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Spatial Social Polarization and Cardiometabolic Disease Prevalence and Incidence: What Is the Role of the Neighborhood Environment?

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Abstract

This study examines the spatial polarization of income and racial-ethnic groups as predictors of prevalent and incident cardiometabolic disease and tests the extent to which local environmental features act as mediators. Spatial income and racial polarization are defined using the Index of Concentration at the Extremes. Using two waves of data from the Midlife in the United States study, generalized Poisson regression model results indicate that county- and tract-level income polarization are independently associated with prevalence and incidence of cardiometabolic disease. Results from path models showed that more income-privileged counties and tracts generally had greater parkland availability, lower social risks, less air pollution, fewer extreme heat days, and more tree canopy cover—but lower walkability. However, associations between income polarization and cardiometabolic disease are not substantively attenuated when accounting for these tract-level features. The findings show how income polarization locally and regionally patterns both environmental inequities and cardiometabolic disease.

Keywords

cardiometabolic disease, Index of Concentration at the Extremes (ICE), neighborhood, spatial social polarization

In the United States, nearly 50% of Americans ages 20 and older have prevalent cardiovascular disease, including hypertension, coronary heart disease, heart failure, or stroke (Tsao et al. 2023), and the prevalence of related metabolic diseases (e.g., diabetes) has increased in recent decades (Selvin et al. 2014). Thus, cardiovascular and metabolic (CMB) diseases remain among the chief contributors to the burden of disease in the United States and have contributed to stalled progress in life expectancy (Mehta, Abrams, and Myrskylä 2020). Understanding the social and contextual determinants of CMB disease can inform policy responses aimed at improving population health and life expectancy in the United States.

Multiple area-level determinants of CMB disease are established (Gary-Webb et al. 2020; Robinette,

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Charles, and Gruenewald 2018), with consistent evidence for the contextual effects of residential segregation and economic disadvantage. Residential segregation refers to the spatial distribution and separation of individuals into different areas based on characteristics such as their socioeconomic status and/or racial background (Barber et al. 2018). In turn, the spatial separation of residents based on social characteristics generally results in the concentration of socioeconomic resources in the neighborhoods of privileged households and the clustering of deprivation-linked social problems among disadvantaged neighborhoods (Diez Roux and Mair 2010). Although this spatial separation of resources is likely a fundamental cause of geographic inequities in health (Phelan, Link, and Tehranifar 2010), the processes linking concentration of privilege and deprivation with health are not well understood. Prior studies on segregation and health have typically been limited by their reliance on cross-sectional data, focus on single geographic levels, and lack of comprehensive examination of neighborhood-level mediators. The current study examines whether spatial social polarization at different geographic levels predicts CMB disease and tests whether diverse neighborhood features act as mediators.

INCOME AND RACIAL RESIDENTIAL SEGREGATION

Residential segregation based on race and income is a persistent social challenge in the United States. The causes of residential segregation are complex and numerous, including discriminatory housing policies and real estate practices, zoning regulations, and disparities in wealth and income (Gao et al. 2022; Williams and Collins 2001). The specific mechanisms driving residential segregation have similarly evolved over time because policies and practices have shifted and vary by geography and the social marginalization of individual groups.

The experiences of Black Americans illustrate this evolution. From the 1930s through 1960s, discriminatory federal policies explicitly restricted mortgage lending in areas concentrated with Black residents (e.g., the practice of redlining) while Federal Housing Administration and Veteran Affairs loan programs disproportionately denied mortgages to Black borrowers (Rothstein 2017). At the same time, White families benefited from these federal policies, building wealth through increased access to housing and mortgages that enabled increased housing equity (Golash-Boza 2022). Racial segregation intensified during the 1950s to 1970s due to the suburbanization of metropolitan areas because White Americans were more likely to move to the suburbs and discriminatory practices confined Black Americans to urban areas (Massey and Denton 1988; Massey and Tannen 2018). After the Fair Housing Act of 1968 and the Equal Credit Opportunity Act of 1974 banned discrimination in housing and mortgage lending, covert discriminatory practices persisted (e.g., steering by real estate agents; Golash-Boza 2022). Despite the disproportionate barriers to housing that Black Americans continued to experience, levels of Black–White residential segregation steadily decreased after 1970 (Massey and Tannen 2018). The racial composition of cities and suburbs also became more diverse during this period with immigration by individuals of Hispanic and Asian origin and the rise of the Black middle class (Massey and Tannen 2018; Wen, Lauderdale, and Kandula 2009).

In contrast to declining racial segregation, income segregation has increased in the United States since the 1970s (Reardon and Bischoff 2011). Rising income inequality is a likely cause of the increased income segregation (Fogli and Guerrieri 2019; Jargowsky 1996). As incomes have disproportionately risen at the upper end of the distribution, income-based residential preferences appear to have strengthened as affluent households differentially moved into wealthy suburbs and exurbs (Reardon and Bischoff 2011). Low-income households also became more segregated from high-income households but at a smaller geographic scale (e.g., moving into neighborhoods in the city or suburbs). Income segregation for Black and Hispanic groups has grown even faster than among White groups (Reardon and Bischoff 2011).

RESIDENTIAL SEGREGATION AND CARDIOMETABOLIC DISEASE

Prior research on segregation and health has primarily focused on racial segregation, with limited attention to income segregation. Given recent, contrasting trends for racial and income segregation, their associations with health may have become less intertwined. Residence in racially segregated neighborhoods is associated with higher CMB disease risk among racial-ethnic minorities, independent of individual sociodemographic characteristics (Kershaw and Albrecht 2015; Kershaw et al. 2015; Pool et al. 2018). The segregation–health relationship has been most studied and is especially strong for Black–White segregation and the health outcomes of Black residents (Kershaw and Albrecht

2015). The health risks of racial segregation are likely broader, however, given that Anderson (2016) identified consistent associations between group-specific metropolitan area racial segregation and lower self-rated health among multiple racial-ethnic groups (i.e., Black Americans, Latinos, and Asians) compared to White groups.

Few studies have examined income segregation as a predictor of CMB disease (Feldman et al. 2015; Krieger et al. 2018; Sonderlund et al. 2022). Income polarization was associated with diabetes mortality in New York City, an association that appeared stronger than that found for premature mortality (Krieger et al. 2016). Residence in segregated, income-deprived areas compared to affluent ones predicted higher likelihood of hypertension and diabetes in Brazil independent of individual socioeconomic status (Barber et al. 2018). Other research has also linked greater income segregation in metropolitan areas to higher mortality rates independent of income inequality (Lobmayer and Wilkinson 2002; Ross, Nobrega, and Dunn 2001). Thus, prior evidence is consistent with income segregation influencing CMB disease, but additional research is warranted.

MECHANISMS CONNECTING RESIDENTIAL SEGREGATION TO CARDIOMETABOLIC DISEASE

Residential segregation by race and income tends to concentrate resources in some areas while marginalizing others. These household-level resource disparities are amplified by inequities in neighborhood resources (Diez Roux and Mair 2010). For instance, higher housing costs result in greater property tax revenue to support quality public amenities (Bischoff and Reardon 2014), and higher homeownership rates result in increased civic participation and political influence over local land use decisions and public amenities (McCabe 2013). The clustering of privilege or, alternatively, deprivation also may induce investment or disinvestment in areas (Boone et al. 2009) such that privileged areas attract new community amenities while policy decisions and market forces concentrate environmental hazards in marginalized areas (Mohai, Pellow, and Roberts 2009). The quality of neighborhood environments then reinforces segregation patterns because socioeconomically advantaged households differentially move into areas with health-promoting features, such as green space and lower air pollution (Curtis et al. 2024). Segregation patterns therefore likely correlate with multiple neighborhood features, including built, natural, and social environmental attributes, and these features may explain the association between income or racial segregation and CMB disease.

The built environment may influence CMB disease risk because neighborhood design and physical spaces facilitate or constrain health behaviors. In particular, living in a walkable neighborhood—typically characterized by high residential density, mixed land use, and interconnected streets—has been associated with reduced CMB disease (Chandrabose et al. 2019). Additionally, access to green space, especially parks, has been associated with reduced CMB disease (Doubleday et al. 2022), although findings from prior studies have been mixed and the majority cross-sectional (Browning and Lee 2017).

Multiple attributes of the natural environment, especially human-linked environmental degradation, likely influence CMB disease. Specifically, long-term exposure to higher concentration of ambient particulate matter has been consistently linked with CMB disease (Yang et al. 2020). Extreme heat exposure also is associated with CMB disease (Cleland et al. 2023). By contrast, higher tree canopy coverage may reduce exposure to such environmental harms and is associated with reduced cardiovascular disease (Astell-Burt and Feng 2020).

The clustering of economic resources and deprivation also results in the patterning of social resources, such as social capital, disorder, and crime. These social resources and risks may relate to CMB disease risk by influencing neighborhood perceptions, social well-being, and stress exposure (Robinette et al. 2018). For instance, in the Moving to Opportunity experiment, households selected to move into low-poverty neighborhoods had considerably lower neighborhood poverty exposure over the next 10 to 15 years, reported more social resources, and had healthier metabolic outcomes (i.e., diabetes, extreme obesity)—plausibly through increased social well-being (Ludwig et al. 2013).

THE INDEX OF CONCENTRATION AT THE EXTREMES MEASURE

Massey (2001) developed the Index of Concentration at the Extremes (ICE) to measure the spatial patterning of social polarization, as defined by the relative share of residents at the extremes of a specified social distribution (e.g., ends of the income distribution). ICE has a few notable advantages compared to other measures of segregation, such as the isolation index (Anderson 2016; Kershaw, Albrecht, and Carnethon 2013) or the index of dissimilarity (Massey and Denton 1988).

First, the theoretical range of ICE (−1 to +1) provides information on both the direction and degree of social polarization, with negative values indicating a greater share of residents in the deprived category and positive values indicating more residents in the privileged category (Krieger et al. 2015). Second, unlike traditional measures of racial segregation and income inequality (e.g., index of dissimilarity, Gini coefficient) that capture relative distribution or evenness, ICE directly measures the composition of groups. Relative measures can yield similar values for areas with distinctly different racial-ethnic or income composition. For example, neighborhoods with homogenous income levels would have a low Gini coefficient regardless of whether households were extremely poor or extremely affluent. Third, ICE can be effectively used at local and regional geographic scales. Most segregation measures are used for larger geographical areas, such as metropolitan areas or counties, but the local context may more closely influence health (Boing et al. 2020). ICE has been regularly used at diverse geopolitical and spatial levels (Krieger et al. 2016; Massey 2001), such as the county (Chambers et al. 2019; Krieger et al. 2016) and census tracts (Krieger et al. 2015, 2018). Prior research has included ICE measures at multiple geographic scales and found that local measures are especially predictive of mortality outcomes (Krieger et al. 2017, 2018).

CURRENT STUDY

This study examines spatial social polarization for both income and racial-ethnic groups as predictors of prevalent and incident CMB disease. We focus on spatial polarization to capture the product of residential segregation (i.e., the concentration of social groups) because we expect the key context for health is the unequal patterning of privilege and deprivation. We test whether income and racial-ethnic polarization predict CMB disease independent of poverty rates and income inequality because we assume ICE measures are especially predictive of population health outcomes. In particular, income polarization contains information on the concentration of affluence that is missing from poverty rates, whereas income polarization is an absolute measure of the spatial concentration of income groups compared to the relative measure of income dispersion captured by the Gini coefficient.

In addition, because residential segregation occurs at regional and local levels, we model social polarization for both counties and tracts. This approach recognizes that residential selection is a multilevel process, with individuals making residential decisions due to regional factors (e.g., employment opportunities, climate) and local attributes (e.g., physical infrastructure, available green space). Prior research indicates that when modeled together, income polarization at the tract level more strongly predicts premature mortality compared to the city/town level, but income polarization at both levels independently predicts mortality from cardiovascular disease and diabetes (Krieger et al. 2018). Finally, both county- and tract-level social polarization may influence the patterning and quality of local environmental features. Thus, we examine tract-level built, social, and natural environmental features as mediators of the associations between ICE and CMB disease.

This study addresses gaps in the prior literature. First, we use longitudinal models to investigate the prospective association between spatial social polarization and CMB disease. Second, although most studies have included regional segregation measures, we simultaneously estimate the independent effects of regional and local polarization. Third, we examined built, social, and natural environmental features as mediators of the association between spatial social polarization and CMB disease. Prior research has rarely included a diverse range of neighborhood features when examining their role as mediators of the segregation and health association.

DATA AND METHODS

Data for this study were derived from Waves 2 and 3 of the Midlife in the United States (MIDUS) study. Beginning in 1995–1996, the initial MIDUS sample (Wave 1) was recruited using probability sampling through random digit dialing and additionally included oversamples in select metropolitan areas, siblings of the main sample, and a twin sample. Follow-up data collection for Waves 2 (M2) and 3 (M3) occurred in 2004–2005 and 2013–2014, respectively, with a response rate of approximately 75% among living participants at each point (Radler and Ryff 2010). An oversample of Black Americans from Milwaukee was added to the MIDUS study in 2005–2006 (commensurate with M2), with follow-up in 2016 (M3; University of Wisconsin-Madison 2011). Of a total 5,555 individuals participating at M2, 4,135 had complete data on the outcome of

CMB disease, and another 445 observations were lost due to missing data for independent variables and covariates (n = 3,690 participants). When modeling CMB disease incidence, we required data on CMB disease and other predictors at M2 and M3 (n = 2,383 participants).

Participant addresses at M2 and M3 were used to identify the county and tract in which participants resided and assign accompanying area-level data. Area-level variables were linked to MIDUS records by the administrative staff, with geographic identifiers removed prior to returning linked variables to our team. Using 2010 census boundaries, we used multiple data sources to derive county- and tract-level measures for approximately 2006 to 2010 (see Appendix Table A1 in the online version of the article). We assumed that area features were relatively constant over a brief period and thus conditions circa 2006 to 2010 likely reflected the environment to which participants were exposed in the period leading up to M2, collected between 2004 and 2006. Thus, M2 geocoded address was used to identify area-level exposures for CMB disease at M2. When modeling outcomes over time, for individuals who moved between waves, we weighted area-level measurements using the proportion of time between waves at the residential address in M2 and in M3; these weights were determined based on the proportion of time between M2 and M3 in which the participant resided at the M3 address. The study was reviewed and exempted by the University of Utah Institutional Review Board (No. 00157282).

Dependent Variable

Our measure of CMB disease encompassed six cardiovascular or metabolic diseases and related health behaviors: diagnosis or treatment for high blood pressure or hypertension in past 12 months, diagnosis or treatment for diabetes or high blood sugar in past 12 months, heart trouble ever suspected or confirmed by doctor (e.g., heart attack, angina, blocked artery), current abdominal obesity, yearly physical inactivity, and current cigarette smoking. Respondents self-reported hypertension, diabetes, and heart trouble (1 = yes, 0 = no). Abdominal obesity was measured by waist circumference thresholds of ≥102 cm for males and ≥88 cm for females (1 = yes, 0 = no). Respondents were provided with a tape measure to measure waist circumference at their navel. We included abdominal obesity instead of general obesity due to its greater predictive validity for CMB disease and mortality (Ashwell, Gunn, and Gibson 2012). Physical inactivity was assessed as the frequency of moderate and vigorous leisurely physical activity during summer and winter, measured with a 6-point scale; summer and winter activity were separately assessed and averaged together (Liu et al. 2022). Following recommendations of a minimum of weekly 150-minute moderate or 75-minute vigorous physical activities, we categorized respondents as physically inactive if they engaged in moderate activity fewer than several times a week or vigorous activity fewer than once a week, similar to a prior study (Liu et al. 2022). Respondents reported if they were a current cigarette smoker (1 = yes, 0 = no). To create the CMB disease score, we summed the six variables, creating a count variable ranging from 0 to 6.

We selected these indicators based on data available in the main MIDUS study and due to conceptual overlap with commonly used metrics (e.g., Life's Simple 7 and metabolic syndrome criteria; Hasbani et al. 2022). Although self-reported health conditions and behaviors are prone to reporting bias and measurement error (e.g., from undiagnosed cases), prior research has shown substantial agreement between self-reported hypertension, diabetes, and myocardial infarction, evident by kappa coefficients ranging from .75 to .80, with moderate agreement for heart failure (Okura et al. 2004). In an analysis of biomarker data among select MIDUS participants, those self-reporting heart trouble had substantially elevated cardiovascular biomarkers (e.g., triglycerides; Chai, Ayanian, and Almeida 2021). We also found substantial agreement between abdominal obesity derived from self-reported and technician-measured waist circumference for these participants (n = 1,201, κ = .66).

Independent Variables

We used ICE to assess spatial income and racial-ethnic polarization. Using American Community Survey (ACS) 2006–2010 five-year estimates, obtained through the National Historical Geographic Information System (Manson et al. 2022), we calculated ICE measures at two separate geographic levels using the following formula:

$$ICE_i = \frac{A_i - P_i}{T_i},$$

where A_i denotes the population in socially privileged categories in county$_i$ (or tract$_i$), P_i denotes the population in socially deprived or marginalized groups, and T_i represents the total population. The privileged group is defined for ICE_{income} as households above approximately the 80th income percentile or ≥$100,000, and deprived households are below approximately the 20th household income percentile or ≤$25,000. For ICE_{race}, the privileged group is defined as non-Hispanic [NH] White householders, and the socially marginalized group refers to householders of Black, Hispanic, or Native America/ Alaska Native race-ethnicity. Both variables were continuous with a range from −1 (complete deprivation) to 1 (complete privilege). We generated ICE at two geographic scales: (1) county level and (2) tract level residualized for county differences (i.e., the residuals after regressing tract ICE on county ICE).

Poverty Rate and Income Inequality

Using ACS 2006–2010 data (Manson et al. 2022), we defined the poverty rate as percentage of the population with an income-to-poverty ratio below 100%. The Gini coefficient was used to assess income inequality, with scores ranging from 0 (perfect equality) to 1 (perfect inequality). The poverty rate and Gini coefficient were included at county and tract levels, with the tract measure residualized by the county measure for each respective variable.

Mediators: Tract-Level Environmental Features

For the built environment, walkability in 2010 was assessed using the compactness composite index from the National Cancer Institute (Ewing and Hamidi 2014; Slotman et al. 2022). The index includes gross population density, gross employment density, job-population balance, degree of job mixing, weighted average walk score, percentage of small urban blocks, average block size, intersection density, and percentage of four-or-more-way intersections. Parkland availability was a continuous variable representing the percentage of total land that consists of parks accessible for outdoor recreation, as defined for tracts and the surrounding .5-mile buffer. Data came from the Parks and Protected Areas Database of the U.S (Version 2.1) but includes only parks that are publicly accessible for outdoor recreation (Browning et al. 2022).

To assess social risks, we created a composite measure that reflects six social and socioeconomic risks or resources: incarceration rate, census return rate, homeownership rate, rate of female-headed households with kids, unemployment rate, and labor force nonparticipation rate. The incarceration rate came from the Opportunity Atlas and was defined by the share of individuals age ≈30 incarcerated in 2010 among individuals whose parents were at the 25th income percentile and pooled across race and gender groups; this rate is calculated using the neighborhood where individuals lived for most of their childhood (Chetty et al. 2018). The 2010 decennial census return rate was included as a proxy for social capital (Rupasingha, Goetz, and Freshwater 2006). The homeownership rate, rate of female-headed households with own kids and no husband present, unemployment rate among adults 25 to 64, and labor force nonparticipation rate among males ages 35 to 64 came from the 2006–2010 ACS. A composite score of the six indicators was produced using principal component analysis, with higher scores indicating more social risks. In sensitivity tests, we excluded indicators that are arguably predominantly economic factors, retaining the incarceration rate, census mail return rate, and female-headed household rate, with results similar to those reported herein.

Three continuous variables were included to assess natural environmental features. We included a multiyear average of tract-level $PM_{2.5}$ concentration in μg/m^3 (fine particles with diameters of 2.5 micrometers or smaller) using data from the Center for Air, Climate, and Energy Solutions (Kim et al. 2020). Because pollution levels show greater year-to-year variability compared to other measures, we included the average $PM_{2.5}$ at two time periods: 2001 to 2005 for prevalent CMB at M2 and 2006 to 2010 for incident CMB from M2 to M3.

To assess the frequency of extreme summer heat, we calculated the number of heat island days using daily air temperature from the parameter-elevation regressions on independent slopes model (PRISM; Daly et al. 2007). PRISM uses data from 10,000 weather stations to estimate temperature for 800-meter gridded cells. The influence of each station is determined based on distance from the grid cell and its physiographic and climatic similarity, as determined by elevation, proximity to a coastline, aspect, topographic position, and atmospheric layer (Daly et al. 2007). We transformed the gridded data into daily tract- and county-level data for the contiguous United States using zonal statistics (2000–2019). We then calculated the sum of heat island days during summer months in 2000 to 2010 for each tract, defined as the sum of days when the average temperature was ≥95th percentile of that tract's host county summertime temperature between 2000 and 2019 (Clark et al. 2024).

Tree canopy cover was derived from the 2011 National Land Cover Database using U.S. Forest

Service (USFS) data. USFS calculates canopy cover using multispectral Landsat imagery and other ground and ancillary information (Coulston et al. 2012). We determined the census tract percentage of tree canopy cover from 30-meter gridded data using zonal statistics.

Covariates

Individual-level sociodemographic covariates included age in years, biological sex (male, female), race-ethnicity (NH White, NH Black American, Hispanic any race, NH Native American, NH Asian, NH other race), marital status (married/cohabiting, separated/divorced, widowed, never married), education (less than high school, completed high school, some college, four-year college degree or more), total household income (ln[1+household income]), nativity status (immigrant, born in the United States), and the MIDUS sampling approach (i.e., random digit dial, sibling, twin, city oversample, Milwaukee oversample). We included race-ethnicity, household income, and education in all models to capture associations with spatial social polarization independent of individual sociodemographic characteristics. As an area-level covariate, we included tract-level urban–rural classifications based on urban–rural locale definitions from the National Center for Education Statistics (city, suburb, town, rural, mixed; Slotman et al. 2022).

Analysis

We initially fit regression models to separately estimate ICE_{income} and ICE_{race} as predictors of CMB disease prevalence at M2 and incidence from M2 to M3. When modeling CMB disease incidence through M3, we adjusted for M2 CMB disease in autoregressive models (i.e., modeling residualized change from M2 to M3). We used generalized Poisson regression because CMB disease was measured as a count variable. In Model 1, we included only the respective ICE measure and the covariates described previously. Then, to test whether each ICE measure was associated with CMB disease independent of poverty and income inequality, we included the poverty rate (Model 2) and Gini coefficient (Model 3). Both county- and tract-level measures of ICE, poverty rate, and Gini coefficient were simultaneously modeled to estimate independent associations at different geographic levels.

To test mediation by local environmental features, we used path analysis to model predictors of CMB disease prevalence and incidence while estimating associations between county and tract ICE measures and the hypothesized mediators. To quantify the extent to which ICE and CMB associations were mediated, we used the difference-in-coefficients approach; this involved comparing the coefficients for ICE measures in models that omitted and then added mediators (Judd and Kenny 1981; MacKinnon et al. 2002). Initially, all potential mediators were simultaneously added to examine the extent to which the set of environmental features acted as mediators. In ad hoc tests, we individually tested tract features that were associated with ICE measures and CMB disease in a direction consistent with the hypothesized mediation. CMB disease included individual- and area-level covariates, and tract-level environmental mediators were adjusted only for tract urban-rural classifications. Path models were fit in Stata/SE 18.0 using the *gsem* command with maximum likelihood estimation, which requires only the conditional normality assumption be met for variables and can flexibly model variables with different response distributions. This method uses equation-wise deletion such that for a given equation, all observations with complete data are used. Due to missingness for select hypothesized mediators, the analytical sample included 2,468 participants for CMB disease prevalence and 1,658 participants for CMB disease incidence.

We conducted two sensitivity tests. First, we used quintiles for the ICE measures because prior research has shown that the relationship between social polarization and CMB disease may be nonlinear (Chambers et al. 2019; Krieger et al. 2016, 2018). Second, in the path model, we adjusted all endogenous variables for tract- and county-level Gini coefficient. Because income inequality is a likely cause of income polarization (Fogli and Guerrieri 2019; Jargowsky 1996), adjusting for the Gini coefficient allowed us to estimate the independent association between income polarization and CMB disease—but such associations are likely conservative.

RESULTS

Table 1 reports the descriptive statistics of the sample characteristics, and Table 2 presents the descriptive statistics for area-level variables. Respondents had an average of 1.86 CMB diseases or risk factors at M2 and 2.01 at M3. Compared to ICE_{income}, where the mean respondent did not live in an income-privileged or income-deprived area, the mean for ICE_{race} shows that participants lived in areas with a

Table 1. Sample Characteristics, the Midlife in the United States Study.

Variables	Mean ± SD	%
M2 cardiometabolic disease	1.86 ± 1.27	
Hypertension		31.49
Diabetes		10.51
Heart trouble		17.45
Abdominal obesity		49.38
Cigarette smoking		15.85
Physical inactivity		60.81
M3 cardiometabolic disease	2.01 ± 1.32	
Hypertension		39.52
Diabetes		14.78
Heart trouble		21.97
Abdominal obesity		56.66
Cigarette smoking		10.00
Physical inactivity		57.83
M2 age, in years	55.51 ± 12.13	
Female biological sex		54.17
Race		
NH White		83.79
NH Black American		10.68
Hispanic, any race		2.49
NH Native American		1.30
NH Asian		.46
NH other race		1.27
M2 marital status		
Married/cohabiting		68.89
Separated/divorced		15.23
Widowed		6.91
Never married		8.97
Education		
Less than high school		6.18
Completed high school		26.80
Some college		28.70
4-year college degree or more		38.32
M2 household income (in $1,000)	71.99 ± 58.43	
Nativity (U.S.-born)		96.18

Note: M2 sample size = 3,690; M3 sample size = 2,381. M2 = Wave 2; M3 = Wave 3; NH = non-Hispanic.

relatively high concentration of the privileged racial-ethnic group (i.e., NH White persons).

Associations between ICE Measures and CMB Disease

We used Poisson regression to estimate the association between ICE measures and CMB disease prevalence and incidence. Findings are presented in Table 3. As shown in Model 1, both county and tract ICE_{income} were associated with CMB disease prevalence and incidence. In particular, individuals in more income-privileged relative to income-deprived counties and tracts had reduced CMB disease prevalence at M2 and reduced incidence between M2 and M3. The prevalence rate was 34.0% and 20.2% lower with a 1-unit increase in ICE_{income} at the county and tract levels, respectively, whereas the incidence rate was 16.6% and 15.9% lower with a 1-unit increase in county and tract ICE_{income}, respectively. These associations remained significant and were of a comparable magnitude after adjusting for the county and tract poverty rate (Model 2) and Gini coefficient (Model 3). By contrast, county and tract

Table 2. Descriptive Statistics for Participant Exposure to Area-Level Variables, the Midlife in the United States Study.

Area Variables	Mean ± SD
ICE measures, range = −1 to 1	
County ICE_{income}	−.04 ± .16
Tract ICE_{income}	.00 ± .28
County ICE_{race}	.58 ± .31
Tract ICE_{race}	.59 ± .48
Poverty rate, %	
County	13.46 ± 5.01
Tract	12.21 ± 10.50
Income inequality (Gini), range = 0–1	
County	.44 ± .03
Tract	.41 ± .06
Tract environmental features	
Walkability	95.74 ± 23.23
Parkland availability, %	8.08 ± 11.82
Social risks[a]	−.14 ± 1.68
$PM_{2.5}$ concentration (2001–2005), μg/m^3	11.50 ± 2.66
$PM_{2.5}$ concentration (2006–2010), μg/m^3	10.00 ± 2.23
Heat island days, *n*	50.88 ± 36.73
Tree canopy cover, %	22.83 ± 20.10

Note: Descriptive statistics refer to exposure at Wave 2, with the exception of $PM_{2.5}$ (2006–2010), which uses a weighted average of Wave 2 and Wave 3 residence. The sample size is 3,690 for area-level economic measures. Sample sizes are smaller for most tract environmental features (generally, *n* = 3,684; although, *n* = 2,473 for walkability). Data sources for area-level variables are described in Appendix Table A1 in the online version of the article. ICE = Index of Concentration at the Extremes; $PM_{2.5}$ = particulate matter with diameter of 2.5 micrometers or smaller.
[a]The social risks composite was calculated using principal component analysis with six indicator variables.

ICE_{race} were not associated with CMB disease prevalence or incidence in any of the models (see Table 4).

Mediation Analysis for Environmental Features

Given our findings that ICE_{income} predicts CMB disease prevalence and incidence, we used path analysis to test tract-level environmental features as mediators of these associations. Environmental features were standardized to facilitate the comparison of estimates across predictors. The estimates are presented in Table 5 and Figure 1. Model results indicated that both county and tract ICE_{income} remained associated with CMB disease prevalence and incidence after adjustment for tract environmental features. Moreover, we found limited evidence of mediation. In particular, accounting for tract environmental features, associations between tract ICE_{income} and CMB disease prevalence and incidence increased by 42.9% and 17.5%, respectively, whereas estimates for county ICE_{income} increased by 13.8% for CMB prevalence but was attenuated by 10.8% for CMB disease incidence. The increased magnitude of coefficients represents the magnitude of suppression rather than mediation. Unlike mediation, where controlling for a third variable reduces and obscures the true association, suppression occurs when controlling for a third variable strengthens the relationship (MacKinnon, Krull, and Lockwood 2000).

County and tract ICE_{income} were independently associated with nearly all tract environmental features. In particular, higher county and tract ICE_{income} were associated with lower walkability, greater parkland availability, fewer social risks, lower $PM_{2.5}$ concentration, and fewer heat island days. Higher tract but not county ICE_{income} was associated with more tree canopy coverage. Although the direction of most of these estimates is consistent with the potential for tract environmental features to mediate the association between ICE_{income} and CMB disease, only $PM_{2.5}$ concentration and heat island days were associated with either CMB

Table 3. Poisson Regression Model Results for County and Tract ICE_{income} as Predictors of Cardiometabolic Disease Prevalence and Incidence, the Midlife in the United States Study.

	Model 1	Model 2	Model 3
Predictor Variable	IRR (95% CI)	IRR (95% CI)	IRR (95% CI)
Outcome: CMB disease prevalence			
County ICE_{income}	.66*** (.56, .78)	.57*** (.43, .76)	.61*** (.51, .73)
Tract ICE_{income}	.80*** (.71, .89)	.76** (.65, .89)	.78*** (.69, .88)
County poverty rate		.99 (.99, 1.00)	
Tract poverty rate		1.00 (1.00, 1.00)	
County Gini coefficient			.51⁺ (.24, 1.11)
Tract Gini coefficient			.56** (.38, .83)
Outcome: CMB disease incidence			
County ICE_{income}	.83* (.71, .98)	.72* (.56, .94)	.80** (.68, .94)
Tract ICE_{income}	.84** (.76, .93)	.82** (.70, .95)	.85** (.76, .95)
County poverty rate		.99 (.99, 1.00)	
Tract poverty rate		1.00 (1.00, 1.00)	
County Gini coefficient			.46* (.22, .99)
Tract Gini coefficient			.89 (.60, 1.32)

Note: Wave 2 sample size = 3,690; Wave 3 sample size = 2,381. All models controlled for Wave 2 covariates: age, biological sex, race-ethnicity, marital status, education, total household income, nativity status, MIDUS sampling, and urban-rural classifications. Wave 2 CMB disease was adjusted in the longitudinal models. Standard errors were adjusted to account for clustering of participants within census tracts. IRR = incidence rate ratio; CI = confidence interval; CMB disease = cardiometabolic disease; ICE = Index of Concentration at the Extremes.
⁺$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 4. Poisson Regression Model Results for County and Tract ICE_{race} as Predictors of Cardiometabolic Disease Prevalence and Incidence, the Midlife in the United States Study.

	Model 1	Model 2	Model 3
Predictor Variables	IRR (95% CI)	IRR (95% CI)	IRR (95% CI)
Outcome: CMB disease prevalence			
County ICE_{race}	.98 (.90, 1.07)	1.04 (.95, 1.15)	.97 (.88, 1.06)
Tract ICE_{race}	.96 (.90, 1.04)	1.00 (.92, 1.09)	.96 (.90, 1.03)
County poverty rate		1.01** (1.00, 1.01)	
Tract poverty rate		1.00⁺ (.99, 1.01)	
County Gini coefficient			.66 (.29, 1.49)
Tract Gini coefficient			.74 (.51, 1.09)
Outcome: CMB disease incidence			
County ICE_{race}	1.04 (.96, 1.13)	1.07 (.98, 1.16)	1.01 (.93, 1.10)
Tract ICE_{race}	.98 (.92, 1.05)	1.00 (.92, 1.09)	.98 (.92, 1.06)
County poverty rate		1.00 (1.00, 1.01)	
Tract poverty rate		1.00 (1.00, 1.00)	
County Gini coefficient			.54 (.24, 1.18)
Tract Gini coefficient			1.04 (.71, 1.53)

Note: Wave 2 sample size = 3,690; Wave 3 sample size = 2,381. All models controlled for Wave 2 covariates: age, biological sex, race-ethnicity, marital status, education, total household income, nativity status, MIDUS sampling, and urban-rural classifications. Wave 2 CMB disease was adjusted in the longitudinal models. Standard errors were adjusted to account for clustering of participants within census tracts. IRR = incidence rate ratio; CI = confidence interval; CMB disease = cardiometabolic disease; ICE = Index of Concentration at the Extremes.
⁺$p < .10$. **$p < .01$.

Table 5. Path Analysis Results Testing Tract Environmental Features as Mediators of the Associations between ICE_{income} and Cardiometabolic Disease Prevalence and Incidence, the Midlife in the United States Study.

Endogenous Variables	Exogenous Variables	IRR (95% CI)
M2 CMB disease	County ICE_{income}	.93*** (.90, .97)
	Tract ICE_{income}	.94** (.90, .98)
	Walkability	.93** (.90, .97)
	Parkland availability	1.01 (.98, 1.05)
	Social risks	.99 (.94, 1.03)
	$PM_{2.5}$ concentration	1.03+ (1.00, 1.06)
	Heat island days	1.00 (.98, 1.03)
	Tree canopy cover	.98 (.95, 1.02)
M3 CMB disease	County ICE_{income}	.97+ (.94, 1.00)
	Tract ICE_{income}	.96* (.92, 1.00)
	Walkability	.98 (.94, 1.01)
	Parkland availability	.98 (.94, 1.02)
	Social risks	.98 (.94, 1.03)
	$PM_{2.5}$ concentration	1.03+ (1.00, 1.06)
	Heat island days	1.02+ (1.00, 1.04)
	Tree canopy cover	.99 (.96, 1.03)
	M2 CMB disease	1.38*** (1.35, 1.41)
		B (95% CI)
Walkability	County ICE_{income}	−.07** (−.09, −.03)
	Tract ICE_{income}	−.22*** (−.25, −.19)
Parkland availability	County ICE_{income}	.13*** (.10, .17)
	Tract ICE_{income}	.08*** (.06, .11)
Social risks	County ICE_{income}	−.34*** (−.37, −.31)
	Tract ICE_{income}	−.61*** (−.66, −.55)
$PM_{2.5}$ concentration	County ICE_{income}	−.13*** (−.16, −.11)
	Tract ICE_{income}	−.12*** (−.15, −.09)
Heat island days	County ICE_{income}	−.06*** (−.09, −.02)
	Tract ICE_{income}	−.04** (−.07, −.01)
Tree canopy cover	County ICE_{income}	.02 (−.01, .05)
	Tract ICE_{income}	.09*** (.06, .11)

Note: Wave 2 sample size = 2,468; Wave 3 sample size = 1,658. All area-level variables were standardized such that estimates refer to standard deviation units. For CMB disease outcomes, we controlled for Wave 2 covariates: age, biological sex, race-ethnicity, marital status, education, total household income, nativity status, MIDUS sampling, and urban-rural classifications. For tract environmental features, only urban–rural classification is adjusted as a covariate. IRR = incidence rate ratio; CI = confidence interval; *B* = regression coefficient; CMB disease = cardiometabolic disease; ICE = Index of Concentration at the Extremes; $PM_{2.5}$ = particulate matter with diameters of 2.5 micrometers or smaller.
$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

disease prevalence or incidence in the direction consistent with mediation (only at $p < .10$). Specifically, higher ICE_{income} was associated with reduced CMB prevalence and incidence, partially attributed to decreased exposure to $PM_{2.5}$ concentrations and fewer heat island days, respectively. By contrast, tract walkability, lower in counties and tracts with higher ICE_{income}, was associated with reduced CMB disease prevalence such that walkability likely acts as a suppressor.

To increase the specificity of mediation tests, we individually tested $PM_{2.5}$ and heat island days as mediators. For results, see Tables A2 and A3 in the Appendix in the online version of the article. $PM_{2.5}$

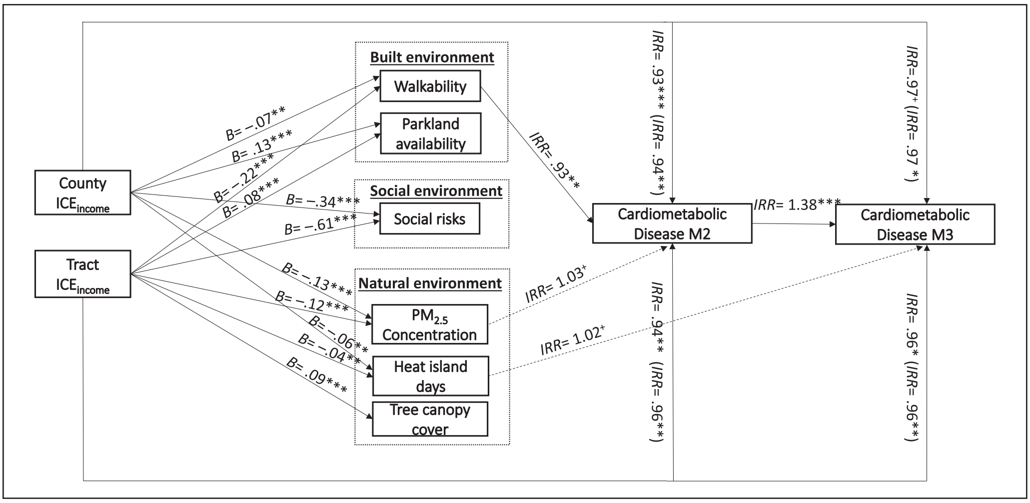

Figure 1. Path Model Testing Tract-Level Environmental Features as Mediators of the Associations between ICE_{income} and Cardiometabolic Disease Prevalence and Incidence, the Midlife in the United States Study.

Note: Wave 2 sample size = 2,468; Wave 3 sample size = 1,658. For direct effects of county and tract ICE_{income}, incidence risk ratios (IRR) from a model that excludes the mediators are reported in parentheses. Only paths significant at $p < .05$ are shown as a solid line, dashed lines are used for paths significant at $p < .10$, and all tract environmental features are included as predictors of cardiometabolic (CMB) disease outcomes. ICE = Index of Concentration at the Extremes; $PM_{2.5}$ = Particulate matter with diameters of 2.5 micrometers or smaller.
$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

concentration was associated with CMB disease prevalence (but not incidence) and attenuated the estimates of county and tract ICE_{income} by 2.6% and 3.8%, respectively. Heat island days was associated with CMB disease incidence and attenuated estimates of county and tract ICE_{income} as predictors by 5.2% and 2.8%, respectively.

Sensitivity tests are presented in the Appendix in the online version of the article. Results using quintiles for ICE_{income}, as shown in Appendix Table A4 (in the online version of the article), show that higher levels of county and tract ICE_{income} were associated with reduced CMB disease prevalence and incidence, with estimates showing a gradient for the prevalence rate. The gradient was less distinct for CMB disease incidence because the rate was lowest for Quintiles 3 and 5, whereas Quintiles 2 and 4 showed a reduced but nonsignificant difference. Results for ICE_{race} quintiles are presented in Appendix Table A5, in the online version of the article, and show reduced but nonsignificant differences in CMB prevalence and incidence at higher quintiles relative to the lowest. We also tested whether adjusting for county and tract Gini coefficient altered the mediation findings (see Appendix Table A6 in the online version of the article). The pattern of findings is similar with some notable differences. The estimate for tract ICE_{income} and CMB disease incidence is similar but nonsignificant. The associations between county ICE_{income} and walkability, tract ICE_{income} and social risks, and tract ICE_{income} and $PM_{2.5}$ concentration were reduced when controlling for income inequality.

DISCUSSION

The spatial concentration of both privilege and deprivation likely contributes to CMB disease. Using longitudinal data from a sample of U.S. adults, this study is among the first to examine how spatial polarization by income and racial groups at multiple geographic levels is associated with CMB disease. The results indicate that higher county- and tract-level ICE_{income} (i.e., the concentration of privileged relative to deprived income groups) were independently associated with reduced CMB disease prevalence and incidence. The findings are consistent with cross-sectional research showing that higher ICE_{income} is associated with lower risk of hypertension and cardiovascular-related mortality (Feldman et al. 2015; Krieger et al. 2018) but extends this evidence using longitudinal data.

Associations between income polarization and CMB disease were independent of area-level poverty and income inequality and individual sociodemographic characteristics. The present study offers evidence that county and tract income polarization may be especially predictive of CMB disease compared to more commonly used measures of economic conditions (Krieger et al. 2016).

In addition, we find that both county and tract ICE_{income} are independently associated with most tract environmental features but that such features do not mediate the association between ICE_{income} and CMB disease. In particular, areas with more income-privileged relative to income-deprived groups generally had more health-promoting environmental features, including greater parkland availability, fewer social risks, lower $PM_{2.5}$ concentration, fewer heat island days, and more tree canopy cover. However, tract environmental features did not mediate the association between ICE_{income} and CMB disease, and estimates for tract ICE_{income} increased when accounting for environmental features. Although not all potential area-level mediators were included, this study offers among the most thorough tests of whether the link between income polarization and health is mediated by local environment features. These results broadly support fundamental cause theory (Phelan et al. 2010), as income polarization is associated with an array of resources and disamenities while independently predicting CMB disease. Notably, the patterning of local environmental features by income may have increased in recent decades with the rise in income polarization (Curtis et al. 2024).

Three tract environmental features were associated with CMB disease: walkability, $PM_{2.5}$ concentration, and heat islands days. Walkability may act as a suppressor, however, given that ICE_{income} was inversely associated with walkability and greater walkability was associated with reduced CMB disease prevalence. This finding aligns with research showing that more socioeconomically advantaged areas are generally less walkable and that less walkable areas show larger increases in socioeconomic status over time (Curtis et al. 2024). County and tract ICE_{income} may predict CMB disease prevalence through reduced exposure to $PM_{2.5}$ concentration, whereas county and tract ICE_{income} predict lower CMB disease incidence through fewer heat island days. $PM_{2.5}$ and heat island days were relatively weak mediators given that associations between ICE_{income} and CMB disease outcomes were attenuated by less than 10%. Nonetheless, findings are consistent with the environmental justice and epidemiological literature. Exposure to ambient particulate matter may discourage health-promoting physical activity and increase systemic inflammation and oxidative stress, thereby increasing CMB disease risk (Raza et al. 2021; Yang et al. 2020). Additionally, residing in income-privileged areas may confer a health advantage by reducing exposure to extreme heat events (e.g., by affecting sleep quality; Ashe et al. 2025). Notably, in the past decades, $PM_{2.5}$ has declined while extreme heat exposure has increased, such that the relationship between income polarization and the natural environment likewise may be evolving (Clark et al. 2024).

Other area features may plausibly account for the relationship between income polarization and CMB disease. For instance, lower ICE_{income} may be associated with perceptions of neighborhood disorder and a lack of social cohesion. Perceived neighborhood disorder could, in turn, increase mental health problems while discouraging healthy behaviors, such as physical activity (Barber et al. 2018; Lee 2009). Furthermore, unequal access to health care services may exacerbate health disparities between income-privileged and income-deprived areas (Kirby and Kaneda 2005). Future research should explore additional neighborhood features as potential mechanisms.

Policy interventions may be necessary to reduce income polarization and therefore prevent CMB disease. Zoning reforms that promote mixed-income neighborhoods, such as increasing the supply of affordable housing in affluent areas, can allow lower-income households to access higher quality neighborhoods and community amenities. Housing voucher programs, informed by the Moving to Opportunity for Fair Housing program, could reduce income segregation by enabling low-income families to move outside of high-poverty neighborhoods, thereby improving access to health-promoting resources (Ludwig et al. 2013). Lastly, policies aimed at reducing disproportionate exposure to $PM_{2.5}$ pollution and heat island days in more income-deprived areas—such as stricter pollution regulations—may reduce the link between income polarization and CMB disease risk.

We also found that county and tract ICE_{race} were not associated with CMB disease outcomes, a finding that contradicts a few prior studies (Feldman et al. 2015; Pool et al. 2018). Existing studies have consistently demonstrated that racial segregation is associated with CMB disease, especially among Black Americans (Kershaw and Albrecht 2015). The null association in the present study may result from the MIDUS sample composition or limitations in the ICE measure. In particular, the MIDUS sample is predominantly White, and participants may have been in counties and tracts with a higher concentration of privileged relative to marginalized racial-ethnic groups and with less variation in this measure compared to prior research. Additionally, our construct of racial polarization encompasses three racial-ethnic groups, with Black and Hispanic being the predominant groups. Prior research has shown that residents in Hispanic ethnic enclaves may have improved health outcomes due to culture-specific health resources (Kershaw et al. 2013). Therefore, the contextual health risks related to racial polarization may vary across racial-ethnic groups. The strength of the relationship between racial segregation and health is likely to vary based on the extent to which segregation results in unequal spatial concentration of resources, deprivation-linked problems, and environmental conditions (Anderson 2016).

The study has some notable limitations. First, the dependent variable relied on self-reports of CMB disease, which introduces the potential for bias stemming from undiagnosed condition or social desirability bias. Research on segregation and health is needed that includes biomarkers of CMB functioning, especially as economically disadvantaged individuals may be more likely to have undiagnosed conditions. Second, neighborhoods are not randomly assigned, and we could not account for residential self-selection bias where individuals who are healthier also are more likely to move to neighborhoods with health-promoting features. We attempted to mitigate against such bias through the use of longitudinal analysis and adjustment for individual-level characteristics (e.g., household income) that are correlates of housing quality and residential moves, yet residential preferences remain a potential confounder. Third, participant attrition reduces generalizability and may result in biased estimates, particularly for the longitudinal relationship. The MIDUS sampling methodology also has limitations, such as a lack of national representativeness and limited racial-ethnic diversity (Carbone and Clift 2021). Relatedly, the oversampling of Black Americans from Milwaukee results in limited variation for area measurements and reduced sample generalizability. Research with a more racial-ethnic diverse sample testing mediators of the association between spatial social polarization and health is warranted.

The findings from this study demonstrate that greater income polarization, capturing the concentration of income-based privilege relative to deprivation in tracts and counties, predicts lower prevalence and incidence of CMB disease. Accounting for tract environmental features increased associations between tract ICE_{income} and CMB prevalence and incidence rather than mediating these relationships. However, natural environmental features (i.e., $PM_{2.5}$ concentration and heat island days) acted as partial, albeit weak, mediators. These findings advance the prior literature through the use of longitudinal design, the incorporation of income and racial-ethnic polarization at county and tract levels, and the investigation of tract environmental features as mediators. Income polarization locally and regionally patterns both environmental inequities and cardiometabolic disease.

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DATA AVAILABILITY

The Midlife in the United States (MIDUS) Study has publicly available data for analysis. Area-level data were merged using participants' residential addresses by the research team in the MIDUS study.

SUPPLEMENTAL MATERIAL

Tables A1 through A6 are available in the online version of the article.

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