger indicator of health than individual traits and health behaviors (Ratliff, 2019; Goodman, 2014) and make efforts to close the gap in research by emphasizing the daily lived experience of place as a critical driver of health (Alvidrez et al., 2019). Social work researchers have an important methodological contribution to make in health disparities research, identifying and addressing the intersection of place and its relationship to health outcomes of diverse groups.

Limitations

There are two potential limitations to this study. The first is that, due to privacy laws protecting personal health records, the study's dependent variable is not disaggregated by racialized/ethnic group at the census tract level and disaggregated data at the county level had much missingness. Therefore, the study could not measure the life expectancy of different groups by census tract. Instead, it measures the variable as an aggregate represented as the mean life expectancy of a census tract where a group is relatively overrepresented. Further, model power was compromised by missing data for counties. Such gaps in health data are a matter of data justice. Until disaggregated health data is publicly available, the relationship between neighborhood level segregation and health outcomes cannot be accurately measured.

A second potential limitation is the use of the 2015-2019 American Community Survey five-year estimates as the primary dataset for index construction. As previously noted, these estimates are the most reliable dataset when analyzing small populations. However, given the impact of the COVID-19 pandemic on population and life expectancy estimates, the 2015-2019 ACS lacks accuracy in estimating the current population. Nevertheless, the pandemic's reported impact on data collection during the 2020 decennial census (U.S. Census Bureau, 2021e) confirmed the decision to use the 2015-2019 estimates.

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Table 1

Data Sources

Variable	Dataset	Data Source	Years	Geography
	Independent Variable: Segregation Degree = A - B			
Representation Index				
A = census tract	% Population of all people who were Hispanic or Latino	ACS[1]	2015-2019	Census tract, 2010
	% Population of all people who were non-Hispanic white	ACS	2015-2019	Census tract, 2010
	% Population of all people who were non-Hispanic Black	ACS	2015-2019	Census tract, 2010
	% Population of all people who were Asian	ACS	2015-2019	Census tract, 2010
B = city	% Population of all people who were Hispanic or Latino	ACS	2015-2019	Census tract, 2010
	% Population of all people who were non-Hispanic white	ACS	2015-2019	Census tract, 2010
	% Population of all people who were non-Hispanic Black	ACS	2015-2019	Census tract, 2010
	% Population of all people who were Asian	ACS	2015-2019	Census tract, 2010
Dependent Variable				
Life expectancy (county and census tract levels)				
Hispanic	Life expectancy at birth	USALEEP[2]	2010-2015	Census tract and TX counties, 2010
Non-Hispanic white	Life expectancy at birth	USALEEP	2010-2015	Census tract and TX counties, 2010
Non-Hispanic Black	Life expectancy at birth	USALEEP	2010-2015	Census tract and TX counties, 2010
Asian	Life expectancy at birth	USALEEP	2010-2015	Census tract and TX counties, 2010
Covariates				
Poverty	Estimated % of all people that are living in poverty	ACS	2016-2020	Census tract, 2010
Uninsurance	Estimated % of all people without health insurance	ACS	2016-2020	Census tract, 2010
High school diploma	Estimated % of people with at least a high school diploma	ACS	2016-2020	Census tract, 2010
Food insecurity	Low income low access tracts, at 1 and 10 miles	ERS/USDA[3]	2019	Census tract, 2010

[1]American Community Survey, U.S. Census Bureau

[2]U.S. Small-area Life Expectancy Estimates Project

[3]U.S. Department of Agriculture Economic Research Service

Table 2

Unadjusted Means of Segregation Degree and Life Expectancy at Birth for Fourth Quartile Census Tracts and Texas Counties, Stratified by Racialized/Ethnic Group

	Fourth Quartile Census Tracts				
Segregation Degree	*n*	Range	*M*	*SE*	95% CI
Latinx	75	[13.31, 54.03]	32.87	1.3279	[30.25724, 35.48356]
Non-Hispanic white	75	[31.01, 69.43]	47.84	1.094	[45.68237, 49.98803]
Non-Hispanic Black	75	[8.75, 70.73]	33.79	1.8191	[30.2141, 37.37337]
Asian	75	[1.93, 57.96]	8.77	1.1079	[6.585548, 10.94592]
	Fourth Quartile Census Tracts				
Life Expectancy	*n*	Range	*M*	*SE*	95% CI
Relative Latinx overrepresentation	67	[71.3, 81.4]	76.67	0.2679	[76.13383, 77.20348]
Relative white overrepresentation	67	[76.9, 86.1]	81.15	0.2509	[80.6469, 81.64863]
Relative Black overrepresentation	66	[64.2, 83.5]	73.38	0.4759	[72.42685, 74.3277]
Relative Asian overrepresentation	54	[73.8, 86.1]	79.99	0.3357	[79.3118, 80.65857]
	Texas Counties				
Life Expectancy	*n*	Range	*M*	*SE*	95% CI
Latinx	170	[70.2, 100]	80.82	0.4277	[79.98421, 81.6652]
Non-Hispanic white	180	[68.5, 100]	76.25	0.2224	[75.80911, 76.68311]
Non-Hispanic Black	99	[65.9, 91.5]	73.62	0.3699	[72.89497, 74.34948]
Asian	38	[79.5, 100]	87.99	0.7683	[86.48349, 89.50598]

Table 3

Unadjusted Means of Neighborhood Characteristics for Texas and Fourth Quartile Census Tracts, Stratified by Racialized/Ethnic Group

Control Variable	Texas Counties						
	n	Range	*M*	*SE*	95% CI	*Δ pp* (1st Q)[1]	*Δ pp* (TX)[2]
% Poverty	254	[0, 42.6]	15.32	0.400	[14.53539, 16.11264]		
% Uninsurance	254	[11, 36]	21.79	0.262	[21.27135, 22.30346]		
% High school diploma	254	[22, 97]	81.79	0.532	[80.7388, 82.836]		
	Fourth Quartile Census Tract: Relative Latinx Overrepresentation						
% Poverty	75	[4.86, 42.00]	22.47	0.968	[20.54129, 24.39711]	13.60	7.15
% Uninsurance	75	[17.07, 60.29]	33.1	0.965	[31.17259, 35.01808]	25.03	11.31
% High school diploma	75	[27.74, 83.89]	56.7	1.162	[54.3819, 59.0141]	-38.94	-25.11
LILA	75	*n* = 21	% = 28.00			20.00	
	Fourth Quartile Census Tract: Relative White Overrepresentation						
% Poverty	75	[0.62, 25.15]	5.55	0.479	[4.600689, 6.508111]	-23.02	-9.77
% Uninsurance	75	[0.44, 29.88]	6.64	0.581	[5.484978, 7.800355]	-21.87	-15.15
% High school diploma	75	[71.57, 100]	96.49	0.535	[95.42536, 97.55571]	31.76	14.70
LILA	75	*n* = 0	% = 0.0			-55.26	
	Fourth Quartile Census Tract: Relative Black Overrepresentation						
% Poverty	75	[9.07, 50.83]	28.00	1.117	[25.77719, 30.22681]	18.39	12.68
% Uninsurance	75	[11.18, 43.14]	24.87	6.693	[23.33282, 26.41252]	8.24	3.08
% High school diploma	75	[52.14, 97.23]	76.36	1.181	[74.00343, 78.71044]	-4.60	-5.43
LILA	75	*n* = 40	% = 53.33			48.07	
	Fourth Quartile Census Tract: Relative Asian Overrepresentation						
% Poverty	75	[0.62, 49.19]	12.35	1.137	[10.08609, 14.61577]	-14.24	-2.97
% Uninsurance	75	[0.57, 39.68]	14.78	1.276	[12.23645, 17.32142]	-13.72	-7.01
% High school diploma	75	[56.85, 100]	90.48	1.321	[87.85185, 93.11509]	24.84	8.69
LILA	75	*n* = 3	% = 4.0			-46.67	

[1]Percentage point change between first and fourth quartiles
[2]Percentage point change between fourth quartile and state

Table 4

Adjusted Estimates of Differences Between Mean Life Expectancy at Birth for Fourth Quartile Census Tracts and Texas, Stratified by Racialized/Ethnic Group

Life Expectancy	*β*	*SE*	*t*	*p*	95% CI
Latinx	0.4892	1.2066	0.41	0.686	[-1.888139, 2.866465]
Uninsurance	0.1001	0.0807	1.24	0.216	[-0.058936, 0.2591786]
Poverty	-0.0641	0.0558	-1.15	0.251	[-.1740295, 0.0457629]
High school diploma	0.1731	0.0536	3.23	0.001	[0.0674085, 0.2787748]
Non-Hispanic white	-3.7344	0.7433	-5.02	**0.000**	[-5.198519, -2.270274]
Uninsurance	-0.0943	0.0555	-1.70	0.091	[-0.2036384, 0.0150638]
Poverty	-0.0165	0.0454	-0.36	0.717	[-0.1059872, 0.0729819]
High school diploma	-0.0288	0.0396	-0.73	0.468	[-0.1067309, 0.0491703]
Non-Hispanic Black	-2.0201	0.7983	-2.53	**0.012**	[-3.596667, -0.4434536]
Uninsurance	0.0917	0.0795	1.15	0.250	[-0.0652423, 0.2487214]
Poverty	-0.1374	0.0494	-2.78	0.006	[-0.2350556, -0.0397917]
High school diploma	0.0820	0.0611	1.34	0.182	[-0.0387149, 0.2026229]
Asian	8.5168	0.7815	10.90	**0.000**	[6.963425, 10.0702]
Uninsurance	-0.1991	0.0878	-2.27	0.026	[-0.3736018, -0.0246876]
Poverty	0.0078	0.0656	0.12	0.905	[-0.1225194, 0.1381438]
High school diploma	-0.1139	0.0840	-1.36	0.179	[-0.280902, 0.0530665]

Note. Models controlled for uninsurance, poverty, and high school diploma.